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Idiosyncratic volatility, option-based measures of informed trading, and investor attention

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Abstract

We establish a direct link between sophisticated investors in the option market, private stock market investors, and the idiosyncratic volatility (IVol) puzzle. To do so, we employ three option-based volatility spreads and attention data from Google Trends. In line with the IVol puzzle, the volatility spreads indicate that sophisticated investors indeed consider high-IVol stocks as being overvalued. Moreover, the option measures help to distinguish overpriced from fairly priced high-IVol stocks. Thus, these measures are able to predict the IVol puzzle's magnitude in the cross-section of stock returns. Further, we link the origin of the IVol puzzle to the trading activity of irrational private investors as the return predictability only exists among stocks that receive a high level of private investor attention. Overall, our joint examination of option and stock markets sheds light on the behavior of different investor groups and their contribution to the IVol puzzle. Thereby, our analyses support the intuitive idea that noise trading leads to mispricing, which is identified by sophisticated investors and exploited in the option market.

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1 Introduction

Investor groups differ with respect to their behavior in financial markets. In particular, sophisticated and private investors deviate with respect to their relation to stock mispricing. Theoretical evidence suggests that sophisticated investors recognize mispricing and try to exploit it, while irrational traders cause prices to diverge from fundamental values in the first place (De Long et al. 1990; Shleifer and Vishny 1997). We test this theoretical prediction on the idiosyncratic volatility (IVol) puzzle. The IVol puzzle depicts a stock market anomaly that has recently received increased attention in both research and investment industry (Ang et al. 2006; Boyer et al. 2010; Stambaugh et al. 2015; Hou and Loh 2016; Li et al. 2016).[1] We find support for the theoretical prediction relying on option-based measures of informed trading, which indicate that sophisticated investors trade against overvalued high-IVol stocks in the option markets. Moreover, we show that the magnitude of the IVol puzzle depends on these option-based measures of informed trading. Turning to the underlying source of the mispricing, we find the IVol puzzle to be statistically significant only if a shock in private investor attention moves stock prices beyond their fundamental values. These overall insights support and extend behavioral explanations for the IVol puzzle. In addition, they provide comprehensive evidence on how different investor groups influence market efficiency and thereby the efficient allocation of capital in financial markets.

More specifically, we test three hypotheses to examine the empirical link between the IVol puzzle and different investor groups. First, we expect the IVol puzzle to be strongest among stocks that are considered to be overvalued by sophisticated investors. Since not every single high-IVol stock is overvalued, we hypothesize that the opinion of sophisticated investors can be used to distinguish between mispriced and fairly priced high-IVol stocks. To measure the opinion of sophisticated investors empirically, we apply the three option-implied volatility spreads proposed by Bali and Hovakimian (2009), Cremers and Weinbaum (2010), and Xing et al. (2010). The authors argue that these measures show demand pressure in call versus put options (Bollen and Whaley 2004; Garleanu et al. 2009). As a consequence, the measures reflect the superior information of sophisticated investors that is not immediately reflected in stock prices.[2] Applying the three measures, we find that the IVol puzzle is more pronounced among stocks for which informed

[1] The IVol puzzle refers to the anomaly that high-IVol stocks yield comparably low subsequent returns despite their high level of idiosyncratic risk.

[2] Empirically differentiating between private investors and sophisticated investors is rather difficult as both investor groups are present in both the stock and the option markets. However, as shown by Lemmon and Ni (2014), discount customers (private investors with small trades) are responsible for only about 15% of all trades in individual stock options. Thus, the proportion of sophisticated investors dominates trading

trading points towards an overvaluation. Vice versa, we show the return spreads associated with IVol to be smaller if the measures of informed trading indicate no overvaluation.

Second, we hypothesize that the IVol puzzle is particularly strong if stocks experience high private investor attention since theoretical considerations frequently link irrational private investors to the origin of mispricing. We use Google Search volume as a direct attention measure proposed by Da et al. (2011).[3] 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 confirm that the IVol puzzle's magnitude increases from insignificant 0.09% per week among low-attention stocks to significant 0.16% among high-attention stocks.

Our third central hypothesis is that the IVol puzzle is most pronounced for stocks that are both considered overvalued by sophisticated investors and prone to high private investor attention. This hypothesis is supported in conditional triple sorts that jointly investigate the interplay of informed trading, investor attention, and idiosyncratic volatility. During low investor attention periods, the IVol puzzle disappears. In high investor attention periods, on the contrary, we observe a very pronounced IVol puzzle among the stocks with negative sophisticated trader opinion. These results strongly support the following intuitive line of argument for the IVol puzzle: irrational noise trading can lead to an overvaluation of high-IVol stocks, which is identified by sophisticated investors and exploited in the option market.

To further support these behavioral arguments, we refer to previous empirical evidence and investigate the role of illiquidity and short-sell constraints. Studies have shown that first, mispricing is more likely to persist if limits to arbitrage are high, that is, if liquidity is low (see, for example, Lam and Wei 2011). Second, Blau and Brough (2015) argue that sophisticated investors especially prefer to trade in the option market if shorting in the stock market is constrained. In line with these arguments, we show that the previously documented phenomena tend to be stronger among stocks with high Amihud (2002) illiquidity, low institutional ownership, high bid-ask-spreads, and high option-implied volatility.

The remainder of this paper is organized as follows. Section 2 introduces the empirical data as well as the construction of the key and control variables. Moreover, we provide summary statistics for these variables. Section 3 tests our three hypotheses. Section 3.1 examines the relation between the IVol puzzle and informed trading. Section 3.2 presents our analyses on the interaction between the IVol puzzle and private investor attention. Section 3.3 tests the joint interplay of the IVol puzzle, sophisticated investors, and private investor attention. In Sect. 3.4, we provide further empirical evidence with respect to the impact of illiquidity and short-sell constraints. Finally, Sect. 4 concludes.

activity in the option market (Jarrow et al. 2018), which justifies the use of option data to elicit sophisticated investors' opinions.

[3] While Google Trends directly measures search activity for a specific company, other attention measures such as a firm's press coverage represent only indirect attention proxies that assume a positive relation between information demand and information supply.

2 Data and summary statistics

We construct our sample by merging weekly option market data from OptionMetrics (IvyDB) with weekly stock market data from the Center for Research in Security Prices (CRSP), covering the period from January 1996 to April 2016. Further, accounting data comes from Compustat. Daily data on the risk-free rate and the Fama-French-Carhart (FFC) factors are obtained from Kenneth R. French's homepage. Our analyses make use of all common ordinary shares trading on NYSE, AMEX, or NASDAQ. Observations are included if idiosyncratic volatility, measures of informed trading, and all control variables as elaborated in this section are available. This procedure leads to 797,169 firm-week-observations in total. To measure investor attention, we use Google Trends data for a truncated sample period beginning in 2005. We apply a weekly framing for two reasons. First, the measures of informed trading are particularly able to identify short-run mispricing. Second, Google Trends data is provided at a weekly frequency.

2.1 Variable construction

2.1.1 Idiosyncratic volatility

IVol is the annualized idiosyncratic return volatility of the most recent week based on FFC-adjusted returns. These FFC-adjusted returns are calculated as the difference between realized daily excess returns and FFC-implied daily returns. More precisely, we estimate the FFC-factor loadings using daily returns over the previous year, skipping one month, and calculate the FFC-implied daily returns as FFC-factor returns times estimated factor loadings. 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 regressions with, at maximum, five observations and four explanatory variables, which would imply very unreliable factor loading estimates. Moreover, comparing these two methodologies, differences are marginal: the untabulated correlation between IVol based on pre-estimated factor loadings and IVol based on the Ang et al. (2006)-approach is 0.97 for monthly estimates.

2.1.2 Measures of informed trading

The three measures of informed trading are based on implied volatility data from OptionMetrics. We use data from the last trading day of each week (usually Friday) for all individual stock options maturing within 10 to 180 days.[4] 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. All implied volatilities are adjusted for dividends

[4] The choice of maturities is similar to Bali and Hovakimian (2009), Xing et al. (2010), or Stilger et al. (2017). Moreover, no significant correlation exists between measures of informed trading and option maturities such that our findings are not driven by the term structure of option-implied volatility.

and potential early exercise premiums. To ensure sufficient option availability and liquidity, we consider only those maturities with at least four options—two out-of-the-money put options and two out-of-the-money call options—and discard options with nonstandard settlement. If different option maturities are available for a given stock, we choose the option set with the shortest time to maturity.

The volatility spread measure $\mathrm{VS}_{\mathrm{CW}}$ by Cremers and Weinbaum (2010) is calculated based on differences between call-implied volatilities IV_C and put-implied volatilities IV_P, where call and put have identical strike prices. These spreads are aggregated across strike prices using the underlying options' open interest as weights w. Formally, the measure for firm i in week t reads

$$\mathrm{VS}_{\mathrm{CW}}^{i,t} = \sum_{j=1}^{N^{i,t}} w_j^{i,t} \left(IV_{C,j}^{i,t} - IV_{P,j}^{i,t} \right),$$

where $N^{i,t}$ is the number of valid call-put-option-pairs j on stock i at week t. Cremers and Weinbaum (2010) show that their measure captures demand differences in call versus put options and thus reflects informational price pressure in the option market.

A similar finding is put forward by Bali and Hovakimian (2009), who also show that differences between call- and put-implied volatility proxy for option-embedded superior information. The corresponding volatility spread $\mathrm{VS}_{\mathrm{BH}}$ is computed as the difference in average implied volatilities between near-the-money call ($\overline{IV}_{NTMC}^{i,t}$) and put options ($\overline{IV}_{NTMP}^{i,t}$), i.e.,

$$\mathrm{VS}_{\mathrm{BH}}^{i,t} = \overline{IV}_{NTMC}^{i,t} - \overline{IV}_{NTMP}^{i,t}$$

for firm i in week t. Thereby, an option is considered near-the-money if its log-moneyness is below 0.1 in absolute terms.

Finally, we examine the implied volatility SMIRK following Xing et al. (2010). They argue that informed traders with negative information in particular buy out-of-the-money put options—either to hedge existing positions or to speculate on negative returns. To measure these demand effects, Xing et al. (2010) define SMIRK as the difference between out-of-the-money put (OTMP) and at-the-money call (ATMC) implied volatility. To allow for a directional consistent comparison with $\mathrm{VS}_{\mathrm{CW}}$ and $\mathrm{VS}_{\mathrm{BH}}$, we set

$$\mathrm{SMIRK}^{i,t} = IV_{ATMC}^{i,t} - IV_{OTMP}^{i,t}.$$

The ATMC option is defined as the call option that shows the smallest deviation from a moneyness of 1 in absolute terms. The OTMP option is the put option with a moneyness closest to but below 0.95. All three measures—$\mathrm{VS}_{\mathrm{CW}}$, $\mathrm{VS}_{\mathrm{BH}}$, and SMIRK—are signed, i.e., low values indicate an overhang of negative information and vice versa.

2.1.3 Investor attention

To examine the impact of private investors on the IVol puzzle, we use Google Trends data to identify stocks that receive unusually high investor attention. Google provides weekly relative search frequency data (https://trends.google.com/) from 2004 onwards. According to Da et al. (2011), these search volume indices provide a timely measure of firm-level investor attention. Moreover, they consider Google Search volumes to reflect, in particular, private investor behavior such that we can use the data to test our second hypothesis that the IVol puzzle is related to 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. Note that we adjust the Compustat firm names as we delete the legal form of the entity and share class codes. Moreover, we undo abbreviations. Based on this data set, following Da et al. (2011), the abnormal search volume index (ASVI) is calculated as the log-difference between the Google Search Volume Index ($GSVI$) of one week and the median Google Search Volume Index of the previous eight weeks, i.e.,

$$\mathrm{ASVI}_t = \log GSVI_t - \log\left(\mathrm{median}\left(GSVI_{t-1}, \ldots, GSVI_{t-8}\right)\right).$$

2.1.4 Control variables

All control variables are measured at the portfolio formation date at the end of each week unless stated otherwise. Being strongly correlated with IVol, we consider the maximum daily return of the previous week (MAX) as the weekly version of the maximum daily return of the previous month, as proposed by Bali et al. (2011). REV denotes the stock return of the previous week as a proxy for short-term reversal (Jegadeesh 1990). The market value of equity (MV) is calculated as the closing share price times the number of shares outstanding. The book value of equity is used in accordance with Fama and French (1993), i.e., we exclude firms with negative book values and do not use annual balance sheet data 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. Further, we include momentum (Jegadeesh and Titman 1993) measured as the return over the previous year skipping the most recent month (MOM). Finally, we estimate the illiquidity measure, ILLIQ, following Amihud (2002): ILLIQ is the ratio of absolute daily return to daily dollar trading volume averaged over the previous year.

2.2 Summary statistics

Table 1 presents pooled descriptive statistics on IVol, the three measures of informed trading, MAX, short-term reversal, the logarithm of firm size, book-to-market, momentum, Amihud (2002) illiquidity, and the abnormal search volume index. Moreover, correlation coefficients are provided.[5] Several points are noteworthy. Our sample con-

[5] In Online Appendix Table A1, we also state time-series averages of cross-sectional summary statistics and correlation coefficients.

sists of rather large, liquidly traded stocks with a median market capitalization of 3.8 bn USD and a median Amihud measure of 0.47.[6] The distributions of VS_{CW} and VS_{BH} are very similar. Their negative average values show that put-implied volatilities tend to exceed call-implied volatilities. SMIRK is even more negative on average since it does not only reflect implied volatility spreads between calls and puts, but also the on average negative slope of the implied volatility curve, i.e., it also takes the skewness of the risk-neutral density into account.

Turning to the correlations, we find support for a negative relationship between IVol and the three measures of informed trading: Each of the three measures tends to be higher for low- compared to high-IVol stocks. This observation is in line with the hypothesis that sophisticated investors recognize the overvaluation of high-IVol stocks and buy corresponding put options. This demand would imply comparably high put-implied volatilities and result in low option-implied volatility spreads. Not surprisingly, as all these three volatility spreads are used to proxy informed trading, the correlation among VS_{CW}, VS_{BH}, and SMIRK is strongly positive indicating similar information content. 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) for a monthly sample. Finally, IVol and investor attention are positively correlated with a correlation coefficient of 0.13, indicating comparably high attention for stocks with high idiosyncratic volatility.

3 Empirical results

3.1 The IVol puzzle and sophisticated investors

The cross-sectional return predictability of IVol and option-implied volatility spreads is well-documented in the previous literature. Referring to the former, Han and Kumar (2013), Stambaugh et al. (2015), Hou and Loh (2016), and Kumar et al. (2018) provide empirical evidence on the overvaluation of high-IVol stocks, leading to their low subsequent returns. Referring to the latter, Bali and Hovakimian (2009), Cremers and Weinbaum (2010), and Xing et al. (2010) argue that the proposed volatility spreads reflect demand effects of sophisticated investors and thus allow for the prediction of subsequent returns.

To confirm these base-line effects while simultaneously taking control variables into account, we run regressions following Fama and MacBeth (1973), with the stock return of the subsequent week as the dependent variable. The corresponding regression estimates are presented in Table 2. First, we examine the relation between IVol and subsequent returns. The IVol puzzle has been commonly investigated in larger samples that begin far before 1996 and that contain the entire cross-section of U.S. stocks (see, for example, Ang et al. 2006). On the contrary, our analyses are restricted to a comparably large and liquidly traded subset of stocks among which the magnitude of

[6] If we would use the entire CRSP universe from 1996 to 2016 without imposing the option availability restriction, median market capitalization would drop from 3.8 bn USD to 0.2 bn USD while the median Amihud illiquidity measure would increase from 0.47 to 3.82.

Table 1 Summary statistics and correlation coefficients

	IVol	VS_{CW}	VS_{BH}	SMIRK	MAX	REV	ln(MV)	BM	MOM	ILLIQ	ASVI
Mean	0.303	−0.009	−0.010	−0.050	0.029	0.002	22.169	0.404	0.263	2.629	−0.003
SD	0.266	0.056	0.052	0.056	0.032	0.062	1.488	0.438	0.848	96.070	0.263
$q_{0.05}$	0.076	−0.086	−0.078	−0.138	0.002	−0.089	19.924	0.038	−0.428	0.034	−0.379
$q_{0.5}$	0.229	−0.006	−0.007	−0.042	0.021	0.001	22.059	0.308	0.135	0.467	0.000
$q_{0.95}$	0.771	0.057	0.049	0.011	0.083	0.096	24.803	1.107	1.253	8.502	0.357
Correlation coefficients											
IVol	1.000										
VS_{CW}	−0.090	1.000									
VS_{BH}	−0.069	0.878	1.000								
SMIRK	−0.045	0.589	0.609	1.000							
MAX	0.746	−0.115	−0.096	−0.086	1.000						
REV	0.102	−0.122	−0.111	−0.088	0.540	1.000					
ln(MV)	−0.287	0.075	0.063	0.064	−0.192	0.011	1.000				
BM	−0.037	−0.021	−0.027	−0.085	−0.011	−0.016	−0.051	1.000			
MOM	0.147	0.001	0.007	0.075	0.090	−0.036	−0.041	−0.199	1.000		
ILLIQ	0.018	−0.002	−0.003	−0.001	0.011	−0.001	−0.036	−0.014	0.036	1.000	
ASVI	0.131	−0.009	−0.009	0.003	0.103	0.027	0.003	−0.008	0.009	0.002	1.000

The table reports pooled 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. IVol is the stock's idiosyncratic return volatility. It is estimated over the previous week based on FFC-adjusted returns where factor loadings are estimated over the previous year, skipping 1 month. 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. 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 1 month. ILLIQ corresponds to the illiquidity measure of Amihud (2002) in billions estimated over the previous year. 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 8 weeks. ASVI summary statistics refer to a truncated sample period from January 2005 to April 2016

Table 2 Fama–MacBeth-regressions

	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.0033	0.0023	0.0023	0.0032	0.0040	0.0069
	(4.40)	(2.46)	(2.49)	(3.50)	(5.40)	(1.83)
IVol	−0.0041				−0.0037	−0.0043
	(−3.73)				(−3.37)	(−4.60)
VS_{CW}		0.0348			0.0128	0.0119
		(11.48)			(2.91)	(2.85)
VS_{BH}			0.0385		0.0179	0.0206
			(11.69)		(3.65)	(4.55)
SMIRK				0.0280	0.0114	0.0096
				(9.39)	(3.49)	(3.66)
MAX						0.0030
						(0.25)
REV						−0.0108
						(−2.19)
ln(MV)						−0.0002
						(−1.05)
BM						0.0003
						(0.44)
MOM						0.0005
						(0.87)
ILLIQ						0.0000
						(0.26)

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. 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. 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. 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 1 month. ILLIQ corresponds to the illiquidity measure of Amihud (2002) in billions estimated over the previous year. The t-statistics in parentheses are based on standard errors following Newey and West (1987) using five lags

mispricing is usually assumed to be less strong. Nevertheless, regression (1) supports the significantly negative relation between IVol and subsequent returns in our sample.

In line with the original studies, each of the volatility spreads VS_{CW}, VS_{BH}, and SMIRK positively predicts subsequent returns in columns (2) to (4). Moreover, all three measures stay significant if they are jointly used as explanatory variables in regression (5). Although the coefficient magnitude sharply declines due to multicollinearity (see correlation coefficients in Table 1), each of the three measures reflects a slightly different part of the option universe and thus retains significant explanatory power. These results support the idea that sophisticated investors might trade on superior information in the option market—for example because of short-sell constraints or because they might want to express their opinion in a levered way (Black 1975; Easley et al. 1998).[7] As a consequence of this informed option demand, cross-market return predictability emerges. This supports our analyses' baseline prerequisite that the measures are suited to identify overvalued stocks. Finally, IVol and the three measures of informed trading remain significant when we introduce further well-known cross-sectional return determinants in regression (6).[8]

After verification of these base-line effects, the focus of our analysis lies in the interaction between the IVol puzzle and the measures of informed trading. Recall that the correlation coefficients in Table 1 depict a negative relationship between IVol and each of the three measures. This is consistent with the conjecture that sophisticated investors identify high-IVol stocks as overvalued and trade in order to exploit this anomaly.[9] From a behavioral point of view, trading against high-IVol stocks can be attractive for sophisticated investors for the following three reasons: First, sophisticated investors can easily calculate IVol and trade in order to exploit the mispricing. Second, the corresponding literature largely favors a behavioral explanation for the IVol puzzle 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 such that sophisticated investors might turn to the option market in order to exploit the IVol puzzle.

Extending this line of argument, previous research shows that the IVol puzzle is driven by the overvaluation of high-IVol stocks rather than the undervaluation of low-

[7] These arguments might especially apply to informed trading on the IVol puzzle. Bali et al. (2018) argue that margin call risk is particularly high for high-IVol stocks such that shorting these stocks is rather unattractive.

[8] 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) and Ammann and Feser (2019)). However, our robustness tests (see Online Appendix Table A2) 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 informed trading compared to VS_{CW}, VS_{BH}, and SMIRK. Given this finding and since MFIS relies on potentially noisy extrapolation and interpolation techniques, we investigate its predictability in a robustness test only. In Table A3 of the 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. Further, Table A4 shows that the return predictability of the option-implied volatility spreads is not the mere result of potential nonsynchronoeity in stock and option market closing time (Battalio and Schultz 2006).

[9] This view is also supported by untabulated findings with respect to option trading volume: the put trading volume is 33% higher in the highest IVol-quintile of stocks compared to the lowest IVol-quintile. These findings are also in line with a model of informed trading introduced by An et al. (2014). They argue that option measures of informed trading should be particularly informative if trading volume is high. However, one might also suspect the relationship between sophisticated trading measures and IVol 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 measures of informed trading if optimistic opinions are predominantly reflected in the stock price while pessimistic investors buy puts in the option market. For Table A5 in the Online Appendix, we use analyst forecast dispersion data from the Institutional Brokers Estimate System (I/B/E/S) to examine this alternative hypothesis. Analyst forecast dispersion is measured as the standard deviation of annual earnings per share forecasts scaled by the most recent stock price. Indeed, we find support for the negative relation between disagreement and measures of informed trading. However, this effect does not subsume the relation between IVol and the measures of informed trading in Fama-MacBeth-regressions.

IVol stocks (see corresponding return asymmetry in seminal portfolio sorts of Ang et al. (2006)).[10] Consequently, we expect that the return effects associated with the IVol puzzle are particularly strong if sophisticated investor trading also points towards an overvaluation. Vice versa, we expect the return spreads associated with IVol to be smaller if the measures of informed trading indicate no overvaluation. For example, a correctly priced, fundamentally driven increase in idiosyncratic volatility does not imply an overvaluation and should not induce any return predictability. Thus, the measures of informed trading should be helpful in identifying those high-IVol stocks that are most likely prone to severe overvaluation.

Table 3 empirically examines this hypothesis on the relationship between measures of informed trading and IVol, presenting 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 3 presents the equally-weighted FFC-adjusted portfolio returns of the subsequent week and the return differences between the extreme terciles.[11] The results support a behavioral explanation for the IVol puzzle since it is especially pronounced for those stocks that are considered 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.[12] Referring to the SMIRK-based analyses, for example, the IVol puzzle amounts to significant 0.29% per week in the low-SMIRK tercile and to insignificant 0.10% in the high-SMIRK tercile. The difference between these two figures is also statistically significant.

Moreover, Table 3 supports our hypothesis that the measures of informed trading can be used to distinguish between overvalued and fairly priced high-IVol stocks. While high-IVol stocks subsequently underperform on average, this effect does not apply to all high-IVol stocks. For example, high-IVol stocks show a substantial negative abnormal return of −0.34% for the low-CS_{CW} tercile but an even slightly positive abnormal return for the high-CS_{CW} tercile (0.07%). In addition, Table 3 shows that the return spreads associated with VS_{CW}, VS_{BH}, and SMIRK are particularly strong for high-IVol stocks.[13] This underpins our conjecture that informed option trading is presumably most successful for the most overvalued stocks, which offer the largest return opportunities.

Table A20 in the Online Appendix further supports this mispricing hypothesis. First, the return predictability associated with IVol should be strongest when new

[10] This return asymmetry can also be observed in our sample (see portfolio sorts in Table A16 in the Online Appendix).

[11] The Online Appendix shows all portfolio sort analyses in this paper for unadjusted returns and value-weighted returns (see Tables A6 to A15).

[12] In the Online Appendix Table A17, we show that this interaction effect is not merely driven by an asymmetry in IVol spreads, that is, stronger IVol-spreads in the negative sophisticated investor opinion portfolios. This supports our interpretation that the measures of informed trading help to identify overvalued high-IVol stocks.

[13] Strictly speaking, this interpretation of Table 3 implies a conditional double sort where idiosyncratic volatility is the first sorting criterion and the measures of informed trading are the second sorting criterion. However, in our Online Appendix Table A18, we show that the sorting criterion order does not affect the results in this case. In addition, we also run unconditional double sorts (Table A19) which confirm our conditional sort findings.

Table 3 Conditional double sorts on measures of informed trading and idiosyncratic volatility

	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)		

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 %

fundamental information on the stock is released (Engelberg et al. 2018). Second, informed option trading is supposed to be most successful before substantial information becomes public (Atilgan 2014). We therefore expect that the observed return patterns in Table 3 become stronger if the return measurement period contains a quarterly earnings announcement. Indeed, the return spreads on average more than double for this subsample of firm-week-observations.

To sum up, the IVol puzzle is most pronounced for those stocks that sophisticated investors perceive as overvalued. Thus, our findings are in line with those of Stambaugh et al. (2015) who also find a strong dependence of the IVol puzzle on the direction of a stock's mispricing. However, they proxy overvaluation through a combination of eleven market anomalies. Thus, their measure of mispricing does not allow for a link to the opinion of sophisticated investors and their trading on overvaluation. Moreover, Table A21 in the Online Appendix shows that the return patterns in Table 3 are not subsumed by the measure proposed by Stambaugh et al. (2015). If we only use the parts of VS_{CW}, VS_{BH}, and SMIRK that are orthogonal to their mispricing score, the findings from Table 3 remain qualitatively unchanged.

3.2 The IVol puzzle and private investors

The correlation figures in Table 1 and the double sorts in Table 3 suggest that sophisticated investors trade against overvalued high-IVol stocks 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 that could arbitrage away the mispricing. In this context, the theoretical models of De Long et al. (1990) and Shleifer and Vishny (1997) imply that noise traders can cause stock mispricing even in the presence of rational market participants (see also an empirical application in Aabo et al. (2017)). In reality, these noise traders are often considered to be unsophisticated private investors. In this context, Han and Kumar (2013) show that the IVol puzzle only exists among stocks that are strongly traded by private investors. Similarly, Stambaugh et al. (2015) show that the IVol puzzle's magnitude is substantially higher following periods of high market-wide investor sentiment.

Beyond sentiment, Kumar et al. (2018) consider investor attention a key driver of the IVol puzzle as it only appears among stocks that show up on daily winner and loser rankings in newspapers. This finding is related to the following line of argument. Given the enormous amount of stock market information, paying attention to every piece would exceed individuals' cognitive abilities (Kahneman 1973) such that only a few stocks end up in the choice set of unsophisticated private investors. Barber and Odean (2008) formalize the idea of attention-induced trading. Only if investors pay attention to a stock, they can exert buying pressure and trigger the stock's overvaluation. In conclusion, these studies suggest that private sentiment-driven investors are responsible for the overvaluation of attention-grabbing stocks like high-IVol stocks. Therefore, our second hypothesis implies a positive relationship between the IVol puzzle's magnitude and private investor attention.

We test this hypothesis by using Google Trends data as a direct stock-specific measure for sentiment-related private investor attention. Supporting our methodological

Table 4 Conditional double sort on private investor attention and idiosyncratic volatility

IVol	Private investor attention 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)

The table reports equally-weighted FFC-adjusted portfolio returns for the week after portfolio formation from January 2005 to April 2016. First, each stock is allocated to one tercile (columns) based on the stock's ASVI. ASVI is the abnormal search volume index calculated as the log Google Search volume of the previous week minus the median log Google Search volume of the preceding 8 weeks. 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 %

approach, Da et al. (2011, 2014) show that Google Search volume can be used to proxy for private investor attention and sentiment.[14] Table 1 has already provided initial indication that IVol and investor attention are related as the respective correlation coefficient is 0.13.

Table 4 reports conditional double sorts where we first sort on private investor attention (a stock's abnormal search volume) and then on IVol. The corresponding 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.[15] This finding supports our hypothesis that links the origin of the IVol puzzle to the trading behavior of sentiment-driven private investors.[16]

3.3 The IVol puzzle, sophisticated investors, and private investors

The natural follow-up question is how the IVol puzzle interacts with both the sophisticated and the private investor group. Hence, our final central hypothesis is that the IVol puzzle is most pronounced for stocks that are considered overvalued by sophisticated investors and that receive high private investor attention at the same time.

We test this relation in conditional triple sorts. At the end of each week, we first allocate stocks into three portfolios based on their abnormal search volume. Then within each tercile, we form portfolios based on each of the three measures of informed trad-

14 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.

15 Note that the overall lower magnitude of the IVol puzzle in Table 4 is due to the Google Trends sample restriction. Among the 468,064 firm-week-observations that are examined in Table 4, the IVol puzzle amounts to 0.12% per week in tercile portfolio single sorts.

16 Tables A22 and A23 in the Online Appendix present analyses where we use the sentiment index of Baker and Wurgler (2006) to identify periods of high investor sentiment. In line with Stambaugh et al. (2015), the IVol puzzle is stronger in months with high investor sentiment in our sample as well. However, as this is a market-wide sentiment proxy, it is not able to identify cross-sectional differences in investor attitudes.

ing. Finally, the stocks in each sub-portfolio are allocated to one of three IVol terciles. Table 5 shows the FFC-adjusted subsequent portfolio returns for the high-ASVI tercile in Panel A and the low-ASVI tercile in Panel B. The results show that the IVol puzzle is indeed strongest if both attention is high and sophisticated trader opinion is low. Referring to the VS_{BH}-based analyses in the high-ASVI tercile, the corresponding weekly return effect associated with IVol decreases from significant 0.23% for negative sophisticated trader opinion to 0.12% for positive sophisticated trader opinion. Comparing these figures with the low-ASVI tercile, the IVol puzzle becomes smaller and insignificant. Moreover, we find additional evidence that the overvaluation and low subsequent returns of high-IVol stocks are no overarching phenomenon, but most pronounced for high-attention stocks with low measures of informed trading. These results strongly support a behavioral explanation of the return patterns associated with idiosyncratic volatility: private investors can cause an overvaluation of high-IVol stocks if the market power of sophisticated investors does not suffice to compensate demand effects of these investors. In this case, sophisticated investors trade on the mispricing in the option market. This interpretation directly implies that we should observe stronger return effects for stocks with high illiquidity and severe short-sell constraints. We explore this line of argument in the following subsection.

3.4 The impact of market frictions

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 can be higher if limits to arbitrage are more severe. Since we consider IVol as a potential mispricing indicator, spreads associated with IVol should be more pronounced for constrained stocks. Indeed, 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. In addition, stock market constraints should also imply that sophisticated investors trade on their superior information in the option market rather than in the stock market. Thus, we hypothesize that the measures of informed trading are particularly able to identify overvalued high-IVol stocks if short-selling is restricted. Hence, these constrained high-IVol stocks with negative sophisticated investor opinion should earn the lowest subsequent returns. Similarly, illiquidity and short-sell constraints can prevent sophisticated investors from immediately correcting the mispricing stemming from private investor activity. We therefore expect that high-IVol stocks with potential sentiment-driven price pressure from private investors and restricted short-selling earn very low subsequent returns as well.

Tables 6 and 7 examine this line of argument using conditional cross-sectional triple sorts. We include four proxies for market frictions and limits to arbitrage. First, we use the Amihud (2002) illiquidity measure, as defined in Sect. 2. Second, 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

Table 5 Conditional triple sorts on private investor attention, measures of informed trading, and idiosyncratic volatility

	Panel A: high private 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 private 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)		

The table reports equally-weighted FFC-adjusted portfolio returns for the week after portfolio formation from January 2005 to April 2016. First, each stock is allocated to a tercile portfolio based on private investor attention (measured by ASVI). 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 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 %

Table 6 Conditional triple sorts on market frictions, measures of informed trading, and idiosyncratic volatility

	Panel A: high amihud illiquidity									Panel B: low amihud illiquidity								
	VS_{CW}			VS_{BH}			SMIRK			VS_{CW}			VS_{BH}			SMIRK		
IVol	Low	2	High	Low	2	High	Low	2	High	Low	2	High	Low	2	High	Low	2	High
Low	−0.22	−0.05	0.25	−0.20	−0.03	0.25	−0.18	−0.01	0.17	−0.03	0.04	0.19	0.00	0.04	0.18	0.01	0.07	0.14
2	−0.23	−0.08	0.15	−0.32	−0.08	0.20	−0.16	−0.11	0.13	−0.13	0.07	0.23	−0.12	0.05	0.23	0.01	0.02	0.16
High	−0.45	−0.17	0.06	−0.50	−0.19	0.12	−0.47	−0.19	0.09	−0.20	−0.03	0.18	−0.18	−0.02	0.14	−0.16	0.00	0.06
3-1	−0.23	−0.12	−0.19	−0.29	−0.15	−0.13	−0.29	−0.17	−0.07	−0.16	−0.08	−0.02	−0.18	−0.06	−0.04	−0.18	−0.07	−0.08
t(3-1)	(−3.04)	(−1.64)	(−2.53)	(−3.90)	(−2.07)	(−1.87)	(−3.73)	(−2.43)	(−1.02)	(−2.66)	(−1.35)	(−0.31)	(−2.91)	(−1.12)	(−0.58)	(−2.82)	(−1.21)	(−1.29)
	Panel C: low residual inst. ownership									Panel D: high residual inst. ownership								
	VS_{CW}			VS_{BH}			SMIRK			VS_{CW}			VS_{BH}			SMIRK		
IVol	Low	2	High	Low	2	High	Low	2	High	Low	2	High	Low	2	High	Low	2	High
Low	−0.12	0.01	0.26	−0.13	0.02	0.25	−0.06	0.02	0.15	−0.07	0.02	0.20	−0.05	0.04	0.16	−0.03	0.04	0.13
2	−0.19	−0.00	0.15	−0.22	−0.03	0.19	−0.12	0.02	0.12	−0.15	0.02	0.14	−0.15	−0.01	0.17	−0.07	0.02	0.09
High	−0.42	−0.17	0.02	−0.46	−0.14	0.05	−0.41	−0.11	−0.06	−0.36	−0.05	0.08	−0.37	−0.05	0.09	−0.30	−0.12	0.06
3-1	−0.30	−0.18	−0.24	−0.33	−0.16	−0.20	−0.35	−0.12	−0.21	−0.29	−0.07	−0.12	−0.32	−0.09	−0.07	−0.27	−0.16	−0.06
t(3-1)	(−3.64)	(−2.48)	(−3.26)	(−3.93)	(−2.22)	(−2.66)	(−4.50)	(−1.73)	(−2.71)	(−4.32)	(−1.18)	(−1.90)	(−5.18)	(−1.47)	(−1.02)	(−4.28)	(−2.67)	(−0.96)

Table 6 continued

	Panel E: high bid-ask-spread									Panel F: low bid-ask-spread								
	VS_{CW}			VS_{BH}			SMIRK			VS_{CW}			VS_{BH}			SMIRK		
IVol	Low	2	High	Low	2	High	Low	2	High	Low	2	High	Low	2	High	Low	2	High
Low	−0.18	−0.04	0.29	−0.16	−0.04	0.29	−0.12	0.02	0.19	−0.05	0.01	0.19	−0.05	0.05	0.18	−0.01	0.06	0.12
2	−0.26	−0.02	0.18	−0.31	−0.02	0.19	−0.14	−0.11	0.12	−0.04	0.06	0.19	−0.06	0.02	0.23	−0.04	0.05	0.16
High	−0.39	−0.15	0.08	−0.45	−0.09	0.09	−0.42	−0.08	0.05	−0.18	−0.03	0.12	−0.17	−0.02	0.09	−0.15	−0.00	0.08
3-1	−0.21	−0.11	−0.21	−0.29	−0.05	−0.20	−0.30	−0.10	−0.14	−0.13	−0.04	−0.07	−0.12	−0.07	−0.09	−0.14	−0.06	−0.03
t(3-1)	(−2.82)	(−1.67)	(−2.96)	(−4.02)	(−0.81)	(−2.77)	(−3.86)	(−1.58)	(−1.96)	(−1.96)	(−0.67)	(−0.94)	(−1.85)	(−1.02)	(−1.20)	(−2.05)	(−0.96)	(−0.39)

	Panel G: high option-implied volatility									Panel H: low option-implied volatility								
	VS_{CW}			VS_{BH}			SMIRK			VS_{CW}			VS_{BH}			SMIRK		
IVol	Low	2	High	Low	2	High	Low	2	High	Low	2	High	Low	2	High	Low	2	High
Low	−0.22	−0.07	0.23	−0.29	−0.05	0.26	−0.17	−0.05	0.23	−0.03	0.05	0.16	−0.02	0.07	0.16	0.02	0.09	0.09
2	−0.30	−0.03	0.18	−0.26	−0.05	0.19	−0.24	−0.05	0.10	−0.01	0.06	0.20	−0.00	0.06	0.18	0.02	0.06	0.15
High	−0.53	−0.28	−0.02	−0.57	−0.28	−0.01	−0.58	−0.25	−0.03	−0.08	0.00	0.12	−0.10	0.00	0.14	−0.03	−0.02	0.11
3-1	−0.31	−0.21	−0.25	−0.28	−0.23	−0.27	−0.41	−0.20	−0.26	−0.06	−0.05	−0.04	−0.08	−0.07	−0.01	−0.05	−0.11	0.01
t(3-1)	(−3.65)	(−2.78)	(−3.04)	(−3.33)	(−3.09)	(−3.28)	(−4.90)	(−2.42)	(−3.13)	(−1.79)	(−1.42)	(−1.09)	(−2.24)	(−2.01)	(−0.43)	(−1.74)	(−3.51)	(0.35)

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 a tercile portfolio based on Amihud illiquidity (Panels A and B), residual institutional ownership (Panels C and D), the stock's average bid-ask-spread over the previous year (Panels E and F), and option-implied volatility (Panels G and H). The table shows top and bottom tercile only. 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 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 %

se or provide a sufficient number of lendable shares to enable short-selling.[17] The calculation of residual institutional ownership follows Nagel (2005): the fraction of shares held by institutional investors is winsorized at 0.01% and 99.99%; then 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.[18] As a third measure, we apply the stock's average closing bid-ask-spread over the previous year (Goyenko et al. 2009). Fourth, we use the stock's model-free option-implied volatility (MFIV). MFIV corresponds to the standardized second moment of the risk-neutral density and is calculated from option prices following the methodology of Bakshi et al. (2003). Similar to the VIX on the market level, MFIV represents a forward-looking measure of volatility on the individual stock level. According to Pontiff (2006), volatility is one of the major factors limiting arbitrage activity.

In the first analyses of Table 6, we assign stocks to Amihud (2002) illiquidity terciles and sort on the option-implied volatility spreads and IVol afterwards. The empirical results support our line of argument: the most negative subsequent FFC-adjusted portfolio returns are obtained for those high-IVol stocks that are illiquid and overvalued based on the sophisticated investors' opinion. On the contrary, for the most liquid stocks with positive sophisticated investor opinion, the IVol puzzle largely disappears. Overall, the strength of the IVol puzzle seems to depend on both the opinion of sophisticated investors about the stock's overpricing and the stock's exposure to market frictions. We repeat this analysis for the other three limits to arbitrage proxies. The picture remains broadly the same and supports the suggested mechanisms. Merely the results with respect to residual institutional ownership are slightly weaker; this might indicate that—within our sample of comparably large firms—short-sell constraints play a less strong role as arbitrage impediments compared to general illiquidity proxies.

Next, we assess the origin of the IVol puzzle by relating it to attention-driven investors (see Table 7). Again, we first assign stocks to one of the limits to arbitrage portfolios and sort on investor attention and IVol afterwards. For all limits to arbitrage proxies, the IVol puzzle is strongest for those stocks that are illiquid/short-sell constrained and exposed to high investor attention. These findings are in line with our conjecture that the IVol puzzle particularly emerges if private investors are active and if sophisticated investors cannot eliminate the mispricing due to market frictions.

[17] Note that Bali et al. (2014) interpret institutional ownership as a measure for sophisticated investor attention. Thus, if sophisticated investor attention is high, mispricing is lower. The results of our analysis are also in line with such a line of argumentation. Private investor attention can drive prices beyond their fundamental value, while sophisticated investor attention should mitigate this effect.

[18] The corresponding institutional ownership data comes from the Thomson Financial Institutional Holdings (13F) database. Note that other studies also use estimated shorting fees as related proxy. However, for its estimation the availability of options is used as dummy variable which would be one for all companies in our analysis (Boehme et al. 2006) such that large parts of the proxy would be meaningless.

Table 7 Conditional triple sorts on market frictions, private investor attention, and idiosyncratic volatility

	Panel A: high Amihud illiquidity			Panel B: low Amihud illiquidity		
	Private investor attention			Private 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: high residual inst. ownership		
	Private investor attention			Private 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)

Table 7 continued

IVol	Panel E: high bid-ask-spread Private investor attention Low	2	High	Panel F: low bid-ask-spread Private investor attention 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)

IVol	Panel G: high option-implied volatility Private investor attention Low	2	High	Panel H: low option-implied volatility Private investor attention 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)

The table reports equally-weighted FFC-adjusted portfolio returns for the week after portfolio formation from January 2005 to April 2016. First, each stock is allocated to a tercile portfolio based on Amihud illiquidity (Panels A and B), residual institutional ownership (Panels C and D), the stock's average bid-ask-spread over the previous year (Panels E and F), and option-implied volatility (Panels G and H). The table shows top and bottom tercile only. Second, each observation is allocated to one tercile (columns) based on investor attention. For investor attention, the allocation depends on 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 8 weeks. Third, 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 %

4 Conclusion

The paper provides an in-depth analysis on the impact of different investor groups on the IVol puzzle. Our results support behavioral explanations for the IVol puzzle and also shed new light on how anomalies are driven by private investor attention.

We employ three measures of informed trading calculated from option data as proxies for sophisticated investor opinion. We show that all of these three measures as well as IVol have incremental value in forecasting stock returns and are not subsumed by other commonly used control variables. Compared to conventional measures, the use of option-implied measures of informed trading 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 is 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 empirical evidence consistent with sophisticated investor trading against overvalued high-IVol stocks. Furthermore, the return spreads associated with IVol are strongest for those stocks that are identified as overvalued by the measures of informed trading. These findings provide further support to a behavioral explanation of the IVol puzzle.

We are not only interested in the interplay of sophisticated investors and the IVol puzzle but also in 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 private investor attention is high, which directly links noise traders to the mispricing's origin. The magnitude of these effects further increases among stocks that are prone to market frictions. 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 acknowledgment of a very heterogeneous investor base is a necessary condition to fully understand capital market phenomena.

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