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addition, the model implies that, among overpriced stocks, the negative IVOL effect should be stronger for stocks that are less easily shorted.

Our explanation of the IVOL puzzle is supported by the data. A key element of our empirical work is constructing a proxy for mispricing. To do so, for each stock, we average its rankings associated with 11 return anomalies that survive adjustment for the three factors of Fama and French (1993). Sorting stocks based on this composite anomaly ranking allows us to investigate the IVOL effect for various degrees of relative mispricing within the cross-section. As predicted, the IVOL effect is significantly negative (positive) among the most overpriced (underpriced) stocks, and the negative effect among the overpriced stocks is significantly stronger. Moreover, consistent with our simple model, we find that the negative IVOL effect among overpriced stocks is stronger for stocks less easily shorted, as proxied by stocks with low institutional ownership (IO). We also find that the dependence of the IVOL effect on the direction of mispricing is robust to excluding smaller firms. At the same time, small-firm stocks also exhibit a stronger negative IVOL effect when overpriced, consistent with small-firm stocks being less easily shorted than large-firm stocks.

Additional implications of our explanation emerge when we consider variation over time in the market-wide direction of mispricing. When overpricing is strongest, we should observe the strongest negative IVOL effect among stocks classified as relatively overpriced by the cross-sectional anomaly ranking. Similarly, when underpricing is its strongest, we should observe the strongest positive IVOL effect among stocks classified as relatively underpriced. With arbitrage asymmetry, this variation in IVOL effects over time should be stronger for stocks that are relatively overpriced. When aggregating across all stocks, the average negative relation between IVOL and expected return observed by previous studies should be stronger when there is a market-wide tendency for overpricing.

To identify periods in which a given mispricing direction is more likely, we use the index of market-wide investor sentiment constructed by Baker and Wurgler (2006).[5] Consistent with the above predictions, the negative IVOL effect among overpriced stocks is significantly stronger following months when investor sentiment is high, and the positive IVOL effect among underpriced stocks is significantly stronger following months when investor sentiment is low. These inferences are further supported by evidence that a time-series regression of an IVOL return spread (high minus low) on investor sentiment produces a significantly negative coefficient for both overpriced and underpriced stocks. Arbitrage asymmetry implies that this variation over time in IVOL effects should be stronger among the overpriced stocks. Consistent with this prediction, the time-series regression reveals significantly stronger

[5] Related studies that investigate the role of investor sentiment in cross-sectional returns include Baker and Wurgler (2006, 2007), Lemmon and Portniaguina (2006), Bergman and Roychowdhury (2008), Kaniel, Saar, and Titman (2008), Frazzini and Lamont (2008), Livnat and Petrovic (2008), Baker, Wurgler, and Yuan (2012), Chung, Hung, and Yeh (2012), Shen and Yu (2012), Stambaugh, Yu, and Yuan (2012, 2014), and Antoniou, Doukas, and Subrahmanyam (2013, 2014).

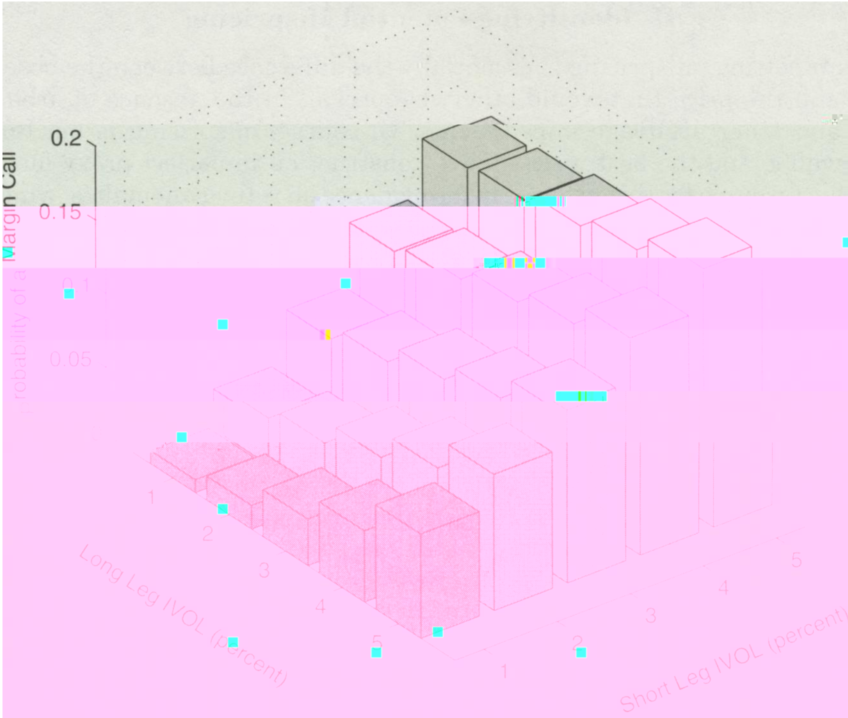
sentiment-related variation in the IVOL effect among the overpriced stocks. When aggregating across stocks, the overall negative IVOL effect on expected return should be stronger following high sentiment, and this prediction is confirmed in our results.

The relation between IVOL and expected return has been explored extensively in the literature. Numerous studies consider interactions between IVOL and average anomaly returns, often viewing the latter as a reflection of mispricing. Several studies also explore interactions between short selling and the IVOL effect. While various empirical results in previous studies are consistent with our explanation of the IVOL effect, those studies include neither our explanation of the IVOL effect nor our set of empirical results that strongly support this explanation. The literature also includes alternative explanations of the IVOL puzzle that may be at work to some degree, but they are unable to explain the joint set of empirical results we present. The related literature is too extensive to review comprehensively, but as we present our evidence, we address the extent to which (i) our explanation of the IVOL puzzle is consistent with previous results and (ii) alternative explanations are inconsistent with our results.

The remainder of the paper is organized as follows. Section I discusses the joint roles of arbitrage asymmetry and arbitrage risk in allowing a stock's mispricing to survive the forces of arbitrage. The analysis includes the simple model mentioned above, as well as a discussion of how a given level of IVOL can contribute more to the arbitrage risk of short positions than that of long positions. Section II describes our empirical measure of relative cross-sectional mispricing, based on a composite ranking that combines 11 return anomalies. Section III presents our basic cross-sectional results analyzing the effect of mispricing on the IVOL effect. We first use portfolio sorts to show that the IVOL effect is positive among underpriced stocks but is more strongly negative among overpriced stocks. We then use the cross-section of individual stocks to estimate the form of the relation between mispricing and the IVOL effect. Finally, we show that the negative IVOL effect among overpriced stocks is stronger among stocks with low IO, for which short-sale impediments are likely to be more important. Section IV explores the time-series implications of our setting, using investor sentiment as a proxy for the direction of market-wide tendencies toward overpricing or underpricing. Section V shows that, while the negative IVOL effect among overpriced stocks is stronger among smaller stocks, consistent with smaller stocks being shorted less easily, the dependence of the IVOL effect on mispricing is robust to eliminating smaller stocks. Section VI reviews the study's main conclusions.

I. Arbitrage Risk and Arbitrage Asymmetry

Our setting combines two familiar concepts: arbitrage risk and arbitrage asymmetry. Arbitrage risk is the risk that deters arbitrage. Arbitrage asymmetry is the greater ability or willingness of an investor to take a long position as opposed to a short position when perceiving mispricing in a security.


0.2
0.15
0.1
0.05
Probability of a Margin Call
1
2
3
4
5
Long Leg IVOL (percent)
1
2
3
4
5
Short Leg IVOL (percent)

growth receive the highest rank. The higher the rank, the greater the relative degree of overpricing according to the given anomaly variable. A stock's composite rank is then the arithmetic average of its ranking percentile for each of the 11 anomalies. We refer to the stocks with the highest composite ranking as the most "overpriced" and to those with the lowest ranking as the most "underpriced." The mispricing measure is purely cross-sectional, so it is important to note that these designations at best denote only relative mispricing. At any given time, for example, a stock identified as the most underpriced might actually be overpriced. The mispricing measure would simply suggest that this stock is the least overpriced within the cross-section. We return to this point later, when investigating the role of investor sentiment over time. Throughout the study, the stock universe each month consists of all NYSE/Amex/NASDAQ stocks with share prices greater than five dollars and for which at least five of the anomaly variables can be computed. We remove penny stocks because Chen et al. (2012) find that the IVOL effect—the puzzle we seek to explain—is especially robust when those stocks are excluded. The five-anomaly requirement typically eliminates about 10% of the remaining stocks.

Evidence that our mispricing measure is effective in diversifying some of the noise in anomaly rankings can be found in the range of average returns produced by sorting on our measure. For example, in each month, we assign stocks to 10 categories based on our measure and then form a value-weighted portfolio for each decile. The following month's spread in benchmark-adjusted returns between the two extreme deciles averages 1.48% over our sample period, August 1965–January 2011. (The returns are adjusted for exposures to the three equity benchmarks constructed by Fama and French (1993): MKT, SMB, and HML.) In comparison, if value-weighted decile portfolios are first formed for each individual anomaly ranking, and the returns on those portfolios are then combined with equal weights across the 11 anomalies, the corresponding spread between the extreme deciles is 0.87%. In other words, averaging the anomaly rankings produces an extra 61 bps per month as compared to averaging the anomaly returns. (The t-statistic of the difference is 4.88.)

We also find in the above comparison that ranking on our mispricing measure creates additional abnormal return primarily among the stocks classified as overpriced. For example, of the 61 bps improvement in the long-short return spread reported above, 57 bps come from the most overpriced portfolio—the short leg of the corresponding arbitrage strategy—and only 4 bps come from the most underpriced—the long leg. This asymmetry in improvement in arbitrage profits is consistent with arbitrage asymmetry: With the latter asymmetry, one expects overpricing to be greater than underpricing, so a better identification of mispricing should yield greater improvement in arbitrage profits for overpriced stocks than for underpriced stocks.

III. IVOL Effects in the Cross-Section

We compute individual stock IVOL, following Ang et al. (2006), as the standard deviation of the most recent month's daily benchmark-adjusted returns.

The latter returns are computed as the residuals in a regression of each stock's daily return on the three factors defined by Fama and French (1993): MKT, SMB, and HML. We estimate IVOL in this manner primarily to address the puzzling negative relation between IVOL and expected return found by Ang et al. (2006) and confirmed by a number of subsequent studies using the same approach. There are alternative approaches to estimating IVOL, such as the EGARCH model in Fu (2009) based on monthly returns, but the simple estimate used here performs relatively well as a measure of forward-looking IVOL. Indeed, in a comparison of a number of IVOL estimation methods in terms of their cross-sectional rank correlations with realized daily IVOL in the subsequent month, Jin (2013) finds that past realized volatility, as used here, outperforms GARCH and EGARCH estimates and performs similarly to estimates from a simple autoregressive model.

In this section, we investigate the role of mispricing in the cross-sectional relation between alpha and IVOL. Section III.A presents the results based on portfolio sorts, an approach robust to the functional form of the relation between the IVOL effect and mispricing. We then estimate this functional form in Section III.B, using the cross-section of individual stocks. The role of stock-level arbitrage asymmetry is explored in Section III.C, using IO as a proxy for shorting impediments.

A. Mispricing and IVOL Effects

Each month, portfolios are constructed by first sorting on individual stock IVOL, forming five categories, and then sorting independently by the mispricing measure, again forming five categories. We next construct 25 portfolios defined by the intersections of this 5×5 sort, and we value-weight the stocks' returns when computing portfolio returns. Panel A of Table I reports the typical individual stock IVOL within each portfolio. Note that, given the independent sorting, the range for IVOL is very similar across the different levels of mispricing. The IVOL within each mispricing level, reported in the last column, increases monotonically from the most underpriced to the most overpriced stocks. This pattern also emerges in Panel B of Table I, which reports the average number of stocks in each portfolio: the high-IVOL portfolio contains significantly more (less) stocks than the low-IVOL portfolio among the most overpriced (underpriced) stocks. To the extent that overpriced stocks are more likely to be shorted, a related result appears in Duan, Hu, and McLean (2010), who find that stocks with high short interest have higher IVOL.

The tendency for overpriced stocks to have high IVOL is consistent with combining two effects. First, high-volatility stocks are difficult to value accurately and thus especially susceptible to being viewed with excess optimism or pessimism by noise traders (e.g., Baker and Wurgler (2006)). Second, noise traders face shorting impediments that constrain negative demands for stocks viewed too pessimistically, but there is no similar constraint on positive demand fueled by excess optimism. These combined roles of volatility and shorting

Table I

Individual Stock IVOL and Number of Stocks in the Double-Sorted Portfolios

Panel A reports the typical individual stock IVOL within each portfolio, first computing the median IVOL each month and then averaging the medians across months. Panel B reports the average number of stocks in each portfolio. The 25 portfolios are formed by independently sorting on IVOL and the mispricing measure. The latter is the average of the ranking percentiles produced by 11 anomaly variables. We compute IVOL, following Ang et al. (2006), as the standard deviation of the most recent month's daily benchmark-adjusted returns, with the latter equal to the residuals in a regression of each stock's daily return on the three factors defined by Fama and French (1993): MKT, SMB, and HML. The sample period is from August 1965 to January 2011.

	Highest IVOL	Next 20%	Next 20%	Next 20%	Lowest IVOL	All Stocks
			Panel A: IVOL			
Most Overpriced	3.36	1.47	0.82	0.46	0.20	1.29
Next 20%	3.22	1.45	0.81	0.45	0.19	0.88
Next 20%	3.15	1.44	0.81	0.45	0.19	0.75
Next 20%	3.11	1.43	0.80	0.44	0.19	0.68
Most Underpriced	3.06	1.42	0.80	0.44	0.19	0.63
All Stocks	3.21	1.44	0.81	0.45	0.19	0.81
			Panel B: Number of Stocks			
Most Overpriced	196	148	115	90	73	622
Next 20%	131	132	128	120	111	623
Next 20%	110	121	127	131	133	623
Next 20%	98	114	127	138	145	623
Most Underpriced	88	107	125	144	159	623
All Stocks	622	623	623	623	622	3,113

impediments imply that high-volatility stocks are more likely to be overpriced than underpriced as a result of excessive optimism or pessimism—sentiment—of noise traders. Of course, nonsentiment components of noise-trader demand, such as those reflecting slow recognition of information relevant even to stocks easier to value, can contribute to mispricing at all levels of volatility. Our explanation of the IVOL puzzle is neither supported nor refuted by volatility-related components of noise-trader demand; the model presented earlier treats such demand (denoted by z) as exogenous.

Table II, which contains the first set of our main results, reports average benchmark-adjusted monthly returns for each of the 25 portfolios. We see evidence consistent with the role of IVOL-driven arbitrage risk in mispricing. Among the stocks most likely to be mispriced, as identified by our mispricing measure, we expect to see the magnitude of mispricing increase with IVOL. The patterns in average returns are consistent with this prediction. For the most overpriced stocks, the average returns are negative and monotonically *decreasing* in IVOL, with the difference between the highest and lowest IVOL

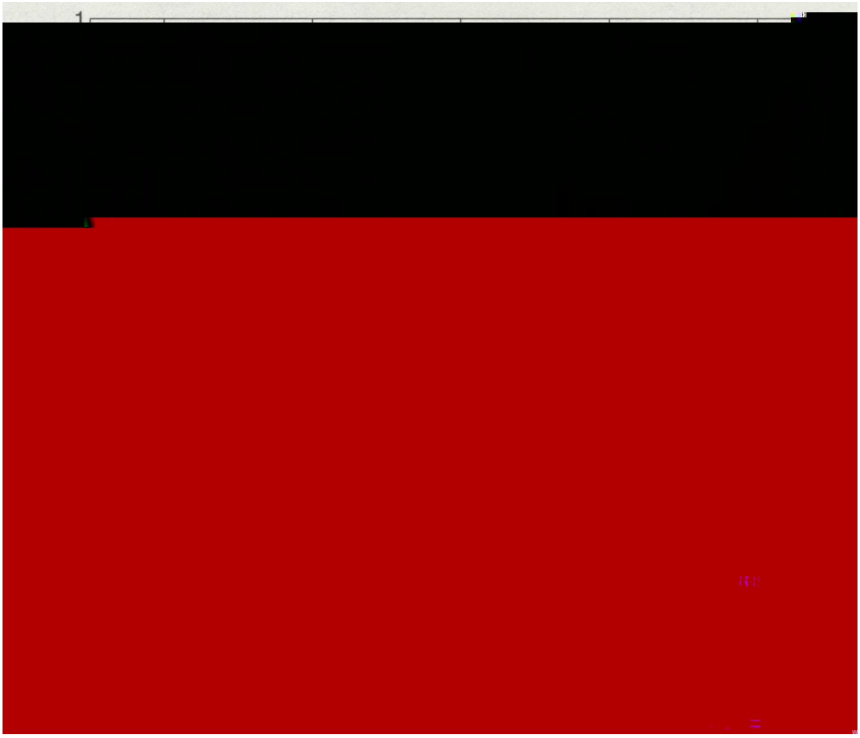


Figure 2. Monthly abnormal returns of portfolios ranked by mispricing level and IVOL. The figure plots the average monthly abnormal return on portfolios formed in a 5 $\times$ 5 sort that ranks independently by mispricing level and IVOL. Abnormal returns are calculated by adjusting for exposures to the three Fama-French (1993) factors. The average ranking percentile of 11 anomalies is used to measure the relative level of mispricing. The sample period covers August 1965–January 2011.

same across the mispricing quintiles in Table II and that the ranges of average IVOLs are therefore very similar across the mispricing quintiles. As a result, we can see that the negative IVOL effect among the overpriced stocks is stronger than the positive IVOL effect among the underpriced stocks. The negative highest-versus-lowest difference among the most overpriced stocks is 3.7 times the magnitude of the corresponding positive difference among the most underpriced stocks.

Given the asymmetry in the strengths of the negative and positive IVOL effects among ovepriced and underpriced stocks, aggregating across all stocks results in the negative overall IVOL effect reported in the last row of Table II. Among all stocks, consistent with the IVOL puzzle observed in the literature, average return is monotonically decreasing in IVOL, with the highest-versus-lowest difference equal to -0.78% per month (t-statistic: -5.50).

Chen et al. (2012) show that the overall negative IVOL effect is quite robust, especially when penny stocks and other highly illiquid stocks are excluded. Excluding such stocks is particularly relevant to the results of Huang et al. (2010),

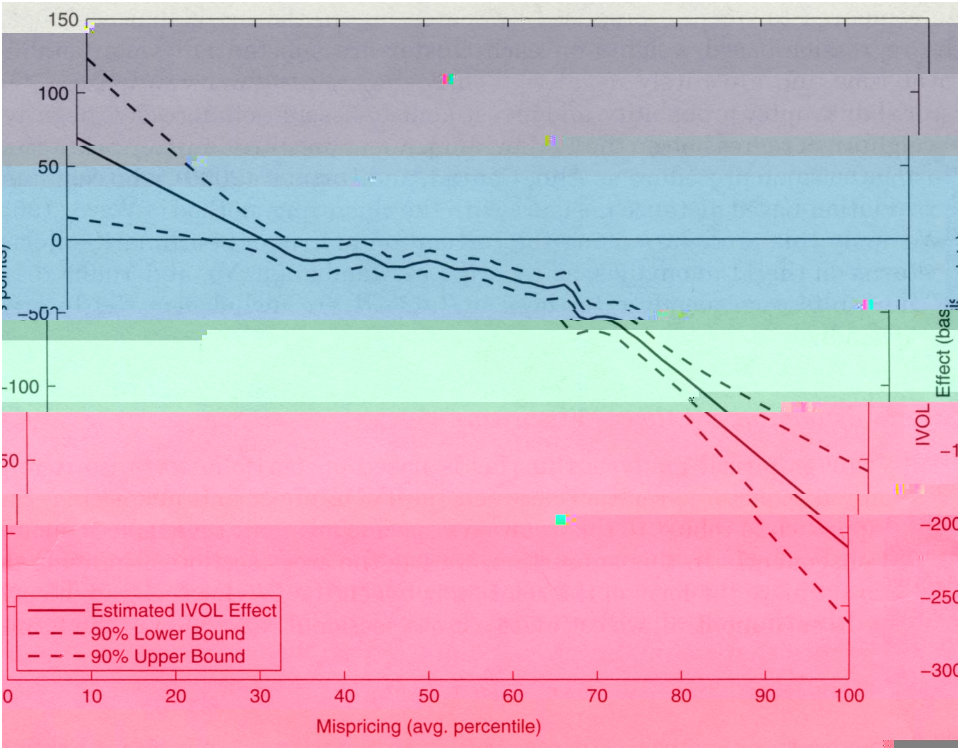


Figure 3. Estimated IVOL effects. The figure plots estimates of $f(M)$, which is the effect of standardized IVOL on the abnormal monthly return for a stock whose mispricing ranking percentile (averaged over 11 anomalies) is equal to M. Estimates are computed using the August 1965–January 2011 sample period.

The function $f_t(M)$ in (8) characterizes the relation between the IVOL effect and mispricing. The month-by-month procedure described above yields an estimated function $f_t(M)$ for each month t in our sample (August 1965 through January 2011). These monthly values are then used in a procedure following the spirit of Fama and MacBeth (1973). For each value of mispricing (M) in 0.01 increments within [0, 1], we take the mean of the monthly function values as an estimate of the desired function, $f(M) = (1/T)\sum_{t=1}^{T} f_t(M)$. We estimate the standard error of $f(M)$ using the monthly series of $f_t(M)$s.

Figure 3 plots the estimated values of $f(M)$—the relation between the IVOL effect and mispricing—as well as the 90% confidence bands (plus/minus 1.65 standard errors). First, note that the estimated IVOL effect is positive among the most underpriced stocks and negative among the most overpriced, consistent with the previous portfolio sort results. Also, consistent with those results is the asymmetry in the dependence of the IVOL effect on mispricing, with the effect among overpriced stocks reaching larger negative magnitudes than those of the positive effect among underpriced stocks. Also, observe that the IVOL effect is more sensitive to M at both extremes of that measure than at the

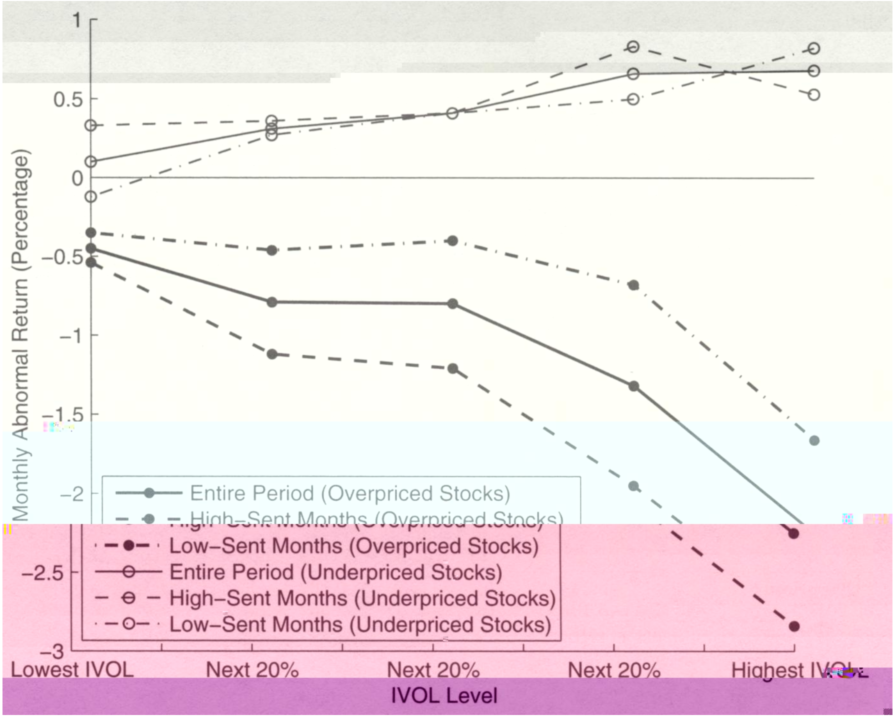
sentiment measure, which removes the effects of six macrovariables. We further include six additional macrovariables that previous empirical studies relate to expected stock returns. Our results point to little or no role for macrofactors in the sentiment-related variation in the IVOL effects that we observe.

A. Investor Sentiment and IVOL Effects

To explore the sentiment-related implications discussed above, we first conduct a sorting-based portfolio analysis, similar to that in Table II, separately for high-sentiment and low-sentiment months. We modify the sorting procedure somewhat due to the shift in focus from the cross-section to the time series when investigating IVOL effects. To compare IVOL effects over time for a given level of mispricing, one would ideally maintain the same volatility break points across different periods. Doing so, however, confronts the fact that average IVOL levels fluctuate substantially over time (e.g., Brandt et al. (2010)). Maintaining fixed IVOL break points in the portfolio sorting is therefore not feasible, as it results in highly unbalanced distributions of stocks in many periods, often producing portfolios with few or no stocks. Therefore, for each mispricing level, we instead set fixed percentage break points for IVOL, forming five portfolios each period with essentially equal numbers of stocks in each portfolio. In addition to presenting results using this portfolio-based analysis, we also rerun the individual-stock-based estimation in Section III.B separately in high-sentiment and low-sentiment months.

Table IV presents the results of the portfolio-based analysis of the IVOL effect following different levels of investor sentiment. The middle three IVOL categories are omitted to save space in the table. Average benchmark-adjusted returns for all five IVOL categories in low-sentiment and high-sentiment months are displayed in Figure 4. A high-sentiment month is one in which the value of the BW sentiment index at the end of the previous month is above the median value for the August 1965–January 2011 sample period, while the low-sentiment months are those with below-median index values in the previous month.

The results in Table IV and Figure 4 are consistent with the hypothesized sentiment-related variation in the IVOL effect discussed earlier. First observe that, among all stocks (bottom row), the negative IVOL effect is significantly stronger following high sentiment, as predicted. The spread between the highest IVOL and lowest IVOL average returns is -1.32% following high sentiment compared to -0.23% following low sentiment—a difference of -1.09% (t-statistic: -3.82). This sentiment-related variation in the overall IVOL effect is similar to a result in Baker and Wurgler (2006), who use the lagged within-year standard deviation of monthly total return instead of IVOL. Our analysis, which investigates IVOL effects separately for different degrees of relative mispricing, reveals that the IVOL effect for the relatively overpriced stocks exhibits the same sentiment-related variation as the overall IVOL effect. Among the most overpriced stocks, the spread between the highest IVOL and lowest IVOL average returns is -2.30% following high sentiment compared to


Monthly Abnormal Return (Percentage)
1
0.5
0
−0.5
−1
−1.5
−2
−2.5
−3
Entire Period (Overpriced Stocks)
High−Sent Months (Overpriced Stocks)
Low−Sent Months (Overpriced Stocks)
Entire Period (Underpriced Stocks)
High−Sent Months (Underpriced Stocks)
Low−Sent Months (Underpriced Stocks)
Lowest IVOL
Next 20%
Next 20%
Next 20%
Highest IVOL
IVOL Level

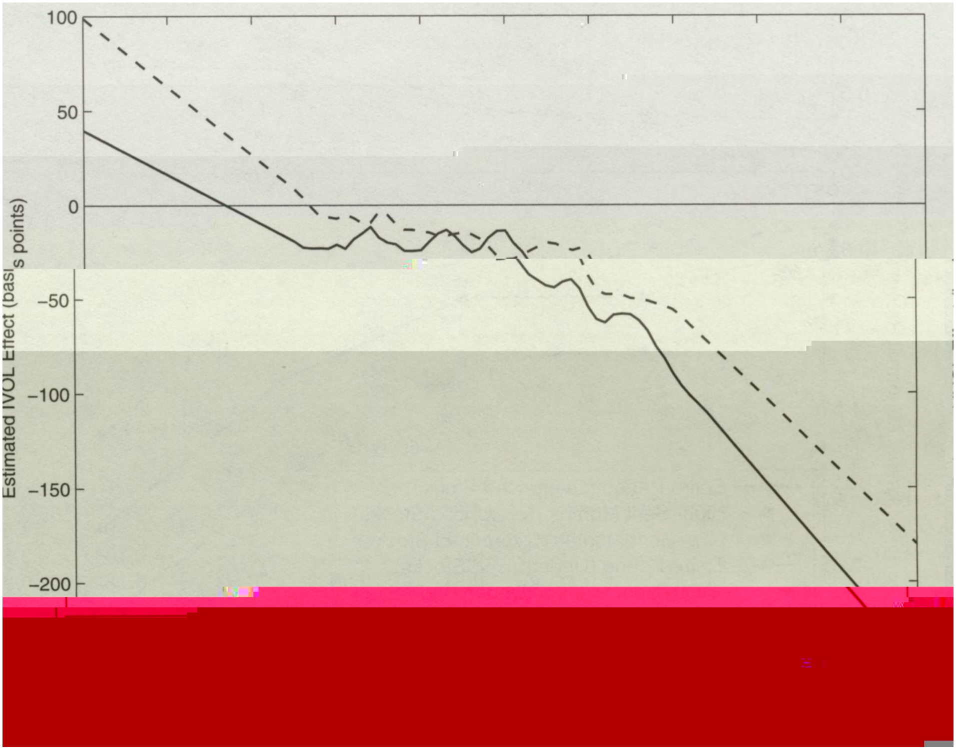


Figure 5. Estimated IVOL effects following high and low sentiment. The figure plots estimates of $f(M)$, which is the effect of standardized IVOL on the abnormal monthly return for a stock whose mispricing ranking percentile (averaged over 11 anomalies), is equal to M. The estimates are computed separately in high-sentiment and low-sentiment months classified using the Baker-Wurgler (2006) index for the August 1965–January 2011 sample period.

previous month. Also included as independent variables are the contemporaneous realizations of the FF factors (MKT, SMB, and HML), so the slope on S_{t-1} reflects sentiment-related variation in the benchmark-adjusted returns. The dependent variable in the regressions is (i) the (excess) return on the highest IVOL portfolio, (ii) the return on the lowest IVOL portfolio, or (iii) the difference between those returns. These three regressions are run separately for each mispricing category and for the overall stock universe.

The results in Table V again support our setting's implications. Consistent with Table IV, the IVOL effect (highest minus lowest IVOL) is negatively related to investor sentiment. For the overall stock universe, the slope on S_{t-1} is equal to -0.66 (t-statistic:-4.25), meaning that a one-standard-deviation swing in S_{t-1} is associated with a 66 bps difference in the IVOL effect. In addition, the negative slope is largest in magnitude among the most overpriced stocks, and the difference between the slopes for the most overpriced versus the most underpriced stocks is equal to -0.50 (t-statistic: -2.20).

VI. Conclusions

We provide an explanation for the negative empirical relation between expected return and IVOL observed in the overall cross-section of equities. Our explanation combines two simple concepts. The first is that higher IVOL, which translates into higher arbitrage risk, allows greater mispricing. As a result, expected return is negatively (positively) related to IVOL among overpriced (underpriced) securities. The second concept is that arbitrage is asymmetric, in that short sellers face greater impediments than purchasers.

Arbitrage asymmetry exists at both the investor level and the stock level. Some investors are more able or willing to short than are other investors, and some stocks are more easily shorted than are other stocks. Our simple model incorporates both dimensions of arbitrage asymmetry, and it captures the basic intuition that, when arbitrage risk is shared by less capital, less mispricing is eliminated in equilibrium.

The combined effects of arbitrage risk and arbitrage asymmetry imply that a given difference in IVOL is associated with a greater average degree of overpricing as compared to underpricing. That is, the negative IVOL effect among overpriced stocks is stronger than the positive effect among underpriced stocks, and thus a negative IVOL effect emerges within the overall cross-section. In addition, among the overpriced stocks, the negative IVOL effect is steeper for stocks less easily shorted.

Our empirical evidence supports these implications. First, using a composite measure based on 11 return anomalies to gauge relative mispricing, we find a significant positive IVOL effect among the most underpriced stocks but a stronger negative effect among the most overpriced ones. We also find that the negative IVOL effect among overpriced stocks is stronger for stocks less easily shorted, as proxied by having low size-adjusted IO.

We also empirically confirm time-series implications of our explanation. Using investor sentiment as a proxy for the likely direction of market-wide mispricing, we find that the negative (positive) IVOL effect among overpriced (underpriced) stocks is stronger when market-wide overpricing (underpricing) is more likely. This negative relation over time between investor sentiment and the return difference between high- and low-volatility portfolios is stronger among overpriced stocks, consistent with the presence of arbitrage asymmetry. Finally, mispricing's role in the IVOL effect, in both the cross-section and time series, is robust to eliminating smaller firms.

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Appendix A

A. Derivation of Equations (5) and (6)

The investors in group I_M face the constraint that the elements of ω must be nonnegative for the last $N_2 \equiv N - N_1$ stocks, whereas the investors in group

I_H face no constraint on ω. The first-order condition for an investor in group I_M is given by

$$\mu - AV\omega_M - \lambda = 0, \tag{A1}$$

where the first N_1 elements of λ are zero and the last N_2 elements of λ are the vector of Lagrange multipliers associated with the nonnegativity constraints on the last N_2 elements of ω. We order the stocks such that they can be partitioned into two groups. The first group includes the first N_1 (unconstrained) stocks and stocks numbered $N_1 + 1$ to $N_1 + N_{nc}$, in which investors in group I_M hold positive allocations. In the second group of stocks, the constraints result in zero allocations for investors in group I_M. Here, N_{nc} is the number of stocks among the last N_2 stocks where the short-sale constraint is not binding for investors in group I_M. Rewriting (A1) with this partitioning gives

$$\begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} - A \begin{bmatrix} V_{11} & V_{12} \\ V_{21} & V_{22} \end{bmatrix} \begin{bmatrix} \omega_{M,1} \\ 0 \end{bmatrix} - \begin{bmatrix} 0 \\ \lambda_2 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \tag{A2}$$

where $\lambda_1 = 0$ and $\omega_{M,2} = 0$. From (A2), we obtain the optimal positive allocations for investors in group I_M as

$$\omega_{M,1} = \frac{1}{A} V_{11}^{-1} \mu_1. \tag{A3}$$

The first-order condition for investors in group I_H gives their optimal allocations as

$$\omega_H = \frac{1}{A} V^{-1} \mu. \tag{A4}$$

Market clearing requires

$$M\omega_M + H\omega_H = y, \tag{A5}$$

or

$$\begin{bmatrix} \frac{M}{A} V_{11}^{-1} \mu_1 \\ 0 \end{bmatrix} + \frac{H}{A} V^{-1} \mu = y. \tag{A6}$$

Multiplying both sides of (A6) by V gives

$$\begin{bmatrix} \frac{M}{A} \mu_1 \\ \frac{M}{A} V_{21} V_{11}^{-1} \mu_1 \end{bmatrix} + \begin{bmatrix} \frac{H}{A} \mu_1 \\ \frac{H}{A} \mu_2 \end{bmatrix} = \begin{bmatrix} V_{11} y_1 + V_{12} y_2 \\ V_{21} y_1 + V_{22} y_2 \end{bmatrix} \tag{A7}$$

From (A7), we obtain the equilibrium expected excess returns as

$$\mu_1 = \frac{A}{M + H} (V_{11} y_1 + V_{12} y_2), \tag{A8}$$

$$\mu_2 = \frac{A}{H} \left(V_{21} y_1 + V_{22} y_2 - \frac{M}{A} V_{21} V_{11}^{-1} \mu_1 \right)$$

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business prospects implied by asset expansions. Asset growth is measured as the growth rate of total assets in the previous fiscal year.

Return on Assets (10): Fama and French (2006) find that more profitable firms have higher expected returns than less profitable firms. Chen, Novy-Marx, and Zhang (2010) show that firms with higher past return on assets earn abnormally higher subsequent returns. Return on assets is measured as the ratio of quarterly earnings to last quarter's assets. Wang and Yu (2010) find that the anomaly exists primarily among firms with high arbitrage costs and high information uncertainty, suggesting that mispricing is a culprit.

Investment-to-Assets (11): Titman, Wei, and Xie (2004) and Xing (2008) show that higher past investment predicts abnormally lower future returns. Titman, Wei, and Xie (2004) attribute this anomaly to investors' initial underreactions to the overinvestment caused by managers' empire-building behavior. Here, investment to assets is measured as the annual change in gross property, plant, and equipment, plus the annual change in inventories, scaled by lagged book value of assets.

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