Arbitrage Asymmetry and the Idiosyncratic Volatility Puzzle

by*

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Abstract

Short selling, as compared to purchasing, faces greater risks and other potential impediments. This arbitrage asymmetry explains the negative relation between idiosyncratic volatility (IVOL) and average return. The IVOL effect is negative among overpriced stocks but positive among underpriced stocks, with mispricing determined by combining 11 return anomalies. The negative effect is stronger, consistent with asymmetry in risks and other impediments inhibiting arbitrageurs in exploiting mispricing. Aggregating across all stocks therefore yields a negative relation, explaining the IVOL puzzle. Further supporting our explanation is a negative relation over time between the IVOL effect and investor sentiment, especially among overpriced stocks.

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1. Introduction

Does a stock's expected return depend on "idiosyncratic" volatility that does not arise from systematic risk factors? This question has been investigated empirically since virtually the inception of classical asset pricing theory. Earlier empirical investigations often find no relation, consistent with classical theory, or they find a positive relation between expected return and idiosyncratic volatility (IVOL). Much of the recent empirical literature on this topic, beginning notably with Ang, Hodrick, Xing, and Zhang (2006), instead finds a negative relation between expected return and IVOL.[1] While a positive relation is accommodated by various theoretical departures from the classical paradigm, the negative relation has presented more of a puzzle.[2]

This study presents an explanation for the observed negative relation between IVOL and expected return. We start with the proposition that IVOL creates arbitrage risk that deters market participants from exploiting mispricing and thereby correcting prices.[3] We then combine this familiar concept with what we term arbitrage asymmetry—the observation that potential short sellers wishing to exploit overpricing face impediments to arbitrage more than do potential purchasers wishing to exploit underpricing.[4]

Combining the effects of arbitrage risk and arbitrage asymmetry implies the observed negative relation between IVOL and expected return. To see this, first note that stocks with greater IVOL, and thus greater arbitrage risk, are more susceptible to mispricing. Among overpriced stocks, the IVOL effect in expected return is therefore negative—those with the highest IVOL are the most overpriced. Similarly, among underpriced stocks, the IVOL effect is positive, as the highest IVOL stocks are then the most underpriced. With arbitrage asym-

[1]Recent studies finding a negative relation include Ang, Hodrick, Xing, and Zhang (2006, 2009), Jiang, Xu, and Yao (2009), Guo and Savickas (2010), and Chen, Jiang, Xu, and Yao (2012). The classic study finding no relation between expected return and IVOL is Fama and MacBeth (1973), who acknowledge the methodological issues raised by Miller and Scholes (1972) in their reexamination of Douglas (1968). A more recent study finding no relation is Bali and Cakici (2008). Studies finding a positive relation include Lintner (1965), Tinic and West (1986), Lehmann (1990), Malkiel and Xu (2002), and Fu (2009).

[2]Explanations for a positive relation include Merton (1987), Barberis and Huang (2001), Malkiel and Xu (2002), and Jones and Rhodes-Kropf (2003).

[3]Studies addressing the role of arbitrage risk in mispricing include DeLong, Shleifer, Summers, and Waldmann (1990), Pontiff (1996), Shleifer and Vishny (1997), Mitchell, Pulvino, and Stafford (2002), and Wurgler and Zhuravskaya (2002).

[4]Studies addressing the role of short-sale constraints and costs in the equity market include Miller (1977), Figlewski (1981), Chen, Hong, and Stein (2002), Diether, Malloy, and Scherbina (2002), Duffie, Garleanu and Pedersen (2002), Jones and Lamont (2002), D'Avolio (2002), Scheinkman and Xiong (2003), Lamont (2004), Lamont and Stein (2004), Ofek, Richardson, and Whitelaw (2004), Nagel (2005), Avramov, Chordia, Jostova, and Philipov (2012), and Stambaugh, Yu, and Yuan (2012a).

metry, however, more of the potential underpricing has been eliminated, thereby reducing the differences in the degree of underpricing associated with different levels of IVOL. As a result, the negative IVOL effect among overpriced stocks is stronger than the positive IVOL effect among underpriced stocks. When aggregating across all stocks, the negative IVOL effect therefore dominates and creates the observed IVOL puzzle.

We argue that a principal source of arbitrage asymmetry is risk. Short sellers are exposed to short-run price fluctuations requiring additional capital contributions more than are purchasers of stock. This observation (novel, to our knowledge) applies in particular to what is often termed "noise-trader" risk (e.g., Shleifer and Vishny, 1997)—the risk that adverse price moves necessitate closing a position before the eventual correction of mispricing would yield a profit. Also, the inherent skewness in compounded returns contributes to greater tail risk for short sellers over holding periods likely to be relevant to professional investment managers.

Adding to the risk-related sources of arbitrage asymmetry are other impediments to short selling that have been previously discussed in the literature. The sizes of institutions engaged in shorting, such as hedge funds, are rather small in aggregate compared to the sizes of mutual funds and other institutions that do not short. Hong and Sraer (2012) place primary emphasis on this disparity in arguing that short sale impediments are important.[5] D'Avolio (2002) finds that shorting costs, while generally low, increase in the dispersion of opinion about a stock, consistent with a setting in which shorting becomes more expensive precisely when less optimistic investors would wish to short a stock whose price is driven up by the more optimistic investors.[6]

Our explanation of the IVOL puzzle is supported by the data. A key element of our empirical work is constructing a proxy for mispricing. For this purpose, we average each stock's 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 within various degrees of relative mispricing. As predicted by arbitrage risk combined with arbitrage asymmetry, the IVOL effect is significantly negative (positive) among the most overpriced (underpriced) stocks, and the negative effect among the overpriced stocks is significantly stronger.

[5]In making this point, the authors cite the low use of actual shorting by mutual funds, often due to investment policy restrictions, as documented by Almazan, Brown, Carlson, and Chapman (2004), as well as mutual funds' low use of derivatives, as documented by Koski and Pontiff (1999).

[6]Lamont (2004) discusses various impediments to short selling, and he also argues that impediments can become more severe precisely when a stock becomes more overpriced, sometimes due to action by a firm to deter shorting of its stock.

Additional implications of our explanation emerge when considering variation through time in the likely market-wide direction of mispricing. Periods when overpricing is its strongest are also those when we should observe the strongest negative IVOL effect among stocks classified as relatively overpriced by the cross-sectional anomaly ranking. Similarly, periods when underpricing is its strongest are those when we should observe the strongest positive IVOL effect among stocks classified as relatively underpriced. With arbitrage asymmetry, this variation in IVOL effects through time should be stronger for the stocks that are relatively overpriced. Compared with low sentiment periods, during high sentiment periods the negative IVOL effect among overpriced stocks is stronger, whereas the positive IVOL effect among the underpriced stocks is weaker. Thus, when aggregating across all stocks, the average negative relation between IVOL and expected return observed by previous studies should be stronger in periods when there is a market-wide tendency for overpricing.

To identify periods when a given mispricing direction is more likely, we use the index of market-wide investor sentiment constructed by Baker and Wurgler (2006).[7] 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 finding that a time series regression of an IVOL return spread (high minus low) on investor sentiment produces a significantly negative coefficient for both the 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 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 also confirmed in our results.

We focus here on explaining the relation between IVOL and expected return, but there are additional empirical implications of our setting. In particular, among high-IVOL stocks, mispricing, especially overpricing, should be stronger than among low-IVOL stocks. These implications are in fact supported by Jin (2012), who finds that long-short spreads based on a wide range of anomalies are more profitable among high-IVOL stocks, and this effect

[7]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), Antoniou, Doukas, and Subrahmanyam (2012), Baker, Wurgler, and Yuan (2012), Chung, Hung, and Yeh (2012), Shen and Yu (2012), and Stambaugh, Yu, and Yuan (2012a, 2012b).

is especially strong for the short-leg profits.[8] In another related study, Cao and Han (2010) explore the role of IVOL-related arbitrage risk in mispricing. Those authors also sort stocks based on a composite of anomaly rankings, and they also find a significantly negative (positive) IVOL effect among the relatively overpriced (underpriced) stocks. Their results do not display a substantial asymmetry in the strength of those IVOL effects, nor do they discuss asymmetry or the IVOL puzzle.[9] Our hypothesized role of arbitrage asymmetry in the IVOL effect is consistent with the event-study results of Doran, Jiang, and Peterson (2012), who conclude that high-IVOL stocks experience negative returns after short-sale constraints are relaxed.

Alternative explanations of the IVOL puzzle appear in a number of studies. Jiang, Xu, and Yao (2009) argue that high IVOL is associated with firms that disclose less and that the market does not correctly assess the negative valuation implication associated with selective low disclosure. Boehme, Danielson, Kumar, and Sorescu (2009) find that the negative IVOL effect flips to positive when firms with high institutional ownership and high shorting activity are eliminated. Boyer, Mitton, and Vorkink (2010) conclude that a negative relation between expected return and idiosyncratic skewness is at least a partial explanation for the IVOL puzzle. Bali, Cakici, and Whitelaw (2011) argue that the IVOL puzzle reflects a preference for lottery-like payoffs, captured better by maximum past return than by IVOL. Huang, Liu, Rhee, and Zhang (2010) conclude that IVOL proxies for a return-reversal effect. Barinov (2011) and Chen and Petkova (2012) conclude that IVOL proxies for sensitivity to a priced volatility factor. While these alternative explanations may all be at work, they seem challenged to reconcile the joint set of empirical results we present here: (i) the sign of the IVOL effect depends on whether stocks are identified as overpriced or underpriced, (ii) the negative (positive) IVOL effect among overpriced (underpriced) stocks is stronger following high (low) investor sentiment, and (iii) both of the previous results are stronger among the overpriced stocks.

The remainder of the paper is organized as follows. Section 2 describes our measure of relative cross-sectional mispricing, based on a composite ranking that combines 11 return

[8] Other studies find greater long-short anomaly returns among high-IVOL stocks but do not document the stronger contribution that the short-leg (overpriced) stocks make to such results. E.g., Mendenhall (2002), Ali, Hwang, and Trombley (2003), Mashruwala, Rajgopal, and Shevlin (2006), Pontiff (2006), Zhang (2006), Cao and Han (2010), Duan, Hu, and McLean (2010), McLean (2010), Lam and Wei (2011), Li and Sullivan (2011), and Larrain and Varas (2012).

[9] A potential reason that asymmetry does not emerge as a feature of their study is that their anomaly ranking measure could contain less information about mispricing, in that it combines only four anomalies, instead of our eleven, and two of those four are size and book-to-market, for which a mispricing interpretation must contend with a significant literature arguing that those variables instead proxy for risk.

anomalies. Section 3 discusses arbitrage asymmetry, focusing in particular on asymmetry in various risks faced by arbitrageurs. Section 4 presents our basic results showing that the IVOL effect is positive among underpriced stocks but more strongly negative among overpriced stocks. Section 5 explores the time-series implications of our setting, using investor sentiment as a proxy for the likely direction of market-wide tendencies toward overpricing or underpricing. Section 6 reviews the study's main conclusions.

2. Identifying Mispricing

In our setting, mispricing is essentially the difference between the observed price and the price that would otherwise prevail in the absence of arbitrage risk and other arbitrage impediments. Of course, mispricing is not directly observable, and the best we can do is to construct an imperfect proxy for it. An obvious resource for this purpose is the evidence on return anomalies, which are differences in average returns that challenge risk-based models. We first describe our approach to constructing a mispricing measure based on anomalies, and we then detail our 11 return anomalies taken from the literature.

2.1. Mispricing Measure

We combine the anomalies to produce a univariate monthly measure that correlates with the degree of relative mispricing in the cross section of stocks. While each anomaly is itself a mispricing measure, our objective in combining them is to produce a single measure that diversifies away some noise in each individual anomaly and thereby increases precision when exploring the empirical implications of our setting.

Our method for combining the anomalies is simple. For each anomaly, we assign a rank to each stock that reflects the sorting on that given anomaly variable, where the highest rank is assigned to the value of the anomaly variable associated with the lowest average abnormal return, as reported in the literature. For example, one documented anomaly is that high asset growth in the previous year is followed by low return (Cooper, Gulen, and Schill, 2008). We therefore rank firms each month by asset growth, and those with the highest 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 ranks for each of the 11 anomalies. Thus, 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 intent of the measure is simply that such stocks would then be the least overpriced within the cross section. We return to this point later, when investigating the role of investor sentiment over time.

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, if each month we assign stocks to ten 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, 8/1965–1/2011. (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 then the returns on those portfolios are 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 basis points 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 62-basis-point improvement in the long-short return spread reported above, 57 basis points come from the most overpriced portfolio—the short leg of the corresponding arbitrage strategy—and only 4 basis points 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.

2.2. Anomalies

To our knowledge, these anomalies constitute a fairly comprehensive list of those that survive adjustment for the three factors of Fama and French (1993). The same anomalies are used by Stambaugh, Yu, and Yuan (2012a).

1 and 2: Financial Distress

Financial distress is often invoked to explain otherwise anomalous patterns in the cross-section of stock returns. However, Campbell, Hilscher, and Szilagyi (2008) find that firms with high failure probability have lower rather than higher subsequent returns (anomaly 1). Campbell et al. suggest that their finding is a challenge to standard models of rational asset pricing. The failure probability is estimated by a dynamic logit model with both accounting and equity market variables as explanatory variables. Using Ohlson's (1980) O-score as the distress measure yields similar results (anomaly 2). Ohlson's (1980) O-score is calculated as the probability of bankruptcy in a static model using accounting variables, such as net income divided by assets, working capital divided by market assets, current liability divided by current assets, and etc. The failure probability is different with the O-score in that it is estimated by a dynamic, rather than a static model, and that the model uses several equity market variables, such as stock prices, book-to-market, stock volatility, relative size to the S&P 500, and cumulative excess return relative to S&P 500.

3 and 4: Net Stock Issues and Composite Equity Issues

The stock issuing market has been long viewed as producing an anomaly arising from sentiment-driven mispricing: smart managers issue shares when sentiment-driven traders push prices to overvalued levels. Ritter (1991) and Loughran and Ritter (1995) show that, in post-issue years, equity issuers underperform matching nonissuers with similar characteristics (anomaly 3). We measure net stock issues as the growth rate of the split-adjusted shares outstanding in the previous fiscal year. Daniel and Titman (2006) study an alternative measure, composite equity issuance, defined as the amount of equity a firm issues (or retires) in exchange for cash or services. Under this measure, seasoned issues and share-based acquisitions increase the issuance measure, while repurchases, dividends and other actions that take cash out of the firm reduce this issuance measure. They also find that issuers underperform nonissuers (anomaly 4).

5: Total Accruals

Sloan (1996) shows that firms with high accruals earn abnormal lower returns on average than firms with low accruals, and suggests that investors overestimate the persistence of the accrual component of earnings when forming earnings expectations. Here, total accruals are calculated as changes in non-cash working capital minus depreciation expense scaled by average total assets for previous two fiscal years.

6: Net Operating Assets

Hirshleifer, Hou, Teoh, and Zhang (2004) find that net operating assets, defined as the difference on the balance sheet between all operating assets and all operating liabilities scaled by total assets, is a strong negative predictor of long-run stock returns. They suggest that investors with limited attention tend to focus on accounting profitability, neglecting information about cash profitability, in which case net operating assets, equivalently measured as the cumulative difference between operating income and free cash flow, captures such a bias.

7: Momentum

The momentum effect, discovered by Jegadeesh and Titman (1993), is one of the most robust anomalies in asset pricing. It refers to the phenomenon that high past recent recent returns forecast high future returns. The momentum portfolios we use are ranked based on cumulative returns from month -7 to month -2, and the holding period for these portfolios is 6-month. That is, it is a 6/1/6 momentum strategy.

8: Gross Profitability Premium

Novy-Marx (2012a) discovers that sorting on gross-profit-to-assets creates abnormal benchmark-adjusted returns, with more profitable firms having higher returns than less profitable ones. Novy-Marx (2012a) argues that gross profits (item GP) scaled by assets (item AT) are the cleanest accounting measure of true economic profitability. The farther down the income statement one goes, the more polluted profitability measures become, and the less related they are to true economic profitability.

9: Asset Growth

Cooper, Gulen, and Schill (2008) find companies that grow their total asset more earn lower subsequent returns. They suggest that this phenomenon is due to investors' initial overreaction to changes in future business prospects implied by asset expansions. Asset growth is measured as the growth rate of the total assets (item AT) in the previous fiscal year.

10: Return on Assets

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 measured as the ratio of the quarterly earnings (item IBQ) and last quarter's assets (item ATQ). 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.

11: Investment-to-Assets

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 are measured as the annual change in gross property, plant, and equipment plus the annual change in inventories scaled by the lagged book value of assets.

3. Arbitrage Risk and Asymmetry

Arbitrageurs face various risks. One source of risk, often termed "noise-trader" risk (e.g., Shleifer and Vishny, 1997), is that adverse price moves can require additional capital in order to maintain positions that involve shorting or leverage. As a result, capital constraints can necessitate closing positions before realizing profits that would ultimately result from corrections of mispricing. Another source of risk is simply new information. An arbitrageur can purchase a stock today that he correctly identifies as underpriced based on available information, but negative information about the stock's fundamental value can later be revealed and cause a loss. Investment managers often care about performance over relatively short periods such as a year. Sufficiently bad performance over such periods, whether from noise traders or new information, could cost a manager his job, or at least reduce the capital that investors allow him to manage.

Our setting combines two simple concepts. First, greater arbitrage risk allows greater mispricing, as such risk deters arbitrageurs from exploiting mispricing and thereby correcting it. Second, arbitrage impediments are asymmetric, inhibiting short selling of overpriced stocks more than they inhibit purchasing of underpriced stocks. Combining these two concepts yields the implication that a given difference in arbitrage risk is associated with a greater average degree of overpricing as compared to underpricing.

The above implication follows generally, whatever the source of asymmetry in arbitrage impediments. As discussed earlier, previously noted potential sources of asymmetric impediments include restrictions against short selling faced by many institutions, such as mutual funds, as well as occasionally high shorting costs. A key source of asymmetric impediments,

although perhaps one less recognized, is arbitrage risk itself. In the first subsection below, we discuss why short sellers face greater arbitrage risk than purchasers.

If arbitrageurs can neutralize their exposure to benchmark risks, a seemingly reasonable assumption, then idiosyncratic volatility (IVOL), as opposed to total volatility, is more closely related to arbitrage risk. Moreover, arbitrageurs can hold positions in multiple stocks at a given time, thereby enjoying diversification benefits. Therefore, the IVOL of the return on a portfolio of stocks that are overpriced more directly translates to arbitrage risk for a short seller, as compared to the IVOL's of the individual stocks. Similarly, the IVOL of a portfolio of underpriced stocks translates more directly to arbitrage risk for a purchaser.[10] In the second subsection below, we examine the idiosyncratic volatilities of returns on portfolios formed within various levels of our mispricing measure.

3.1. Asymmetric Arbitrage Risk

The risks faced by arbitrageurs are likely to be greater for short sellers than for purchasers. Consider first the risk that additional capital will be required to maintain a position. As noted above, this is a feature of noise-trader risk. In general, shorting requires that a margin deposit be maintained at some percentage of position size. If the price of the shorted stock rises, increasing the position size, additional margin capital can be required. A purchaser who does not employ leverage does not face margin calls, so in that case the greater risk facing the short seller is obvious.

A short seller still faces greater risk of a margin call even compared to a purchaser who buys on margin. To see this, note first that a position's margin ratio, which must typically be maintained above a specified maintenance level, is computed as

$$m = \frac{\text{equity}}{\text{position size}}. \tag{1}$$

Now consider a short seller and a purchaser, identical in terms of both equity and position sizes, who subsequently experience identical adverse rates of return on their underlying securities. Given the identical absolute return magnitudes, the short seller and purchaser lose identical amounts of equity, so they still have identical values for the numerator in (1). The new denominators differ from each other, however. The position size decreases

[10] One might note that the underlying issue is essentially the manner and extent to which correlations among benchmark-adjusted returns enter portfolio volatilities. If the benchmark-adjusted returns are idiosyncratic in the strongest sense—uncorrelated with each other across all stocks—the individual-stock IVOL remains the relevant quantity. See Pontiff (2006) for a discussion of this point.

for the purchaser but increases for the short seller, so the short seller's m declines by a greater amount. This asymmetry leaves short sellers more exposed to margin calls. For example, if both the long and short positions are established with $m = 50\%$, and they both have maintenance requirements of $m = 25\%$, the purchaser receives a margin call if the security price drops by 33%, whereas the short seller receives a call if the price increases by 20%. In practice, this asymmetry is magnified by stricter maintenance requirements for short positions. For example, the Financial Industry Regulatory Authority (FINRA), which regulates U.S. brokerage firms, specifies $m = 25\%$ for long positions but $m = 30\%$ for short positions.[11] With the latter requirement, the above short seller receives a margin call if the price increases by only 15.4%, less than half the percentage move triggering a call on the long position.

The risk of a large loss over an evaluation period such as a year can also be greater for the short seller simply because of the skewness inherent to compounded returns. Suppose a short seller and purchaser initially start with equal position sizes. If each of them experiences the same adverse percentage change in value of their underlying securities in the first month, their dollar losses are the same in that month. If that month is followed by another month of identical adverse percentage changes in security values, the short seller's total two-month loss then exceeds that of the purchaser. The reason is that, after the first month, the purchaser's position size decreases while the short seller's position increases. In essence, the compounding effect positively skews multiperiod returns, and the positive skewness translates to greater tail risk for a short seller. To better see the potential effect of such tail risk, suppose a short seller and a purchaser take equal sized positions in underlying portfolios each having monthly returns that are lognormal with a standard deviation of 4%. The short seller's underlying portfolio has an expected monthly return, after trading costs, equal to -0.50%, whereas the purchaser's portfolio has an expected return of 0.50%. Now consider the 1% Value-at-Risk (VaR) over 12 months—the amount of 12-month dollar loss for which the probability of a greater loss is equal to 1% (assuming both positions remain open). Straightforward calculations reveal that the short seller's VaR is 22% greater than the purchaser's VaR.

Another source of asymmetry in arbitrage risk is that short positions can occasionally be squeezed. As with the noise-trader risk mentioned earlier, this risk can necessitate the premature closing of an eventually profitable position. Specifically, a lender can recall a stock loan, at which point the short seller can find it difficult to locate a new lender.[12] There

[11] See FINRA Rule 4210.

[12] This risk is discussed, for example, by Dechow, Hutton, Meulbroek, and Sloan (2001), who cite circumstances surrounding the stock of Amazon.com in June 1998 as as a notable instance of a short squeeze.

is no corresponding risk for long positions.

3.2. Idiosyncratic Volatilities of Portfolios

This study provides an explanation of the previously reported negative relation between average return and IVOL, where IVOL is computed at the individual-stock level (Ang, Hodrick, Xing, and Zhang, 2006). As noted earlier, arbitrage risk, which is central to our explanation, is more appropriately related to the idiosyncratic volatility of a portfolio than to a single stock. Thus, an important step in our empirical investigation is to confirm that differences among individual-stock IVOL's translate to corresponding differences in portfolio IVOL's.

Table 1 reports idiosyncratic volatilities of portfolio returns sorted by mispricing and individual-stock IVOL. We compute individual-stock IVOL following Ang, Hodrick, Xing, and Zhang (2006), using the most recent month's daily benchmark-adjusted returns.[13] 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. Each month, portfolios are formed by sorting first on the mispricing measure, forming five categories, and then by sorting within each of those categories by individual-stock IVOL, again forming five categories. At both stages, equal numbers of stocks are allocated to each category. The stocks within each of the resulting 25 portfolios are value weighted to form the portfolio returns. The portfolio IVOL's reported in Table 1 are computed using the monthly portfolio returns, adjusted by the Fama-French factors, over the sample period covering 8/1965–1/2011.

The results in Table 1 confirm that within each level of mispricing, portfolio IVOL obeys the same ordering as the underlying individual-stock IVOL used in the sorting. For example, within the category of the most overpriced securities, the highest-IVOL portfolio has a monthly IVOL of 4.43%, and then IVOL's decline monotonically to 2.49% for the lowest-IVOL portfolio. Within the category of the most underpriced, we see portfolio IVOL's decline monotonically from 3.39% for the highest-IVOL portfolio to 1.82% for the lowest-IVOL portfolio. Similar patterns occur in the other three mispricing categories. We can thus conclude that diversification does not eliminate the differences in arbitrage risk that trace to different levels of individual-stock IVOL.

[13]This method is common in recent studies, but there are alternative approaches, such as the EGARCH model in Fu (2009). Guo, Kassa, and Ferguson (2012), and Fink, Fink, and He (2012) argue that the positive relation between expected return and IVOL found by Fu (2009) owes to the use of contemporaneous information in the conditional variance model and does not survive after controlling for such information.

Another result evident in Table 1 is that IVOL is higher among overpriced stocks than among underpriced stocks. This asymmetry in IVOL's is in fact consistent with our hypothesized setting. If arbitrage risk is an important determinant of the degree of mispricing, then the more mispriced securities will tend to have higher risk. With asymmetric impediments to arbitrage, however, overpricing is more likely than underpricing. Sorting on a relative mispricing measure is therefore likely to be more effective at the overpriced end in identifying high-risk stocks. If the impediments to arbitrage were instead symmetric, one should expect a U-shaped pattern in going from the top to the bottom of Table 1. With the asymmetry, the U-shape gets weakened among the underpriced stocks in the bottom rows. As a result, we see at best only the hint of a U-shape.

4. Mispricing and IVOL Effects

Table 2 presents the first set of our main results. The table reports average benchmark-adjusted monthly returns for each of the same 25 double sorted portfolios in Table 1. We see results consistent with the role of IVOL-driven arbitrage risk in mispricing. Among the securities 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 that prediction. For the most overpriced securities, the average returns are negative and monotonically *decreasing* in IVOL, with the difference between the highest- and lowest-IVOL portfolios equal to -1.80% per month (t-statistic: -8.28). For the most underpriced securities, the average returns are positive and monotonically *increasing* in IVOL, with the difference between the highest- and lowest-IVOL portfolios equal to 0.57% per month (t-statistic: 3.30). For the stocks in the middle of the mispricing scale, there is no apparent IVOL effect: there is no monotonicity, and the highest-versus-lowest difference is only -0.18% per month (t-statistic: -0.95). The role of mispricing in determining the strength and direction of IVOL effects is readily apparent in Figure 1, which plots the average benchmark-adjusted returns reported in Table 2.

Also evident in Table 2 and Figure 1 is the asymmetry in IVOL effects predicted by asymmetry in arbitrage impediments. 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 3.2 times the magnitude of the corresponding positive difference among the most underpriced stocks. This asymmetry explains the negative IVOL effect obtained when aggregating across all stocks, as shown in the

last row of Table 2. Among all stocks, consistent with the IVOL puzzle, average return is monotonically decreasing in IVOL, with the highest-versus-lowest difference equal to -0.78% per month (t-statistic: -5.50).

An additional implication of our setting is that the degree of mispricing, especially overpricing, should be greater among high-IVOL stocks than among low-IVOL stocks. We see this implication supported as well. The difference in average portfolio returns between the most overpriced stocks and the most underpriced stocks is negative and decreasing in IVOL, as shown in the next to last row in Table 2. The difference between that short-long difference for the highest-IVOL portfolios versus the lowest-IVOL portfolios is -2.38% per month (t-statistic: -9.08). These results are consistent with those of Jin (2012), who finds that that long-short spreads on each of ten anomalies are more profitable among high-IVOL stocks than among low-IVOL stocks, and that this difference in profitability is attributable primarily to the short legs of each strategy.

Recall that Table 2 is constructed by first sorting stocks into five categories based on the mispricing measure and then, within each mispricing quintile, sorting stocks into five categories based on IVOL. This dependent two-way sort allows us to focus on how IVOL effects depend on the direction and degree of mispricing. At the same time, however, the dependent sort potentially sacrifices some clarity in understanding how these IVOL effects aggregate across stocks to deliver the overall negative IVOL relation, since the breakpoints for IVOL differ across mispricing quintiles. As a robustness check, we also do an independent two-way sort, so that each of the mispricing-IVOL combinations simply contains the intersection of separate one-way sorts on mispricing and IVOL. The same 5×5 array reported in Table 2 is reported in Table 3, but with the independent sort replacing the dependent sort. As before, we see a significantly positive monthly return difference between high-IVOL and low-IVOL stocks among the most underpriced stocks (0.41 percent, t-statistic: 2.16), and we see a stronger negative IVOL effect among the most overpriced stocks (-1.50 percent, t-statistic: -7.36). Since the IVOL breakpoints are the same across the mispricing quintiles in Table 3, it is easier to see how the IVOL effects within those quintiles aggregate to deliver the overall negative IVOL effect reported in the last row of Table 2.[14]

[14]As an additional robustness check, we also recompute Table 2 using equally weighted portfolios rather than value-weighted portfolios, and the results are very similar: (i) a positive IVOL effect among the most underpriced (0.37 percent, t-statistic: 3.19), (ii) a stronger negative IVOL effect among the most overpriced (-1.73 percent, t-statistic: -10.66), and (iii) a negative overall IVOL effect (-0.83 percent, t-statistic: -7.33).

5. Time-Varying IVOL Effects

In our setting, the IVOL effects in expected return hinge on mispricing. If the degree and direction of mispricing vary over time, so should the IVOL effects. To investigate such time-varying IVOL effects, we need to identify variation over time in the tendency for general overpricing or underpricing in the stock market. For this purpose, we rely on the index of market-wide investor sentiment constructed by Baker and Wurgler (2006). The Baker-Wurgler (BW) index is constructed as the first principal component of six underlying measures of investor sentiment: the average closed-end fund discount, the number and the first-day returns of IPO's, NYSE turnover, the equity share of total new issues, and the dividend premium (log difference of average market/book of dividend payers vs. nonpayers).

The first subsection below investigates whether IVOL effects vary over time with investor sentiment in a manner predicted by our explanation. The results indicate that they do. For this initial investigation of sentiment effects, we use the "raw" version of the BW index from which macroeconomic effects are not removed. The reason for doing so is that investor sentiment could be related to macroeconomic factors. For example, when the economy is doing well, investors could also be more optimistic, and thus more likely to push prices above fundamental values. While such macro-related sentiment effects are perfectly consistent with our setting, many readers might ask whether they play a role in our results. In the second subsection below, we investigate this question by using Baker and Wurgler's (2006) alternative sentiment measure, which removes the effects of six macro variables. We further include six additional macro variables that previous empirical studies relate to expected stock returns. Our results point to little or no role for macro factors in the sentiment-related variation in the IVOL effects that we observe.

5.1. Investor Sentiment and IVOL Effects

Recall that our mispricing measure at best identifies only relative mispricing. Periods of high investor sentiment, when overpricing in the stock market is more likely in general, are also those times when our relatively overpriced stocks are more likely to be overpriced in absolute terms. At such times, the negative IVOL effect among our "overpriced" stocks should be stronger than at other times. That is, the IVOL effect (highest minus lowest) should be negatively related to the level of investor sentiment among the overpriced stocks. Similarly, in periods of low investor sentiment, our relatively underpriced stocks are more likely to be underpriced in absolute terms. At those times, the positive IVOL effect among

our "underpriced" stocks should be stronger than otherwise. In other words, among the underpriced stocks as well, the IVOL effect (highest minus lowest) should be negatively related to the level of investor sentiment. Therefore, among both overpriced and underpriced stocks, the IVOL effect should be negatively related to investor sentiment. As a result, the overall negative IVOL effect observed when aggregating across stocks should be stronger following high sentiment.

To explore the above implications, Table 4 repeats the analysis in Table 2 separately for high-sentiment and low-sentiment months. The three intermediate categories of IVOL are omitted to save space in Table 4. Figure 2 displays the averages for all five IVOL categories in low-sentiment and high-sentiment months. 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 1965:8–2011:1 sample period, while the low-sentiment months are those with below-median index values in the previous month.

The results in Table 4 and Figure 2 support the implications of our setting. 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). Also as predicted, the relatively overpriced stocks exhibit this same pattern. Among the most overpriced stocks, the spread between the highest-IVOL and lowest-IVOL average returns is -2.30% following high sentiment compared to -1.30% following low sentiment—a difference of -1.00% (t-statistic: -2.29). For the most underpriced stocks, the positive IVOL effect is stronger following low sentiment than following high sentiment: Among those stocks, the spread between the highest-IVOL and lowest-IVOL average returns is 0.21% following high sentiment compared to 0.94% following low sentiment—a difference of -0.73% (t-statistic: -2.03). These results go in the direction of supporting arbitrage asymmetry as well, in that the sentiment-related difference in IVOL effects is somewhat larger for the most overpriced stocks, although the t-statistic for the difference is modest (-0.53). When interpreting this last result, one should probably consider that a binary split between high- and low-sentiment periods, while useful in its simplicity, does not necessarily yield the most powerful test. We next turn to time-series regression as an alternative approach.

Table 5 reports the results of regressing excess returns or return spreads in month t on the variable S_{t-1}, the level of the BW index at the end of the previous month. Also included as independent variables are the contemporaneous realizations of the Fama-French

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 either (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 within each mispricing category and within the overall stock universe.

The results in Table 5 are again supportive of our setting's implications. Consistent with Table 4, the IVOL effect (highest minus lowest IVOL) is negatively related to investor sentiment. Within 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-basis-point difference in the IVOL effect. In addition, that 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).

Our use of the BW index as an independent variable in time-series regressions follows, for example, Baker and Wurgler (2006) and Stambaugh, Yu, and Yuan (2012a). One potential concern in any time-series regression is that a seemingly significant relation is spurious. This concern looms larger, the weaker is the prior motivation for the independent variable. Investor sentiment has long been entertained as exerting a significant influence on stock prices (e.g., Keynes, 1936), but spurious-regressor concerns can nevertheless arise. Indeed such a concern with regard to investor sentiment is raised by Novy-Marx (2012b). Simulations reported by Stambaugh, Yu and Yuan (2012b) reveal that the spurious regressor concern is greatly diminished when considering the ability of such a regressor to generate predicted results across a number of regressions.

5.2. Exploring macroeconomic effects

As mentioned earlier, investor sentiment could be related to macroeconomic factors. It is quite possible, for example, that when macroeconomic conditions are especially good, some investors also become too optimistic and push equity prices above levels justified by fundamental values. Similarly, during recessions, some investors could become too pessimistic and undervalue stocks as a result. As long as high (low) sentiment makes overpricing (underpricing) more likely, the extent to which sentiment relates to the macroeconomy does not affect the implications explored above. Nevertheless, the extent to which macroeconomic conditions play a role in our results are of potential interest.

Baker and Wurgler (2006) construct an alternative sentiment index that removes macro-

related variation by regressing their raw sentiment measures on six macro variables: the growth in industrial production, the growth in durable, nondurable, and services consumption, the growth in employment, and a flag for NBER recessions. Panel A of Table 6 repeats the regressions in Table 5 using this alternative sentiment index. The results are very similar to those in Table 5, indicating no important role for the six Baker-Wurgler macro variables in the former results. In Panel B of Table 5, we repeat the regression in Panel A but add six additional macro-related independent variables: the default premium, the term premium, the real interest rate, the inflation rate, the consumption surplus ratio, and CAY. These variables are often identified as being related to expected stock returns, so they seem especially relevant for exploring the role of macroeconomic conditions in our results. The default premium is defined as the yield spread between BAA and AAA bonds, and the term premium is defined as the spread between 20-year and 1-year Treasuries. The real interest rate is defined as the most recent monthly difference between the 30-day T-bill return and the CPI inflation rate. The consumption surplus ratio defined in Campbell and Cochrane (1999). Cay is the consumption-wealth variable defined in Lettau and Ludvigson (2001).[15] The conclusions summarized previously based on Table 5 are again essentially unchanged if instead based Panel B of Table 6. Overall, the results in Table 6 indicate that the sentiment-related variation in IVOL effects admit little or no role for the macro variables included in our investigation.

We do not include macro variables directly related to the stock market, such as dividend yield. In this sense, our choice of macro variables differs from that of Sibley, Xing, and Zhang (2012). Those authors investigate whether it is macro-related sentiment or non-macro-related sentiment that displays the ability to predict anomaly returns, as documented in Stambaugh, Yu, and Yuan (2012a). Sibley, Xing, and Zhang conclude that it is largely macro-related sentiment that exhibits the predictive ability. Such a result is consistent with sentiment-driven mispricing in any event, but the distinction between macro and non-macro effects seems less interesting when the macro variables include stock-market variables. Sentiment that affects stock prices is likely to affect dividend yield, lowering yield when sentiment is high, and vice versa. One would expect a sentiment measure purged of those stock-price effects to be less effective in identifying sentiment-driven stock mispricing and, therefore, to be less effective in predicting anomaly returns that reflect such mispricing.[16]

[15]The bond yields are obtained from the St. Louis Federal Reserve, the T-bill return and inflation are obtained from CRSP, and Cay is obtained from Sydney Ludvigson's website. Following Wachter (2006), the surplus ratio is calculated as a smoothed average of past consumption growth.

[16]Additional stock-market variables included by Sibley, Xing, and Zhang (2012) are volatility and a liquidity measure. Liquidity in particular could contain sentiment effects. In fact, Baker and Wurgler (2006) include turnover as one of the variables constituting their sentiment index.

6. Excluding Smaller Firms

In this section we explore the sensitivity of our results to excluding smaller firms. It is well known that smaller firms tend to have higher IVOL, and we also find that firm size tends to decline as our mispricing measure increases (i.e., as the measure moves from underpriced to overpriced). The fact that size is related to both IVOL and our mispricing measure raises the question of whether our results hinge importantly on including small firms. Our use of value-weighted portfolios in the previous results reduces this possibility, but in this section we go further and explore the sensitivity of our results to excluding firms below a given size threshold.

Table 7 repeats the analysis reported earlier in Table 2 but with smaller firms excluded. Before performing the two-way sort on IVOL and the mispricing measure, we eliminate all firms whose equity capitalization falls in the bottom p percent of the stock universe, for various choices of p. Specifically, in Panels A, B, C, and D, of Table 7, we exclude the bottom 20 percent, 40 percent, 60 percent, and 80 percent, respectively. First observe from Table 2 and Table 7 that the overall negative relation between IVOL and average return progressively weakens as the size threshold increases, but even among the largest quintile of stocks (Panel D) the average monthly spread between the high- and low-IVOL portfolios is still -0.37 percent (t-statistic: -2.59). This result is consistent with the results in Ang, Hodrick, Xing, and Zhang (2006), who find that the IVOL puzzle exists within all size quintiles but is weaker for larger firms.

The key result for the purpose of this study is that, as the size threshold increases, the IVOL effect continues to display the same dependence on the direction and degree of mispricing as observed earlier in Table 2. That is, the IVOL effect is significantly negative (positive) among the most overpriced (underpriced) stocks, but the negative effect is significantly stronger. We do observe that the latter asymmetry weakens somewhat as the size threshold increases, which is consistent with the corresponding weakening of the overall IVOL effect. Even for the largest stocks (Panel D), however, the negative IVOL effect among the most overpriced stocks (-0.88 percent, t-statistic: -4.09) exceeds the positive IVOL effect among the most underpriced stocks (0.48 percent, t-statistic: 2.62) by a difference of -1.35 percent (t-statistic: -5.32).

We do observe that the weakening of the asymmetry as the threshold increases comes primarily from the weakening of the negative IVOL effect among the overpriced stocks. For the portfolio of the most overpriced stocks, the IVOL effect starting in Table 2 and then

progressing through the four panels of Table 7 takes the values -1.80, -1.69, -1.58, -1.25, and -0.88, which display a clear increasing pattern. Among the most underpriced stocks, the comparable values are 0.57, 0.58, 0.63, 0.60, and 0.48, which display little or no pattern. In other words, as progressively larger stocks are eliminated, the positive IVOL effect among the most underpriced stocks remains fairly stable in magnitude, whereas the negative IVOL effect among the most overpriced stocks weakens.

Finally, we repeat the analysis in Table 5 under the same progressive elimination of smaller firms employed in Table 7, and the results are reported in Table 8. In all four panels of Table 8, the IVOL effect among overpriced stocks exhibits a significantly negative relation to investor sentiment, with magnitudes ranging from -0.79 to -0.91, comparable to the value of -0.79 in Table 5. The IVOL effect among underpriced stocks exhibits a consistently weaker negative relation to sentiment, again as in Table 5. We do see that excluding smaller firms causes the t-statistics for those negative coefficients to drop below conventional significance levels. Finding a weaker negative relation among the underpriced stocks is consistent with arbitrage asymmetry, as discussed earlier.

7. Conclusions

We provide an explanation for the negative empirical relation between expected return and idiosyncratic volatility (IVOL) observed in the overall cross section of equities. Our explanation combines two simple concepts. The first is that higher IVOL, which translates to 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. Combining these two concepts yields the implication 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 securities is stronger than the positive effect among underpriced, and thus a negative IVOL effect emerges within the overall cross section.

Our empirical evidence supports our explanation. 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, consistent with arbitrage asymmetry. 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.

We argue that risk is a key source of arbitrage asymmetry. One source of risk that is greater for short sellers is having to close prematurely an eventually profitable position due to adverse price moves—often termed noise-trader risk. The risk of a short squeeze necessitating a premature closure also has no long-side counterpart. Short sellers also face tail risk to a greater degree, due to the positive skewness in returns over periods likely to be relevant for professional investment managers.

Table 1
Idiosyncratic Volatility for Double Sorted Portfolios

The table reports monthly idiosyncratic volatility of the 25 double sorted portfolios. The 25 portfolios are formed by sorting stocks on the idiosyncratic volatility (IVOL) of their returns. The sort on IVOL is performed for stocks within a given range of over/under-pricing, as determined by an average of the rankings produced by 11 anomaly variables. The idiosyncratic volatility is calculated as the volatility of the residuals $\epsilon_{i,t}$ in the regression,

$$R_{i,t} = a + bMKT_t + cSMB_t + dHML_t + \epsilon_{i,t},$$

where $R_{i,t}$ is the excess percent return in month t on either the high-IVOL portfolio or the low-IVOL portfolio. The sample period is from 1965m8 to 2011m1.

	Highest IVOL	Next 20%	Next 20%	Next 20%	Lowest IVOL
Most overpriced	4.43	3.55	3.18	3.06	2.49
Next 20%	3.71	2.92	2.37	2.13	2.12
Next 20%	3.37	2.65	2.22	2.17	2.05
Next 20%	3.74	2.55	2.06	1.77	1.80
Most underpriced	3.39	2.66	2.25	1.93	1.82

Table 2
Idiosyncratic Volatility Effects in Underpriced versus Overpriced Stocks

The table reports average benchmark-adjusted returns for portfolios formed by sorting stocks on the idiosyncratic volatility (IVOL) of their returns. The sort on IVOL is performed for stocks within a given range of over/under-pricing, as determined by an average of the rankings produced by 11 anomaly variables. Also reported are results based on sorting by IVOL within the entire stock universe. Benchmark-adjusted returns are calculated as a in the regression,

$$R_{i,t} = a + bMKT_t + cSMB_t + dHML_t + \epsilon_{i,t},$$

where $R_{i,t}$ is the excess percent return in month t on either the high-IVOL portfolio, the low-IVOL portfolio, or the difference. The sample period is from 1965m8 to 2011m1. All t-statistics (in parentheses) are based on the heteroskedasticity-consistent standard errors of White (1980).

	Highest IVOL	Next 20%	Next 20%	Next 20%	Lowest IVOL	Highest −Lowest	All Stocks
Most overpriced	-2.25	-1.32	-0.80	-0.79	-0.45	-1.80	-0.81
(top 20%)	(-11.91)	(-8.72)	(-5.79)	(-5.31)	(-3.92)	(-8.28)	(-8.14)
Next 20%	-0.92	-0.40	-0.21	-0.27	-0.08	-0.84	-0.23
	(-5.76)	(-3.00)	(-2.08)	(-2.83)	(-0.82)	(-4.33)	(-3.88)
Next 20%	-0.13	0.01	0.03	-0.21	0.04	-0.18	-0.07
	(-0.88)	(0.11)	(0.25)	(-2.15)	(0.48)	(-0.95)	(-1.47)
Next 20%	-0.07	0.08	0.23	0.21	0.15	-0.23	0.18
	(-0.42)	(0.69)	(2.54)	(2.69)	(1.93)	(-1.10)	(4.45)
Most underpriced	0.68	0.66	0.41	0.31	0.10	0.57	0.28
(bottom 20%)	(4.63)	(5.68)	(4.22)	(3.90)	(1.37)	(3.30)	(5.67)
Most overpriced −	-2.93	-1.98	-1.21	-1.10	-0.55	-2.38	-1.09
most underpriced	(-12.31)	(-9.81)	(-6.53)	(-6.08)	(-3.69)	(-9.08)	(-8.05)
All stocks	-0.69	-0.12	-0.00	0.05	0.08	-0.78	
	(-6.09)	(-1.56)	(-0.01)	(1.07)	(1.86)	(-5.50)	

Table 3
Idiosyncratic Volatility Effects in Underpriced versus Overpriced Stocks: Independently Double-Sorted Portfolios

The table reports average benchmark-adjusted returns for portfolios formed by sorting stocks independently on the idiosyncratic volatility (IVOL) and the mispricing score. The mispricing score is determined by an average of the rankings produced by 11 anomaly variables. Also reported are results based on sorting by IVOL within the entire stock universe. Benchmark-adjusted returns are calculated as a in the regression,

$$R_{i,t} = a + bMKT_t + cSMB_t + dHML_t + \epsilon_{i,t},$$

where $R_{i,t}$ is the excess percent return in month t on either the high-IVOL portfolio, the low-IVOL portfolio, or the difference. The sample period is from 1965m8 to 2011m1. All t-statistics (in parentheses) are based on the heteroskedasticity-consistent standard errors of White (1980).

	Highest IVOL	Next 20%	Next 20%	Next 20%	Lowest IVOL	Highest −Lowest	All Stocks
Most overpriced	-1.89	-0.95	-0.72	-0.47	-0.39	-1.50	-0.81
(top 20%)	(-12.05)	(-7.39)	(-4.90)	(-3.62)	(-3.04)	(-7.36)	(-8.14)
Next 20%	-0.88	-0.41	-0.31	-0.21	-0.04	-0.84	-0.23
	(-5.86)	(-3.36)	(-3.00)	(-2.08)	(-0.44)	(-4.41)	(-3.88)
Next 20%	-0.09	-0.01	-0.05	-0.12	0.02	-0.10	-0.07
	(-0.53)	(-0.09)	(-0.48)	(-1.29)	(0.18)	(-0.53)	(-1.47)
Next 20%	-0.15	0.07	0.17	0.18	0.23	-0.38	0.18
	(-0.80)	(0.63)	(1.87)	(2.33)	(3.22)	(-1.78)	(4.45)
Most underpriced	0.56	0.68	0.51	0.33	0.14	0.41	0.28
(bottom 20%)	(3.27)	(4.91)	(5.02)	(4.10)	(2.04)	(2.16)	(5.67)
Most overpriced −	-2.44	-1.63	-1.23	-0.81	-0.53	-1.91	-1.09
most underpriced	(-11.07)	(-8.65)	(-6.43)	(-5.02)	(-3.43)	(-7.62)	(-8.05)
All stocks	-0.69	-0.12	-0.00	0.05	0.08	-0.78	
	(-6.09)	(-1.56)	(-0.01)	(1.07)	(1.86)	(-5.50)	

Table 4
Idiosyncratic Volatility Effects in High-Sentiment versus Low-Sentiment Periods

The table reports average benchmark-adjusted returns for portfolios containing stocks with either the highest (top 20%) or lowest (bottom 20%) idiosyncratic volatility (IVOL). The sort on IVOL is performed for stocks within a given range of over/under-pricing, as determined by an average of the rankings produced by 11 anomaly variables. Also reported are results based on sorting by IVOL within the entire stock universe. The benchmark-adjusted returns in high- and low-sentiment periods are estimates of a_H and a_L in the regression,

$$R_{i,t} = a_H d_{H,t} + a_L d_{L,t} + bMKT_t + cSMB_t + dHML_t + \epsilon_{i,t},$$

where $d_{H,t}$ and $d_{L,t}$ are dummy variables indicating high- and low-sentiment periods, and $R_{i,t}$ is the excess percent return in month t on either the high-IVOL portfolio, the low-IVOL portfolio, or the difference. The sample period is from 1965m8 to 2011m1. All t-statistics (in parentheses) are based on the heteroskedasticity-consistent standard errors of White (1980).

	High-Sentiment Periods			Low-Sentiment Periods			High-Sentiment Periods − Low-Sentiment Periods		
	Highest IVOL	Lowest IVOL	Highest −Lowest	Highest IVOL	Lowest IVOL	Highest −Lowest	Highest IVOL	Lowest IVOL	Highest −Lowest
Most overpriced (top 20%)	-2.84	-0.54	-2.30	-1.66	-0.36	-1.30	-1.18	-0.18	-1.00
	(-9.57)	(-3.13)	(-6.79)	(-6.91)	(-2.55)	(-4.75)	(-3.06)	(-0.86)	(-2.29)
Next 20%	-1.24	-0.01	-1.23	-0.60	-0.16	-0.44	-0.64	0.15	-0.79
	(-5.28)	(-0.04)	(-4.31)	(-2.77)	(-1.26)	(-1.71)	(-2.02)	(0.82)	(-2.07)
Next 20%	-0.17	0.31	-0.48	-0.10	-0.22	0.13	-0.07	0.53	-0.60
	(-0.72)	(2.34)	(-1.75)	(-0.54)	(-1.92)	(0.52)	(-0.25)	(3.09)	(-1.68)
Next 20%	-0.10	0.19	-0.29	-0.04	0.11	-0.16	-0.06	0.08	-0.14
	(-0.35)	(1.44)	(-0.84)	(-0.23)	(1.29)	(-0.75)	(-0.18)	(0.49)	(-0.34)
Most underpriced (bottom 20%)	0.54	0.33	0.21	0.82	-0.12	0.94	-0.28	0.45	-0.73
	(2.43)	(2.77)	(0.77)	(4.05)	(-1.21)	(4.16)	(-0.93)	(2.85)	(-2.03)
Most overpriced − most underpriced	-3.38	-0.87	-2.51	-2.48	-0.24	-2.24	-0.90	-0.63	-0.27
	(-9.36)	(-4.02)	(-6.48)	(-7.82)	(-1.22)	(-6.60)	(-1.85)	(-2.23)	(-0.53)
All stocks	-1.06	0.26	-1.32	-0.33	-0.10	-0.23	-0.72	0.36	-1.09
	(-5.75)	(3.81)	(-5.88)	(-2.45)	(-1.87)	(-1.35)	(-3.16)	(4.16)	(-3.82)

Table 5
Idiosyncratic-Volatility Effects and Investor Sentiment: Predictive Regressions

The table reports estimates of b in the regression,

$$R_{i,t} = a + bS_{t-1} + cMKT_t + dSMB_t + eHML_t + u_t,$$

where $R_{i,t}$ is the excess percent return in month t on either the highest-IVOL portfolio (top 20%), the lowest-IVOL portfolio (bottom 20%), or the difference, and S_t is the level of the investor-sentiment index of Baker and Wurgler (2006). The sort on IVOL is performed for stocks within a given range of over/under-pricing, as determined by an average of the rankings produced by 11 anomaly variables. Also reported are results based on sorting by IVOL within the entire stock universe. The sample period is from 1965m8 to 2011m1. All t-statistics are based on the heteroskedasticity-consistent standard errors of White (1980).

	Highest IVOL		Lowest IVOL		Highest − Lowest	
	$\hat{b}$	t-stat.	$\hat{b}$	t-stat.	$\hat{b}$	t-stat.
Most overpriced (top 20%)	-0.78	-3.74	0.01	0.08	-0.79	-3.49
Next 20%	-0.40	-2.50	0.09	0.97	-0.48	-2.50
Next 20%	-0.10	-0.74	0.30	3.20	-0.40	-2.18
Next 20%	-0.13	-0.81	0.05	0.60	-0.18	-0.93
Most underpriced (bottom 20%)	-0.12	-0.92	0.16	1.81	-0.28	-1.80
Most overpriced − most underpriced	-0.66	-2.76	-0.15	-1.12	-0.50	-2.20
All stocks	-0.48	-3.92	0.18	3.77	-0.66	-4.25

Table 6
Idiosyncratic-Volatility Effects and Investor Sentiment: Predictive Regressions with Macroeconomic Controls

The table reports estimates of b in the regressions,

$$R_{i,t} = a + b\tilde{S}_{t-1} + cMKT_t + dSMB_t + eHML_t + u_t \quad \text{(Panel A)}$$

$$R_{i,t} = a + b\tilde{S}_{t-1} + cMKT_t + dSMB_t + eHML_t + \sum_{j=1}^{6} m_j X_{j,t-1} + u_t \quad \text{(Panel B)},$$

where $R_{i,t}$ is the excess percent return in month t on either the highest-IVOL portfolio (top 20%), the lowest-IVOL portfolio (bottom 20%), or the difference, $\tilde{S}_t$ is the level of the investor-sentiment index of Baker and Wurgler (2006) that is orthogonalized with respect to six macro variables, and $X_{1,t}$, $\cdots$, $X_{6,t}$ are the term premium, the default premium, the interest rate, the inflation rate, the surplus ratio, and the wealth consumption ratio. The sort on IVOL is performed for stocks within a given range of over/under-pricing, as determined by an average of the rankings produced by 11 anomaly variables. Also reported are results based on sorting by IVOL within the entire stock universe. The sample period is from 1965m8 to 2011m1. All t-statistics are based on the heteroskedasticity-consistent standard errors of White (1980).

	Highest IVOL		Lowest IVOL		Highest − Lowest	
	$\hat{b}$	t-stat.	$\hat{b}$	t-stat.	$\hat{b}$	t-stat.
Panel A. $R_{i,t} = a + b\tilde{S}_{t-1} + cMKT_t + dSMB_t + eHML_t + u_t$						
Most overpriced (top 20%)	-0.74	-3.56	0.03	0.28	-0.76	-3.42
Next 20%	-0.45	-2.89	0.08	0.92	-0.53	-2.81
Next 20%	-0.17	-1.24	0.29	3.10	-0.46	-2.49
Next 20%	-0.17	-1.12	0.04	0.52	-0.22	-1.14
Most underpriced (bottom 20%)	-0.20	-1.54	0.15	1.63	-0.35	-2.22
Most overpriced − most underpriced	-0.54	-2.28	-0.12	-0.87	-0.42	-1.88
All stocks	-0.52	-4.31	0.17	3.53	-0.69	-4.50
Panel B. $R_{i,t} = a + b\tilde{S}_{t-1} + cMKT_t + dSMB_t + eHML_t + \sum_{j=1}^{6} m_j X_{j,t-1} + u_t$						
Most overpriced (top 20%)	-0.64	-2.68	-0.08	-0.67	-0.56	-2.15
Next 20%	-0.46	-2.52	0.04	0.41	-0.50	-2.29
Next 20%	-0.10	-0.65	0.25	2.56	-0.35	-1.73
Next 20%	-0.09	-0.49	0.09	0.97	-0.17	-0.83
Most underpriced (bottom 20%)	-0.18	-1.21	0.07	0.70	-0.24	-1.42
Most overpriced − most underpriced	-0.46	-1.75	-0.14	-0.94	-0.32	-1.25
All stocks	-0.50	-3.58	0.15	2.84	-0.65	-3.69

Table 7
Idiosyncratic Volatility Effects in Underpriced versus Overpriced Stocks Under Various Thresholds for Market Capitalization

The table reports average benchmark-adjusted returns for portfolios formed by sorting stocks on the idiosyncratic volatility (IVOL) of their returns. The sort on IVOL is performed for stocks within a given range of over/under-pricing, as determined by an average of the rankings produced by 11 anomaly variables. Also reported are results based on sorting by IVOL within the entire stock universe. Benchmark-adjusted returns are calculated as a in the regression,

$$R_{i,t} = a + bMKT_t + cSMB_t + dHML_t + \epsilon_{i,t},$$

where $R_{i,t}$ is the excess percent return in month t on either the high-IVOL portfolio, the low-IVOL portfolio, or the difference. The sample period is from 1965m8 to 2011m1. All t-statistics (in parentheses) are based on the heteroskedasticity-consistent standard errors of White (1980). In Panels A, B, C, and D, the smallest 20%, 40%, 60%, and 80% of the firms are deleted from the portfolio formation, respectively.

	Highest IVOL	Next 20%	Next 20%	Next 20%	Lowest IVOL	Highest −Lowest	All Stocks
			Panel A: 20% Smallest Stocks Deleted				
Most overpriced (top 20%)	-2.15 (-11.08)	-1.29 (-8.59)	-0.84 (-6.04)	-0.75 (-5.02)	-0.46 (-3.91)	-1.69 (-7.69)	-0.80 (-7.98)
Next 20%	-0.89 (-5.72)	-0.40 (-2.92)	-0.25 (-2.51)	-0.30 (-3.12)	-0.10 (-1.03)	-0.79 (-4.16)	-0.26 (-4.33)
Next 20%	-0.13 (-0.89)	0.07 (0.67)	0.05 (0.49)	-0.15 (-1.55)	0.04 (0.46)	-0.17 (-0.93)	-0.05 (-1.15)
Next 20%	-0.04 (-0.22)	0.11 (1.06)	0.21 (2.25)	0.22 (2.72)	0.13 (1.68)	-0.17 (-0.87)	0.16 (4.06)
Most underpriced (bottom 20%)	0.68 (4.40)	0.67 (5.92)	0.40 (4.12)	0.30 (3.67)	0.11 (1.39)	0.58 (3.14)	0.29 (5.77)
Most overpriced − Most underpriced	-2.83 (-11.46)	-1.96 (-9.80)	-1.23 (-6.67)	-1.05 (-5.72)	-0.56 (-3.70)	-2.27 (-8.43)	-1.09 (-7.98)
All stocks	-0.69 (-6.13)	-0.05 (-0.69)	0.03 (0.46)	0.02 (0.51)	0.09 (2.02)	-0.78 (-5.56)	
			Panel B: 40% Smallest Stocks Deleted				
Most overpriced (top 20%)	-2.02 (-10.59)	-1.23 (-7.92)	-0.77 (-4.91)	-0.69 (-4.82)	-0.44 (-3.80)	-1.58 (-7.11)	-0.78 (-7.71)
Next 20%	-0.85 (-5.61)	-0.33 (-2.57)	-0.36 (-3.38)	-0.27 (-2.86)	-0.05 (-0.46)	-0.81 (-4.21)	-0.25 (-4.17)
Next 20%	-0.01 (-0.10)	0.07 (0.67)	0.06 (0.56)	-0.15 (-1.61)	0.04 (0.45)	-0.05 (-0.31)	-0.03 (-0.74)
Next 20%	0.01 (0.09)	0.13 (1.22)	0.17 (1.83)	0.25 (3.14)	0.14 (1.74)	-0.12 (-0.65)	0.17 (4.02)
Most underpriced (bottom 20%)	0.74 (5.05)	0.58 (5.38)	0.33 (3.51)	0.33 (4.11)	0.11 (1.35)	0.63 (3.57)	0.28 (5.66)
Most overpriced − Most underpriced	-2.76 (-11.93)	-1.80 (-9.00)	-1.11 (-5.56)	-1.02 (-5.66)	-0.55 (-3.58)	-2.21 (-8.59)	-1.06 (-7.75)
All stocks	-0.63 (-5.63)	-0.03 (-0.39)	0.08 (1.46)	0.01 (0.25)	0.10 (2.19)	-0.73 (-5.20)	

Table 7 (continued)
Idiosyncratic Volatility Effects in Underpriced versus Overpriced Stocks Under Various Thresholds for Market Capitalization

The table reports average benchmark-adjusted returns for portfolios formed by sorting stocks on the idiosyncratic volatility (IVOL) of their returns. The sort on IVOL is performed for stocks within a given range of over/under-pricing, as determined by an average of the rankings produced by 11 anomaly variables. Also reported are results based on sorting by IVOL within the entire stock universe. Benchmark-adjusted returns are calculated as a in the regression,

$$R_{i,t} = a + bMKT_t + cSMB_t + dHML_t + \epsilon_{i,t},$$

where $R_{i,t}$ is the excess percent return in month t on either the high-IVOL portfolio, the low-IVOL portfolio, or the difference. The sample period is from 1965m8 to 2011m1. All t-statistics (in parentheses) are based on the heteroskedasticity-consistent standard errors of White (1980). In Panels A, B, C, and D, the smallest 20%, 40%, 60%, and 80% of the firms are deleted from the portfolio formation, respectively.

	Highest IVOL	Next 20%	Next 20%	Next 20%	Lowest IVOL	Highest −Lowest	All Stocks
			Panel C: 60% Smallest Stocks Deleted				
Most overpriced (top 20%)	-1.67 (-9.02)	-1.05 (-6.69)	-0.66 (-4.11)	-0.58 (-4.58)	-0.41 (-3.64)	-1.25 (-5.96)	-0.71 (-7.37)
Next 20%	-0.62 (-4.03)	-0.26 (-2.29)	-0.30 (-2.84)	-0.16 (-1.59)	-0.04 (-0.41)	-0.58 (-2.94)	-0.21 (-3.65)
Next 20%	0.08 (0.62)	0.12 (1.15)	0.02 (0.21)	-0.14 (-1.45)	0.06 (0.63)	0.02 (0.14)	-0.01 (-0.31)
Next 20%	0.11 (0.83)	0.19 (1.88)	0.06 (0.61)	0.35 (4.03)	0.19 (2.15)	-0.07 (-0.46)	0.17 (3.69)
Most underpriced (bottom 20%)	0.71 (4.91)	0.59 (5.42)	0.31 (3.02)	0.31 (3.70)	0.10 (1.28)	0.60 (3.43)	0.28 (5.39)
Most overpriced − Most underpriced	-2.37 (-10.89)	-1.64 (-7.94)	-0.97 (-4.72)	-0.89 (-5.17)	-0.52 (-3.44)	-1.86 (-7.89)	-1.00 (-7.41)
All stocks	-0.44 (-3.94)	0.00 (0.06)	0.01 (0.26)	0.06 (1.29)	0.09 (1.98)	-0.53 (-3.79)	
			Panel D: 80% Smallest Stocks Deleted				
Most overpriced (top 20%)	-1.18 (-6.28)	-0.83 (-4.90)	-0.56 (-3.76)	-0.45 (-3.34)	-0.30 (-2.57)	-0.88 (-4.09)	-0.59 (-6.02)
Next 20%	-0.44 (-3.00)	-0.21 (-1.98)	-0.21 (-1.99)	-0.16 (-1.49)	0.06 (0.59)	-0.50 (-2.57)	-0.17 (-3.15)
Next 20%	0.06 (0.45)	0.12 (1.15)	0.08 (0.73)	-0.01 (-0.08)	0.09 (0.95)	-0.03 (-0.17)	0.05 (0.97)
Next 20%	0.16 (1.26)	-0.02 (-0.16)	0.18 (1.77)	0.26 (2.86)	0.13 (1.38)	0.03 (0.18)	0.15 (2.89)
Most underpriced (bottom 20%)	0.54 (3.75)	0.56 (5.20)	0.34 (3.22)	0.32 (3.56)	0.06 (0.71)	0.48 (2.62)	0.28 (4.96)
Most overpriced − Most underpriced	-1.72 (-7.47)	-1.39 (-6.33)	-0.90 (-4.64)	-0.77 (-4.16)	-0.36 (-2.33)	-1.35 (-5.32)	-0.87 (-6.28)
All stocks	-0.28 (-2.58)	0.05 (0.86)	0.02 (0.33)	0.09 (1.84)	0.09 (1.73)	-0.37 (-2.59)	

Table 8
Idiosyncratic-Volatility Effects and Investor Sentiment: Predictive Regressions Under Various Thresholds for Market Capitalization

The table reports estimates of b in the regression,

$$R_{i,t} = a + bS_{t-1} + cMKT_t + dSMB_t + eHML_t + u_t,$$

where $R_{i,t}$ is the excess percent return in month t on either the highest-IVOL portfolio (top 20%), the lowest-IVOL portfolio (bottom 20%), or the difference, and S_t is the level of the investor-sentiment index of Baker and Wurgler (2006). The sort on IVOL is performed for stocks within a given range of over/under-pricing, as determined by an average of the rankings produced by 11 anomaly variables. Also reported are results based on sorting by IVOL within the entire stock universe. The sample period is from 1965m8 to 2011m1. All t-statistics are based on the heteroskedasticity-consistent standard errors of White (1980). In Panels A, B, C, and D, the smallest 20%, 40%, 60%, and 80% of the firms are deleted from the portfolio formation, respectively.

	Highest IVOL		Lowest IVOL		Highest − Lowest	
	$\hat{b}$	t-stat.	$\hat{b}$	t-stat.	$\hat{b}$	t-stat.
Panel A: 20% Smallest Stocks Deleted						
Most overpriced (top 20%)	-0.79	-3.82	0.00	0.04	-0.79	-3.54
Next 20%	-0.44	-2.83	0.10	1.10	-0.53	-2.80
Next 20%	-0.11	-0.84	0.31	3.38	-0.42	-2.41
Next 20%	-0.10	-0.65	0.08	0.95	-0.18	-0.97
Most underpriced (bottom 20%)	-0.07	-0.52	0.14	1.50	-0.20	-1.29
Most overpriced − most underpriced	-0.72	-3.07	-0.13	-0.95	-0.59	-2.62
All stocks	-0.46	-3.80	0.18	3.76	-0.64	-4.15
Panel B: 40% Smallest Stocks Deleted						
Most overpriced (top 20%)	-0.83	-4.03	-0.02	-0.24	-0.80	-3.56
Next 20%	-0.38	-2.31	0.15	1.60	-0.53	-2.58
Next 20%	-0.19	-1.48	0.31	3.13	-0.50	-2.80
Next 20%	0.01	0.11	0.12	1.53	-0.11	-0.61
Most underpriced (bottom 20%)	-0.03	-0.24	0.14	1.45	-0.17	-1.02
Most overpriced − most underpriced	-0.79	-3.45	-0.16	-1.12	-0.63	-2.79
All stocks	-0.43	-3.48	0.19	3.93	-0.62	-3.93
Panel C: 60% Smallest Stocks Deleted						
Most overpriced (top 20%)	-0.78	-3.86	0.04	0.39	-0.81	-3.77
Next 20%	-0.33	-2.14	0.11	1.23	-0.44	-2.25
Next 20%	-0.01	-0.09	0.27	2.64	-0.29	-1.51
Next 20%	0.03	0.21	0.14	1.73	-0.11	-0.70
Most underpriced (bottom 20%)	0.03	0.20	0.14	1.44	-0.11	-0.64
Most overpriced − most underpriced	-0.80	-3.46	-0.10	-0.70	-0.70	-3.23
All stocks	-0.35	-2.82	0.17	3.49	-0.52	-3.27
Panel D: 80% Smallest Stocks Deleted						
Most overpriced (top 20%)	-0.80	-3.87	0.11	0.94	-0.91	-3.93
Next 20%	-0.34	-2.29	0.18	1.75	-0.52	-2.63
Next 20%	0.00	0.01	0.29	2.82	-0.29	-1.52
Next 20%	0.02	0.16	0.16	1.76	-0.14	-0.85
Most underpriced (bottom 20%)	0.04	0.25	0.11	1.11	-0.07	-0.41
Most overpriced − most underpriced	-0.84	-3.37	0.00	0.01	-0.84	-3.28
All stocks	-0.31	-2.62	0.16	2.97	-0.47	-2.99

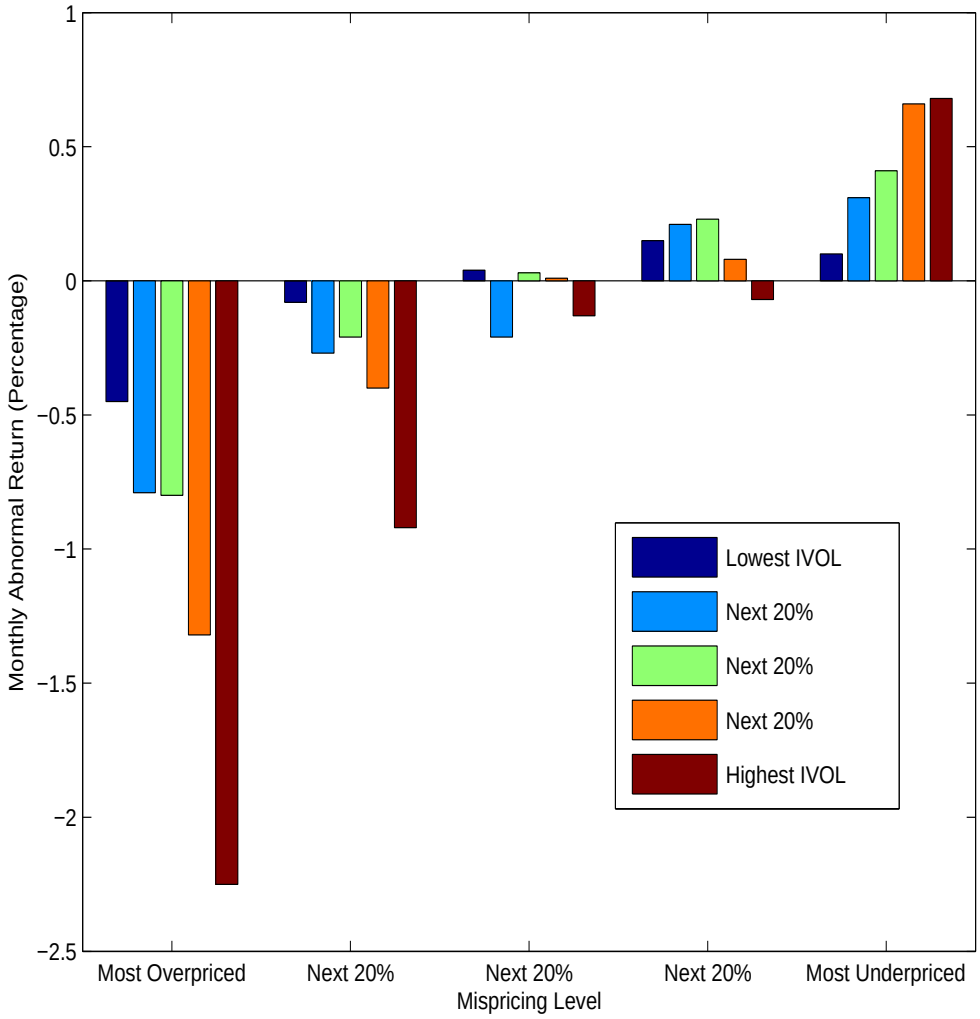


Figure 1. Monthly Abnormal Returns of Portfolios Ranked by Mispricing Level and IVOL. The figure plots the average monthly abnormal return on portfolios formed in a 5×5 sort that ranks first by mispricing level and then by IVOL. Abnormal returns are calculated by adjusting for exposures to the three Fama-French factors. The average ranking of 11 anomalies is used to measure the relative level of mispricing. The sample period covers 8/1965–1/2011.

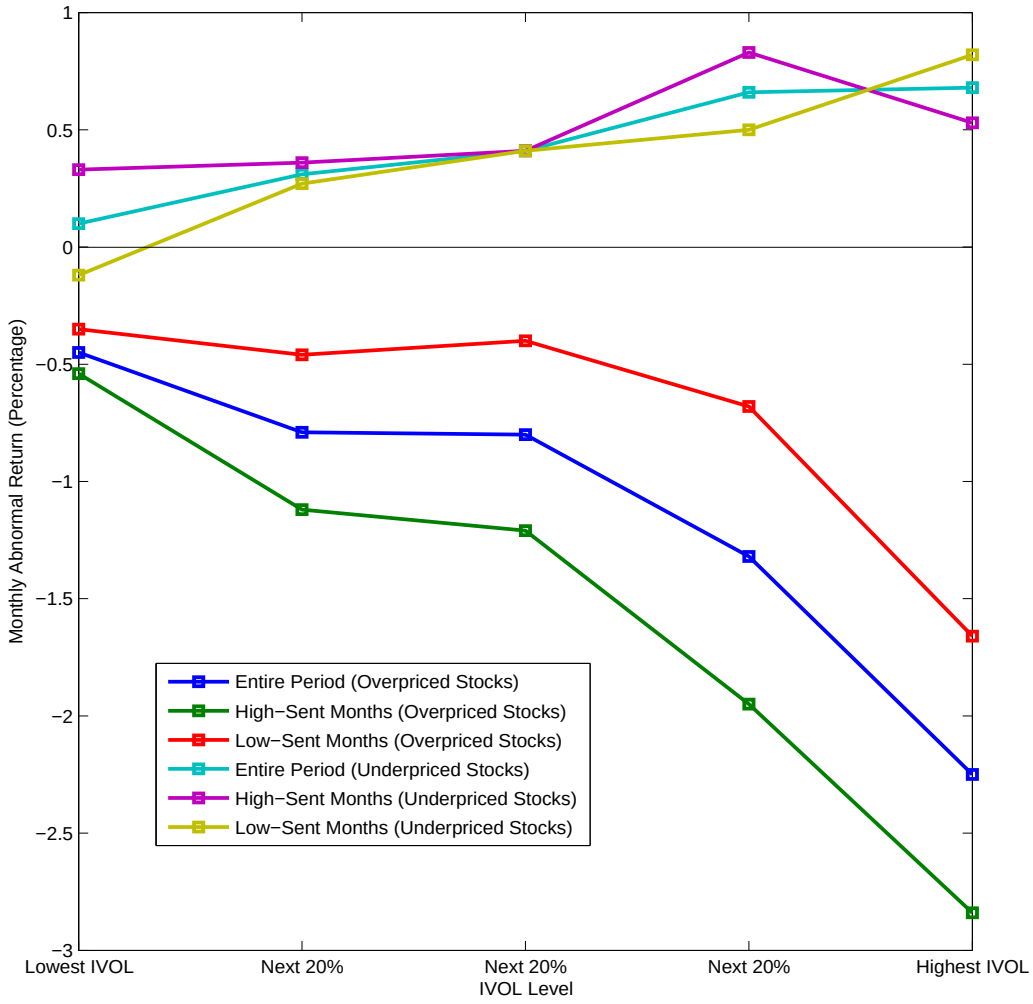


Figure 2. IVOL Effects and Investor Sentiment. The figure plots the average monthly abnormal return on portfolios formed in a 5×5 sort that ranks first by mispricing level and then by IVOL. Results are displayed for the five portfolios in the most underpriced quintile and the five portfolios in the most overpriced quintile. Abnormal returns are calculated by adjusting for exposures to the three Fama-French factors. The average ranking of 11 anomalies is used to measure the relative level of mispricing. Averages are reported for the overall 8/1965–1/2011 sample period as well as for high-sentiment and low-sentiment months classified using the Baker-Wurgler index.

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