Arbitrage Asymmetry and the Idiosyncratic Volatility Puzzle

by*

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Abstract

Many investors purchase stock but are reluctant or unable to sell short. Combining this arbitrage asymmetry with the arbitrage risk represented by idiosyncratic volatility (IVOL) explains the negative relation between IVOL and average return. The effect of IVOL on return 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 arbitrage asymmetry, and therefore aggregating across all stocks yields a negative relation. 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).[1] Much of the current empirical research on this topic, beginning notably with Ang, Hodrick, Xing, and Zhang (2006), instead finds a negative relation between expected return and IVOL. Chen, Jiang, Xu, and Yao (2012) conclude that this negative relation is robust to various issues raised by a number of recent studies.[2] While a positive relation is accommodated by various theoretical departures from the classical paradigm, the negative relation has presented more of a puzzle.[3]

This study presents an explanation for the observed negative relation between IVOL and expected return. We start with the proposition that IVOL represents risk that deters arbitrage and the resulting reduction of mispricing. In keeping with previous literature, we refer to risk that deters arbitrage as arbitrage risk.[4] We then combine this familiar concept with what we term arbitrage asymmetry: Many investors who would buy a stock they see as underpriced are reluctant or unable to short a stock they see as overpriced.[5]

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

[1] 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] Specifically, Chen et al. show that the negative IVOL effect is not due to illiquidity or reversal and that it is very robust once penny stocks and other very illiquid stocks are excluded. Other studies reporting a negative relation include Jiang, Xu, and Yao (2009) and Guo and Savickas (2010).

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

[4] 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).

[5] Studies addressing the role of such asymmetry 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).

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 asymmetry, 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.

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.

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).[6] Consistent with the above predictions, the negative IVOL effect among overpriced stocks is significantly

[6]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).

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 is especially strong for the short-leg profits.[7] 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.[8] 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

[7]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).

[8]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.

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 discusses the joint roles of arbitrage asymmetry and arbitrage risk in allowing a stock's mispricing to survive the forces of arbitrage. Section 3 describes our empirical measure of relative cross-sectional mispricing, based on a composite ranking that combines 11 return anomalies. 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 uses the cross-section of individual stocks to estimate the form of the relation between mispricing and the IVOL. Section 7 shows that the dependence of the IVOL effect on mispricing is robust to eliminating smaller stocks. Section 8 shows that the negative IVOL effect among overpriced stocks is stronger among stocks with low institutional ownership, for which short-sale impediments are likely to be more important. Section 9 reviews the study's main conclusions.

2. Arbitrage Risk and Arbitrage Asymmetry

Our setting combines two familiar concepts, arbitrage risk and arbitrage asymmetry. Arbitrage risk is risk that deters arbitrage. Arbitrage asymmetry is the greater ability or willingness of investors to take long positions as opposed to short positions. Mispricing in a security is less likely to be corrected the greater is the security's arbitrage risk, and thus the greater is the deterrence to price-correcting arbitrage. With arbitrage asymmetry, overpricing in a security is less likely to invoke arbitrage than is underpricing. Combining the concepts of arbitrage risk and arbitrage asymmetry yields the implication that a given degree of arbitrage risk is associated with a greater degree of overpricing as compared to underpricing. With arbitrage asymmetry, an underpriced security is met with greater arbitrage activity than is an equally overpriced security possessing the same arbitrage risk. In essence, a security's arbitrage risk is less of a deterrent to correcting underpricing as opposed to overpricing when there is arbitrage asymmetry.

Arbitrage asymmetry is well established. 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. They 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). 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. 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.

Arbitrage risk is related to idiosyncratic volatility (IVOL). If arbitrageurs can neutralize their exposure to benchmark risks, a seemingly reasonable assumption, then idiosyncratic volatility, as opposed to total volatility, is more closely related to arbitrage risk. Pontiff (2006), for example, shows how a stock's idiosyncratic volatility (IVOL) represents its arbitrage risk. In the first subsection below, we analyze this role of IVOL using a simple one-period setting in which mean-variance investors subject to arbitrage asymmetry exploit mispricing induced by the presence of noise traders. With arbitrage asymmetry, there is less capital available to bear the arbitrage risk in shorting overpriced securities than there is to bear the same arbitrage risk in going long. As a result, for a given level of IVOL, the demands of noise traders can exert a relatively greater effect in producing alpha—mispricing—when those demands go in the direction of producing overpricing as opposed to underpricing.

In the basic mechanism illustrated in the one-period setting, there is arbitrage asymmetry, but arbitrage risk—IVOL—does not depend on whether a position is long or short. In that setting, what differs between long and short positions is the amount of capital available to bear the arbitrage risk. In the second subsection, we discuss how a given level of volatility can translate to arbitrage risk that is itself asymmetric when considering issues that are essentially more multiperiod in nature. In particular, short positions involve a greater risk of margin calls as well as negative tail risk that arises from the positive skewness of multiperiod returns. To the extent that these additional considerations further deter shorting, they increase the asymmetry of IVOL's role in overpricing as compared to underpricing.

2.1. A Simple Model

Securities are held by mean-variance investors and noise traders. The mean-variance investors have the single-period objective

$$\max_{\omega}(\omega'\mu - \frac{A}{2}\omega' V\omega), \tag{1}$$

where μ is the vector of expected excess returns on the N risky assets, the i-th element of ω is the fraction of wealth invested in asset i, and V is the variance-covariance matrix of returns, assumed to be of the form

$$V = \sigma_m^2 \beta\beta' + \Sigma \tag{2}$$

where σ_m^2 is the variance of the market return, β is the vector of the assets' market betas, and Σ is a diagonal matrix whose i-th diagonal element is $\sigma_{\epsilon,i}^2$, the idiosyncratic return variance of asset i.[9] The noise traders have asset demands given exogenously by the N-vector z. We assume that the elements of z and β are uncorrelated in the cross section, and we also assume that the market equity premium, μ_m, is the same as what it would be if z were the zero vector. Specifically, $\mu_m = A\sigma_m^2$.

Arbitrage asymmetry is incorporated by having the mean-variance investors be composed of two types. The first type, long-only, does not short. Those investors have total capital M, which is allocated across assets according to the vector of optimal asset weights ω_M. The second type, long-short, can go either long or short each asset. The total amount of their invested capital is H, and the vector of their optimal weights is ω_H. Market clearing requires

$$M\omega_M + H\omega_H = s - z, \tag{3}$$

where s is the vector of total market capitalizations of the assets.

[9] To specify Σ as literally diagonal (and thus nonsingular) must be an approximation, given that the capitalization-weighted average of market-adjusted returns must be zero, so we are assuming the approximation error is negligible.

For each asset i, this model delivers the following result for α_i ($= \mu_i - \beta_i \mu_m$) as N grows large. If the long-only investors hold some of stock i (i.e., $\omega_{M,i} > 0$), then

$$\alpha_i = A(s_i - z_i) \frac{\sigma^2_{\epsilon,i}}{M + H}. \tag{4}$$

If the long-only investors do not hold stock i, (i.e., $\omega_{M,i} = 0$), then

$$\alpha_i = A(s_i - z_i) \frac{\sigma^2_{\epsilon,i}}{H} \tag{5}$$

Derivations are provided in the Appendix.

Equations (4) and (5) reveal the potential asymmetry in the relation between α_i and $\sigma_{\epsilon,i}$. If noise trader demand z_i is sufficiently large to make $z_i > s_i$, then the long-short mean-variance investors are short, and the (negative) alpha is given by equation (5). Note also in that case that the amount of long-short capital H appears in the denominator. In contrast, the denominator in equation (4) contains the total amount of mean-variance capital, $M + H$. If H is substantially smaller than M, a seemingly reasonable assumption, then for a given magnitude of $|s_i - z_i|$, the implied magnitude of alpha will be substantially larger in the overpriced case for the same value of $\sigma_{\epsilon,i}$. In other words, for a given magnitude of $|s_i - z_i|$, the effect of IVOL on alpha is stronger when the stock is overpriced and sold short by the long-short investors ($z_i > s_i$) than when it is underpriced and held long ($z_i < s_i$).

What we see from this simple model is that, when arbitrage risk ($\sigma_{\epsilon,i}$) is borne by a smaller pool of capital, its role in the resulting mispricing (α_i), ceteris paribus, is correspondingly greater. To say more about alphas requires assumptions about the size and distribution of noise trader demands, and that is beyond our intent. A more realistic setting would also acknowledge that a portion of the total supply s_i is held by investors who limit deviations from a benchmark portfolio. Such investors certainly include index funds, but it seems likely that they also include a substantial fraction of institutional management defined more broadly. The holdings of such investors would essentially serve to augment noise-trader demand, so that shorting by the long-short investors would occur at levels of z_i below the total supply s_i.

2.2. Asymmetric Arbitrage Risk

In the setting above there is arbitrage asymmetry, but arbitrage risk does not depend on whether a position is long or short. Instead what differs between long and short positions is the amount of capital bearing the arbitrage risk. In addition to that source of asymmetry, however, the risks to arbitrageurs can differ for long versus short positions for a given level of volatility. One source of arbitrage 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. Such adverse moves can force capital-constrained investors to reduce their positions before realizing profits that would ultimately result from corrections of mispricing. Savor and Gamboa-Cavazos (2011) present empirical evidence on short positions that is consistent with this effect. They find that short sellers typically reduce their positions following adverse price moves, particularly if the short selling appears to be aimed at profiting from overpricing.

When IVOL is higher, substantial adverse price moves are more likely for both long and short positions, but such moves can have different implications depending on whether the position is long or short 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 asymmetry in the effects of adverse price moves is obvious. Asymmetry is still present even if purchases are made 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

$$m = \frac{\text{equity}}{\text{position size}}. \tag{6}$$

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 (6). The new denominators differ from each other, however. The position size decreases 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.[10] With the latter requirement, the above short seller receives a margin call if the

[10]See FINRA Rule 4210.

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.[11] There is no corresponding risk for long positions.

3. Identifying Potential 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

[11] 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.

first describe our approach to constructing a mispricing measure based on anomalies, and we then detail our 11 return anomalies taken from the literature. Our mispricing measure, a composite rank based on a stock's various stock characteristics, is best interpreted as representing potential mispricing, possibly due to noise traders, rather than as the actual mispricing that survives after arbitrage. In particular, a firm with a less extreme mispricing rank but high IVOL could potentially have more mispricing that survives arbitrage than does a firm with a more extreme ranking but low IVOL.

3.1. 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 61-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.

3.2. 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 from 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 he 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 the 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 (low) past recent recent returns forecast high (low) 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. He argues that gross profits scaled by assets is 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 total assets 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 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.

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 is 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.

4. Mispricing and IVOL Effects

We compute individual-stock IVOL following Ang, Hodrick, Xing, and Zhang (2006), using the most recent month's daily benchmark-adjusted returns.[12] 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.

Table 1 presents the first set of our main results. 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 table reports average benchmark-adjusted monthly returns for each of the portfolios. 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 1.

Also evident in Table 1 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

[12] 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.

last row of Table 1. 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 1. 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 1 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 1 is reported in Table 2, 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 2, 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 1.[13]

[13] As an additional robustness check, we also recompute Table 1 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 3 repeats the analysis in Table 1 separately for high-sentiment and low-sentiment months. The three intermediate categories of IVOL are omitted to save space in Table 3. 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 3 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 4 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 4 are again supportive of our setting's implications. Consistent with Table 3, 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 5 repeats the regressions in Table 4 using this alternative sentiment index. The results are very similar to those in Table 4, indicating no important role for the six Baker-Wurgler macro variables in the former results. In Panel B of Table 4, 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).[14] The conclusions summarized previously based on Table 4 are again essentially unchanged if instead based Panel B of Table 5. Overall, the results in Table 5 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.[15]

[14]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.

[15]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. Estimating the Role of Mispricing

Our empirical analysis thus far is based on portfolio sorts, so it requires only a monotonic relation between the IVOL effect and mispricing. Such an approach is robust to that relation's specific form but reveals less about it as a consequence. In this section we use the cross-section of individual stocks to estimate the form of the relation between the IVOL effect and mispricing.

In each month t we estimate a cross-sectional regression of the form,

$$r^e_{t+1,i} = \beta_0 + f_t(M_{t,i})\sigma_{t,i} + \epsilon_{t+1,i}, \tag{7}$$

where $r^e_{t+1,i}$ is stock i's excess return in month $t+1$ minus its Fama-French factor adjustment, $M_{t,i}$ is the stock's mispricing proxy (the average of its 11 anomaly ranking percentiles) in month t, and $\sigma_{t,i}$ is the stock's IVOL in month t. The values of $\sigma_{t-1,i}$ are standardized each month by subtracting by the cross-sectional mean IVOL within the month and then dividing by the month's cross-sectional standard deviation of IVOL. We estimate $f_t(\cdot)$ as a piecewise linear function:

$$f_t(M) = \sum_{k=1}^{n} I(\theta_{k-1,t} \leq M < \theta_{k,t}) \times (a_{k,t} + b_{k,t}M), \tag{8}$$

where

$$a_{k,t} + b_{k,t}\theta_{k,t} = a_{k+1,t} + b_{k+1,t}\theta_{k,t}, \quad k = 1, \ldots, n-1, \tag{9}$$

$\theta_0 = 0$, and $\theta_n = 100\%$. We let $n = 15$ and set the $\theta_{k,t}$'s to equal various percentiles of the cross-sectional distribution of $M_{t,i}$. Our choices are guided by the fact that reliable estimation of the coefficients ($a_{k,t}$'s and $b_{k,t}$'s) requires each segment to contain both a sufficient range of sample $M_{t,k}$ values as well as a sufficiently large sample. In the tails of the distribution, where values of $M_{t,i}$ are relatively more disperse, we set $\theta_{1,t}, \ldots, \theta_{4,t}$ to percentiles 5, 10, 15, and 20, and we set $\theta_{11,t}, \ldots, \theta_{14,t}$ to percentiles 80, 85, 90, and 95. In the middle of the distribution, where values of $M_{t,i}$ are relatively less disperse, we set $\theta_{5,t}, \ldots, \theta_{10,t}$ to percentiles 30, 40, 50, 60, and 70.

The function $f_t(M)$ in (7) 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.

Panel A of Figure 3 plots the estimated values of $f(M)$—the relation between the IVOL effect and mispricing—as well as the 90-percent 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. Consistent with those results as well 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 intermediate values. This result makes sense if differences in anomaly rankings percentiles toward the middle of the distribution do not identify economically significant differences in mispricing. It seems reasonable that, if the anomaly rankings identify potential mispricing, they would do so more successfully at the extremes of those rankings.

The estimate of $f(M)$ obtained here explains well the overall IVOL effect obtained when aggregating across all levels of mispricing. If in each month we estimate a simple cross-sectional regression of $r^e_{t+1,i}$ on $\sigma_{t,i}$ and then average the slope coefficients across all months in the sample, we obtain a value of -0.0030. That estimate is close to the value of -0.0028 obtained if the estimated values of $f(M)$ plotted in Figure 3 are weighted by the cross-sectional sample density of M values.[16] Also, if each month we run a cross-sectional regression of $r^e_{t+1,i}$ on both $f(M_{t,i})\sigma_{t,i}$ and $\sigma_{t,i}$, the average slope on the latter is -0.00017 with a t-statistic of -0.39.

We also average the values of $f_t(M)$ separately over high- and low-sentiment months, as classified earlier in Table 3 and Figure 2. Panel B displays the resulting estimates of $f(M)$ in the two subsamples. Consistent with the portfolio results in Section 5, the negative IVOL effect in overpriced stocks is stronger following high sentiment, and the positive IVOL effect among underpriced stocks is stronger following low sentiment. The t-statistics for the differences between the two curves exceed -2.0 in magnitude for values of M between 20% to 30% (underpricing) as well as between 70% and 80% (overpricing). As M takes more extreme values at both ends, the t-statistics decline in magnitude to about -1.0, consistent with there being fewer observations in the tails and thus less precision in the estimates of $f(M)$. We also see that sentiment exerts little if any effect on the relation between the IVOL effect and M for intermediate values of M, which is consistent with there being minimal mispricing at such values.

[16] The latter density is obtained by computing the cross-sectional frequency distribution of $M_{t,i}$ each month and then averaging those frequency distributions across months.

7. 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 6 repeats the analysis reported earlier in Table 1 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 6, we exclude the bottom 20 percent, 40 percent, 60 percent, and 80 percent, respectively. First observe from Table 1 and Table 6 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 1. 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 1 and then progressing through the four panels of Table 6 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 4 under the same progressive elimination of smaller firms employed in Table 6, and the results are reported in Table 7. In all four panels of Table 7, 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 4. The IVOL effect among underpriced stocks exhibits a consistently weaker negative relation to sentiment, again as in Table 4. 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.

8. Institutional Ownership and the IVOL Effect

Short-sale impediments are likely to be more important among stocks with lower institutional ownership. When institutional ownership is low, stock loan supply tends to be sparse, and thus short selling tends to be more expensive. D'Avolio (2002) finds that lending fees on shorted shares are negatively associated with institutional ownership. In addition, low ownership of a stock by institutions can imply that short-sale constraints are binding for that stock among institutions that view the stock as overpriced. Institutional ownership has been used as a proxy for short-sale constraints in many studies (see, e.g., Nagel (2005), Duan, Hu, and McLean (2010) and Hirshleifer, Teoh, and Yu (2011)). If low institutional ownership (IO) is indeed a proxy for short-selling impediments, we should expect the negative IVOL effect among the overpriced stocks to be stronger among firms with lower IO than among firms with higher IO.

Since IO is positively correlated with firm size, we follow Nagel (2005) and compute residual IO, which is the residual in a cross-sectional regression that fits the logit of IO (in percent) as a quadratic function of the logarithm of firm size. Our data on institutional holdings are obtained from Thomson Financial Institutional Holdings and run from 4/1980 through 1/2011. Each month we identify the top 30% and bottom 30% of firms based on residual IO, and then within each of those two groups we repeat the double-sort analysis in

Table 1.

Table 8 reports the results. First, the average IVOL effect among firms with low (residual) IO exceeds the average IVOL effect among firms with high IO by a difference of 0.55 percent, consistent with the findings in Nagel (2005). Second, among the firms with high IO, the negative IVOL effect among the most overpriced stocks (-1.09 percent, t-statistic: -2.55) exceeds the positive IVOL effect among the most underpriced stocks (0.54 percent, t-statistic: 1.87) by a difference of -1.62 percent (t-statistic: -3.04). Among the firms with low IO, the negative IVOL effect among the most overpriced stocks (-2.87 percent, t-statistic: -6.81) exceeds the positive IVOL effect among the most underpriced stocks (0.25 percent, t-statistic: 0.78) by a difference of -3.12 percent (t-statistic: -6.34). Thus, the asymmetry in the IVOL effect—the difference between the effect in overpriced versus underpriced stocks—is stronger among firms with lower IO.

The stronger asymmetry reflects primarily a stronger negative IVOL effect among the overpriced stocks. That negative effect is stronger for the low-IO stocks, as compared to high-IO stocks, by 1.78 percent per month (-2.87 percent versus -1.09 percent), an economically significant difference (t-statistic: 3.26). In contrast, the positive IVOL effect among the most underpriced stocks is similar for high IO versus low IO—0.54 percent versus 0.25 percent—and the difference of 0.28 per month is statistically insignificant (t-statistics: 0.75). The result that IO bears significantly on the strength of the IVOL effect only among the overpriced stocks is consistent with our explanation for the IVOL effect, coupled with a relation between institutional ownership and short-sale impediments.

9. 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. Also consistent with our explanation is the stronger negative IVOL effect among overpriced stocks stocks that have low size-adjusted institutional ownership and thus a greater likelihood of short-sale impediments. Finally, mispricing's role in the IVOL effect is robust to eliminating smaller firms.

Appendix

In this appendix we derive equations (4) and (5). The long-only investors face the constraint that the elements of ω must be non-negative, whereas the long-short investors face no constraint on ω. The first-order condition for a long-only investor is given by

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

where λ is the vector of Lagrange multipliers associated with the non-negativity constraints on ω. We partition the assets into two groups, the first in which mutual funds hold positive allocations and the second in which the constraints result in zero allocations. Rewriting (A1) with this partitioning gives,

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

noting that $\lambda_1 = 0$ and $\omega_{M,2} = 0$. From (A2) we obtain the mutual fund's optimal positive allocations as

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

The first-order condition for a hedge fund gives its 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

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

$$\begin{aligned} \mu_2 &= \frac{A}{H} \left(V_{21} y_1 + V_{22} y_2 - \frac{M}{A} V_{21} V_{11}^{-1} \mu_1 \right) \\ &= \frac{A}{H} \left(V_{21} y_1 + V_{22} y_2 - \frac{M}{A} V_{21} V_{11}^{-1} \left[\frac{A}{M+H} \left(V_{11} y_1 + V_{12} y_2 \right) \right] \right) \\ &= \frac{A}{H} \left(V_{22} - \frac{M}{M+H} V_{21} V_{11}^{-1} V_{12} \right) y_2 + \frac{A}{M+H} V_{21} y_1. \end{aligned} \tag{A9}$$

Partition V in (2) as

$$V = \begin{bmatrix} \sigma_m^2\beta_1\beta_1' + \Sigma_{11} & \sigma_m^2\beta_1\beta_2' \\ \sigma_m^2\beta_2\beta_1' & \sigma_m^2\beta_2\beta_2' + \Sigma_{22} \end{bmatrix}, \tag{A10}$$

we then have

$$\begin{aligned} \mu_1 &= \frac{A}{M+H}\left[\left(\sigma_m^2\beta_1\beta_1' + \Sigma_{11}\right)y_1 + \sigma_m^2\beta_1\beta_2'y_2\right] \\ &= \frac{A}{M+H}\Sigma_{11}y_1 + \beta_1\left(\frac{\sigma_m^2 A}{M+H}\right)\beta' y, \end{aligned} \tag{A11}$$

and

$$\begin{aligned} \mu_2 &= \frac{A}{H}\left(\sigma_m^2\beta_2\beta_2' + \Sigma_{22} - \frac{M\sigma_m^4}{M+H}\beta_2\beta_1'[V_{11}^{-1}]\beta_1\beta_2'\right)y_2 + \frac{A\sigma_m^2}{M+H}\beta_2\beta_1'y_1 \\ &= \frac{A}{H}\left(\sigma_m^2\beta_2\beta_2' + \Sigma_{22} - \frac{M\sigma_m^4}{M+H}\beta_2\beta_1'\left[\Sigma_{11}^{-1} - \frac{\sigma_m^2}{1+\sigma_m^2\beta_1'\Sigma_{11}^{-1}\beta_1}\Sigma_{11}^{-1}\beta_1\beta_1'\Sigma_{11}^{-1}\right]\beta_1\beta_2'\right)y_2 \\ &\quad + \frac{A\sigma_m^2}{M+H}\beta_2\beta_1'y_1 \\ &= \frac{A}{H}\left(\sigma_m^2\beta_2\beta_2' + \Sigma_{22} - \frac{M\sigma_m^2}{M+H}\left[\frac{\sigma_m^2\beta_1'\Sigma_{11}^{-1}\beta_1}{1+\sigma_m^2\beta_1'\Sigma_{11}^{-1}\beta_1}\right]\beta_2\beta_2'\right)y_2 + \frac{A\sigma_m^2}{M+H}\beta_2\beta_1'y_1 \\ &= \frac{A}{H}\Sigma_{22}y_2 + \beta_2\frac{A\sigma_m^2}{H}\left(1 - \frac{M}{M+H}\left[\frac{\sigma_m^2\beta_1'\Sigma_{11}^{-1}\beta_1}{1+\sigma_m^2\beta_1'\Sigma_{11}^{-1}\beta_1}\right]\right)\beta_2'y_2 + \frac{A\sigma_m^2}{M+H}\beta_2\beta_1'y_1 \qquad \text{(A12)} \\ &= \frac{A}{H}\Sigma_{22}y_2 + \beta_2\left(\frac{A\sigma_m^2}{H}\left[1 - \frac{M}{M+H}\left(\frac{\sigma_m^2\beta_1'\Sigma_{11}^{-1}\beta_1}{1+\sigma_m^2\beta_1'\Sigma_{11}^{-1}\beta_1}\right)\right]\beta_2'y_2 + \frac{A\sigma_m^2}{M+H}\beta_1'y_1\right) \qquad \text{(A13)} \end{aligned}$$

Let μ_M denote the expected excess return on the market portfolio. Then from (A11), we have that for each asset i for which long-only investors hold a positive allocation,

$$\alpha_i = \frac{A}{M+H}y_i\sigma_{\epsilon,i}^2 + \delta\beta_i, \tag{A14}$$

where

$$\delta = \left(\frac{\sigma_m^2 A}{M+H}\right)\beta' y - \mu_M. \tag{A15}$$

From (A13), we have that for each asset i for which mutual funds hold a zero allocation,

$$\alpha_i = \frac{A}{H}y_i\sigma_{\epsilon,i}^2 + \psi\beta_i, \tag{A16}$$

where

$$\psi = \frac{A\sigma_m^2}{H}\left[1 - \frac{M}{M+H}\left(\frac{\sigma_m^2\beta_1'\Sigma_{11}^{-1}\beta_1}{1+\sigma_m^2\beta_1'\Sigma_{11}^{-1}\beta_1}\right)\right]\beta_2'y_2 + \frac{A\sigma_m^2}{M+H}\beta_1'y_1 - \mu_M. \tag{A17}$$

To compare ψ with δ, we notice that

$$\frac{1}{H}\left[1 - \frac{M}{M+H}\left(\frac{\sigma_m^2\beta_1'\Sigma_{11}^{-1}\beta_1}{1+\sigma_m^2\beta_1'\Sigma_{11}^{-1}\beta_1}\right)\right] > \frac{1}{H}\left[1 - \frac{M}{M+H}\right] = \frac{1}{M+H} \tag{A18}$$

and thus

$$\psi < \delta \Longleftrightarrow \beta_2' y_2 < 0.$$

As the number of assets (N) grows large, observe that

$$\left(\frac{\sigma_m^2 \beta_1' \Sigma_{11}^{-1} \beta_1}{1 + \sigma_m^2 \beta_1' \Sigma_{11}^{-1} \beta_1} \right) \to 1,$$

since $\beta_1' \Sigma_{11}^{-1} \beta_1 = \sum_{i=1}^{N} \beta_i^2 / \sigma_{\epsilon,i}^2$. Therefore, for large N, the inequality in (A18) approaches an equality, and

$$\psi \to \delta. \tag{A19}$$

With $z = 0$, $\delta = 0$. To see this, first note that, by definition, the market-capitalization-weighted average of the betas is equal to one,

$$\frac{1}{\iota' s} \beta' s = 1, \tag{A20}$$

and thus in general, $\beta' s = S$, where $S = \iota' s$ is the total market capitalization of all assets. With no noise demands, $S = M + H$, and thus

$$\begin{aligned} \delta &= \left(\frac{\sigma_m^2 A}{M + H} \right) \beta' y - \mu_M \\ &= \left(\frac{\sigma_m^2 A}{M + H} \right) \beta' s - \mu_M \\ &= \left(\frac{\sigma_m^2 A}{M + H} \right) (M + H) - \mu_M. \\ &= \sigma_m^2 A - \mu_M. \end{aligned} \tag{A21}$$

In addition, with $z = 0$, note that non-negativity constraints on long-only investors would not bind: If both long-only investors and long-short investors have demands given by the unconstrained MV-optimal portfolio, allocations in that portfolio must all be positive—equal to market-portfolio allocations. With market allocations equal to the unconstrained solution ω_H in (A4), multiplying both sides of that equation by $\omega_H' V$ gives $\omega_H' V \omega_H = \sigma_m^2 = \frac{1}{A} \mu_m$, and thus the last line in (A21) is equal to zero.

With $z \neq 0$, $E(\delta) = 0$ if we assume

(N1) noise traders do not cause the equity premium to be different from what it would otherwise be

(N2) noise trader demands in the cross section are uncorrelated with beta's.

To see this, rewrite (A15) as

$$\begin{aligned}\delta &= \left(\frac{\sigma_m^2 A}{M+H}\right)(\beta' s - \beta' z) - \mu_M \\ &= \left(\frac{\sigma_m^2 A}{M+H}\right)(S - \beta' z) - \mu_M \\ &= \left(\frac{\sigma_m^2 A}{M+H}\right)(M + H + \iota' z - \beta' z) - \mu_M \\ &= \sigma_m^2 A - \mu_m - \left(\frac{\sigma_m^2 A}{M+H}\right)(\beta - \iota)' z. \end{aligned} \tag{A22}$$

The first two terms combine to zero under (N1), and the third term equals zero in expectation under (N2), noting that $E(\beta) = \iota$.

Table 1
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 2
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 3
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	-2.84	-0.54	-2.30	-1.66	-0.36	-1.30	-1.18	-0.18	-1.00
(top 20%)	(-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	0.54	0.33	0.21	0.82	-0.12	0.94	-0.28	0.45	-0.73
(bottom 20%)	(2.43)	(2.77)	(0.77)	(4.05)	(-1.21)	(4.16)	(-0.93)	(2.85)	(-2.03)
Most overpriced −	-3.38	-0.87	-2.51	-2.48	-0.24	-2.24	-0.90	-0.63	-0.27
most underpriced	(-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 4
Idiosyncratic-Volatility Effects and Investor Sentiment: Predictive Regressions

The table reports estimates of b in the regression,

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

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 5
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 6
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	-2.15	-1.29	-0.84	-0.75	-0.46	-1.69	-0.80
(top 20%)	(-11.08)	(-8.59)	(-6.04)	(-5.02)	(-3.91)	(-7.69)	(-7.98)
Next 20%	-0.89	-0.40	-0.25	-0.30	-0.10	-0.79	-0.26
	(-5.72)	(-2.92)	(-2.51)	(-3.12)	(-1.03)	(-4.16)	(-4.33)
Next 20%	-0.13	0.07	0.05	-0.15	0.04	-0.17	-0.05
	(-0.89)	(0.67)	(0.49)	(-1.55)	(0.46)	(-0.93)	(-1.15)
Next 20%	-0.04	0.11	0.21	0.22	0.13	-0.17	0.16
	(-0.22)	(1.06)	(2.25)	(2.72)	(1.68)	(-0.87)	(4.06)
Most underpriced	0.68	0.67	0.40	0.30	0.11	0.58	0.29
(bottom 20%)	(4.40)	(5.92)	(4.12)	(3.67)	(1.39)	(3.14)	(5.77)
Most overpriced −	-2.83	-1.96	-1.23	-1.05	-0.56	-2.27	-1.09
Most underpriced	(-11.46)	(-9.80)	(-6.67)	(-5.72)	(-3.70)	(-8.43)	(-7.98)
All stocks	-0.69	-0.05	0.03	0.02	0.09	-0.78	
	(-6.13)	(-0.69)	(0.46)	(0.51)	(2.02)	(-5.56)	
			Panel B: 40% Smallest Stocks Deleted				
Most overpriced	-2.02	-1.23	-0.77	-0.69	-0.44	-1.58	-0.78
(top 20%)	(-10.59)	(-7.92)	(-4.91)	(-4.82)	(-3.80)	(-7.11)	(-7.71)
Next 20%	-0.85	-0.33	-0.36	-0.27	-0.05	-0.81	-0.25
	(-5.61)	(-2.57)	(-3.38)	(-2.86)	(-0.46)	(-4.21)	(-4.17)
Next 20%	-0.01	0.07	0.06	-0.15	0.04	-0.05	-0.03
	(-0.10)	(0.67)	(0.56)	(-1.61)	(0.45)	(-0.31)	(-0.74)
Next 20%	0.01	0.13	0.17	0.25	0.14	-0.12	0.17
	(0.09)	(1.22)	(1.83)	(3.14)	(1.74)	(-0.65)	(4.02)
Most underpriced	0.74	0.58	0.33	0.33	0.11	0.63	0.28
(bottom 20%)	(5.05)	(5.38)	(3.51)	(4.11)	(1.35)	(3.57)	(5.66)
Most overpriced −	-2.76	-1.80	-1.11	-1.02	-0.55	-2.21	-1.06
Most underpriced	(-11.93)	(-9.00)	(-5.56)	(-5.66)	(-3.58)	(-8.59)	(-7.75)
All stocks	-0.63	-0.03	0.08	0.01	0.10	-0.73	
	(-5.63)	(-0.39)	(1.46)	(0.25)	(2.19)	(-5.20)	

Table 6 (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	-1.67	-1.05	-0.66	-0.58	-0.41	-1.25	-0.71
(top 20%)	(-9.02)	(-6.69)	(-4.11)	(-4.58)	(-3.64)	(-5.96)	(-7.37)
Next 20%	-0.62	-0.26	-0.30	-0.16	-0.04	-0.58	-0.21
	(-4.03)	(-2.29)	(-2.84)	(-1.59)	(-0.41)	(-2.94)	(-3.65)
Next 20%	0.08	0.12	0.02	-0.14	0.06	0.02	-0.01
	(0.62)	(1.15)	(0.21)	(-1.45)	(0.63)	(0.14)	(-0.31)
Next 20%	0.11	0.19	0.06	0.35	0.19	-0.07	0.17
	(0.83)	(1.88)	(0.61)	(4.03)	(2.15)	(-0.46)	(3.69)
Most underpriced	0.71	0.59	0.31	0.31	0.10	0.60	0.28
(bottom 20%)	(4.91)	(5.42)	(3.02)	(3.70)	(1.28)	(3.43)	(5.39)
Most overpriced −	-2.37	-1.64	-0.97	-0.89	-0.52	-1.86	-1.00
Most underpriced	(-10.89)	(-7.94)	(-4.72)	(-5.17)	(-3.44)	(-7.89)	(-7.41)
All stocks	-0.44	0.00	0.01	0.06	0.09	-0.53	
	(-3.94)	(0.06)	(0.26)	(1.29)	(1.98)	(-3.79)	
			Panel D: 80% Smallest Stocks Deleted				
Most overpriced	-1.18	-0.83	-0.56	-0.45	-0.30	-0.88	-0.59
(top 20%)	(-6.28)	(-4.90)	(-3.76)	(-3.34)	(-2.57)	(-4.09)	(-6.02)
Next 20%	-0.44	-0.21	-0.21	-0.16	0.06	-0.50	-0.17
	(-3.00)	(-1.98)	(-1.99)	(-1.49)	(0.59)	(-2.57)	(-3.15)
Next 20%	0.06	0.12	0.08	-0.01	0.09	-0.03	0.05
	(0.45)	(1.15)	(0.73)	(-0.08)	(0.95)	(-0.17)	(0.97)
Next 20%	0.16	-0.02	0.18	0.26	0.13	0.03	0.15
	(1.26)	(-0.16)	(1.77)	(2.86)	(1.38)	(0.18)	(2.89)
Most underpriced	0.54	0.56	0.34	0.32	0.06	0.48	0.28
(bottom 20%)	(3.75)	(5.20)	(3.22)	(3.56)	(0.71)	(2.62)	(4.96)
Most overpriced −	-1.72	-1.39	-0.90	-0.77	-0.36	-1.35	-0.87
Most underpriced	(-7.47)	(-6.33)	(-4.64)	(-4.16)	(-2.33)	(-5.32)	(-6.28)
All stocks	-0.28	0.05	0.02	0.09	0.09	-0.37	
	(-2.58)	(0.86)	(0.33)	(1.84)	(1.73)	(-2.59)	

Table 7
Idiosyncratic-Volatility Effects and Investor Sentiment: Predictive Regressions Under Various Thresholds for Market Capitalization

The table reports estimates of b in the regression,

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

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

Table 8
Idiosyncratic Volatility Effects in High-IO versus Low-IO Subsamples

The table reports average benchmark-adjusted returns for double sorted portfolios on mispricing score and idiosyncratic volatility (IVOL) within high- and low-IO subsamples. Here the high-IO (low-IO) subsample consists the top (bottom) 30% stocks sorted on residual IOs by following Nagel (2005): Each quarter regress logit IO percent on log size and the square of log size. The regression residuals are defined as residual IOs. The data on institutional holdings are obtained from Thomson Financial Institutional Holdings database. Within the high-IO (and low-IO) firms, 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 high-IO and low-IO stock universe. The benchmark-adjusted returns are estimates of 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 1980m4 to 2011m1. All t-statistics (in parentheses) are based on the heteroskedasticity-consistent standard errors of White (1980).

	High-IO Sample			Low-IO Sample			High-IO Sample − Low-IO Sample		
	Highest IVOL	Lowest IVOL	Highest −Lowest	Highest IVOL	Lowest IVOL	Highest −Lowest	Highest IVOL	Lowest IVOL	Highest −Lowest
Most overpriced	-1.84	-0.75	-1.09	-3.09	-0.22	-2.87	1.25	-0.53	1.78
(top 20%)	(-5.39)	(-3.59)	(-2.55)	(-8.39)	(-1.10)	(-6.81)	(2.64)	(-2.14)	(3.26)
Next 20%	-0.80	-0.01	-0.79	-1.51	0.22	-1.73	0.71	-0.23	0.94
	(-2.88)	(-0.04)	(-2.46)	(-4.90)	(1.30)	(-4.74)	(1.70)	(-0.96)	(2.03)
Next 20%	0.04	0.13	-0.09	-0.34	0.10	-0.44	0.38	0.03	0.35
	(0.14)	(0.82)	(-0.27)	(-1.02)	(0.61)	(-1.11)	(0.88)	(0.12)	(0.72)
Next 20%	0.13	0.42	-0.29	-0.17	0.30	-0.47	0.30	0.12	0.18
	(0.53)	(2.91)	(-1.02)	(-0.56)	(1.91)	(-1.34)	(0.79)	(0.56)	(0.40)
Most underpriced	0.70	0.16	0.54	0.41	0.15	0.25	0.29	0.01	0.28
(bottom 20%)	(2.76)	(1.17)	(1.87)	(1.53)	(1.08)	(0.78)	(0.86)	(0.04)	(0.75)
Most overpriced −	-2.53	-0.91	-1.62	-3.49	-0.37	-3.12	0.96	-0.54	1.50
most underpriced	(-6.01)	(-3.43)	(-3.04)	(-8.25)	(-1.44)	(-6.34)	(1.73)	(-1.72)	(2.28)
All stocks	-0.56	0.18	-0.73	-1.14	0.15	-1.28	0.58	0.03	0.55
	(-3.10)	(1.99)	(-3.50)	(-5.12)	(1.56)	(-5.14)	(2.34)	(0.23)	(2.10)

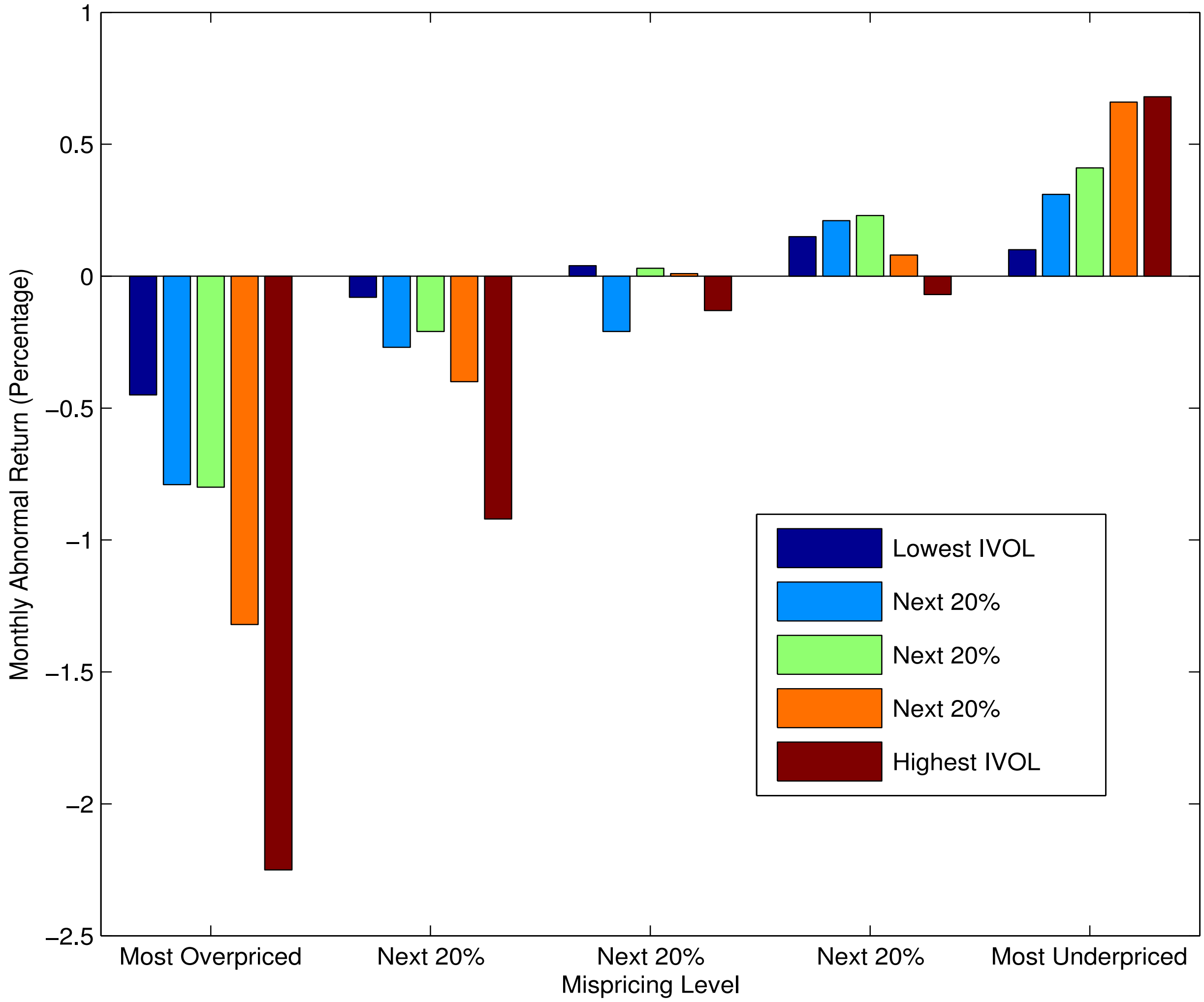

Figure 1. Monthly Abnormal Returns of Portfolios Ranked by Mispricing Level and IVOL. The figure plots the average monthly abnormal return on portfolios formed in a 5 × 5 sort that ranks first by mispricing level and then by IVOL. Abnormal returns are calculated by adjusting for exposures to the three 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.

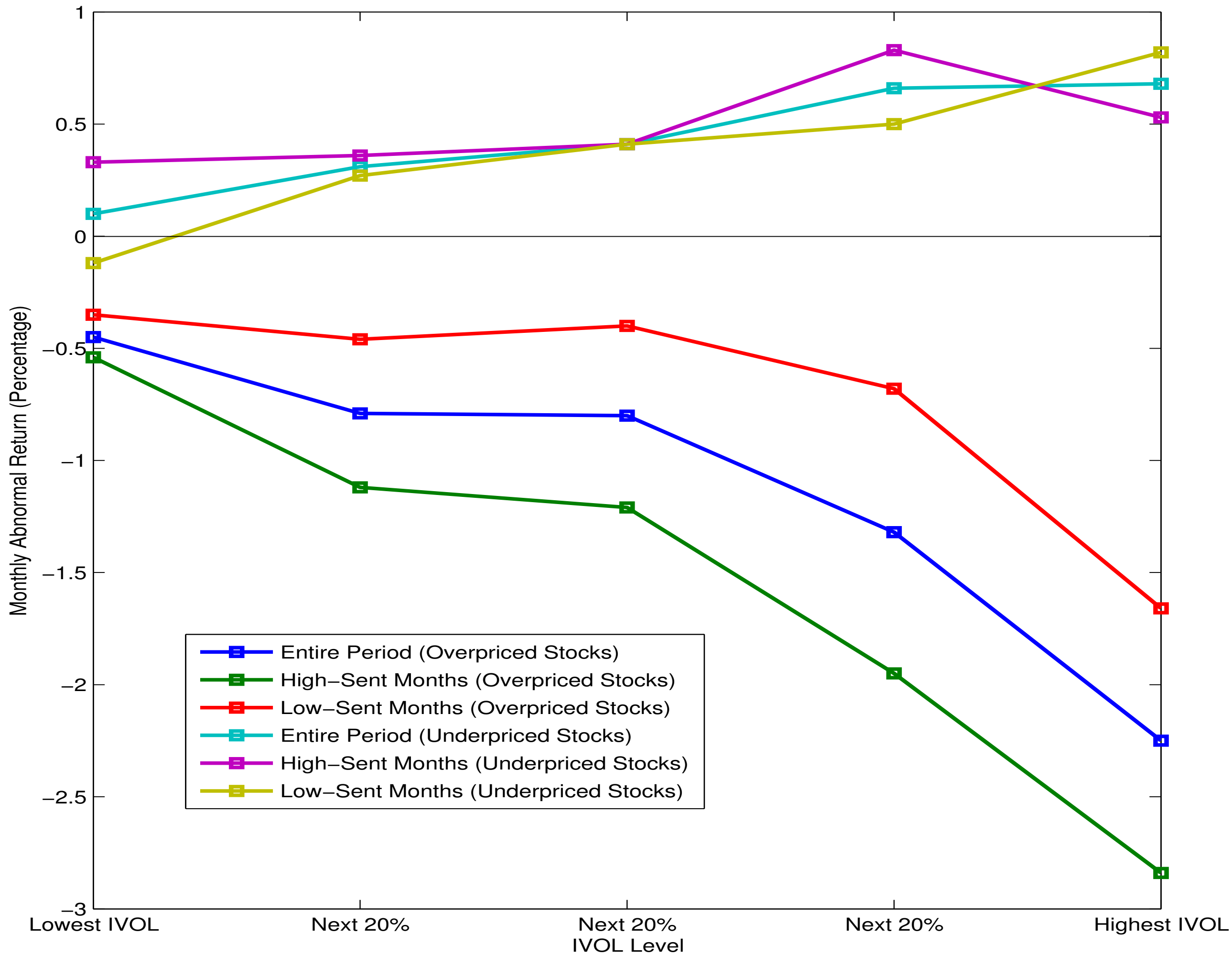

Figure 2. IVOL Effects and Investor Sentiment. The figure plots the average monthly abnormal return on portfolios formed in a 5 × 5 sort that ranks first by mispricing level and then by IVOL. Results are displayed for the five portfolios in the most underpriced quintile and the five portfolios in the 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.

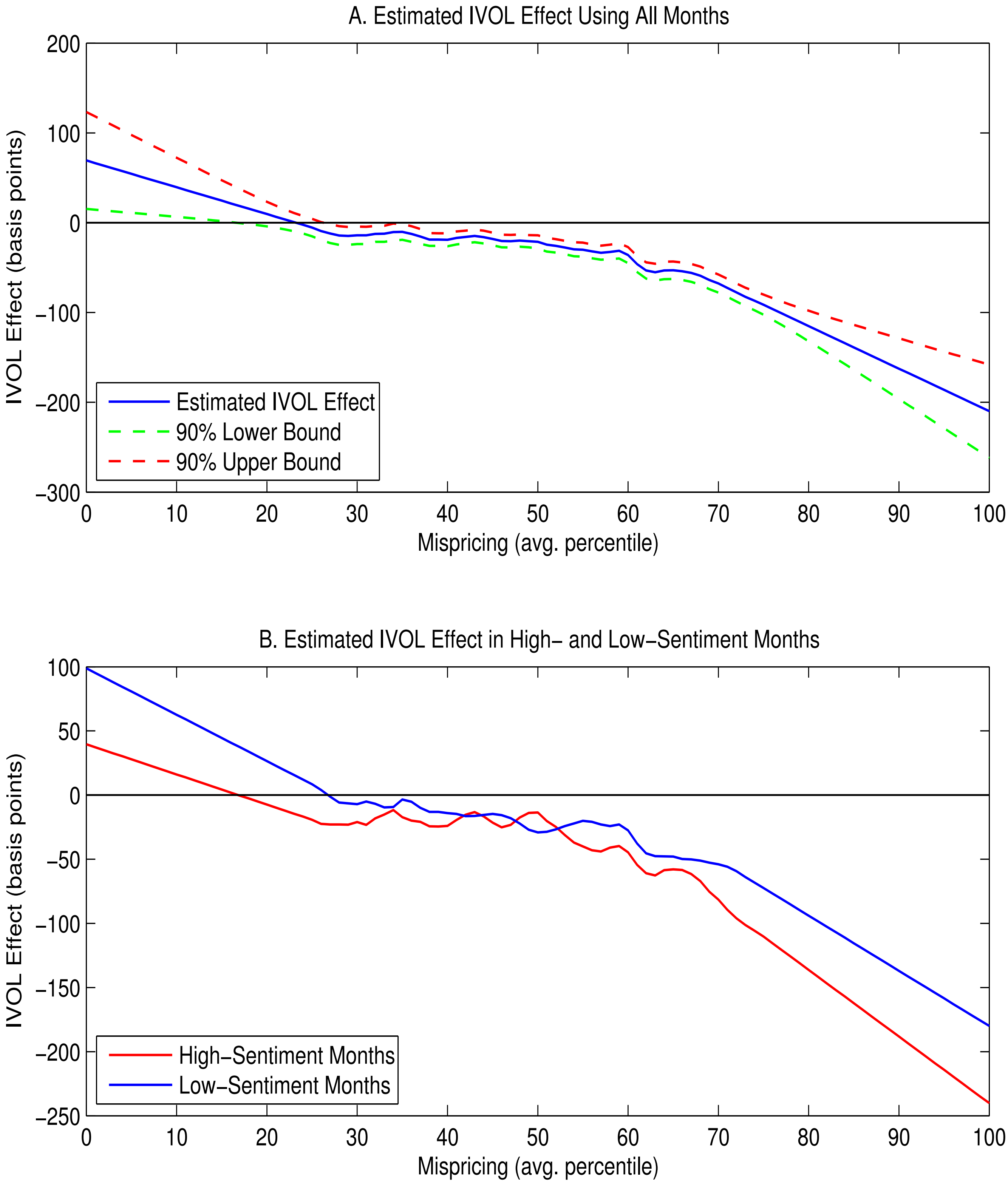

Figure 3. Estimated IVOL Effects. The figure plots estimates of $f(M)$, which is the effect of standardized IVOL on abnormal monthly return for a stock whose mispricing ranking percentile (averaged over 11 anomalies) is equal to M. Panel A plots the estimate of $f(M)$ for the overall 8/1965–1/2011 sample period. Panel B plots the estimates computed separately in high-sentiment and low-sentiment months classified using the Baker-Wurgler index.

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