The Market State and Asset Pricing Anomalies*

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Abstract

This paper examines the role of the market state in predicting asset pricing anomalies. We find that the sign, size, and significance of anomaly returns depend crucially on whether they follow a positive or negative market return. This is the case when we examine anomalies individually and when we aggregate them using an aggregate mispricing measure. We conjecture that the findings can be explained by market frictions for investors with short positions and behavioural biases for investors with long positions. Our hypothesis is supported by empirical evidence on short interest, liquidity, and fund flows.

Keywords: Asset Pricing Anomalies; Market State; Mispricing; Idiosyncratic Volatility; Arbitrage Asymmetry; Arbitrage Risk; Disposition Effect.

JEL classification: G11; G12.

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1 Introduction

Return anomalies garner a lot of interest in the asset pricing literature. A return anomaly generally represents a spread in expected return among firms with a varying underlying firm characteristic. As an example, the size anomaly stems from the empirical fact that small firms tend to outperform large firms. Accordingly, the return to a net-zero-cost (or high-minus-low, henceforth H-L) portfolio which is long a portfolio of small firms and short a portfolio of large firms is a representation of the size anomaly. Return anomalies matter as they account for much of the variation in the cross section of expected returns. Variation above and beyond what is implied by the Capital Asset Pricing Model (CAPM) of Sharpe (1964), Lintner (1965) and Black (1972), which posits returns vary exclusively with exposures to market risk. The source of return anomalies has been a constant topic of debate. Common explanations, detailed well in Wang et al. (2021), include compensation for systematic risk, mispricing, and data mining. Understanding the source of anomaly returns is critical in understanding and properly modeling capital markets.

This paper examines the role of the market state in predicting asset pricing anomalies. We define a positive and negative market state as a period of positive and negative excess-return. We show that many of the well-known return anomalies vary widely in size, sign and significance depending on the preceding market state. The Fama-French (2015) five-factor model anomalies related to firm size, value, profitability, and investment are included. In addition, the beta anomaly as demonstrated in Frazzini et al. (2014) is included, as well as anomalies shown to be related to beta such as idiosyncratic volatility (Liu et al., 2018) and lottery demand (Bali et al., 2011), among others.

We use the mispricing measure of Stambaugh et al. (2015) to assist in identifying and explaining the source of the common time-variation in the wide set of anomaly returns. The mispricing measure identifies firms with high or low expected returns as implied by an aggregation of firm anomaly rankings. In addition to the mispricing measure, we focus on firm variation in arbitrage risk (proxied by idiosyncratic volatility, henceforth IVOL), as prescribed by the arbitrage asymmetry model of Stambaugh et al. (2015), which describes well the empirical returns related to mispricing. Negative one-month ahead return momentum is identified, among firms with a high mispricing score and high IVOL (henceforth Overpriced/High IVOL firms), following negative market states. We show that anomaly returns load significantly on a portfolio comprised of these firms. As such, these firms are the channel through which anomaly returns display a common time-variation with the preceding market state. We then provide the mechanisms which generate the momentum observed among the Overpriced/High IVOL firms. The mechanisms contributing to the observed abnormal returns are consistent with a mispricing explanation. Concurrently, this identifies mispricing as the cause for the observed time-variation in anomaly returns.

To demonstrate how anomaly returns vary with the preceding market state, we use tradeable one-month ahead anomaly returns (H-L portfolios that are long the top quintile portfolio and short the bottom quintile portfolio, sorting on the underlying firm characteristic). The size anomaly averages a risk-adjusted return of -0.64% following a positive market state and 0.42% following a negative market state. The beta anomaly averages a risk-adjusted return of 0.12% following a positive market state and -0.60%

following a negative market state. We find a similar pattern with excess-returns, as well as with the larger set of anomaly returns. To study in aggregate the observed time variation in anomaly returns, the mispricing measure of Stambaugh et al. (2015) is used, with specific focus on portfolios sorted on the mispricing measure and IVOL. The most overpriced-high IVOL portfolio averages an insignificant one-month ahead risk-adjusted return of -0.26% following a positive market state and a staggering significant -1.46% return following a negative market state. Put differently, after a negative market state abnormal returns are almost six times larger relative to periods after a positive market state. Next, we provide the likely mechanisms which generate the predictive ability of the market state on the Overpriced/High IVOL firms.

We posit that there exists two distinct but complementary effects behind our findings. The first is the loosening of arbitrage capital, during negative market states, which contributes to the one-month ahead momentum among Overpriced/High IVOL firms. Specifically, during negative market states, these firms average a monthly excess-return of -7.03%. Accordingly, the constraints on arbitrage capital, which hold short positions on these firms, *loosen* as margin ratios improve (both from an increase in equity and a decrease in position size). We then show that on average, short interest ratios increase significantly for the Overpriced/High IVOL firms following a negative market state. We argue that a feedback effect among short investors is taking place: prices drop, improved margin ratios for short investors lower arbitrage risk (a reduced likelihood of a margin call), these investors increase short positions in the future. The increased short positions create downward price pressure, contributing to the return momentum among

Overpriced/High IVOL firms observed following negative market states. Ultimately, this mechanism infers that the loosening of capital constraints among short investors generates the return momentum.

The second mechanism we identify as a contributor to the observed return momentum among Overpriced/High IVOL firms, following negative states, is a behavioural bias among long investors. Building again on the observed underperformance of Overpriced/High IVOL firms during negative markets, we identify a disposition effect (Shefrin and Statman, 1985) among long investors which likely contributes to the observed return momentum. The disposition effect refers to the greater propensity of investors to hold stocks that have fallen in value rather than risen in value since purchase. We posit that when Overpriced/High IVOL firms perform poorly, during negative market states, a subset of investors are placed in a state of loss and refuse to sell, succumbing to the behavioural bias implied by the disposition effect. Grinblatt and Han (2005) suggest that the disposition effect causes price underreaction to information. In addition, Frazzini (2006) shows that such an effect generates return momentum. We contend that this is the case during negative market states among the Overpriced/High IVOL firms, fostering the observed one-month ahead return momentum. We find a significant positive relation between innovations in aggregate liquidity and negative market states. We then demonstrate at the firm level that Amihud (2002) illiquidity is increasing in both the mispricing measure and IVOL. Additionally, during negative market states it is the Overpriced/High IVOL firms which suffer the largest and most significant increases in illiquidity. These results lend support to the claim that

Overpriced/High IVOL firm prices are most likely to underreact, during negative market states, contributing to the observed one-month ahead return momentum as implied by the disposition effect. We then show a significant negative relation between aggregate net exchanges of U.S. all equity mutual funds and preceding negative market states. This shows a negative market state predicts net selling in the next period, behaviour consistent with that of the disposition effect.

Lastly, we show that the mispricing measure is very closely related, empirically, to the value-at-risk measure of Altigan et al. (2020) who find left-tail momentum among U.S. firms. Interestingly, the results of Altigan et al. (2020) are directly opposed to the theoretical predictions on left-tail risk. We argue that the arbitrage asymmetry model of Stambaugh et al. (2015) may serve as a better characterization of what is observed. In addition, we observe left-tail risk momentum exclusively following negative market states. In summary, the mechanisms described in our paper serve as an explanation of the results in Altigan et al. (2020) that are aligned with theoretical predictions.

This paper introduces the predictive power of the market state in identifying spreads in anomaly returns. The mispricing literature characterizes well how mispricing influences return anomalies. What we identify is the important role of the market state in the returns related to mispricing. It is exclusively following negative market states, where the large ex-ante underperformance of the overpriced-difficult to arbitrage firms are observed. Concurrently, this is an important finding for anomaly returns which are affected greatly by this relation. Our results supplement the argument that a large component of anomalous returns are related to mispricing.

The remainder of the paper is organized as follows. In the next section, we describe the cross-sectional data on U.S. stock returns and methodology. The empirical motivation for our work is presented in Section 3. In Section 4, we use the mispricing measure and idiosyncratic volatility, a proxy for arbitrage risk, to identify which firms demonstrate return variation across market states. In Section 5, we identify mechanisms related to mispricing which contribute to the observed return variation. In Section 6, we perform robustness checks of our main results for a variety of different specifications. We then conclude in Section 7.

2 Data Description & Methodology

2.1 Data

Our empirical analysis of the cross section of stock returns is based on all firms with common stock traded on the NYSE, AMEX, and NASDAQ exchanges (share codes of 10 or 11 and exchange codes of 1, 2 or 3) with a share price above five dollars. All data are monthly and the sample period ranges from August 1965 to January 2017.[1] When a firm is delisted from an exchange on a given month, we add delisting returns provided by CRSP to avoid a delisting bias (see, e.g., Shumway, 1997).

The focus of the empirical analysis is a comprehensive set of 14 asset pricing anomalies, which require data on several firm characteristics. In what follows, we

[1] The end date of the sample is due to data availability for the Stambaugh et al. (2015) mispricing measure.

describe how we obtain the 14 anomalies. For each stock, we calculate the following: market beta (BETA), volatility (VOL), and correlation with the market (COR) as in Asness et. al (2020); idiosyncratic volatility (IVOL) as in Ang et al. (2006); firm size (ME), book-to-market (BM), operating profitability (OP) and asset growth (INV) as in Fama and French (2015); momentum (MOM) defined as the cumulative return from month t-12 to t-2 as in Carhart (1997); short-term reversal (STR) as the month t-1 return; MAX defined as the average of the five largest daily returns over the last month and MAX (M1) defined as the average of the twenty largest daily returns over the last year as in Bali et al. (2011) and Asness et al. (2020); illiquidity (ILLIQ) as in Amihud (2002); Value-at-Risk at the 1 percent (VaR1) and 5 percent (VaR5) empirical threshold as in Altigan et al. (2020). Finally, we obtain the Stambaugh et al. (2015) mispricing measure from Robert Stambaugh's website.[2] Note that to be included in month t, a firm must have all characteristics available in month t-1.

We also obtain mutual fund flow data from the Investment Company Institute (ICI). These are monthly aggregate flow data for all US equity mutual funds. The data include net exchanges (exchanges in less exchanges out) and net sales (sales less redemptions), the sum representing net flows for US equity mutual funds. All fund flow data are reported as a proportion of aggregate fund size, i.e., month t flows are divided by net asset value in month t-1. The sample period for the mutual fund data ranges from

[2] https://finance.wharton.upenn.edu/~stambaug/

February 1984 to January 2017.[3] The same data have been used by Warther (1995), Edwards and Zhang (1998), Fant (1999) and Ben-Raphael (2012).

Short interest data are obtained from COMPUSTAT. We define the short interest ratio as the number of shares held short over the number of shares outstanding. These data are available beginning in 1973.

Finally, the bond yields to measure the term spread and default spread are obtained from the St. Louis Federal Reserve. The risk-free T-Bill return and inflation data are obtained from CRSP. The sentiment index of Baker and Wurgler (2006) is retrieved from Jefferey Wurgler's website.[4] Innovations in the aggregate US market liquidity, as in Pastor and Stambaugh (2003), are from Robert Stambaugh's website.

2.2 Risk-Adjusted Returns

At the center of our empirical analysis is the use of risk-adjusted returns, which are calculated using the cross-sectional factor model of Fama and French (2020). The advantage of this approach is that it allows for time-varying factor loadings and has been shown to outperform alternative approaches that do not allow for time variation in factor loadings. To achieve time variation in factor loadings, the Fama and French approach (2020) relies on using the time series of ME, BM, OP, INV and MOM as follows.

[3] Note that the mutual fund flow data are released with a one-month delay.
[4] https://pages.stern.nyu.edu/~jwurgler/

In the first step, at every month t, we estimate the cross-sectional premium, λ_t, associated with each underlying characteristic using the following regression:

$$r_{i,t} = r_{z,t} + \lambda_{1,t} ME_{i,t-1} + \lambda_{2,t} BM_{i,t-1} + \lambda_{3,t} OP_{i,t-1} + \lambda_{4,t} INV_{i,t-1} + \lambda_{5,t} MOM_{i,t-1} + \varepsilon_{i,t}, \quad (1)$$

where $r_{i,t}$ is the excess return to base asset i in month t regressed on the lagged base asset characteristics. We use the same base assets as recommended in Fama and French (2020).[5] We then collect the time series of estimated premia, $\hat{\lambda}$, which represent the cross-sectional factors.

In the second step, the risk-adjusted returns for asset i are defined as the pricing error of the following cross-sectional model:

$$\hat{\alpha}_{i,t} = r_{i,t} - \left[\hat{r}_{z,t} + ME_{i,t-1}\hat{\lambda}_{1,t} + BM_{i,t-1}\hat{\lambda}_{2,t} + OP_{i,t-1}\hat{\lambda}_{3,t} + INV_{i,t-1}\hat{\lambda}_{4,t} + MOM_{i,t-1}\hat{\lambda}_{5,t}\right]. \quad (2)$$

Although our main results are based on this Fama and French (2020) model, for robustness we also use the standard six factor model based on the five Fama and French (2015) factors plus momentum.

2.3 Subsamples: Positive vs Negative Market State

Our empirical examination focuses on assessing performance in two subsamples defined as: (1) all periods following a positive market excess return (i.e., the positive market state), and (2) all periods following a negative market excess return (i.e., the negative market

[5] The base assets are four sets of 2x3 value-weighted portfolios formed with NYSE breakpoints. Each set of portfolios is generated by first sorting on ME (small vs big) and then sorting on the underlying characteristic (low, middle and high).

state). This is done by estimating the following regression for the time series of risk-adjusted returns:

$$\alpha_t = \alpha_P d_{t,r>0} + \alpha_N d_{t,r<0} + \varepsilon_t, \tag{3}$$

where $d_{t,r>0}$ is a dummy variable, which is equal to 1 when the market return in month t-1 is positive and 0 otherwise, and $d_{t,r<0}$ is equal to 1 when the market return in month t-1 is negative and 0 otherwise. In this framework, the parameter estimates of α_P and α_N reflect the portfolio risk-adjusted returns for the months following a positive market state and the months following a negative market state. Note that throughout our analysis we calculate Newey and West (1987) standard errors to account for heteroskedasticity and autocorrelation.

3 The Effect of the Market State on Anomaly Returns

3.1 Evidence on the Market State

If the market return is persistent, then a positive market return is likely to be followed by a positive return and vice versa.[6] As a result, on average the market return following a positive market return should be higher than the market return following a negative market return. In this section, we show that this is indeed the case.

Table 1 displays the estimation results for a simple AR(1) model on the market excess return. Panel A is without additional controls, whereas Panel B also controls for

[6] To be more precise, if the persistence is positive the conditional probability that a positive market excess return will be followed by a positive market excess return is higher than the unconditional probability.

inflation, the riskless rate, the term spread, the default spread and the sentiment index of Baker and Wurgler (2006) to proxy for time variation in systematic risk. In both cases, the result is the same: the intercept and the slope are positive and statistically significant. Under the AR(1) model, if the persistence parameter is equal to zero, the intercept represents the unconditional expected return above the riskless rate and can be interpreted as compensation for systematic risk. The significant coefficient on the lagged market return can be interpreted as predictable time variation in the market excess return.

As mentioned previously, there are three common explanations for asset pricing anomalies (see, e.g., Wang et al., 2021): time variation in systematic risk, mispricing, and data mining. The same possible explanations can be applied to the time variation in the market premium. Note, however, that the persistence parameter in the AR(1) model remains significant when we condition on the control variables that proxy for time variation in systematic risk. We take this as evidence that market persistence is unlikely to be related to systematic risk compensation and is more likely to be related to mispricing or data mining.

We build on this empirical result by showing that market excess return following a positive market state is consistently higher than the market return following a negative market state. Specifically, we form the two subsamples discussed earlier: one subsample comprises the months that immediately follow a positive market state, and (2) one subsample comprises the remaining months that immediately follow a negative market state. In Figure 1, we plot the rolling average for each subsample against the full sample. We find that the average monthly excess return on the market is equal to 0.83% (or 9.96%

per year) following a positive market state and only 0.05% (or 0.60% per year) following a negative market state. Importantly, the return following a positive market state is always higher than that following a negative market state across the entire sample. The consistency of this finding across time effectively precludes data mining as a reasonable explanation of market persistence. This leaves mispricing as the only remaining explanation. In short, these findings establish that the market state has a strong effect on the one-month ahead market excess return and this is likely due to mispricing. Next, we investigate how the market state affects the cross section of stock returns.

3.2 The Market State and the Capital Asset Pricing Model

We begin by investigating how the market state can predict BETA portfolios implied by the Capital Asset Pricing Model (CAPM). In Figure 2, we plot the Securities Market Line (SML) for value-weighted (VW) quintile portfolios formed by sorting stocks on their most recent BETA. The portfolios use NYSE breakpoints. Panel A displays excess returns, and Panel B risk-adjusted returns.

The leftmost graphs display a flat unconditional SML, which is consistent with the well-known empirical failure of the CAPM. This picture, however, changes drastically when in the rightmost graphs we plot an SML that is conditional on the preceding market state. In this case, we observe two distinct lines, one that is consistently upward sloping following a positive market state against one that is steep and negatively sloped following a negative market state. Hence, conditional on the market state, the SML is no longer flat and the beta portfolios perform very differently depending on the preceding market state. This is the case for both excess returns and risk-adjusted returns. In short, therefore, the market state has a strong effect on the cross section of stock returns as illustrated by portfolios that differ in their systematic risk (i.e., beta).

3.3 The Market State and Asset Pricing Anomalies

In this section, we provide a comprehensive analysis of how expected returns vary with the market state by focusing on 14 well-known asset pricing anomalies. These anomalies are described in Section 2.1 and, in brief, include the following: BETA, ME, BM, OP, INV, MOM, STR, VOL, IVOL, COR, MAX, M1, ILLIQ and VaR1. In all cases, we use VW quintile portfolios formed by sorting on the relevant firm characteristic. Table 2 reports the mean one-month ahead excess returns of each anomaly for the full sample and across the two subsamples.

The results are remarkable. None of the anomalies displays a significant H-L spread of the same sign in the two subsamples. In all cases, either the anomaly spread is significant in only one of the market states or it is significant in both states but with a *different* sign. Specifically, for six anomalies the spread is significant in both states but it flips sign: VOL, IVOL, M1, ILLIQ and VaR1 flip sign from positive (in the positive market state) to negative (in the negative market state), whereas ME flips sign in the other direction. Five anomalies are only significant in the negative market state: BETA, OP, INV, MOM and MAX. Three anomalies are only significant in the positive market state: BM, STR and COR. Finally, there are six anomalies for which the spread is insignificant for the full sample but it is significant for one of the market states (BETA, MAX) or both market states but with opposing sign (VOL, IVOL, M1, VAR1).

For example, consistent with Figure 2, the BETA spread in the negative market state is negative (-0.77) and significant (t-stat=-2.33) but in the positive market state it is insignificant. The BM spread in the positive market state is positive (0.48) and significant (t-stat=2.55) but in the negative market state it is insignificant. The ME spread in the positive market state is negative (-1.09) and significant (t-stat=-5.17) but in the negative state it flips sign so that it is positive (0.55) and significant (t-stat=-2.28). VOL flips in the opposite direction: in the positive market state the VOL spread is positive (0.69) and significant (t-stat=2.40) but in the negative state it is negative (-1.08) and significant (t-stat=-2.92).

Next, in Table 3 we report results for risk-adjusted returns, which are calculated using the Fama and French (2020) cross-sectional model. The results are similar. For seven anomalies, the spread is significant only following a negative market state: BETA, INV, VOL, IVOL, M1, ILLIQ and VaR1. For three anomalies, the spread is significant only following a positive market state: BM, MOM, STR. Finally, for two anomalies, the spread is significant following both a positive and a negative state: OP and MAX. For risk-adjusted returns, no anomaly flips sign from significant positive to significant negative or vice versa.

Based on this evidence we conclude that the preceding market state is a crucial predictor of the sign and significance of the excess returns or risk-adjusted returns of well-known anomalies. Overall, more anomalies tend to be significant following a negative market state than a positive market state. In short, the evidence indicates that there is a time-varying component in anomaly returns that is market state dependent.

3.4 The Market State and the Mispricing Measure

In the previous section, we assess asset pricing anomalies individually. In this section, we aggregate across anomalies using the mispricing measure of Stambaugh et al. (2015). For the remainder of the paper, this will be the main tool of our analysis. The Stambaugh et al. (2015) measure (henceforth the "mispricing measure") represents a firm's average percentile ranking across 11 firm characteristics, which reflect various asset pricing anomalies. The mispricing measure provides an aggregate view on which firms are most likely to be relatively mispriced in the cross section. This is based on the following concept: firms that rank well (poorly) on a given characteristic are valued by investors more (less), their prices are bid up (down), and hence future expected returns are low (high). For each characteristic, the mispricing score is increasing in the direction that predicts lower future expected returns. [7]

In Table 4 (Panel A), we report the excess returns and risk-adjusted returns of quintile portfolios sorted on the mispricing measure. We find that the spread for both excess returns and risk-adjusted returns is significantly negative. Indeed, both the excess

[7] For example, asset growth (INV) is considered to be a positive firm trait. Consequently, firms with high (low) asset growth exhibit high (low) prices, low (high) future expected returns and are associated with a high (low) mispricing measure.

returns and risk-adjusted returns of the quintile portfolios decline monotonically as we move from Low to High. In other words, underpriced firms (Low) consistently perform better than overpriced firms (High). For example, the excess return to the H-L mispricing portfolio is equal to -0.53% per month with a t-stat=-3.82.

Consistent with our previous results, the full sample results change drastically when we consider the two subsamples based on the preceding market state. Following a positive market state, both the excess return and the risk-adjusted return of the H-L portfolio are insignificant. Following a negative market state, both the excess return and the risk-adjusted return are strongly negative and significant. In the latter case, the excess return spread is equal to -1.14 with a t-stat=-5.45. We conclude, therefore, that the superior performance of underpriced firms together with the inferior performance of overpriced firms occurs primarily following a negative market state. Consequently, the market state is a crucial predictor of the performance of mispricing portfolios.

Next, we examine the individual characteristics of the quintile portfolios formed by sorting on the mispricing measure. These are reported in Panel B of Table 4. For example, the first column (BETA) reports the VW betas of the five quintile mispricing portfolios. The main finding here is that the mispricing portfolios identify significant spreads in characteristics for 13 out of the 14 anomalies (STR being the exception). For example, the beta of the most overpriced portfolio (High) exceeds the beta of the most underpriced portfolio (Low) by 0.11 with a t-stat=3.43. Moreover, in the vast majority of cases, the portfolio characteristics change monotonically as we move from Low to High portfolios.

In summary, the evidence suggests that the mispricing measure is effective in identifying spreads in firm characteristics related to practically all the anomalies we consider. In addition, the mispricing measure identifies large significant spreads in excess returns and risk-adjusted returns for the full sample. Interestingly, these spreads are significant exclusively when following a negative market state. Overall, these results motivate the use of the mispricing measure as the focal point of our remaining analysis, as it appears to be an ideal candidate to study the market state dependence in anomaly returns in the cross section of US stock returns.

4 The Effect of the Market State on Mispricing and Arbitrage Risk

4.1 The Arbitrage Asymmetry Model of Stambaugh et al. (2015)

In this section, we discuss the main insights of the arbitrage asymmetry model of Stambaugh et al. (2015), which provides the theoretical foundation for the empirical relation between mispricing and expected returns. The model is based on the interaction of two key mechanisms: arbitrage risk and arbitrage asymmetry.

Arbitrage risk is the risk that deters arbitrage. It is proxied by IVOL since stocks with higher IVOL are more susceptible to mispricing that is not eliminated by arbitrageurs. For overpriced stocks, the IVOL effect is negative: stocks with the highest IVOL are the most overpriced and hence have the lowest expected returns. For underpriced stocks, the IVOL effect is positive: stocks with the highest IVOL are the most underpriced and hence have the highest expected returns.

Arbitrage asymmetry refers to the fact that for many equity investors buying is easier than shorting. This is because (1) some investors are less able or less willing to short than other investors and (2) some stocks are more difficult to short than other stocks. With arbitrage asymmetry, arbitrage can eliminate more underpricing than overpricing due to the greater amount of arbitrage capital devoted to long positions as opposed to short positions. Importantly, arbitrage asymmetry implies that the negative IVOL effect among overpriced stocks is stronger than the positive IVOL effect among underpriced stocks so that the overall IVOL-return relation is negative.

Overall, the Stambaugh et al. (2015) arbitrage asymmetry model motivates the use of double-sorted portfolios on the mispricing measure and IVOL that we examine for the rest of the paper. As we will see, consistent with the Stambaugh et al. (2015) model, it is the combination of high IVOL with mispricing that delivers the strongest results.

4.2 Mispricing and IVOL Portfolios

For the remainder of our analysis, we focus on portfolios which are conditionally double-sorted on the mispricing measure and IVOL. First, each month all stocks are sorted on the mispricing measure to form quintile portfolios. Second, within each mispricing quintile, stocks are sorted again into quintiles based on IVOL to create 5x5 conditionally sorted portfolios. As previously, we form VW portfolios with NYSE breakpoints.

Panel A of Table 5 reports one-month ahead risk-adjusted returns for each of the 25 portfolios. This effectively replicates the portfolios examined by Stambaugh et al. (2015). The results indicate that the more overpriced and the higher the IVOL, the lower the risk-adjusted returns. In other words, there is a significant negative H-L spread between overpriced and underpriced stocks as well as between the highest and the lowest IVOL stocks. The interaction of most overpriced and highest IVOL is the strongest. By far the lowest risk-adjusted return is associated with the most overpriced/highest IVOL portfolio, which delivers a risk-adjusted return of -0.76% (or -9.12% per year) with a t-stat=-5.35. These findings confirm the underperformance of the most mispriced (i.e., most overpriced) stocks and the importance of IVOL as a proxy for arbitrage risk.

In the second panel of Table 5, we assess the relation between risk-adjusted returns and the market state. We do so by regressing the portfolio risk-adjusted returns on the contemporaneous and lagged market return as well as a set of the following contemporaneous and lagged control variables: innovations in the inflation rate, the risk-free rate, the term spread, the default spread and the sentiment index of Baker and Wurgler (2006). Panel B of Table 5 presents the beta estimate of each portfolio on the lagged market return and the corresponding Newey-West (1987) t-statistic.

Our main finding here is that there is a significant positive relation between the risk-adjusted return and the lagged market return only for the most overpriced/highest IVOL portfolio, with a coefficient of 0.14 and a t-stat=4.52. There are no other portfolios with a significant positive slope on the lagged market return. We conclude, therefore, that the portfolio that underperforms the most and is the prime driver of the mispricing/IVOL results is also the portfolio with the strongest relation to the lagged market state. Next, we explore further this relation.

4.3 The Effect of the Market State on Mispricing and IVOL Portfolios

In Table 6, we report the risk-adjusted returns of the double-sorted mispricing/IVOL portfolios for the two subsamples. Panel A reports results for periods following the positive market state and Panel B for periods following the negative market state.

Our main finding is that the risk-adjusted returns tend to be weak for the positive market state but very strong for the negative market state. For example, following the positive market state, the most overpriced/highest IVOL portfolio delivers a risk-adjusted return of -0.26 with a t-stat=-1.51. However, following the negative market state, the most overpriced/highest IVOL portfolio delivers a risk-adjusted return of -1.46% (or -17.52% per year) with a t-stat=-7.09. Put differently, following the negative market state, the most overpriced/highest IVOL firms average a significant risk-adjusted return that is almost six times that following the positive market state. Overall, these results clearly indicate that mispricing and arbitrage risk occur primarily following a negative market state. This is a novel finding in the literature that further refines the original Stambaugh et al. (2015) findings.

5 What Happens During the Negative Market State?

In the previous section, we establish a relation between the market state and the one-month ahead risk-adjusted return of the most overpriced/highest IVOL portfolio. We now turn our attention to the mechanisms that can potentially explain this predictive relation.

5.1 The Market State and Contemporaneous Risk-Adjusted Returns

We begin with an examination of the contemporaneous relation between the market state and risk-adjusted returns. Whereas previously we reported risk-adjusted returns following a market state, we now do so *during* a market state. Table 7 reports the one-month ahead risk-adjusted return for the mispricing-IVOL double sorted portfolios during a positive (Panel A) or negative (Panel B) market state.

Our main finding here is similar to our previous findings: the risk-adjusted returns tend to be weak for the positive market state but very strong for the negative market state. For example, following the positive market state, the most overpriced/highest IVOL portfolio delivers a risk-adjusted return of -0.01 with a t-stat=-0.05. However, following the negative market state, the most overpriced/highest IVOL portfolio delivers a very high risk-adjusted return of -1.81% (or -21.72% per year) with a t-stat=-8.23. Clearly, the strong negative return of the most overpriced/highest IVOL portfolio is observed exclusively during the negative market state. In addition, the two H-L spreads of the most overpriced minus most the underpriced and highest IVOL minus lowest IVOL are both negative and significant during the negative market state.

In Panel C of Table 7, we also report the excess (not risk adjusted) returns during the negative market state. In this case, the performance of the most overpriced/highest IVOL portfolio is astounding. It delivers a mean excess return of -7.03% (or -84.36% per year) with a t-stat=-14.05. This is an astonishingly low return (or an enormous return for short investors) by any standard. Based on this evidence, we conclude that mispricing excess returns and risk-adjusted returns can be significantly negative and occur exclusively during a negative market state.

In this section we focus on the contemporaneous relation between the market state and risk-adjusted returns because it can potentially explain their predictive relation through a mechanism that Stambaugh et al. (2015) term "the loosening of arbitrage capital." The main idea is as follows: in the negative market state, as stock prices fall, the margin ratios improve for investors who are short in the most overpriced/highest IVOL stocks. Higher margin ratios are likely to encourage investors to add to their short positions. This increases short interest in the next period and puts additional pressure on prices, which drop further. The end result is a feedback effect between prices and short interest, which generates return momentum among the most overpriced/highest IVOL stocks following a negative market state. This momentum can explain the return persistence of the most overpriced/highest IVOL portfolio thus creating a predictive relation between the market state and risk-adjusted returns. This is the essence of the loosening of arbitrage capital mechanism proposed by Stambaugh et al. (2015).

5.2 Short Interest Following Different Market States

In this section, we assess the empirical validity of the loosening of arbitrage capital theory by examining short interest data. We begin by reporting in Panel A of Table 8 the average short interest ratio, in percent, for the 5x5 mispricing-IVOL portfolios. We first note that the short interest ratios are positive for all portfolios and increase monotonically as we move from underpriced to overpriced portfolios and from low IVOL to high IVOL. As a result, all H-L spreads in Panel A are positive and significant. The highest short interest ratio is associated with the most overpriced/highest IVOL portfolio and is equal to 3.82%.

Next we examine *changes* in the short interest ratios across portfolios following a positive (Panel B) or a negative (Panel C) market state.[8] Following a positive market state, changes in short interest ratios tend to be small, insignificant and of different sign across the 25 portfolios. For example, for the most overpriced/highest IVOL portfolio, the change in the short interest ratio is equal to 0.01% with a t-stat=0.70.

In contrast, following a negative market state, the changes in the short interest ratio tend to be positive and significant. The most overpriced/highest IVOL portfolio exhibits the highest change of 0.08% with a t-stat=3.38. Among the most overpriced portfolios, the highest IVOL minus the lowest IVOL spread is equal to 0.07% with a t-stat=3.10. Among the highest IVOL portfolios, the most overpriced minus the most underpriced spread is equal to 0.05% with a t-stat=2.45.

These empirical results align perfectly with theoretical predictions of the loosening of arbitrage capital. The main theoretical prediction is that, following a negative market state, arbitrage capital that is short the most overpriced/highest IVOL stocks becomes less constrained and short interest subsequently increases. This is exactly what we find: the short interest ratio of the most overpriced/highest IVOL stocks rises significantly by a higher amount than any other portfolio, and this is only observed following a negative

[8] It is important to note that short interest data are reported mid-month. To avoid a forward looking bias, we report changes in short interest from month t-1 to t conditioning on the market state in month t-2.

market state. We conclude, therefore, that there is strong empirical support for the loosening of arbitrage capital theory, which is mechanism contributing to the momentum among the most overpriced/highest IVOL firms following a negative market state.

5.3 The Disposition Effect

The loosening of arbitrage capital theory supports our empirical results by focusing on the short positions of investors. Now turn to an alternative mechanism, the disposition effect, which focusses on the long positions of investors. The disposition effect of Shefrin and Statman (1985) refers to the propensity of investors to avoid selling stocks that exhibit capital losses. The basic notion of this effect stems from prospect theory introduced by Kahneman and Tversky (1979), which posits that investors make decisions not on expected outcomes, but on losses and gains.

The disposition effect is illustrated in Figure 3 (based on a graph used by Frazzini, 2006). The figure displays a utility function that is concave for positive outcomes but convex for negative outcomes. Consider an investor who maximizes expected utility and faces a capital loss over which she has convex preferences. The investor will not sell the investment to avoid realizing the capital loss thus holding the position into the next period. This is simply because not selling has higher utility than selling and realizing the loss.

The disposition effect can be readily applied to explain the strongly negative risk-adjusted returns of the most overpriced/highest IVOL stocks following a negative market state. Since the most overpriced/highest IVOL stocks suffer the largest negative returns during the negative market state, long investors are placed in a state of loss. According to the disposition effect, these investors will avoid selling. In turn, this will inhibit price discovery during the negative market state (see, e.g., Grinblatt and Han, 2005). Then, as shown in Frazzini (2006), initial price underreaction will foster one-month ahead return momentum so that the completion of price discovery occurs in the following month. In this framework, the disposition effect provides an explanation for the momentum in the most overpriced/highest IVOL stock portfolio following a negative market state.

5.4 Market States and Innovations in Aggregate Liquidity

We assess the empirical validity of the theoretical predictions of the disposition effect by examining the role of liquidity during different market states We begin with the relation between the market state and aggregate liquidity. We use innovations in aggregate US market liquidity, as in Pastor and Stambaugh (2003), as our proxy for changes in liquidity in the US market. In Table 9, we regress liquidity on a set of contemporaneous and lagged economic controls, as well as the contemporaneous and lagged market return divided, using dummy variables, into periods of positive and negative market states[9]. The use of the dummy variables is critical to examine if the relation between the market and liquidity varies with the market state. The loading on the contemporaneous market return during positive market states is 0.01 with a t-stat=0.06. In contrast, the loading

[9] We use absolute returns in the negative market state for ease of interpretation.

during negative market states is -0.77 (Newey-West (1987) t-statistic of -8.98). Obviously, the market return during negative market states has large significant negative effects on aggregate liquidity. In contrast, there appears to be no relation between the market return and aggregate liquidity during positive market states. These results support the notion that inhibited price discovery is possible during negative market states. These results are also aligned with Wang et al. (2021) who show that behavioral explanations predict that anomaly momentum should be negatively related with market liquidity. We next study liquidity shocks at the firm level.

5.5 Liquidity Shocks in Different Market States

We inquire now into the matter of how firm liquidity levels differ among the mispricing and IVOL portfolios, and into which firms experience the most severe liquidity shocks during negative market periods. Table 10 utilizes the Amihud (2002) measure of illiquidity to measure individual firm liquidity.

Panel A of Table 10 reports the value weighted average illiquidity levels of the double sorted portfolios over the full sample. We find that liquidity falls as firm mispricing or IVOL increase. The illiquidity measure of the highest IVOL-most overpriced portfolio is 0.27, which is the largest measure of the 25 portfolios. In addition, we observe large differences in illiquidity across the mispricing and IVOL portfolios. Overpriced/High IVOL firms tend to be the most illiquid firms, as such any market frictions (i.e., a negative market state) that may cause further illiquidity in the market should adversely affect these firms the most.

Panel B and Panel C of Table 10 provide the value weighted average changes in the portfolio illiquidity measure following a positive market state and a negative market state. The average change in illiquidity of the highest IVOL-most overpriced portfolio is -0.016 (Newey-West (1987) t-statistic of -2.77) during positive market states, whereas during negative market states, the same portfolio averages an illiquidity increase of 0.036 (Newey-West (1987) t-statistic of 5.29). We have identified Overpriced/High IVOL firms as the least liquid firms. Accordingly, they are the most susceptible to any market frictions that may inhibit price discovery. Further, during a negative market state, these are the firms adversely effected with the largest decreases in liquidity. The results presented demonstrate that the Overpriced/High IVOL firms are most susceptible to the initial price underreaction and subsequent price momentum that is implied by a disposition effect. In other words, we posit that a lack of willingness of investors to sell the underperforming Overpriced/High IVOL firms in a negative market state inhibits price discovery and contributes to the observed one-month ahead return momentum.

5.6 Market Returns and Mutual Fund Flows

We now turn to aggregate U.S. all equity mutual fund data to see if the disposition effect is supported by mutual fund investors. The variable of interest is net exchanges (exchanges in less exchanges out). We regress net exchanges on the set of contemporaneous and lagged economic control variables as well as the contemporaneous and lagged market return divided into positive and negative market states as in Table 9. First, we note the large significant loading of net exchanges on the market state, net flows have a very strong positive relation with contemporaneous market returns (this is well documented by Warther (1995), Edwards and Zhang (1998), Fant (1999) and Ben-Raphael (2012)). The main result is the difference between the coefficient on the lagged market return in positive and negative market states. The loading of net exchanges on lagged positive market states is insignificant, whereas the coefficient on lagged negative periods is significant with a Newey-West (1987) t-statistic of -2.07.[10]

We have shown that flows display momentum following a negative market state. In other words, there is selling during a negative state, but the selling continues into the next period. Therefore, the downward persistence of net exchanges following a negative market state ought to have a negative effect on one-month ahead returns (given the well-established positive relation between net exchanges and returns). In contrast, there appears to be no relation between the lagged positive market return and flows. This result is consistent with the disposition effect, that a subset of investors prefer to hold during negative market states, and then proceed to sell in the future generating return momentum.

5.7 Mispricing and Left-tail Momentum

Altigan et al. (2020) investigate the relation between left-tail risk and the cross-section of expected stock returns. They present theory that predicts that investors ought to pay

[10] The lagged negative market state loads on net sales and net flows significantly also, results are available upon request.

lower prices to hold stocks with high left-tail risk, and as such expected returns are high. However, a negative relation between left-tail risk and expected stock returns is observed. A behavioral explanation for this anomaly is provided, based on underreaction behavior of individual investors. They argue that investors may overprice securities with high left-risk, and as such returns in the left-tail of the empirical return distribution will persist into the future causing left-tail return momentum. Interestingly, limited arbitrage is identified as a potential explanation, as their anomaly is more pronounced among stocks that are costlier to arbitrage. It is of interest to see the extent to which the portfolios that vary in mispricing and IVOL are related to left-tail risk, as Overpriced/High IVOL firms are the worst performing firms and thus likely have above average left-tail risk.

Table 12 reports on how the main variable in Altigan et al. (2020), the Value-at-Risk at 1% (VaR1) measure, varies across the portfolios we analyze. Panel A reports the average value weighted VaR1 measure for the double sorted portfolios in Table 5, which are sorted conditionally on mispricing and IVOL. We find that left-tail risk, as proxied by VaR1, is closely related to mispricing and IVOL. The VaR1 measure of the most overpriced-high IVOL portfolio is 8.41, which is the largest measure of all portfolios. The difference in left-tail risk is significant between the highest and the lowest IVOL portfolios within the most overpriced ranking, averaging 4.39. Additionally, the difference in left-tail risk is significant between the most overpriced and the most underpriced portfolio within the highest IVOL ranking, averaging 2.47. The IVOL relation is aligned with the findings of Altigan et al. (2020) who find that left-tail risk and limited arbitrage are closely related. A unique insight we provide in Panel A is that overpriced firms are more susceptible to large adverse price movements. Put differently, the firms most valued by investors, as identified by the mispricing measure, have the largest empirical left-tails. The next question we investigate is how left-tail risk is related to the market state.

Panels B and C of Table 12 report the value weighted changes in firm VaR1 measures following a positive and negative market return. What we observe is that left-tail events at the firm level are more likely to occur during negative market states. The average change in VaR1 of the highest IVOL-most overpriced portfolio is 0.09% (Newey-West (1987) t-statistic of 3.65) during a positive market state, whereas during a negative market state, the same portfolio averages a significant change of 0.38% (Newey-West (1987) t-statistic of 6.27). Panel D shows on aggregate how the VaR measures, VaR1 and VaR5, change during the two distinct market states. Both the VaR1 and VaR5 measures increase for a larger portion of firms (both equal weighted and value weighted) during negative market states compared to positive market states. This result is important as Altigan et al. (2020) find strong empirical support for the left-tail risk anomaly when sorting stocks based on an increase in the VaR1 measure of the last two-month period. Additionally, double sorted portfolios on VaR1 and IVOL perform qualitatively the same as portfolios sorted on mispricing and IVOL when conditioning on the preceding market state (as in Table 5). In other words, it is exclusively following a negative market state where most of the variation in the abnormal ex-ante performance associated with left-tail momentum are observed.[11]

We have shown on average that it is the overpriced firms who suffer the largest losses, which creates a close alignment between mispricing and empirical left-tails. Additionally, most large losses in the cross-section are experienced during negative market states. The mechanisms we identify, loosening arbitrage capital and the disposition effect, can serve as alternative explanations to the findings identified by Altigan et al. (2020) which are not opposed to what is predicted by economic theory. Importantly, as we have identified ex-ante when the underperformance is significant among Overpriced/High IVOL firms, we have identified when left tail-risk is significant, namely after negative market states.

5.8 Performance Beyond One-Month Ahead Returns

We have identified one-month ahead return momentum among the Overpriced/High IVOL firms following a negative market state. The loosening of arbitrage capital among short investors and a disposition effect among long investors have been demonstrated as mechanisms contributing to this momentum. The nature of these mechanisms are transitory, so we expect firm performance to revert to the full sample mean at some point into the future. Figure 4 plots the average risk-adjusted return of the most overpriced-high IVOL portfolio for months 1 to 12 following a negative market state. We find that

[11] These results are available upon request.

the underperformance of the Overpriced/High IVOL firms persist one-month ahead exclusively. After which, the returns revert roughly to the full sample mean for the remaining 11 months. Table 13 gives a simple summary of average most overpriced-high IVOL portfolio performance and characteristics for the short term (2 to 12 months ahead) and long term (13 to 60 months ahead). The Overpriced/High IVOL firms remain overpriced into the long-term, however IVOL reverts towards the average among the most overpriced firms (averaging 2.59 and 2.23 for months t+2 to t+12 and months t+13 to t+60 compared to a full sample average of 1.59 among the most overpriced quintile). This explains why the average underperformance of the most overpriced-high IVOL portfolio is significant in months t+2 to t+12, as these firms remain difficult to arbitrage, due to above average IVOL, relative to the other overpriced firms. In contrast, average risk-adjusted returns from months t+13 to t+60 are no longer significant. This appears to be the case because these firms become easier to arbitrage, as IVOL moves toward the average for the overpriced firms. In summary, we identify momentum in the overpriced high IVOL firms solely for the one-month ahead period. This is further support for the mechanisms we claim contribute to the relation between the market state and the one-month ahead return momentum among the Overpriced/High IVOL firms.

5.9 Anomaly Exposure to The Most Overpriced-Highest IVOL Firms

We now study how anomaly returns, constructed using the Fama-French methodology, vary with the preceding market state. We also want insight into how these returns are related to the Overpriced/High IVOL firms. This will help determine if the anomalies are affected by the return momentum driven by the preceding market state. As stated earlier, we construct all anomalies based on the Fama–French methodology. Each anomaly is formed by sorting independently on size and the underlying characteristic to create value weighted portfolios. For size, firms are broken into the big or small category using the median NYSE firm ME as the breakpoint. For the underlying characteristic, firms have high or low rankings if their measure is above the 70th NYSE percentile or below the 30th NYSE percentile. Two value weighted portfolios are formed using the intersection of big firms with high and low rankings. Two additional value weighted portfolios are formed using the intersection of small firms with high and low rankings. The anomaly return is then,

$$Anomaly\ Return = \frac{Big\ High + Small\ High}{2} - \frac{Big\ Low + Small\ Low}{2},$$

representing a net-zero cost portfolio which is long firms with high exposure to the underlying characteristic and short firms with low exposure to the underlying characteristic, while controlling for potential size effects. We set the long and short legs of each anomaly to make each return positive for simplicity, except for COR, to remain consistent with the Betting-Against-Correlation factor of Asness et al. (2020). The size factor related to ME is constructed differently, as in Fama-French (2015).

Table 14 reports the mean one-month ahead risk-adjusted returns for the anomalies, built using the Fama-French methodology, as well as the long and short legs of each anomaly. Consistent with our findings with the anomaly quintile portfolios, the difference in risk-adjusted anomaly returns vary when conditioning on the preceding market state in Panels B and C. This is true for the return anomalies, as well as the long and short legs. Panel D reports how each anomaly loads on the most overpriced-high IVOL portfolio. We regress the anomaly alphas on the most overpriced-high IVOL portfolio alpha as well as a set of contemporaneous and lagged economic controls. Many of the anomalies we consider load negatively on the most overpriced-high IVOL portfolio. Interestingly, many of the negative anomaly loadings arise from both negative loadings in the long legs and positive loadings on the short legs. We conclude that Overpriced/High IVOL firms influence anomaly returns, through a positive relation with the short leg, as well as a negative relation with the long leg.[12] We have identified a strong relation between Overpriced/High IVOL firms and anomaly returns. We posit that this is the channel through which the anomaly returns display a common time variation depending on the preceding market state.

6 Conclusion

This paper examines the influence of the market state in one-month ahead anomaly returns. We find that many of the well-known return anomalies vary widely in size, sign and significance depending on the preceding market state. The mispricing measure of Stambaugh et al. (2015) and IVOL, a proxy for arbitrage risk, identify the source of the common time-variation in the wide set of anomaly returns. Negative one-month ahead return momentum is identified, among the Overpriced/High IVOL firms, following a

[12] For the anomaly results we chose the Fama-French methodology in constructing anomalies for the sake of variety The cross-sectional factor model of Fama-French (2020) is successful in removing any size effects that single sorted portfolios may correlate with. The beta estimates for the single sorted anomaly portfolios from Tables 2 and 3 lead to the same conclusions and are available upon request.

negative market state. We then show that anomaly returns load significantly on a portfolio comprised of these firms. As such, these firms are the channel through which anomaly returns display a common time-variation with the preceding market state.

The most overpriced-high IVOL portfolio averages an insignificant one-month ahead risk-adjusted return of -0.26% following a positive market state and a staggering significant -1.46% one-month ahead risk-adjusted return following a negative market state. Our hypothesis is that there exists two distinct but complementary effects behind our findings. The first is concerned with the loosening of arbitrage capital among short investors. Specifically, during negative market states, the constraints on arbitrage capital short Overpriced/High IVOL firms *loosen* as these firms perform very poorly and resulting arbitrage risk lowers (represented by a margin ratio improvement resulting in a reduced likelihood of a margin call). We show that as a result, short interest ratios increase significantly for Overpriced/High IVOL firms following a negative market state. As such, we posit that a feedback effect among these investors generates this result. First prices drop, improved margin ratios among short arbitrage capital lower arbitrage risk, and short positions increase into the future. The increase in short positions create downward price pressure, contributing to the observed return momentum among the Overpriced/High IVOL firms.

We next identify a behavioural bias among long investors as an additional complimentary effect behind the return momentum observed among the Overpriced/High IVOL firms. We posit that the well-known disposition effect (Shefrin and Statman, 1985) plagues long investors which contributes to the observed return momentum. The disposition effect refers to the greater propensity of investors to hold stocks that have fallen in value rather than risen in value since purchase. We posit that when Overpriced/High IVOL firms perform poorly, during negative market states, a subset of investors are placed in a state of loss and refuse to sell. The resulting effect of this bias is an initial price underreaction to information (Grinblatt and Han, 2005), generating one-month ahead return momentum (Frazzini, 2006) among the Overpriced/High IVOL firms. We find a significant relation between innovations in aggregate liquidity and negative market states. We then demonstrate that Amihud (2002) illiquidity increases with both the mispricing measure and IVOL. Additionally, during negative market states it is the Overpriced/High IVOL firms which suffer the largest and most significant increases in illiquidity. These results are aligned with the claim that Overpriced/High IVOL firm prices are most likely to underreact as implied by the disposition effect, during negative market states, contributing to the observed one-month ahead return momentum. We then show a significant negative relation between aggregate net exchanges of U.S. all equity mutual funds and preceding negative market states. This supports the position that a negative market state predicts future net selling, behaviour consistent with that of the disposition effect.

Lastly, we show that the mispricing measure is very closely related, empirically, to the value-at-risk measure shown by Altigan et al. (2020) to identify left-tail momentum in U.S. firms. We observe left-tail risk return momentum exclusively following negative market states. The mechanisms discussed in this paper serve as an explanation of the results in Altigan et al. (2020) that are aligned with theoretical predictions.

This paper introduces the predictive power of the market state on return anomalies. What we identify is the important role of the market state in the returns related to mispricing. It is exclusively following negative market states, where the large ex-ante underperformance of the overpriced-difficult to arbitrage firms are observed. Concurrently, this is an important finding for anomaly returns which are affected greatly by this relation. Our results supplement the argument that a large component of anomalous returns are related to mispricing.

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Table 1: Persistence of the Market Portfolio Return

This table reports the estimation results of standard AR(1) regressions on the market portfolio excess return. The control variables used in Panel B include inflation, the riskless rate, the term spread, the default spread and the sentiment index of Baker and Wurgler (2006). The t-statistics are based on Newey and West (1987). The sample period ranges from August 1965 to January 2017.

Panel A: AR(1) Regression

$$[r_m - r_f]_t = \beta_0 + \beta_1 [r_m - r_f]_{t-1} + \varepsilon_t$$

	Coefficient	SE	t-statistic	p-value
β_0	0.005**	0.002	2.56	0.011
β_1	0.08*	0.04	1.87	0.061

Panel B: AR(1) Regression with Controls

$$[r_m - r_f]_t = \beta_0 + \beta_1 [r_m - r_f]_{t-1} + \lambda Controls_t + \gamma Controls_{t-1} + \varepsilon_t$$

	Coefficient	SE	t-statistic	p-value
β_0	0.005**	0.002	2.57	0.010
β_1	0.07*	0.04	1.71	0.087

Table 2: Asset Pricing Anomaly Returns in Different Market States

This table presents the mean excess returns of quintile portfolios sorted on firm characteristics representing well-known asset pricing anomalies. In each column, stocks are sorted into quintile portfolios every month based on their most recent characteristic measure. We form monthly value-weighted portfolios based on NYSE portfolio breakpoints. The "H-L" row represents the difference in mean excess returns between the High and Low quintile portfolios. Newey–West (1987) t-statistics are reported in parentheses. The sample period ranges from August 1965 to January 2017.

Panel A: Mean Excess Returns - Full Sample

	BETA	ME	BM	OP	INV	MOM	STR	COR	VOL	IVOL	MAX	M1	ILLIQ	VaR1
High	0.36	0.45	0.78	0.59	0.44	0.88	0.31	0.41	0.44	0.42	0.45	0.50	0.71	0.43
4	0.51	0.66	0.60	0.52	0.53	0.57	0.46	0.65	0.64	0.62	0.55	0.61	0.71	0.57
3	0.50	0.74	0.57	0.52	0.51	0.43	0.54	0.55	0.61	0.60	0.57	0.64	0.67	0.64
2	0.58	0.83	0.53	0.45	0.55	0.49	0.66	0.60	0.54	0.62	0.59	0.50	0.62	0.57
Low	0.56	0.86	0.45	0.40	0.73	0.20	0.70	0.63	0.49	0.50	0.55	0.49	0.47	0.48
H-L	-0.20	-0.41	0.32	0.19	-0.29	0.68	-0.39	-0.22	-0.05	-0.08	-0.10	0.01	0.25	-0.04
t(H-L)	(-0.86)	(-2.37)	(2.04)	(1.66)	(-2.32)	(3.23)	(-2.72)	(-1.69)	(-0.19)	(-0.39)	(-0.46)	(0.04)	(1.71)	(-0.17)

Panel B: Mean Excess Returns Following Market Price Appreciation: $[r_m - r_f]_{t-1} > 0$

	BETA	ME	BM	OP	INV	MOM	STR	COR	VOL	IVOL	MAX	M1	ILLIQ	VaR1
High	0.91	0.66	1.20	0.91	0.86	1.18	0.56	0.68	1.27	1.17	1.05	1.31	1.50	1.22
4	0.86	1.05	0.89	0.78	0.82	0.83	0.71	0.89	1.17	1.05	0.96	1.12	1.28	1.07
3	0.76	1.24	0.84	0.73	0.73	0.68	0.75	0.86	0.96	0.94	0.83	1.01	1.11	0.98
2	0.77	1.48	0.87	0.71	0.76	0.76	0.92	0.90	0.79	0.79	0.84	0.74	0.99	0.86
Low	0.70	1.76	0.72	0.85	1.07	0.75	1.22	1.09	0.58	0.67	0.72	0.58	0.69	0.56
H-L	0.21	-1.09	0.48	0.06	-0.20	0.43	-0.66	-0.41	0.69	0.49	0.33	0.73	0.82	0.66
t(H-L)	(0.77)	(-5.17)	(2.55)	(0.42)	(-1.47)	(1.52)	(-3.48)	(-2.47)	(2.40)	(2.16)	(1.29)	(2.58)	(4.53)	(2.45)

Panel C: Mean Excess Returns Following Market Price Depreciation: $[r_m - r_f]_{t-1} < 0$

	BETA	ME	BM	OP	INV	MOM	STR	COR	VOL	IVOL	MAX	M1	ILLIQ	VaR1
High	-0.41	0.16	0.19	0.14	-0.15	0.45	-0.05	0.03	-0.72	-0.61	-0.39	-0.62	-0.39	-0.66
4	0.02	0.13	0.19	0.15	0.13	0.21	0.11	0.31	-0.10	0.01	-0.01	-0.11	-0.09	-0.13
3	0.13	0.03	0.20	0.23	0.19	0.08	0.24	0.11	0.11	0.12	0.20	0.13	0.05	0.16
2	0.33	-0.08	0.05	0.09	0.26	0.10	0.31	0.19	0.20	0.39	0.25	0.17	0.11	0.16
Low	0.36	-0.39	0.09	-0.24	0.25	-0.57	-0.02	0.00	0.36	0.27	0.31	0.38	0.16	0.36
H-L	-0.77	0.55	0.10	0.38	-0.40	1.03	-0.03	0.03	-1.08	-0.88	-0.69	-1.00	-0.55	-1.02
t(H-L)	(-2.33)	(2.28)	(0.43)	(2.16)	(-2.04)	(3.70)	(-0.09)	(0.17)	(-2.92)	(-2.96)	(-2.24)	(-2.70)	(-2.76)	(-2.88)

Table 3: Risk-Adjusted Returns in Different Market States

This table presents the mean risk-adjusted returns (alphas) of quintile portfolios for the same asset pricing anomalies as in Table 2. Risk-adjusted returns are calculated using the cross-sectional factor model of Fama and French (2020). For each anomaly, we compute alphas omitting the relevant factor from the model. For example, when computing risk-adjusted returns for the BM portfolios, we use omit BM from the model. In each column, stocks are sorted into quintile portfolios every month based on their most recent characteristic measure. We form monthly value-weighted portfolios based on NYSE portfolio breakpoints. The "H-L" row represents the difference in mean risk-adjusted returns between the High and Low quintile portfolios. Newey–West (1987) t-statistics are reported in parentheses. The sample period ranges from August 1965 to January 2017.

Panel A: Mean Risk-Adjusted Returns - Full Sample

	BETA	ME	BM	OP	INV	MOM	STR	COR	VOL	IVOL	MAX	M1	ILLIQ	VaR1
High	-0.16	-0.11	0.11	0.13	-0.09	0.30	-0.36	-0.03	-0.26	-0.27	-0.27	-0.27	-0.08	-0.19
4	-0.03	0.03	0.06	0.01	0.06	0.06	-0.12	0.05	-0.01	-0.01	-0.08	-0.03	-0.03	-0.04
3	0.01	0.07	0.09	0.00	0.00	-0.06	0.05	-0.04	0.02	0.01	-0.01	0.05	-0.04	0.10
2	0.09	0.10	0.02	-0.03	0.05	-0.02	0.23	-0.06	0.04	0.10	0.11	0.00	-0.04	0.03
Low	0.02	0.08	-0.03	-0.21	0.11	-0.28	0.31	-0.02	0.06	0.06	0.16	0.08	0.00	0.03
H-L	-0.18	-0.20	0.14	0.34	-0.21	0.58	-0.67	-0.01	-0.32	-0.33	-0.43	-0.34	-0.08	-0.22
t(H-L)	(-1.16)	(-1.99)	(1.26)	(3.91)	(-2.33)	(3.14)	(-5.97)	(-0.12)	(-2.11)	(-2.66)	(-3.37)	(-2.39)	(-1.70)	(-1.50)

Panel B: Mean Risk-Adjusted Returns Following Market Price Appreciation: $[r_m - r_f]_{t-1} > 0$

	BETA	ME	BM	OP	INV	MOM	STR	COR	VOL	IVOL	MAX	M1	ILLIQ	VaR1
High	0.00	-0.26	0.20	0.20	-0.03	0.30	-0.45	0.01	0.01	-0.06	-0.13	0.01	0.00	0.05
4	0.04	-0.04	0.09	-0.03	0.09	0.03	-0.16	-0.02	0.05	0.00	-0.07	0.03	-0.09	0.02
3	-0.01	0.09	0.06	-0.09	-0.05	-0.07	0.01	-0.13	0.00	-0.02	-0.02	0.03	-0.15	0.07
2	0.02	0.20	0.08	-0.06	0.03	-0.02	0.23	-0.17	-0.01	-0.02	0.09	-0.04	-0.14	0.03
Low	-0.12	0.38	-0.03	-0.10	0.13	-0.10	0.48	-0.02	-0.02	0.05	0.13	-0.02	0.00	-0.07
H-L	0.12	-0.64	0.23	0.30	-0.15	0.40	-0.93	0.03	0.04	-0.11	-0.26	0.03	0.01	0.11
t(H-L)	(0.63)	(-5.08)	(1.72)	(2.89)	(-1.55)	(1.60)	(-6.36)	(0.29)	(0.21)	(-0.73)	(-1.68)	(0.16)	(0.13)	(0.71)

Panel C: Mean Risk-Adjusted Returns Following Market Price Depreciation: $[r_m - r_f]_{t-1} < 0$

	BETA	ME	BM	OP	INV	MOM	STR	COR	VOL	IVOL	MAX	M1	ILLIQ	VaR1
High	-0.39	0.09	-0.02	0.03	-0.18	0.29	-0.25	-0.09	-0.64	-0.57	-0.47	-0.65	-0.19	-0.52
4	-0.13	0.11	0.03	0.05	0.01	0.10	-0.07	0.15	-0.10	-0.02	-0.08	-0.12	0.05	-0.11
3	0.04	0.04	0.13	0.11	0.07	-0.05	0.12	0.09	0.06	0.05	0.02	0.09	0.10	0.14
2	0.18	-0.03	-0.06	0.02	0.08	-0.02	0.22	0.11	0.11	0.26	0.13	0.07	0.11	0.03
Low	0.21	-0.33	-0.04	-0.37	0.09	-0.54	0.07	-0.02	0.17	0.08	0.21	0.21	0.00	0.15
H-L	-0.60	0.42	0.02	0.40	-0.28	0.83	-0.32	-0.07	-0.81	-0.65	-0.68	-0.86	-0.19	-0.68
t(H-L)	(-2.79)	(3.16)	(0.11)	(3.12)	(-1.89)	(3.48)	(-1.39)	(-0.49)	(-4.16)	(-3.84)	(-3.52)	(-4.37)	(-3.21)	(-3.45)

Table 4: Mispricing Portfolios in Different Market States

This table reports the performance of quintile portfolios sorted on the mispricing measure of Stambaugh, Yu and Yuan (2015). In Panel A we report the mean excess returns and risk-adjusted returns for the full sample, as well as two subsamples following either a positive or a negative market state. Risk-adjusted returns are calculated using the cross-sectional factor model of Fama-French (2020). We form value-weighted portfolios based on NYSE portfolio breakpoints. The “H-L” row represents the difference in risk-adjusted excess returns between the High and Low quintile portfolios. Panel B reports the average value-weighted portfolio characteristics of the same mispricing quantile portfolios reported in Panel A. Newey–West (1987) t-statistics are reported in parentheses. The sample period ranges from August 1965 to January 2017.

Panel A: Mispricing Portfolio Returns

	Full Sample			$[r_m - r_f]_{t-1} > 0$			$[r_m - r_f]_{t-1} < 0$		
	r	α	*t(a)*	r	α	*t(a)*	r	α	*t(a)*
High	0.13	-0.20	(-3.65)	0.69	-0.11	(-1.60)	-0.64	-0.33	(-3.77)
4	0.43	-0.02	(-0.43)	0.74	-0.07	(-1.18)	-0.01	0.05	(0.72)
3	0.53	0.02	(0.64)	0.89	0.06	(1.47)	0.04	-0.03	(-0.54)
2	0.60	0.05	(1.34)	0.89	0.09	(2.05)	0.19	-0.01	(-0.21)
Low	0.67	0.10	(2.40)	0.79	0.04	(0.82)	0.50	0.18	(2.54)
H-L	-0.53	-0.30		-0.10	-0.15		-1.14	-0.51	
t(H-L)	(-3.82)	(-3.64)		(-0.62)	(-1.46)		(-5.45)	(-3.80)	

Panel B: Firm Characteristics of Mispricing Portfolios

	BETA	ME	BM	OP	INV	MOM	STR	COR	VOL	IVOL	MAX	M1	ILLIQ	VaR1
High	0.84	15.71	0.70	0.26	0.29	7.12	1.37	0.34	2.21	1.59	2.69	4.45	0.07	5.48
4	0.79	16.20	0.69	0.31	0.16	13.12	1.48	0.36	1.98	1.42	2.43	3.99	0.06	4.88
3	0.77	16.44	0.67	0.33	0.12	16.69	1.49	0.37	1.87	1.33	2.29	3.79	0.05	4.58
2	0.75	16.70	0.60	0.68	0.09	18.48	1.47	0.37	1.77	1.25	2.18	3.59	0.04	4.31
Low	0.73	17.25	0.50	0.43	0.06	23.46	1.51	0.38	1.68	1.17	2.06	3.41	0.03	4.04
H-L	0.11	-1.54	0.20	-0.17	0.23	-16.35	-0.14	-0.04	0.53	0.42	0.62	1.04	0.04	1.44
t(H-L)	(3.43)	(-8.79)	(5.19)	(-7.31)	(11.1)	(-11.2)	(-1.04)	(-2.90)	(6.33)	(12.5)	(7.20)	(5.78)	(5.97)	(7.69)

Table 5: Double-Sorted Mispricing Portfolios

This table reports mean risk-adjusted returns for portfolios formed by sorting stocks conditionally on the mispricing measure and idiosyncratic volatility (IVOL). First, stocks are sorted on mispricing into quintiles. Next, within each mispricing quintile, stocks are sorted into quintiles based on IVOL to create a 5x5 grid of conditionally sorted portfolios. We form value-weighted portfolios based on NYSE breakpoints. Panel A reports mean risk-adjusted returns. Panel B reports the slope of regressing each portfolio's risk-adjusted return on the lagged market portfolio return and additional controls. Risk-adjusted returns are calculated using the cross-sectional factor model of Fama and French (2020). Newey–West (1987) *t*-statistics are reported in parentheses. The sample period is from August 1965 to January 2017.

Panel A: Risk-Adjusted Returns

Risk-Adjusted Returns	Most Overpriced	Next 20%	Next 20%	Next 20%	Most Underpriced	Overpriced-Underpriced
Highest IVOL	-0.76	-0.37	-0.27	-0.19	0.02	-0.78
(Top 20%)	(-5.35)	(-2.89)	(-2.47)	(-1.38)	(0.19)	(-4.57)
Next 20%	-0.04	-0.02	-0.01	-0.06	0.22	-0.26
	(-0.35)	(-0.23)	(-0.10)	(-0.61)	(2.58)	(-1.83)
Next 20%	-0.22	-0.13	0.13	0.09	0.02	-0.24
	(-2.18)	(-1.40)	(1.70)	(1.18)	(0.23)	(-1.76)
Next 20%	-0.17	0.06	-0.01	0.25	0.12	-0.29
	(-1.83)	(0.66)	(-0.20)	(3.22)	(1.48)	(-2.44)
Lowest IVOL	0.01	0.04	0.08	-0.01	-0.04	0.05
(Bottom 20%)	(0.15)	(0.48)	(0.98)	(-0.13)	(-0.51)	(0.47)
Highest IVOL -	-0.77	-0.41	-0.35	-0.18	0.06	
Lowest IVOL	(-4.15)	(-2.37)	(-2.25)	(-1.20)	(0.38)	

Panel B: Slopes of Regressing Risk-Adjusted Returns on Lagged Market Returns

Risk-Adjusted Returns	Most Overpriced	Next 20%	Next 20%	Next 20%	Most Underpriced	Overpriced-Underpriced
Highest IVOL	0.14	0.00	-0.01	0.03	-0.02	0.03
(Top 20%)	(4.52)	(-0.01)	(-0.23)	(1.16)	(-0.64)	(1.79)
Next 20%	0.01	-0.02	-0.03	0.01	-0.05	-0.01
	(0.44)	(-0.82)	(-1.40)	(0.38)	(-1.98)	(-1.38)
Next 20%	0.01	-0.02	-0.03	-0.02	-0.04	-0.02
	(0.57)	(-0.64)	(-1.41)	(-1.06)	(-1.63)	(-1.61)
Next 20%	-0.01	-0.03	0.01	-0.02	-0.05	-0.02
	(-0.61)	(-1.38)	(0.71)	(-0.99)	(-3.00)	(-2.68)
Lowest IVOL	0.02	0.02	0.01	0.01	-0.01	0.02
(Bottom 20%)	(1.01)	(0.70)	(0.54)	(0.68)	(-0.74)	(2.01)
Highest IVOL -	0.03	0.00	0.01	0.02	-0.02	
Lowest IVOL	(2.19)	(-0.10)	(0.56)	(1.70)	(-1.82)	

Table 6: Double-Sorted Mispricing Portfolios Risk Following Different Market States

This table reports mean risk-adjusted returns following either positive or negative market states for portfolios formed by double-sorting stocks conditionally on the mispricing measure and IVOL. First, all stocks are sorted on mispricing into quintiles. Next, within each mispricing quintile, stocks are sorted into quintiles based on IVOL to create a 5x5 grid of conditionally sorted portfolios. We form value-weighted portfolios based on NYSE breakpoints. Risk-adjusted returns are calculated using the cross-sectional factor model of Fama and French (2020). Newey–West (1987) t-statistics are reported in parentheses. The sample period ranges from August 1965 to January 2017.

Panel A: Risk-Adjusted Returns Following Market Appreciation: $[r_m - r_f]_{t-1} > 0$

	Most Overpriced	Next 20%	Next 20%	Next 20%	Most Underpriced	Overpriced-Underpriced
Highest IVOL	-0.26	-0.16	-0.12	0.01	0.00	-0.25
(Top 20%)	(-1.51)	(-1.05)	(-0.87)	(0.06)	(-0.01)	(-1.29)
Next 20%	0.10	-0.08	-0.06	-0.05	0.12	-0.01
	(0.77)	(-0.65)	(-0.51)	(-0.40)	(1.03)	(-0.08)
Next 20%	-0.16	-0.23	0.06	0.04	-0.06	-0.10
	(-1.36)	(-2.10)	(0.63)	(0.43)	(-0.56)	(-0.62)
Next 20%	-0.23	-0.10	0.01	0.12	-0.13	-0.10
	(-2.21)	(-0.83)	(0.08)	(1.37)	(-1.31)	(-0.65)
Lowest IVOL	-0.02	-0.08	0.06	0.00	-0.10	0.08
(Bottom 20%)	(-0.15)	(-0.73)	(0.59)	(-0.06)	(-1.11)	(0.53)
Highest IVOL -	-0.24	-0.08	-0.18	0.01	0.10	
Lowest IVOL	(-1.07)	(-0.40)	(-0.93)	(0.08)	(0.51)	

Panel B: Risk-Adjusted Returns Following Market Depreciation: $[r_m - r_f]_{t-1} < 0$

	Most Overpriced	Next 20%	Next 20%	Next 20%	Most Underpriced	Overpriced-Underpriced
Highest IVOL	-1.46	-0.65	-0.48	-0.46	0.06	-1.52
(Top 20%)	(-7.09)	(-3.53)	(-2.79)	(-2.15)	(0.31)	(-5.49)
Next 20%	-0.24	0.06	0.06	-0.06	0.37	-0.61
	(-1.39)	(0.37)	(0.52)	(-0.45)	(2.52)	(-2.75)
Next 20%	-0.30	0.00	0.22	0.16	0.13	-0.43
	(-1.84)	(0.03)	(1.82)	(1.29)	(0.97)	(-1.97)
Next 20%	-0.10	0.29	-0.04	0.42	0.47	-0.56
	(-0.58)	(2.07)	(-0.38)	(3.26)	(3.60)	(-2.77)
Lowest IVOL	0.06	0.21	0.10	-0.01	0.06	0.00
(Bottom 20%)	(0.41)	(1.53)	(0.72)	(-0.13)	(0.48)	(0.02)
Highest IVOL -	-1.52	-0.86	-0.58	-0.45	0.00	
Lowest IVOL	(-5.30)	(-3.33)	(-2.38)	(-1.86)	(0.00)	

Table 7: Double-Sorted Mispricing Portfolios During Different Market States

This table reports mean risk-adjusted returns and excess-returns *during* different market states for portfolios formed by double-sorting on the mispricing measure and IVOL. First, all stocks are sorted on mispricing into quintiles. Next, within each mispricing quintile, stocks are sorted into quintiles based on IVOL to create a 5x5 grid of conditionally sorted portfolios. We form value-weighted portfolios based on NYSE breakpoints. Risk-adjusted returns are calculated using the cross-sectional factor model of Fama and French (2020). Newey–West (1987) t-statistics are reported in parentheses. The sample period ranges from August 1965 to January 2017.

Panel A: Risk-Adjusted Returns **During** Market Appreciation: $[r_m - r_f]_t > 0$

	Most Overpriced	Next 20%	Next 20%	Next 20%	Most Underpriced	Overpriced-Underpriced
Highest IVOL	-0.01	0.31	0.32	0.27	0.34	-0.35
(Top 20%)	(-0.05)	(1.95)	(2.40)	(1.68)	(2.08)	(-1.42)
Next 20%	0.53	0.42	0.27	0.26	0.21	0.32
	(4.04)	(3.50)	(2.30)	(2.09)	(1.76)	(1.89)
Next 20%	0.24	-0.03	0.36	0.20	0.06	0.18
	(1.99)	(-0.22)	(3.54)	(1.97)	(0.58)	(1.12)
Next 20%	-0.27	-0.09	-0.03	0.22	-0.08	-0.19
	(-2.34)	(-0.70)	(-0.37)	(2.07)	(-0.73)	(-1.08)
Lowest IVOL	-0.40	-0.53	-0.32	-0.28	-0.47	0.07
(Bottom 20%)	(-3.18)	(-5.16)	(-3.25)	(-2.76)	(-5.04)	(0.44)
Highest IVOL -	0.40	0.84	0.64	0.55	0.81	
Lowest IVOL	(1.83)	(4.23)	(3.56)	(2.94)	(3.86)	

Panel B: Risk-Adjusted Returns **During** Market Depreciation: $[r_m - r_f]_t < 0$

	Most Overpriced	Next 20%	Next 20%	Next 20%	Most Underpriced	Overpriced-Underpriced
Highest IVOL	-1.81	-1.31	-1.09	-0.83	-0.42	-1.39
(Top 20%)	(-8.23)	(-6.69)	(-5.57)	(-4.29)	(-2.63)	(-5.94)
Next 20%	-0.83	-0.64	-0.40	-0.49	0.24	-1.07
	(-4.83)	(-3.75)	(-3.14)	(-3.65)	(1.95)	(-4.99)
Next 20%	-0.87	-0.28	-0.20	-0.06	-0.04	-0.83
	(-5.17)	(-1.99)	(-1.60)	(-0.44)	(-0.30)	(-3.92)
Next 20%	-0.04	0.27	0.02	0.29	0.40	-0.44
	(-0.20)	(2.03)	(0.14)	(2.87)	(3.35)	(-2.34)
Lowest IVOL	0.60	0.84	0.63	0.36	0.57	0.03
(Bottom 20%)	(3.77)	(5.15)	(4.98)	(3.69)	(5.10)	(0.15)
Highest IVOL -	-2.41	-2.15	-1.72	-1.19	-0.99	
Lowest IVOL	(-8.39)	(-7.33)	(-6.39)	(-5.30)	(-4.56)	

Panel C: Excess-Returns **During** Market Depreciation: $[r_m - r_f]_t < 0$

	Most Overpriced	Next 20%	Next 20%	Next 20%	Most Underpriced	Overpriced-Underpriced
Highest IVOL (Top 20%)	-7.03	-5.63	-5.00	-4.52	-3.74	-3.29
	(-14.05)	(-13.79)	(-12.80)	(-12.16)	(-12.06)	(-9.09)
Next 20%	-5.50	-4.61	-4.16	-4.00	-3.01	-2.48
	(-13.50)	(-12.83)	(-14.02)	(-13.91)	(-11.27)	(-7.96)
Next 20%	-5.20	-4.02	-3.64	-3.43	-3.18	-2.02
	(-13.50)	(-12.86)	(-12.67)	(-13.68)	(-14.09)	(-6.11)
Next 20%	-4.08	-3.38	-3.50	-2.99	-2.69	-1.39
	(-13.28)	(-12.65)	(-12.58)	(-12.26)	(-12.16)	(-5.95)
Lowest IVOL (Bottom 20%)	-3.18	-2.55	-2.56	-2.73	-2.45	-0.74
	(-10.19)	(-10.42)	(-10.83)	(-12.75)	(-11.13)	(-3.12)
Highest IVOL - Lowest IVOL	-3.84	-3.08	-2.44	-1.79	-1.29	
	(-9.14)	(-8.20)	(-6.95)	(-5.33)	(-4.85)	

Table 8: Short Interest in Different Market States

This table reports short interest ratios following different market states for portfolios formed by double-sorting stocks conditionally on the mispricing measure and IVOL. First, all stocks are sorted on mispricing into quintiles. Next, within each mispricing quintile, stocks are sorted into quintiles based on IVOL to create a 5x5 grid of conditionally sorted portfolios. We form value-weighted portfolios based on NYSE breakpoints. Panel A reports the mean value-weighted short interest ratios for each portfolio. Panel B (Panel C) report mean innovations in short interest ratios following positive (negative) market states. Panel D reports the loading of each portfolio innovation in short interest on the lagged market portfolio return. Newey–West (1987) t-statistics are reported in parentheses. The sample period begins in January 1973 and ends in January 2017.

Panel A: Short Interest (%)

	Most Overpriced	Next 20%	Next 20%	Next 20%	Most Underpriced	Overpriced-Underpriced
Highest IVOL	3.82	2.78	2.32	1.98	1.74	2.07
(Top 20%)						(5.03)
Next 20%	2.68	2.04	1.75	1.46	1.34	1.34
						(5.99)
Next 20%	1.99	1.63	1.45	1.20	1.07	0.92
						(5.90)
Next 20%	1.56	1.34	1.21	1.03	0.90	0.66
						(4.83)
Lowest IVOL	1.25	1.12	1.05	0.91	0.77	0.48
(Bottom 20%)						(5.28)
Highest IVOL -	2.57	1.66	1.27	1.07	0.98	
Lowest IVOL	(4.18)	(5.19)	(4.77)	(4.40)	(4.57)	

Panel B: Δ Short Interest (%) Following Market Appreciation: $[r_m - r_f]_{t-2} > 0$

	Most Overpriced	Next 20%	Next 20%	Next 20%	Most Underpriced	Overpriced-Underpriced
Highest IVOL	0.01	0.01	0.03	0.01	-0.01	0.03
(Top 20%)	(0.70)	(0.38)	(1.93)	(0.65)	(-1.18)	(1.31)
Next 20%	0.01	0.01	0.01	0.00	0.00	0.00
	(0.39)	(0.43)	(0.69)	(-0.52)	(0.31)	(0.26)
Next 20%	-0.02	-0.02	-0.01	0.00	-0.02	0.00
	(-1.41)	(-1.32)	(-0.86)	(-0.60)	(-2.26)	(-0.04)
Next 20%	-0.02	0.00	-0.02	-0.01	-0.01	0.00
	(-1.84)	(0.04)	(-2.12)	(-2.10)	(-2.38)	(-0.39)
Lowest IVOL	-0.01	0.00	-0.01	0.00	-0.01	0.00
(Bottom 20%)	(-1.03)	(0.08)	(-1.14)	(-0.41)	(-2.83)	(0.58)
Highest IVOL -	0.02	0.01	0.04	0.01	0.00	
Lowest IVOL	(1.15)	(0.38)	(2.43)	(0.81)	(-0.11)	

Panel C: Δ Short Interest (%) Following Market Depreciation: $[r_m - r_f]_{t-2} < 0$

	Most Overpriced	Next 20%	Next 20%	Next 20%	Most Underpriced	Overpriced-Underpriced
Highest IVOL	0.08	0.04	0.06	0.05	0.02	0.05
(Top 20%)	(3.38)	(2.83)	(3.59)	(3.80)	(1.88)	(2.45)
Next 20%	0.05	0.02	0.02	0.01	0.00	0.05
	(3.24)	(1.20)	(1.24)	(1.33)	(0.28)	(2.81)
Next 20%	0.02	0.02	0.00	0.02	0.00	0.02
	(1.98)	(1.58)	(0.26)	(2.52)	(0.42)	(1.47)
Next 20%	0.01	0.01	0.01	0.00	0.01	0.00
	(0.66)	(1.38)	(1.33)	(0.35)	(1.32)	(-0.21)
Lowest IVOL	0.01	0.02	0.00	0.00	0.01	0.00
(Bottom 20%)	(1.02)	(2.04)	(-0.07)	(0.46)	(1.54)	(-0.21)
Highest IVOL -	0.07	0.02	0.06	0.05	0.01	
Lowest IVOL	(3.10)	(1.42)	(3.87)	(3.29)	(0.97)	

Panel D: Δ Short Interest (%) Loadings on Lagged Market Returns

	Most Overpriced	Next 20%	Next 20%	Next 20%	Most Underpriced	Overpriced-Underpriced
Highest IVOL	-0.0068	-0.0055	-0.0028	-0.0050	-0.0048	-0.0020
(Top 20%)	(-2.21)	(-2.26)	(-1.30)	(-2.25)	(-2.25)	(-0.57)
Next 20%	-0.0078	-0.0022	-0.0017	-0.0025	0.0002	-0.0080
	(-3.09)	(-1.23)	(-0.80)	(-1.56)	(0.12)	(-3.04)
Next 20%	-0.0053	-0.0042	-0.0025	-0.0017	-0.0020	-0.0033
	(-2.59)	(-2.20)	(-1.86)	(-1.25)	(-1.67)	(-1.30)
Next 20%	-0.0030	-0.0028	-0.0044	-0.0016	-0.0023	-0.0007
	(-1.91)	(-1.94)	(-2.81)	(-1.76)	(-2.11)	(-0.42)
Lowest IVOL	-0.0019	-0.0021	0.0002	0.0016	-0.0018	-0.0001
(Bottom 20%)	(-1.69)	(-1.84)	(0.12)	(0.75)	(-2.35)	(-0.06)
Highest IVOL -	-0.0049	-0.0034	-0.0031	-0.0066	-0.0029	
Lowest IVOL	(-1.56)	(-1.48)	(-1.11)	(-2.04)	(-1.46)	

Table 9: Aggregate Liquidity in Different Market States

This table reports the estimation results of a standard OLS time-series regression of innovations in aggregate liquidity on the following variables: r_m is the monthly excess market return, $\Delta infl$ is the monthly innovation in inflation, Δdfy is the monthly innovation in the default spread, Δtms is the monthly innovation in the term spread, Δrf is the monthly innovation in the risk-free rate, and $\Delta sent$ is the monthly innovation in the investor sentiment index of Baker and Wurgler (2006). We include dummy variables for the market return as follows: $d_{r>0}$ is equal to one when the (contemporaneous or lagged) market return is positive and zero otherwise, and $d_{r<0}$ is defined in the same way when the market return is negative. Newey-West (1987) t-statistics are reported in parentheses. The sample period ranges from October 1965 to January 2017.

	$Y = \Delta$ *Liquidity*			
X	b	*T(b)*	b	*T(b)*
$r_{m,t} * d_{r>0}$			0.01	(0.06)
$\lvert r_{m,t}\rvert * d_{r<0}$			-0.77	(-8.98)
$r_{m,t-1} * d_{r>0}$			-0.06	(-0.68)
$\lvert r_{m,t-1}\rvert * d_{r<0}$			-0.37	(-4.14)
$\Delta infl_t$	-1.07	(-1.49)	-1.08	(-1.64)
Δdfy_t	-0.94	(-0.45)	3.91	(1.99)
Δtms_t	0.04	(0.73)	0.04	(0.80)
Δrf_t	-5.74	(-1.56)	-3.66	(-1.08)
$\Delta sent_t$	-0.02	(-1.08)	-0.01	(-0.85)
$\Delta infl_{t-1}$	-0.10	(-0.13)	0.45	(0.69)
Δdfy_{t-1}	2.43	(1.18)	3.55	(1.89)
Δtms_{t-1}	-0.04	(-0.72)	-0.09	(-1.57)
Δrf_{t-1}	-0.81	(-0.22)	-0.17	(-0.05)
$\Delta sent_{t-1}$	0.04	(2.66)	0.05	(3.33)
R^2	0.02		0.21	
N	616		616	

Table 10: Portfolio Illiquidity in Different Market States

This table reports the average illiquidity (ILLIQ) during different market states for portfolios formed by double-sorting stocks conditionally on the mispricing measure and IVOL. Illiquidity is measured as in Amihud (2002). First, all stocks are sorted by mispricing into quintiles. Next, within each mispricing quintile stocks are sorted into quintiles based on IVOL to create a 5x5 grid of conditionally sorted portfolios. We form value-weighted portfolios based NYSE breakpoints. Panel A reports average value-weighted illiquidity levels for the full sample. Panel B (Panel C) reports average changes in illiquidity levels in periods during a positive (negative) monthly market excess return. Panel D reports the loading of each portfolio change in ILLIQ on the market portfolio return. Newey–West (1987) *t*-statistics is reported in parentheses. The sample period ranges from August 1965 to January 2017.

Panel A: Illiquidity (ILLIQ) Levels

	Most Overpriced	Next 20%	Next 20%	Next 20%	Most Underpriced	Overpriced-Underpriced
Highest IVOL	0.27	0.25	0.23	0.21	0.19	0.08
(Top 20%)						(4.86)
Next 20%	0.11	0.09	0.09	0.07	0.08	0.03
						(4.63)
Next 20%	0.07	0.05	0.05	0.04	0.04	0.02
						(5.20)
Next 20%	0.04	0.04	0.03	0.02	0.02	0.02
						(5.21)
Lowest IVOL	0.02	0.02	0.02	0.01	0.01	0.01
(Bottom 20%)						(7.51)
Highest IVOL -	0.25	0.23	0.22	0.19	0.18	
Lowest IVOL	(12.66)	(12.81)	(11.17)	(9.64)	(8.35)	

Panel B: Δ ILLIQ **During** Market Price Appreciation: $[r_m - r_f]_t > 0$

	Most Overpriced	Next 20%	Next 20%	Next 20%	Most Underpriced	Overpriced-Underpriced
Highest IVOL	-0.016	-0.022	-0.015	-0.019	-0.017	0.001
(Top 20%)	(-2.77)	(-3.99)	(-2.76)	(-3.64)	(-3.25)	(0.31)
Next 20%	-0.009	-0.009	-0.006	-0.006	-0.006	-0.002
	(-3.23)	(-4.27)	(-2.60)	(-3.67)	(-3.77)	(-1.08)
Next 20%	-0.005	-0.004	-0.005	-0.003	-0.003	-0.002
	(-3.18)	(-4.69)	(-2.98)	(-3.44)	(-3.34)	(-1.11)
Next 20%	-0.005	-0.003	-0.002	-0.002	-0.002	-0.003
	(-4.30)	(-4.42)	(-2.91)	(-3.17)	(-4.09)	(-2.78)
Lowest IVOL	-0.005	-0.004	-0.003	-0.002	-0.001	-0.004
(Bottom 20%)	(-6.33)	(-4.63)	(-4.48)	(-5.49)	(-4.79)	(-5.69)
Highest IVOL -	-0.011	-0.019	-0.012	-0.017	-0.016	
Lowest IVOL	(-2.07)	(-3.47)	(-2.29)	(-3.36)	(-3.11)	

Panel C: Δ ILLIQ **During** Market Price Depreciation: $[r_m - r_f]_t < 0$

	Most Overpriced	Next 20%	Next 20%	Next 20%	Most Underpriced	Overpriced-Underpriced
Highest IVOL	0.036	0.028	0.034	0.022	0.020	0.016
(Top 20%)	(5.29)	(5.19)	(3.95)	(3.69)	(4.64)	(2.74)
Next 20%	0.017	0.012	0.008	0.013	0.012	0.005
	(4.27)	(4.59)	(1.83)	(5.29)	(4.56)	(1.79)
Next 20%	0.006	0.004	0.005	0.005	0.006	0.000
	(2.41)	(1.90)	(3.43)	(3.78)	(4.78)	(-0.12)
Next 20%	0.002	0.002	0.002	0.002	0.001	0.001
	(1.66)	(2.07)	(2.05)	(3.45)	(2.83)	(0.84)
Lowest IVOL	-0.002	-0.002	-0.002	-0.001	-0.001	-0.002
(Bottom 20%)	(-2.57)	(-3.13)	(-2.36)	(-2.23)	(-3.93)	(-1.86)
Highest IVOL -	0.039	0.030	0.036	0.022	0.021	
Lowest IVOL	(5.65)	(5.61)	(3.99)	(3.79)	(4.80)	

Panel D: Δ ILLIQ Loadings on The Market Return

	Most Overpriced	Next 20%	Next 20%	Next 20%	Most Underpriced	Overpriced-Underpriced
Highest IVOL	0.0054	0.0061	0.0060	0.0044	0.0043	-0.0014
(Top 20%)	(4.97)	(5.44)	(5.11)	(4.11)	(4.83)	(-5.03)
Next 20%	0.0030	0.0022	0.0022	0.0024	0.0018	-0.0012
	(5.19)	(5.59)	(3.74)	(5.21)	(3.88)	(-5.83)
Next 20%	0.0008	0.0010	0.0009	0.0010	0.0011	-0.0010
	(1.69)	(2.93)	(3.03)	(4.33)	(4.26)	(-5.99)
Next 20%	0.0009	0.0004	0.0004	0.0005	0.0004	-0.0007
	(2.70)	(2.20)	(2.60)	(5.64)	(3.96)	(-5.76)
Lowest IVOL	0.0005	0.0003	0.0004	0.0002	0.0001	-0.0005
(Bottom 20%)	(3.15)	(2.15)	(3.44)	(4.15)	(2.06)	(-5.07)
Highest IVOL -	-0.0049	-0.0021	-0.0009	-0.0005	-0.0002	
Lowest IVOL	(-5.93)	(-5.49)	(-4.30)	(-4.58)	(-4.61)	

Table 11: Mutual Fund Flows in Different Market States

This table reports the estimation results of a standard OLS regression of Net All Equity U.S. Mutual Fund Exchanges on the following variables: r_m is the monthly excess market return, $\Delta infl$ is the monthly innovation in inflation, Δdfy is the monthly innovation in the default spread, Δtms is the monthly innovation in the term spread, Δrf is the monthly innovation in the risk-free rate, and $\Delta sent$ is the monthly innovation in the investor sentiment index of Baker and Wurgler (2006). We include dummy variables for the market return and innovations in aggregate liquidity as follows: $d_{r>0}$, is equal to one when the (contemporaneous or lagged) market return is positive and zero otherwise. Newey-West (1987) t-statistics are reported in parentheses. The sample period ranges from February 1984 to January 2017.

	Y = U.S. All Equity Mutual Fund Net Exchanges			
X	b	*t(b)*	b	*t(b)*
$r_{m,t} * d_{r>0}$			0.04	(6.35)
$\lvert r_{m,t}\rvert * d_{r<0}$			-0.05	(-7.83)
$r_{m,t-1} * d_{r>0}$			-0.01	(-0.94)
$\lvert r_{m,t-1}\rvert * d_{r<0}$			-0.01	(-2.07)
$\Delta infl_t$	0.05	(1.02)	0.06	(1.37)
Δdfy_t	-0.09	(-0.49)	0.27	(1.73)
Δtms_t	0.01	(1.86)	0.01	(3.52)
Δrf_t	-0.51	(-1.38)	-0.51	(-1.62)
$\Delta sent_t$	0.00	(-0.91)	0.00	(0.44)
Δliq_t	0.01	(4.79)	0.00	(0.95)
$\Delta infl_{t-1}$	-0.01	(-0.19)	0.04	(0.90)
Δdfy_{t-1}	0.16	(0.96)	0.23	(1.62)
Δtms_{t-1}	0.00	(0.83)	0.00	(0.87)
Δrf_{t-1}	0.67	(1.81)	0.66	(2.13)
$\Delta sent_{t-1}$	0.00	(1.09)	0.00	(1.63)
Δliq_{t-1}	0.01	(1.82)	0.00	(0.08)
R^2	0.093		0.378	
N	396		396	

Table 12: Mispricing and Left-tail Momentum

This table reports the average Value-at-Risk (VaR) during different market states for portfolios formed by double-sorting stocks conditionally on the mispricing measure and IVOL. We compute the most recent annual VaR measure at the 1% and 5% (VaR1 and VaR5) threshold following Altigan et al. (2020). Portfolios are conditionally sorted as in Table 5. We form value-weighted portfolios based on NYSE breakpoints. Panel A reports average value-weighted VaR1 levels for the full sample. Panel B (Panel C) reports average changes in VaR1 levels in periods during a positive (negative) monthly market excess return. Panel D reports the average frequency of positive, negative and zero changes in VaR1 and Var5. Panel E reports the loading of each portfolio change in VaR1 on the market portfolio return. We report both the equal- and value-weighted frequencies of the VaR changes. Newey–West (1987) t-statistics are reported in parentheses. The sample period ranges from August 1965 to January 2017.

Panel A: VaR1 Levels

	Most Overpriced	Next 20%	Next 20%	Next 20%	Most Underpriced	Overpriced-Underpriced
Highest IVOL (Top 20%)	8.41	7.36	6.81	6.37	5.94	2.47
						(18.13)
Next 20%	6.81	5.92	5.55	5.16	4.90	1.91
						(15.53)
Next 20%	5.78	5.12	4.84	4.58	4.35	1.44
						(12.50)
Next 20%	4.96	4.51	4.29	4.08	3.93	1.03
						(8.16)
Lowest IVOL (Bottom 20%)	4.02	3.69	3.57	3.51	3.45	0.57
						(7.11)
Highest IVOL - Lowest IVOL	4.39	3.68	3.25	2.86	2.49	
	(38.23)	(37.06)	(35.27)	(40.10)	(39.56)	

Panel B: Δ VaR1 **During** Market Price Appreciation: $[r_m - r_f]_t > 0$

	Most Overpriced	Next 20%	Next 20%	Next 20%	Most Underpriced	Overpriced-Underpriced
Highest IVOL	0.09	0.08	0.08	0.09	0.12	-0.03
(Top 20%)	(3.65)	(3.10)	(3.35)	(4.36)	(6.64)	(-1.83)
Next 20%	-0.06	-0.05	-0.04	-0.02	-0.01	-0.05
	(-2.63)	(-2.28)	(-1.99)	(-1.10)	(-0.57)	(-4.02)
Next 20%	-0.07	-0.07	-0.06	-0.05	-0.04	-0.03
	(-2.94)	(-3.36)	(-3.60)	(-2.85)	(-3.01)	(-1.78)
Next 20%	-0.09	-0.07	-0.07	-0.06	-0.05	-0.04
	(-4.35)	(-4.32)	(-4.76)	(-4.16)	(-3.86)	(-2.96)
Lowest IVOL	-0.09	-0.07	-0.08	-0.08	-0.06	-0.02
(Bottom 20%)	(-5.24)	(-5.79)	(-6.06)	(-5.58)	(-4.89)	(-2.21)
Highest IVOL -	0.18	0.15	0.15	0.17	0.19	
Lowest IVOL	(11.13)	(9.01)	(10.09)	(13.38)	(13.64)	

Panel C: Δ VaR1 **During** Market Price Depreciation: $[r_m - r_f]_t < 0$

	Most Overpriced	Next 20%	Next 20%	Next 20%	Most Underpriced	Overpriced-Underpriced
Highest IVOL	0.38	0.33	0.30	0.29	0.29	0.10
(Top 20%)	(6.27)	(6.36)	(5.96)	(7.79)	(7.86)	(2.38)
Next 20%	0.12	0.11	0.13	0.12	0.12	0.00
	(2.94)	(3.48)	(3.69)	(3.87)	(4.33)	(0.02)
Next 20%	0.06	0.05	0.06	0.05	0.07	-0.01
	(1.80)	(1.46)	(2.07)	(2.16)	(2.77)	(-0.96)
Next 20%	0.03	0.01	0.02	0.03	0.02	0.00
	(0.98)	(0.49)	(0.72)	(1.43)	(1.14)	(0.30)
Lowest IVOL	-0.01	-0.02	-0.02	-0.02	-0.01	-0.01
(Bottom 20%)	(-0.49)	(-1.35)	(-1.10)	(-0.93)	(-0.31)	(-0.53)
Highest IVOL -	0.40	0.35	0.31	0.30	0.29	
Lowest IVOL	(9.86)	(8.85)	(8.00)	(11.73)	(11.86)	

Panel D: Changes in VaR Measures

	Frequency			Value Weighted Frequency		
	ΔVaR1<0	ΔVaR1>0	ΔVaR1=0	ΔVaR1<0	ΔVaR1>0	ΔVaR1=0
Full	0.19	0.17	0.64	0.19	0.18	0.63
$r_{m,t} > 0$	0.19	0.14	0.67	0.19	0.13	0.67
$r_{m,t} < 0$	0.18	0.23	0.59	0.18	0.24	0.57

	Frequency			Value Weighted Frequency		
	ΔVaR5<0	ΔVaR5>0	ΔVaR5=0	ΔVaR5<0	ΔVaR5>0	ΔVaR5=0
Full	0.36	0.34	0.30	0.36	0.35	0.28
$r_{m,t} > 0$	0.39	0.29	0.33	0.40	0.29	0.31
$r_{m,t} < 0$	0.32	0.41	0.27	0.31	0.45	0.24

Panel D: ΔVaR1 Loadings on The Market Return

	Most Overpriced	Next 20%	Next 20%	Next 20%	Most Underpriced	Overpriced-Underpriced
Highest IVOL	-0.05	-0.04	-0.04	-0.03	-0.03	-0.02
(Top 20%)	(-4.64)	(-4.63)	(-3.82)	(-3.96)	(-3.04)	(-4.08)
Next 20%	-0.03	-0.03	-0.03	-0.03	-0.02	-0.02
	(-3.97)	(-3.82)	(-4.30)	(-3.07)	(-3.49)	(-3.82)
Next 20%	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02
	(-3.27)	(-3.10)	(-3.43)	(-3.10)	(-3.53)	(-3.90)
Next 20%	-0.02	-0.02	-0.02	-0.02	-0.02	-0.02
	(-3.79)	(-3.44)	(-3.50)	(-3.39)	(-2.72)	(-3.15)
Lowest IVOL	-0.02	-0.01	-0.01	-0.01	-0.01	-0.02
(Bottom 20%)	(-2.93)	(-2.99)	(-3.85)	(-2.75)	(-3.23)	(-3.30)
Highest IVOL -	-0.04	-0.03	-0.02	-0.02	-0.01	
Lowest IVOL	(-4.05)	(-3.70)	(-3.47)	(-3.40)	(-3.30)	

Table 13: Long-term Dynamics of Most Overpriced-Highest IVOL Portfolio

This table reports the mean excess return, risk-adjusted return, mispricing score, and IVOL for months following a market depreciation for the double sorted portfolio in Table 5 which contains the most overpriced-highest IVOL firms. Risk-adjusted returns are calculated using the cross-sectional factor model of Fama and French (2020). We report averages for three horizons: one-month ahead, months t+2 to t+12 ahead, and months t+13 to t+60 ahead. Newey–West (1987) *t*-statistics is reported in parentheses. The sample period ranges from August 1965 to January 2017.

	Excess-Return	Alpha	Mispricing Score	IVOL
t+1	-2.36	-1.51	68.46	3.38
	(-4.01)	(-6.98)		
t+2:t+12	-0.39	-0.66	69.64	2.59
	(-0.61)	(-2.77)		
t+13:t+60	0.17	-0.31	68.15	2.23
	(0.33)	(-1.24)		

Table 14: Factors based on Fama-French Methodology

We report results on factors formed on asset pricing anomalies using Fama-French methodology. BETA, for example, is constructed as the unconditional intersection of six value-weighted portfolios formed on ME and beta. The ME breakpoint is the median NYSE market equity. The BETA breakpoints are the 30th and 70th NYSE percentile. Firms are assigned to one of six portfolios based on these breakpoints. Portfolios are formed monthly and are value weighted. The Long Leg of BETA is the average return of the two low BETA portfolios, the Short Leg is the average return of the two high BETA portfolios. Accordingly, the Long-Short portfolio represents the difference between the Long-Leg and Short-Leg, i.e., a net-zero cost tradeable factor portfolio. All factors are set up such that they have a positive alpha, except for correlation, COR, to remain consistent with the Betting-Against-Correlation factor of Asness et al. (2020). Panel A reports mean risk-adjusted returns. Panel B (Panel C) reports mean risk-adjusted returns in periods following a positive (negative) monthly market return. Risk-adjusted returns are calculated using the cross-sectional factor model of Fama and French (2020). Panel D reports the loading of each portfolios risk-adjusted return on the most overpriced-highest IVOL portfolios risk-adjusted return. Newey–West (1987) t-statistics are reported in parentheses. The sample period ranges from August 1965 to January 2017.

Panel A: Risk-Adjusted Returns - Full Sample

	Long-Short	t(LS)	Long Leg	t(L)	Short Leg	t(S)
BETA	0.09	(0.70)	0.03	(0.39)	-0.06	(-0.95)
ME	0.20	(2.65)	0.10	(2.60)	-0.10	(-2.69)
BM	0.18	(1.95)	0.10	(1.69)	-0.09	(-2.13)
OP	0.29	(4.35)	0.12	(4.07)	-0.17	(-4.04)
INV	0.16	(2.84)	0.05	(1.81)	-0.11	(-3.24)
MOM	0.48	(3.37)	0.25	(3.81)	-0.22	(-2.70)
STR	0.67	(6.79)	0.35	(6.10)	-0.32	(-6.49)
COR	-0.10	(-0.99)	-0.05	(-0.86)	0.05	(1.04)
VOL	0.05	(0.30)	-0.01	(-0.08)	-0.05	(-0.59)
IVOL	0.11	(0.98)	0.01	(0.15)	-0.10	(-1.52)
MAX	0.31	(2.75)	0.15	(2.90)	-0.16	(-2.46)
MAX1	0.05	(0.33)	0.00	(0.03)	-0.05	(-0.55)
ILLIQ	0.29	(2.14)	0.07	(0.72)	-0.22	(-3.27)
VaR1	0.04	(0.31)	-0.02	(-0.26)	-0.06	(-0.77)
MISP	0.39	(5.45)	0.15	(4.93)	-0.24	(-5.20)

Panel B: Risk-Adjusted Returns **Following** Market Price Appreciation: $[r_m - r_f]_{t-1} > 0$

	Long-Short	t(LS)	Long Leg	t(L)	Short Leg	t(S)
BETA	-0.12	(-0.79)	-0.10	(-1.22)	0.02	(0.29)
ME	0.47	(4.86)	0.23	(4.85)	-0.24	(-4.86)
BM	0.17	(1.55)	0.10	(1.55)	-0.07	(-1.40)
OP	0.29	(3.60)	0.15	(4.33)	-0.14	(-2.62)
INV	0.13	(2.12)	0.07	(1.99)	-0.06	(-1.76)
MOM	0.31	(1.64)	0.19	(2.17)	-0.12	(-1.07)
STR	0.78	(6.04)	0.40	(5.66)	-0.38	(-5.68)
COR	-0.18	(-1.36)	-0.12	(-1.60)	0.06	(0.95)
VOL	-0.28	(-1.60)	-0.16	(-1.93)	0.12	(1.23)
IVOL	-0.06	(-0.46)	-0.07	(-1.07)	0.00	(-0.06)
MAX	0.18	(1.30)	0.09	(1.40)	-0.09	(-1.11)
MAX1	-0.26	(-1.47)	-0.15	(-1.87)	0.11	(1.05)
ILLIQ	0.17	(0.91)	-0.02	(-0.13)	-0.19	(-2.29)
VaR1	-0.24	(-1.47)	-0.16	(-2.05)	0.08	(0.87)
MISP	0.28	(2.94)	0.09	(2.24)	-0.19	(-3.17)

Panel C: Risk-Adjusted Returns **Following** Market Price Depreciation: $[r_m - r_f]_{t-1} < 0$

	Long-Short	t(LS)	Long Leg	t(L)	Short Leg	t(S)
BETA	0.38	(2.17)	0.20	(2.24)	-0.18	(-1.90)
ME	-0.18	(-1.59)	-0.09	(-1.63)	0.09	(1.54)
BM	0.20	(1.44)	0.09	(1.03)	-0.11	(-1.85)
OP	0.29	(3.09)	0.07	(1.61)	-0.22	(-3.91)
INV	0.20	(2.21)	0.03	(0.64)	-0.17	(-3.13)
MOM	0.71	(3.81)	0.34	(3.78)	-0.37	(-3.43)
STR	0.52	(3.04)	0.27	(2.75)	-0.24	(-3.03)
COR	0.00	(0.03)	0.04	(0.53)	0.04	(0.50)
VOL	0.50	(2.32)	0.21	(2.09)	-0.30	(-2.32)
IVOL	0.35	(2.10)	0.11	(1.45)	-0.24	(-2.40)
MAX	0.50	(2.75)	0.23	(2.92)	-0.27	(-2.47)
MAX1	0.47	(2.20)	0.21	(2.15)	-0.26	(-2.06)
ILLIQ	0.46	(2.34)	0.21	(1.38)	-0.25	(-2.35)
VaR1	0.44	(2.18)	0.18	(1.92)	-0.26	(-2.25)
MISP	0.54	(5.11)	0.23	(4.85)	-0.31	(-4.57)

Panel D: Anomaly Betas on Most Overpriced Highest IVOL Portfolio Alpha

	Long-Short	t(LS)	Long Leg	t(L)	Short Leg	t(S)
BETA	-0.32	(-5.38)	-0.15	(-4.82)	0.18	(5.47)
ME	0.12	(3.89)	0.06	(3.74)	-0.06	(-4.04)
BM	-0.04	(-1.07)	-0.02	(-0.84)	0.02	(1.27)
OP	-0.07	(-2.69)	-0.02	(-1.29)	0.06	(3.50)
INV	-0.01	(-0.21)	0.02	(1.40)	0.02	(1.88)
MOM	-0.18	(-2.45)	-0.04	(-0.99)	0.14	(3.69)
STR	0.15	(3.32)	0.13	(5.79)	-0.02	(-0.85)
COR	-0.17	(-3.28)	-0.09	(-3.57)	0.08	(2.65)
VOL	-0.48	(-6.14)	-0.20	(-6.12)	0.27	(5.97)
IVOL	-0.42	(-7.56)	-0.17	(-7.03)	0.25	(6.99)
MAX	-0.35	(-5.52)	-0.15	(-5.46)	0.20	(5.38)
MAX1	-0.44	(-5.52)	-0.19	(-5.59)	0.25	(5.28)
ILLIQ	0.19	(3.22)	0.07	(1.88)	-0.11	(-4.12)
VaR1	-0.45	(-6.69)	-0.19	(-6.12)	0.26	(6.75)
MISP	-0.18	(-4.84)	-0.06	(-4.69)	0.12	(4.69)

Figure 1: The Market Excess Return Following Different Market States

The figure plots the average monthly excess return of the market portfolio for the full sample (solid line), as well as for months following a positive market excess return (dotted line) or a negative market excess return (dashed line). The market portfolio return is computed using a 20-year window. The sample period ranges from August 1965 to January 2017.

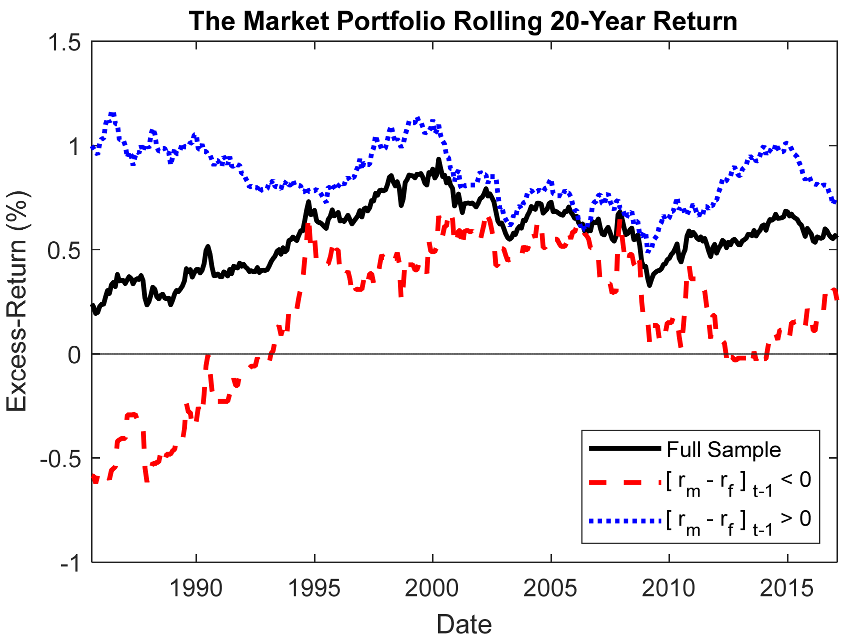
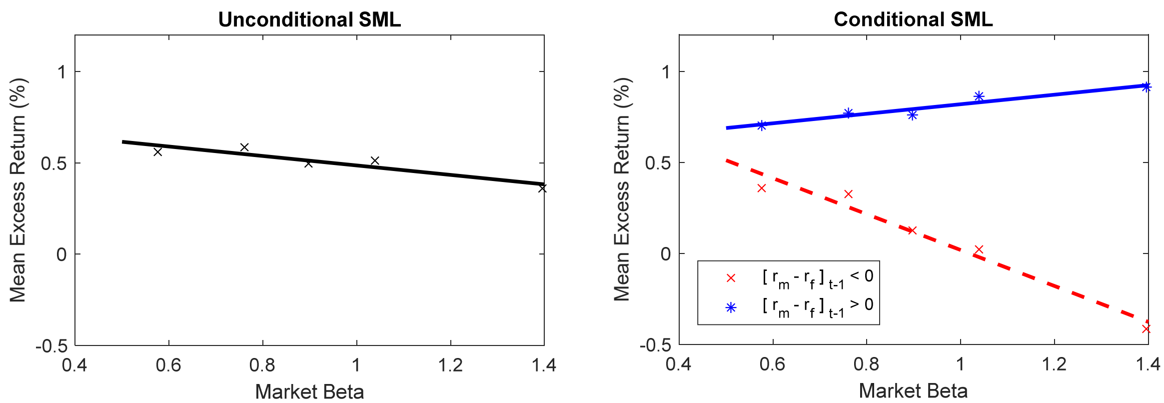


Figure 2: The Security Market Line Following Different Market States

Panel A plots the mean one-month ahead excess returns against the full-sample CAPM betas for quintile value-weighted portfolios sorted on beta. Panel B does the same but for risk-adjusted returns (alphas). Risk-adjusted returns are calculated using the cross-sectional factor model of Fama and French (2020). The unconditional SML figures (leftmost in Panels A and B) report the portfolio performance for the full sample. The conditional SML figures (rightmost in Panels A and B) report portfolio performance for months following a positive (solid line) or negative (dashed line) monthly market state. The sample period ranges from August 1965 to January 2017.

Panel A: Excess Returns



Panel B: Risk-Adjusted Returns

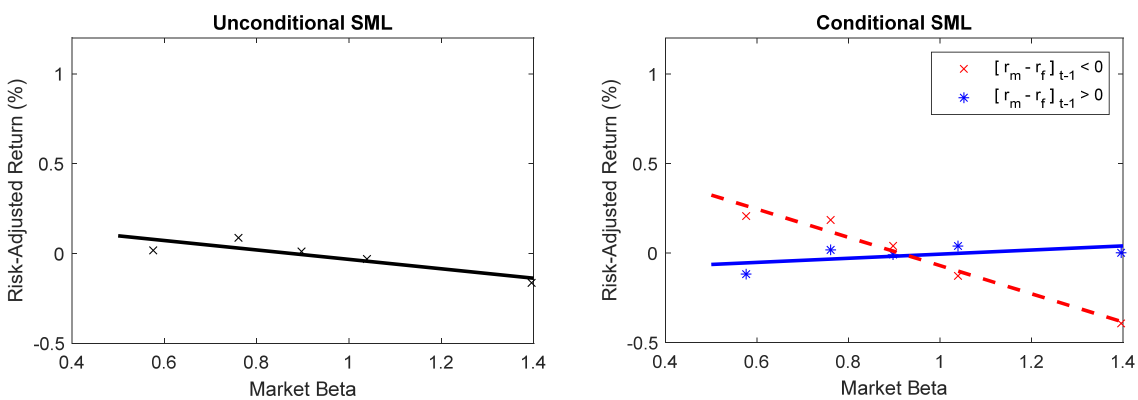


Figure 3: The Disposition Effect

This figure illustrates the disposition effect (Frazzini, 2006). Assume that an investor has purchased one share of stock at $1000, and is facing a current price of $950. Further assume that in the next period, the price will either go up $50 or down $50 with equal probability. The investor must choose to either sell now at $950 and incur a loss of $50 or keep the share for the next period. The figure shows the investor's utility under the two alternatives.

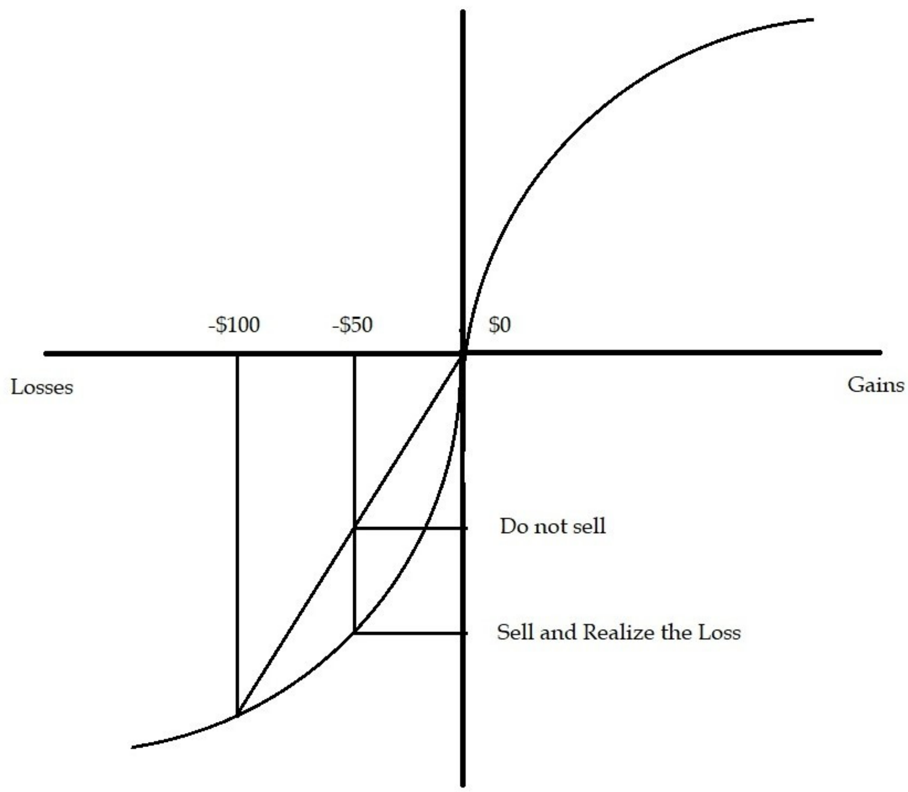


Figure 4: Risk-Adjusted Returns for Different Horizons

This figure plots the average monthly risk-adjusted returns for horizons of 1 to 12 months following a market depreciation for the portfolio that contains the most overpriced and highest IVOL stocks (see Table 5). Risk-adjusted returns are calculated using the cross-sectional factor model of Fama and French (2020). The horizontal line depicts the average one-month ahead risk-adjusted return of this portfolio for the full sample. The sample period ranges from August 1965 to January 2017.