Preference for Skewness and Market Anomalies*

Alok Kumar[1], Mehrshad Motahari[†2], and Richard J. Taffler[2]

[1]University of Miami
[2]University of Warwick

November 30, 2017

ABSTRACT

This study shows that investors' preference for holding assets with positively-skewed payoffs is a common driver of mispricing across a wide range of market anomalies. Using a combined measure of mispricing based on eleven prominent anomaly strategies, we find that stocks with higher levels of skewness are significantly more mispriced than those with lower skewness. Overpricing in anomalies is particularly more prevalent among highly-skewed stocks; on the other hand, underpricing is not affected by skewness. We further demonstrate that investors with a stronger preference for skewness invest disproportionately more in overpriced stocks relative to underpriced ones, which contributes to anomaly mispricing. Lastly, we find that a factor capturing skewness-related mispricing significantly improves the performance of conventional asset-pricing models in accommodating anomalies.

JEL classification: G02, G12, G14.

*We thank seminar participants at Warwick Business School for helpful comments and valuable suggestions. We are responsible for all remaining errors and omissions.

†Please address all correspondence to Mehrshad Motahari, email: phd14mm@mail.wbs.ac.uk. Alok Kumar can be reached at akumar@miami.edu. Richard Taffler can be reached at richard.taffler@wbs.ac.uk.

1 Introduction

Stocks with positively-skewed or lottery-like return distributions generate lower returns in the cross-section (see, for example, Mitton and Vorkink, 2007; Kumar, 2009; Boyer et al., 2010; Bali et al., 2011; Conrad et al., 2014). The prevalent view in the literature is that skewness becomes priced because a group of investors deviate from the standard expected utility framework and choose to underdiversify, in order to to hold positively-skewed positions. Theoretical papers commonly refer to this behavior as *the preference for skewness*, and attempt to justify it using more advanced utility functions (e.g., Mitton and Vorkink, 2007; Brunnermeier et al., 2007; Barberis and Huang, 2008). Various papers use the preference for skewness to explain a number of longstanding puzzles in asset pricing. Examples include IPO returns (Green and Hwang, 2012), underperformance of distressed (Conrad et al., 2014) and going-concern stocks (Kausar et al., 2015), and irregularities in out-of-the-money option returns (Boyer and Vorkink, 2014).

In this study, we investigate whether the preference for skewness has broader implications in generating mispricing patterns in the market. In particular, we explore whether the common mispricing-related component of market anomalies can be linked to the preference for skewness. Market anomalies are patterns in the cross-section of stock returns that are not explained by asset pricing models. These patterns are often in the form of stocks with certain characteristics, generating returns that are not commensurate with their level of risk. It is difficult to ascertain whether anomalies are indications of imperfect models, or signs of market mispricing[1]. Nevertheless, several studies provide evidence showing that anomalies at least partly reflect mispricing. For example, Nagel (2005) and Stambaugh et al. (2015), among many others, demonstrate that anomalies are significantly more prevalent for stocks facing greater arbitrage risks and costs. In addition, most of abnormal anomaly returns are attributable to underperforming, or overpriced, stocks. These stocks are required to be sold short but many investors are reluctant or unable to do so (see, for example, Hirshleifer et al., 2011; Stambaugh et al., 2012; Avramov et al., 2013).

Mispricing, to the extent that it is the underlying driver of anomalies, exhibits commonalities across stocks. Stambaugh et al. (2012), for example, find that there is a common time-varying component across a wide range of anomalies, strongly related to

[1] This argument goes back to Fama (1970) and is referred to as the *joint hypothesis problem*; that is, any test of asset pricing models is a joint test of market efficiency as well as the models themselves

investor sentiment. We conjecture that the common mispricing-related component of anomalies can be explained, at least partly, by the pricing implications of preference for skewness. We motivate the link between the two phenomena by building on the observation of Harvey and Siddique (2000) who claim that stocks that anomaly strategies predict will underperfrom, commonly referred to as short-leg stocks, are often those with the highest levels of skewness in the cross-section. Similarly, stocks that are expected to outperfrom based on anomaly strategies, known as long-leg stocks, have the lowest levels of cross-sectional skewness. As a result, we predict that investors with a preference for skewness would be attracted towards short-leg stocks and away from long-leg ones. In the presence of limits to arbitrage, such behavior contributes to the cross-sectional mispricing predicted by anomaly variables.

We measure the common mispricing-related component of anomalies by adopting the approach of Stambaugh et al. (2015). This measure is constructed by taking the average of each stock's decile ranks with respect to eleven anomaly variables. The anomalies consist of accruals (Sloan, 1996), asset growth (Cooper et al., 2008), composite equity issues (Daniel and Titman, 2006), distress (Campbell et al., 2008), gross profitability (Novy-Marx, 2013), investment-to-assets (Titman et al., 2004), momentum (Jegadeesh and Titman, 1993), net operating assets (Hirshleifer et al., 2004), net stock issues (Ritter, 1991; Loughran and Ritter, 1995), O-score (Ohlson, 1980), and return on assets (Fama and French, 2006). This approach essentially diversifies any anomaly-specific effect by taking the average of anomaly decile ranks across a range of strategies, and offers a measure of likelihood for every stock to be mispriced (see Stambaugh et al., 2015; Stambaugh and Yuan, 2017). We also consider a wide range of prominent skewness measures commonly used in the literature. Such measures include jackpot probability (Conrad et al., 2014), lottery index (Kumar et al., 2016), maximum daily return (Bali et al., 2011), expected idiosyncratic skewness (Boyer et al., 2010) and option-based idiosyncratic skewness.

We investigate three main hypotheses by combining the pricing implication of return skewness and the findings of Stambaugh et al. (2012, 2014) regarding the commonality of mispricing across anomalies. The first hypothesis is that the performance of anomalies, to the extent that it is related to mispricing, should be stronger among stocks with higher skewness. This follows from our argument above that skewness features attract investors with a preference for such features, exacerbating anomaly mispricing. We find strong support for this prediction, using all our five skewness measures. Our measure of anomaly mispricing generates between 1.22% and 1.71% greater long-short monthly abnormal returns among stocks in the highest skewness quintiles, when compared to those in the lowest skewness quintiles. In the regression framework, we find that one standard deviation increase in skewness adds between 30% and 60%, depending on the measure used, to anomaly mispricing.

Our second hypothesis states that the effect of skewness on anomaly mispricing should be driven by the underperformance of short-leg stocks. This is because the prevalent form of mispricing is overpricing (Stambaugh et al., 2012); therefore, any mispricing effect caused by the preference for skewness should mainly affect short-leg stocks. Stocks in the long leg, on the other hand, are unlikely to be affected by the preference for skewness, as they are underpriced, which is easier for arbitragers to adjust. Our findings indicate that short-leg stocks with high levels of skewness generate three to nine times larger negative abnormal returns compared to those with low skewness, whereas returns of long-leg stocks do not significantly change with the level of skewness. We also find short-leg stocks with low levels of skewness in the cross-section do not significantly underperform. This result indicates that the presence of short-selling impediments is not sufficient to explain the commonly reported finding in the literature that anomaly spreads are driven mostly by short-leg stocks (e.g., Hirshleifer et al., 2011; Stambaugh et al., 2012; Avramov et al., 2013). In fact, skewness plays a key role in explaining why overpricing is more prevalent than underpricing in extreme anomaly portfolios.

The last hypothesis examines whether investors that have preferences for skewness invest disproportionately more in short-leg stocks, rather than in long-leg ones. Under this hypothesis, we examine whether investors with a preference for skewness actually trade in a direction that is the opposite of what anomaly strategies suggest. We test this hypothesis by looking at the portfolio holdings data of a sample of retail investors, obtained from a large US discount brokerage house, for the period 1991 to 1996. Our results strongly support the hypothesis. Investors with a history of overweighting stocks with high levels of skewness by one standard deviation of the cross-sectional distribution, allocate between 11.6% and 18.4% higher raw weight (8.7% to 13.9% higher weight in excess of the market weight) to short-leg stocks relative to long-leg ones. We also use an exogenous geographical proxy for the preference for skewness, developed by Kumar et al. (2011), showing that the ratio of Catholics to Protestants in the local population can proxy for local preference for skewness. We find that this ratio is associated with a higher portfolio weight on short-leg stocks in investors' portfolios.

We investigate two alternative explanations for our results. First, we test whether the relationship between skewness and anomaly returns is due to a missing systematic coskewness factor in the asset pricing model, rather than to a mispricing effect generated by the preference for skewness. This argument is based on Harvey and Siddique (2000), showing that extreme anomaly returns are partly explained by the loading on a coskeness factor. Second, we investigate whether our skewness measures indirectly reflect arbitrage costs instead of features that attract investors that like skewness. This is motivated by previous studies documenting the close association between skewness and limits to arbitrage (e.g., Bris et al., 2007; Chang et al., 2007; Xu, 2007). We find that our main results are robust after controlling for coskewness and a wide range of proxies for limits to arbitrage.

In the last part of the paper, we build on Stambaugh and Yuan (2017) and examine whether considering skewness in asset pricing models improves the performance in capturing anomaly returns. Stambaugh and Yuan (2017) demonstrate that factors representing a common source of mispricing in the cross-section can help capture abnormal returns associated with a number of anomaly strategies. We follow the approach of Stambaugh and Yuan (2017) and construct a skewness factor by combining four skewness measures: jackpot probability, lottery index, maximum daily return and expected idiosyncratic skewness. We find that adding this factor to models significantly enhances overall performance in explaining anomalies. Our skewness factor is particularly useful for explaining anomalies that are shown to be driven mostly by skewed stocks, such as distress-related strategies.

We are not aware of any other papers that have studied the pricing implications of skewness as a common contributing factor to a wide range of market anomalies since Harvey and Siddique (2000). Our approach to the problem is fundamentally different from that of Harvey and Siddique (2000). Harvey and Siddique (2000) argue that the effect of skewness on anomalies can be captured by a rational model that accounts for exposure to coskewness, as a measure of undiversifiable downside risk. On the other hand, we attribute the role of skewness to the mispricing effect of trades initiated by investors that have a preference for skewness. In fact, our findings indicate that exposure to a coskewness factor cannot explain the link between various firm-level skewness measures and anomaly returns. Our study mainly relates to the stream of papers investigating the mispricing-related component of market anomalies, such as Nagel (2005), Stambaugh et al. (2012, 2015), Avramov et al. (2013), Hanson and Sunderam (2014), Chordia et al. (2014) and McLean and Pontiff (2016). We contribute to this stream by providing a new explanation for commonality in mispricing across anomalies.

The remainder of the paper is organized as follows. Section 2 briefly discusses the evidence on anomalies and skewness and develops our hypotheses. Section 3 summarizes the data and our main variables. Section 4 presents the main empirical results. Section 5 examines two alternative explanations for our main results. Section 6 investigates if we can build on the implication of our findings and devise a factor. Section 7 concludes.

2 Background and Hypotheses

In this section, we begin by reviewing the relevant literature on the preference for skewness and its link to market anomalies. We then develop a series of testable hypotheses examining whether the mispricing-related component of anomalies is driven by investors' preference to hold positively-skewed assets.

2.1 Skewness, Mispricing and Market Anomalies

Much of the early work on return skewness emphasized that only coskewness, defined as the portion of an assets skewness that is related to market skewness, should be relevant for individual security pricing (e.g., Kraus and Litzenberger, 1976; Harvey and Siddique, 2000; Dittmar, 2002). The logic is that fully-diversified investors would only care about skewness as a measure of undiversifiable downside risk (Harvey et al., 2010) and that idiosyncratic, or firm-level, return skewness should be irrelevant for investment decisions. However, recent empirical findings indicate that idiosyncratic skewness is negatively related to future returns, even more strongly than coskewness is (e.g., Kumar, 2009; Boyer et al., 2010; Bali et al., 2011). Theoretical papers have justified the role of idiosyncratic skewness by arguing that there is a group of investors in the market that have a preference for holding positively-skewed positions at the expense of under-diversification (see Mitton and Vorkink, 2007; Brunnermeier et al., 2007). This preference will then lead to stocks with higher levels of idiosyncratic skewness being overpriced and generating lower returns in the market.

Barberis and Huang (2008) use a model to demonstrate that cumulative prospect theory of Tversky and Kahneman (1992) can explain the reason that investors might have a preference to hold positively-skewed assets. Cumulative prospect theory reveals that individuals overweight the tails of return distributions resulting in overvaluation of securities that are likely to generate positively-skewed, or lottery-like, payoffs. Empirical findings strongly support the role of cumulative prospect theory preferences in skewness pricing. For example, Barberis et al. (2016) show that the prospect theory value function assigns a higher value on positively-skewed stocks and that such stocks are overvalued internationally. Nevertheless, not all investors behave according to cumulative prospect theory. Preference for skewness is peculiar mainly to retail investors, in particular, to those that are less sophisticated and tend to exhibit a strong propensity to gamble in non-financial settings (Kumar, 2009).

Several studies have so far built on the pricing implications of skewness to explain market anomalies. Harvey and Siddique (2000) is the first major study to acknowledge that securities that often generate abnormal returns and drive market anomalies also have the most extreme levels of skewness in the cross-section. They propose a factor capturing systematic coskewness and show that adding it to the CAPM can significantly improve the performance of the model in explaining market anomalies. Harvey and Siddique (2000) essentially attribute market anomalies to the failure of pricing kernels to capturing systematic skewness. In contrast, recent studies suggest that skewness has a mispricing effect that contributes to individual cases market anomalies. The motivation underlying the latter approach is that stocks that anomaly variables suggest will underperform often have high levels of positive skewness. This feature can then attract investors with a preference for skewness leading to the overpricing (underpricing) of more (less) positively-skewed stocks (see Barberis, 2013, for a review of this approach). The resulting mispricing will persist, as it is too risky or costly for other investors that do not have a preference for skewness to adjust the prices (see Barberis and Huang, 2008; Conrad et al., 2014). Examples of market anomalies attributed to the mispricing effect of preference for skewness include IPO stocks (Green and Hwang, 2012), distressed firms (Conrad et al., 2014), out-of-the-money options (Boyer and Vorkink, 2014), and going-concern stocks (Kausar et al., 2015).

Most market anomalies are at least partly related to mispricing. This linkage is backed by the evidence indicating that anomalies are more pronounced among stocks with a higher arbitrage risk (e.g., Nagel, 2005; Stambaugh et al., 2015), and that an increase in arbitrage activity results in a decay of anomaly strategy returns (e.g., Hanson and Sunderam, 2014; Chordia et al., 2014; McLean and Pontiff, 2016). Also, the profitability of anomaly strategies is generated largely by the short side, which consists of overpriced stocks (e.g., Hirshleifer et al., 2011; Stambaugh et al., 2012; Avramov et al., 2013). This observation is in line with the argument of Miller (1977) that mispricing prevails largely because short-selling impediments make it harder to adjust overpricing than underpricing. Stambaugh et al. (2012, 2014) follow this line of argument and show that there is a common mispricing component across major anomaly strategies, which is strongly related to investors sentiment. In the next section, we build on the literature reviewed above to form a series of testable hypotheses.

2.2 Main Testable Hypotheses

We examine the possibility that the mispricing-related component of market anomalies is at least partly driven by the preference of a group of investors for stocks with skewness features. The main motivation behind our argument is the observation that stocks in the short (long) leg of anomaly strategy groups that generate the greatest abnormal returns often have the highest (lowest) levels of skewness in the cross-section. This relationship can be theoretically justified in two ways. First, skewness has a strong negative relationship with past returns (e.g., Chen et al., 2001; Cao et al., 2002; Xu, 2007; Del Viva et al., 2017). Stocks in the short (long) legs generate (higher) lower returns; therefore, they are likely to have relatively higher (lower) levels of skewness. Second, short-sale constraints increase the skewness of individual stocks (e.g., Bris et al., 2007; Chang et al., 2007; Xu, 2007). We know that anomaly strategy returns are generated mostly by stocks in the short-leg, and in particular, those facing significant short-sale constraints (Nagel, 2005). As a result, short-sale constraints lead to the most mispriced group of stocks also having a higher level of skewness in the cross-section.

Combining the pricing implication of return skewness with the findings of Stambaugh et al. (2012, 2014) about the commonality of mispricing across anomalies, results in three main testable predictions outlined below.

H1: To the extent that the cross-sectional return predictability of anomalies is related to mispricing, it should be stronger among stocks with higher skewness

The first hypothesis follows from the literature reviewed in the previous section showing that high skewness features appeal to a host of investors that have a preference for positive skewness. We conjecture that such investors maintain an upward pressure on the prices of positively-skewed stocks contributing to their overpricing. As discussed above, stocks in the short legs of anomaly strategies are, on average, more positively-skewed than those in the long legs. Therefore, investors with a preference for skewness are generally more likely to be attracted towards the short leg and away from the long leg, contributing to the anomaly mispricing. However, due to short-selling impediments there is an asymmetry in the mispricing effect of investor preference for skewness on the short- and long-leg stock returns, which leads to our second hypothesis:

H2: The short legs of anomaly strategies should have lower returns among stocks with higher skewness than among those with lower skewness. Returns of the long legs, however, should not be affected by different levels of skewness

Our second hypothesis suggests that the effect of skewness on anomaly mispricing should be driven by the under-performance of overpriced stocks with high levels of skewness. We follow Stambaugh et al. (2012) and argue that the prevalent form of mispricing is overpricing. Therefore, if the preference for skewness were to lead to mispricing, it would be mainly through an increase in the overpricing in the short leg. On the other hand, the effect of preference for skewness should be limited on the long leg as the stocks in that group are underpriced, which is easier for arbitragers to adjust.

Lastly, we examine the mechanism though which investors with skewness proclivities affect anomaly mispricing. We expect to find that investors with such preferences invest disproportionately more in short-leg stocks than in long-leg ones. Following Barberis and Huang (2008), investors with a preference for skewness deviate from holding a combination of the risk-free asset and the tangency portfolio, placing a relatively higher weight on stocks with higher levels of skewness. Stocks in the short-legs of anomalies are more positively skewed than those in the long legs. Therefore, all else being equal, short-leg stocks should be relatively more attractive for investors with skewness preferences. We formulate this prediction as follows:

H3: Investors exhibiting a preference for skewness assign a higher (lower) weight to stocks in the short- (long-) legs of anomaly strategies than investors without such a preference

3 Data

Our main tests are based on the conventional sample of all common (share code of 10 or 11) NYSE, AMEX and NASDAQ stocks with available data in the Center for Research in Security Prices (CRSP) daily and monthly stock return files for the period January 1963 to December 2015. We exclude all firms with negative book equity, belonging to the financial sector ($6000 \leq SIC \leq 6999$) or those with a share price below \$1[2]. In the case

[2]We consider other share price cutoffs in the robustness tests and show that our results do not depend on the price filter

of missing returns, we use delisting returns.

To construct our main skewness and anomaly variables we use accounting data from Compustat Fundamentals Annual and Quarterly files and option price data from Optionmetrics. Our factor returns and risk-free rates come from Professor Kenneth Frenchs data library[3]. To test the last hypothesis, we use the end-of-month portfolio positions of a sample of retail investors from a major U.S. discount brokerage house covering the 1991 to 1996 time period. Lastly, for robustness tests, we obtain short interest data from Compustat and quarterly data on institutional stock holdings from Thomson Reuters. Definitions and sources of all variables are presented in Table A.1.

3.1 Skewness and Anomaly Mispricing Measures

In this section, we briefly introduce our main skewness and anomaly mispricing variables. Further details regarding the construction of the variables are presented in Table A.1. Our main tests employ four prominent (firm-level) skewness measures commonly used in the literature. The measures are jackpot probability ($JACKPOT$), lottery index ($LIDX$), maximum daily return ($MAXRET$) and expected idiosyncratic skewness ($ESKEW$). $JACKPOT$ is based on Conrad et al. (2014), defined as the out-of-sample probability of a stock generating a log return greater than 100% during the next twelve months. $LIDX$ is an index originally introduced in Kumar et al. (2016), ranking securities by how much they share lottery-like features (i.e., low price, high volatility, and high skewness) that capture the preference for skewness. $MAXRET$ is a stock's maximum one-day return in the past month as used by Bali et al. (2011). $ESKEW$ is defined as an out-of-sample measure of expected idiosyncratic skewness following Boyer et al. (2010).

To provide evidence from the option prices, we also use the option-based idiosyncratic skewness (OS) measure of Conrad et al. (2013). This is defined as the third moment of the (risk-neutral) density function of individual securities formulated by Bakshi et al. (2003). The advantage of OS over the previous measures is that it is based on a non-parametric *ex-ante* estimate of future return expectations. Therefore, it should be able to capture investors' expectations of future return skewness without using other proxy variables that might not directly trigger the preference for skewness. However, we do not rely on OS for all tests, as it is only available for a small subset of stocks with traded options. Finally, we use the coskewness ($COSKEW$) measure of Harvey and Siddique (2000). We incorporate this measure in our robustness tests, in order to distinguish our

[3]http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/

preference for skewness story with the argument of Harvey and Siddique (2000) that skewness relates to the SDF.

We consider the eleven prominent anomaly strategies analyzed in Stambaugh et al. (2012, 2014, 2015). The anomalies consist of accruals (Sloan, 1996), asset growth (Cooper et al., 2008), composite equity issues (Daniel and Titman, 2006), distress (Campbell et al., 2008), gross profitability (Novy-Marx, 2013), investment-to-assets (Titman et al., 2004), momentum (Jegadeesh and Titman, 1993), net operating assets (Hirshleifer et al., 2004), net stock issues (Ritter, 1991; Loughran and Ritter, 1995), O-score (Ohlson, 1980), and return on assets (Fama and French, 2006). As our story is based on the common mispricing component across all of the anomalies, we use the innovative mispricing (*MIS*) measure of Stambaugh et al. (2015). *MIS* is constructed by taking the average of each stock's decile ranks with respect to the eleven anomaly variables. The decile ranks are defined at the end of every month, with the first and the tenth deciles consisting of stocks that each anomaly strategy predicts are going to outperform and underperform in the following month, respectively. Considering that anomalies may not be wholly related to mispricing, *MIS* is a less noisy measure of mispricing across all the anomalies. The reason is that by taking the average of the anomaly decile ranks, we essentially diversify any anomaly-specific effect and will be left with a mispricing component that is common across all the strategies (see Stambaugh et al., 2015; Stambaugh and Yuan, 2017).

Panel C of Table 1 presents the performance of *MIS* and the four key skewness measures (i.e., *JACKPOT*, *LIDX*, *MAXRET*, and *ESKEW*) in predicting future returns. We sort stocks at the end of every month, based on the five variables into quintiles. Then, we measure the value-weighted return of each quintile group, together with the return of the hedge portfolio (going long in quintile five and short in quintile one) for the following month. To adjust the returns for risk, we regress the monthly returns of each portfolio on the three (Fama and French, 1993), the four (Carhart, 1997) and the five (Fama and French, 2015) factors separately and report the alphas. The long-short strategies of all five measures generate statistically significant abnormal returns at the 1% level. The exception is the alpha of the hedge *MAXRET* strategy that seems to be captured by the five-factor model. The hedge portfolio of *MIS* yields highly statistically significant alphas with all the three models ranging from 63 to 109 basis points per month. In line with Stambaugh et al. (2015), we find that the overwhelming majority of hedge *MIS* returns comes from the short leg. With all three factor models, the short *MIS* portfolio (quintile 5) generates alphas that are more than two times larger than those of the long portfolio (quintile 1).

3.2 Summary Statistics: What Are the Characteristics of Mispriced Stocks?

To have a better understanding of stocks with different levels of anomaly mispricing, we present the mean cross-sectional characteristics of *MIS* quintiles in Panel A of Table 1. Quintile rankings are determined monthly by sorting stocks based on their end-of-month *MIS* value. We measure the characteristics at the end of the same month that we define the quintiles for. It appears that the short-leg (quintile 5) firms are, on average, smaller (lower market capitalization), more volatile and have cheaper shares with poorer past return performance, when compared to firms in the long-leg (quintile). Short leg stocks are also relatively less liquid, according to the illiquidity measure of Amihud (2002) and are more heavily sold short. Average holdings indicate that institutional investors tend to target the right group by holding more of the shares of long-leg stocks. On the other hand, the brokerage sample suggests that retail (individual) investors place a higher weight on short-leg stocks.

Part of our story relies on the conjecture that stocks in the short leg have higher skewness which then attracts investors with a preference for skewness, contributing to overpricing. We test this assertion by comparing the mean skewness measures across the *MIS* quintiles. Together with our four main skewness proxies, we also look at coskewness (*COSKEW*), option-based skewness (*OS*), idiosyncratic skewness (*ISKEWNESS*), and total skewness (*SKEWNESS*). *ISKEWNESS* and *SKEWNESS* are computed using daily returns for the same month as *MIS* (for further details see Table A.1). Results are presented in Panel B of Table 1. The average values of all seven skewness measure increase monotonically from *MIS* quintile one to five. In all cases, a simple t-test indicates that the difference between the skewness values of quintiles one and five is statistically significant at the 5 percent level. Altogether, we find results similar to those reported in Harvey and Siddique (2000) and Conrad et al. (2014) that skewness increases as one moves from the long to the short legs of anomaly strategies. However, we must be careful with the generalization of our argument, as the pattern of skewness that we observe is based on an average measure of anomalies, i.e. *MIS*, and not on each individual strategy.

It is beyond the scope of this study to determine why skewness increases as one moves from the long to the short leg. Still, we can speculate about possible causes based on the previous literature and the characteristics in Panel A of Table 1. A first possible explanation might be that stocks in the short leg become more skewed because of their poor past return performance. Several studies have shown that with the presence of low (high) past average returns lead to higher (lower) skewness, due to market imperfections (e.g., Chen et al., 2001; Cao et al., 2002; Xu, 2007; Del Viva et al., 2017). In addition, stocks in the short leg are attractive targets for short sellers due to their underperformance, as captured by a higher average short ratio in Panel A of Table 1. Such stocks are also smaller and have lower institutional holding levels. The combination of these characteristics is a recipe for significant short-sale constraints (Nagel, 2005), which is also shown to directly generate higher skewness (e.g., Bris et al., 2007; Chang et al., 2007; Xu, 2007). A third possible explanation is based on the argument of Conine and Tamarkin (1981), that the limited liability nature of firms implies higher volatility, leading to higher skewness. The average characteristics in Panel A of Table 1 indicate that firms in the short side are not only more volatile, they also have a higher leverage ratio, which can explain their higher skewness.

4 Empirical Results

In this section, we present our main empirical findings. We begin by testing whether skewness exacerbates anomaly mispricing (*H1* and *H2*) using double sorts and Fama-Macbeth regressions. Then, we use the brokerage data, in order to explore how the holdings of investors with a preference for skewness translate into mispricing (*H3*).

4.1 The Effect of Skewness on Anomaly Mispricing

4.1.1 Double Sorts

We test our first and second hypotheses (*H1* and *H2*) by analyzing the performance of portfolios double sorted on the anomaly mispricing variable, i.e., *MIS*, and one of our four main skewness measures, i.e., *JACKPOT*, *LIDX*, *MAXRET*, and *ESKEW*. Portfolios are formed by sorting stocks independently into quintiles based on each of the two variables at the end of every month. We then compute the value-weighted returns of the 25 portfolios over the following month and regress those on the four Carhart (1997) factors, in order to generate the abnormal returns. The sample excludes penny stocks and covers January 1963 to December 2015, except for sorts based on *ESKEW*, which start in January 1988.

Penel A of Table 2 presents the monthly abnormal returns of the double sorted portfolios. As we expected, magnitude of mispricing as captured by *MIS* spreads (most overpriced - most underpriced) increases monotonically with each of the four skewness measures. *MIS* spreads of stocks in the high skewness quintiles are between 1.22% and

1.71% greater in absolute terms than those in the low skewness quintiles. Differences in *MIS* spreads of high and low skewness groups are all highly statistically, as well as economically, significant. For example, the 1.22% difference in the *MIS* spreads of high and low *ESKEW* quintiles is about twice the size of the -0.62% *MIS* spread of the low *ESKEW* quintile. Sorts based on *JACKPOT* yield the strongest results among all of the four measures, high *JACKPOT* stocks generate a *MIS* spread of -2.06%, which is about six times larger than the -0.35% spread of low *JACKPOT* stocks. Findings so far are in line with our first hypothesis (*H1*), that mispricing is concentrated among stocks with higher levels of skewness.

Panel A of Table 2 also shows that the differences in *MIS* spreads across the skewness quintiles come mostly from changes in the returns of the short leg (most overpriced). In fact, the difference between the abnormal returns of the high and the low skewness quintiles is not statistically significant among the most underpriced stocks. In other words, changes in skewness do not significantly affect underpriced stocks. On the other hand, increases in skewness measures are associated with the most overpriced stocks generating three to nine times larger negative abnormal returns. What is more interesting is that negative abnormal returns are not statistically significant for overpriced stocks that are in low *MAX* or low *JACKPOT* quintiles. This means that stocks with low levels of skewness, at least according to those two proxies, are not likely to become overpriced even if the anomaly variables suggest they will. Therefore, the commonly reported finding in the literature that anomaly spreads are driven mostly by short-leg stocks depends heavily on the level of skewness. These results support our second hypothesis (*H2*), looking at whether the effect of skewness on anomaly returns comes mostly from the short side.

To examine the relative distribution of firms across the most mispriced groups, we compute the average number of observations in each of the double-sorted portfolios. Results, presented in Panel B of Table 1, indicate that for the most overpriced stocks, the average number of stocks increases with each of the four skewness measures. In contrast, there are fewer firms in higher skewness quintiles among the most underpriced stocks. This pattern indicates that firms in extreme mispricing quintiles, which are responsible for the *MIS* premium, are also likely to be those that generate the skewness premium. Of course, this observation was predictable based on our summary statistics results in Panel B of Table 1, showing that overpriced firms are more likely to have higher levels of skewness than underpriced ones. Taken together, our double sorting results are consistent with our main conjecture, which posits that the mispricing-related component of anomalies is driven largely by stocks with higher levels of skewness in the cross-section.

Moreover, the effect of skewness on anomaly returns is concentrated in short-leg stocks, which are difficult to arbitrage.

4.1.2 Fama-Macbeth Regressions

To further investigate the relation between skewness and anomaly mispricing, we run a series of Fama and MacBeth (1973) regressions. Specifically, at the end of each month t, we use a set of independent variables, including stock characteristics, as well as our skewness and mispricing measures, to predict the stock returns in month $t + 1$. The main variable of interest is the interaction between each of the skewness measures and the anomaly mispricing variable, *MIS*. In all regressions, we control for market value, the book-to-market ratio, past returns for the previous month and for the prior twelve months skipping the last month. To facilitate result interpretation, we standardize all variables in our regressions to have a mean of zero and a standard deviation of one. Also, all variables are winsorized at their 0.5 and 99.5 percentile levels, to ensure that extreme values do not affect our results.

By running the regressions, we again test our first hypothesis (*H1*), looking at whether the anomaly mispricing premium is higher for stocks with higher levels of skewness. We expect to find that the interaction between the skewness measures and the anomaly mispricing variable has a negative sign. Panel A of Table 3 presents the time-series averages of the baseline Fama-Macbeth regression coefficients, along with Newey and West (1987) t-statistics. The first five regression specifications (columns (1) to (5)) exclude the interaction terms, and test whether MIS and our skewness variables are individually linked to future returns. Each of the five main variables are statistically significant at the 5% level. The *MIS* coefficient is larger and more significant than all the skewness measures. One standard deviation increase in *MIS* is associated with a 0.5% decline (t-statistics of -11.72) in returns in the following months, after controlling for major firm characteristics. Among the skewness measures, $JACKPOT$ is the strongest return predictor with a coefficient of -0.004 (t-statistics of -4.16).

Specifications in columns (6) to (9) each include one of the skewness measures, its interaction with *MIS* and *MIS* itself, as independent variables. Here, we essentially test our main premise that the interaction between skewness and anomaly mispricing predicts future returns beyond what is captured by each of the two variables individually. All four interaction variants are highly statistically significant, with t-statistics larger than the target threshold figure of three suggested by Harvey et al. (2016)[4]. One standard deviation increase in skewness adds between 0.1% to 0.3% to the predictive power of *MIS* on a monthly basis. These figures amount to between 30 to 60 percent of the predictive value of *MIS* by itself. An interesting observation is that the interaction terms fully absorb the statistical significance of *JACKPOT* and *LIDX*. In other words, the return premia of these two variables are generated wholly by stocks that are likely to be mispriced, as suggested by the combined anomaly measure.

To make sure that our regression results are not sensitive to our data filters or driven by specific parts of the sample, we run a series of basic robustness tests. For brevity, we only report the coefficients of our main variables of interest which are the interaction terms in Panel B of Table 3. Altogether, our estimates are robust. Skipping winsorization and exclusion of firms with a share price lower than $5 have negligable effects on the interaction coefficients. An interesting observation is that our results become slightly stronger once we drop micro-cap stocks. Excluding mega-cap stocks, however, has a limited effect on the coefficients. Following Fama and French (2008), we define mirco- and mega-cap stocks as those with market capitalizations below the 20th and above the 80th percentiles of NYSE market capitalization, respectively. In addition, we try removing NASDAQ stocks from our sample. In this case, although the coefficients remain highly significant, their magnitudes slightly shrink in some cases.

We also consider looking at different time periods in the sample. First, we divide the whole sample into recession and expansion periods, based on the NBER Recession Indicator [5], and estimate the interaction coefficients separately for each sub-sample. This is to see if the effect of skewness on mispricing is peculiar to recession times when the market is highly volatile. The results, reported in rows (6) and (7) of Panel B of Table 3, indicate that the interaction coefficient remain significant in both recession and expansion periods. The exception is the $ESKEW \times MIS$ coefficient which is only significant for the expansion periods, probably because the *ESKEW* data start in 1988, so the estimates fail to capture the recessions in the 1970s and 1980s. For the interaction terms based on the other three skewness measures, the coefficient estimates are slightly larger but less significant during the recession periods. Lastly, we divide our sample into two parts; the first involves the period between 1962 and 1990, while the second period between 1991 and 2015. The aim is to see whether the results change over time. We observe

[4]Harvey et al. (2016) argue that due to potential data mining issues, a t-statistics of 3 is a more appropriate significance cutoff in Fama-Macbeth regressions than the usual cutoff of 2

[5]The data is taken from the website of Federal Reserve Bank of St.Louis at: https://fred.stlouisfed.org/series/USREC

that the coefficients are much larger for the second sub-sample. This observation is also interesting, as it suggests that the skewness effect is actually stronger for more recent time periods in the sample. Overall, the baseline regression results presented in this section provide further corroborating evidence for our first hypothesis, showing that skewness increases the level of mispricing predicted by the anomaly strategies.

4.1.3 Evidence from Option-Based Skewness

In the previous sections, we incorporate four prominent measures of firm skewness, to test whether they have an effect on the mispricing associated with anomaly strategies, as captured by the *MIS* measure. All the four skewness variables yield results that are in line with our predictions; however, they are all noisy proxies for investors' perception about future return skewness. To make sure that our results reflect the role of skewness and not an unrelated effect captured by the skewness measures, we repeat our main tests with a skewness measure constructed using option prices. In particular, we use the option-based idiosyncratic skewness measure of Bakshi et al. (2003) and Conrad et al. (2013). This option-based measure offers us information regarding future return skewness, as expected by market participants, without being subject to a hindsight bias and requiring a parametric model for estimation (Conrad et al., 2013). However, we could not use this measure in all our tests as option prices are available only for a small subset of firms in the sample.

Panels A and B of Table 4, respectively, present the results for double sorting and Fama-Macbeth regressions using the option-based idiosyncratic skewness measure (*OS*). We essentially repeat the exercises in sections 4.1 and 4.2 but with the new measure. *OS* is constructed following the methodology of Conrad et al. (2013), as explained in Table A.1. The sample period covering *OS* starts from 1996, as option price data for older periods are not available on the Optionmetrics database. The double sorting results in Panel A of Table 4 suggest a pattern similar to what we observed before. That is, the spread between the most overpriced and the most underpriced stocks is largest among stocks that are in the high-*OS* quintile. As *OS* increases, *MIS* spreads do not grow with a clear monotonic patter; however, there is a 2.06% difference between the monthly abnormal returns (t-statistics of -2.23) of the low- and the high-*OS* quintiles. Also, most of the increase in the *MIS* spread in the high skewness group comes from the change in the returns of the short-leg (most overpriced) stocks. These observations again support our first and second hypotheses.

The Fama-Macbeth regression results in Panel B of Table 4 are also in line with our first hypothesis. In specification (1), we find that *OS* by itself cannot significantly predict returns. Conrad et al. (2013) argue that, due to the limited number of firms with available option data, the relation between *OS* and returns cannot be reliably estimated. Nevertheless, our tests do not require us to have a reliable estimate for the premium associated with *OS*. We are instead interested to see if *OS* exacerbates the mispricing captured by *MIS*. In specification (2), we test this conjecture by adding an interaction term between *OS* and *MIS* in the model. The coefficient of the interaction term is equal to -0.003 (t-statistics of -2.29), indicating that one standard deviation increase in *OS* increases the return predictability of *MIS* by 0.3%. This estimate is also significant economically. Considering that the *MIS* coefficient is also equal to -0.003, the interaction coefficient suggests that a standard deviation increase in *OS* doubles the premium associated with *MIS*. Altogether, the regressions and double sorting tests based on the option-based skewness measure support our previous results about the effect of skewness on the anomaly-based mispricing.

4.2 Do Investors with a Preference for Skewness Hold the Wrong Stocks?

In Section 4, we establish that the common mispricing-related component of anomaly strategies is strongly concentrated among stocks with higher levels of skewness. Moreover, we show that this relationship is driven mostly by the exacerbating effect of skewness on the prices of stocks that the anomaly strategies suggest are overpriced. In this subsection, we put our previous findings into context by providing an explanation for them based on the preference for skewness. We conjecture that a higher skewness level among stocks in the short leg relative to those in the long leg induces investors with a preference for skewness to assign a relatively higher (lower) weight to overpriced (underpriced) stocks. This prediction is summarized by our third hypothesis (*H3*).

We test this hypothesis using the portfolio holdings data of a sample of retail investors obtained from a large US discount brokerage house for the period 1991 to 1996. The reason for using the data for retail investor is that previous papers show that such investors are more likely to have a preference for skewness (Kumar, 2009). Our main dependent variables are the raw and excess weights allocated to overpriced (short-leg) stocks, relative to undepriced (long-leg) ones, in each investor portfolio at the end of every month. The raw and the excess relative weights are defined as $[W_{i,t}^{overpriced} - W_{i,t}^{underpriced}]$ and

$[(W_{i,t}^{overpriced} - W_{mkt,t}^{overpriced}) - (W_{i,t}^{underpriced} - W_{mkt,t}^{underpriced})]$, respectively. $W_{i,t}^{overpriced}$ is the raw weight allocated to overpriced stocks in portfolio i at the end of month t, $W_{i,t}^{underpriced}$ is the raw weight allocated to underpriced stocks in portfolio i at the end of month t, $W_{mkt,t}^{overpriced}$ is the raw weight allocated to overpriced stocks in the market portfolio at the end of month t and $W_{mkt,t}^{underpriced}$ is the raw weight allocated to underpriced stocks in the market portfolio at the end of month t. Overpriced and underpriced stocks are defined as those in the fifth and the first quintiles of *MIS*, respectively.

We regress our relative weight measures on a series of variables capturing investors' preference for skewness, as well as controlling for socioeconomic and portfolio characteristics. We estimate regressions each month and then compute the time series averages of the coefficients using the Fama-Macbeth framework. Since preference for skewness is not directly measurable, we adopt an indirect proxy, by computing the average portfolio weight an investor allocated to stocks with skewness levels above the sample median, over the past twelve months. The stronger an investor's preference for skewness, the more likely she is to have allocated a higher weight to skewed assets in the past. Skewness is measured using our four key proxies, i.e., *JACKPOT*, *LIDX*, *MAXRET*, and *ESKEW*. We also incorporate the Catholic-to-Protestant ratio (*CPRATIO*) used in Kumar et al. (2011) and Kumar et al. (2016) as a measure of local preference for skewness. Kumar et al. (2011) show that investors living in Catholic regions have stronger gambling tendencies and are more likely to be attracted to investments with positively-skewed payoffs than those residing in Protestant regions. *CPRATIO* is defined as the number of Catholic adherents divided by the number of Protestant adherents in the portfolio holder's county. Details about the construction of all variables including the socioeconomic and portfolio characteristics controls are presented in Table A.1. We standardize all independent variables to have a mean of zero and a standard deviation of one, and also winsorize them at their 0.5 and 99.5 percentiles.

Baseline results are presented in Panel A of Table 5. Investors that during the past year overweighted stocks with high levels of skewness by one standard deviation of the cross-sectional distribution, allocate between 11.6% to 18.4% higher raw weight to overpriced stocks, relative to underpriced ones. Excess weight regression estimates (columns (5) to (8)) provide a clearer picture as they are based on weights adjusted for benchmark (market) weights. One standard deviation increase in an investor's past weight on high-skewness stocks predicts between 8.7% to 13.9% higher relative excess weight on overpriced stocks. Coefficient estimates of past weights on high-skewness stocks are highly statistically significant for all four skewness measures even after controlling for a wide range of controls and adjusting standard errors for heteroscedasticity and autocorrelation using the Newey and West (1987) approach. *CPRATIO* coefficients are also statistically significant in all cases, but have relatively small magnitudes. The estimates indicate that one standard deviation increase in regional *CPRATIO* is associated with between 0.4% to 0.6% higher raw weights (0.3% to 0.5% higher excess weights) on overpriced stocks relative to underpriced stocks.

The rest of the coefficients in Panel A of Table 5 are also worth noting as they further highlight the characteristics of the clientele of investors that puts higher weights on stocks that are expected to perform poorly. The estimates indicate that such investors hold smaller and less diversified portfolios with significantly poorer past performance and higher portfolio variance. These investors are also less likely to concentrate their positions in a specific industry or geographical location. The latter is in line with Ivkovi and Weisbenner (2005) showing that local investors have more knowledge about local stocks, therefore, they are less likely to buy local stocks that perform poorly. Investors that put a higher relative weight on overpriced stocks are also likely to be male, single, old, and living in rental properties. Furthermore, they reside in less-populated regions with greater income inequality and poorer levels of education. Most of these characteristics are similar to those documented by previous studies as features of unsophisticated investors exhibiting stronger behavioral biases (e.g., Goetzmann and Kumar, 2008; Korniotis and Kumar, 2013) or a preference for skewness (e.g., Mitton and Vorkink, 2007; Kumar, 2009).

A possible concern with our results in Panel A of Table 5 is that we use the same stocks in each portfolio to compute the weights on both mispriced and high-skewess stocks. Even though all our independent variables are lagged by one month, most investors do not change their positions regularly. Therefore, the relationship between the weights on skewed and overpriced stocks may just reflect the correlation between the skewness measures and our mispricing indicator, *MIS*. In other words, an investor may overweight stocks with high levels of *MIS* (i.e., overpriced) for reasons other than preference for skewness and still have a relatively high portfolio weight on skewed stocks simply because overpriced stocks have higher skewness levels. To address this issue, we adjust our measures of past weight on high-skewness stocks by excluding all stocks that are in *MIS* quintiles one or five. Essentially, we compute the average weight an investor allocated to skewed stocks, excluding those that are mispriced according to *MIS*.

Panel B of Table 5 presents the results based on our alternative measures of weight on high-skewness stocks. We use the same regression specification as in Panel A. For brevity, control variable coefficients are not reported in the table, as they all remain almost intact from the previous regressions. The main results remain both statistically and economically significant with the new weight measures. One standard deviation increase in an investor's past weight on high-skewness stocks that are not in extreme *MIS* quintiles predicts between 7.3% to 13.3% higher relative raw weight on overpriced stocks (t-statistics ranging from 8.51 to 21.44). In relative excess weight regressions, the estimates range between 5.5% to 8.5%.

In short, the findings in this section support our third hypothesis (*H3*). Investors that have a history of holding stocks with higher levels of skewness are more (less) likely to hold stocks that will underperform (outperform), as suggested by the anomaly strategies. Investors that overweight underperforming stocks relative to outperforming ones are also likely to come from Catholic regions in which there is a strong propensity to gamble. Lastly, we observe that such investors possess other characteristics that have been previously linked to investor sophistication and possession of the preference for skewness and other behavioral biases.

5 Robustness Tests

We argue in the previous section that the effect of skewness on anomaly mispricing is driven by the preference of a group of investors to hold positively-skewed assets. In this section, we test two alternative explanations for our results. In particular, we consider skewness as a measure of systematic tail risk, as captured by coskewness, and an indirect proxy for factors deterring arbitragers.

5.1 The Role of Coskewness

Harvey and Siddique (2000) argue that part of the reason anomaly strategies exist is because asset pricing models do not account for downside tail risk captured by skewness. However, they build on Kraus and Litzenberger (1976) and conjecture that only a security's coskewness with the market portfolio should be priced because fully diversified investors do not care about the skewness of individual securities. Harvey and Siddique (2000) propose a coskewness factor and demonstrate that adding it to the CAPM significantly enhances the ability of the model to capture cross-sectional anomalies. In this section, we consider the coskewness measures of Harvey and Siddique (2000) and test whether the relationship between skewness and anomaly returns can be linked to a missing systematic coskewness factor in the asset pricing model rather than to a mispricing effect generated by the preference for skewness.

Harvey and Siddique (2000) measure coskewness in two ways; their original definition, which is the standardized correlation between CAPM residuals and squared market returns, and the alternative measure, defined as the loading on a squared market return factor added to the CAPM. We include both variants of coskewness in our tests. We estimate the former measure using monthly returns data for the past 60 months and the latter measure using daily returns for the past month. Further details about the construction of the variables are provided in Table A.1.

Panel A of Table 6 reports the results of our baseline Fama-Macbeth regressions with the addition of the original coskewness measure of Harvey and Siddique (2000) as a control variable. We also consider an interaction term between coskewness and *MIS* to capture any possible effect coskewness might have on the coefficients of our main interaction terms, which include the other four skewness measures. The results indicate that controlling for coskewness has almost no effect on our previous interaction coefficients. The interaction term between coskewness and *MIS* does not enter the regressions significantly and has negligible coefficients in all cases. The coskewness term itself also does not have a statistically significant coefficient, even in the Column (1) specification without any of the other main variables included in the regression. Barberis et al. (2016) report similar results regarding the insignificance of coskewness in Fama-Macbeth regressions.

We repeat this exercise with the alternative measure of coskewness defined as the coefficient on a squared market factor. Results are very similar to those based on the original definition. For brevity, we only report the main coefficients of interest in Panel B of Table 6. Interaction terms between coskewness and *MIS* are again not statistically significant. Overall, the findings in this subsection indicate that the effect of skewness on anomaly returns cannot be linked to coskewness. In other words, it is firm-specific skewness rather than systematic skewness that affects the predictability of anomaly strategies.

5.2 Skewness as a Proxy for Limits to Arbitrage

Part of our story regarding the role of skewness in generating anomaly mispricing relies on the presence of limits to arbitrage in the market. In the absence of arbitrage risks and costs, any skewness-related mispricing would likely vanish, as expected utility investors would reverse the pricing effect of investors that have a preference for skewness (Barberis and Huang, 2008). However, a possible concern over our findings is that our skewness measures might just indirectly reflect arbitrage costs, instead of features that trigger investors' preference for skewness. If this were to be the case, the exacerbating effect of skewness on anomaly mispricing would be simply due to skewed stocks being more difficult to arbitrage. Previous studies document the close link between skewness and limits to arbitrage. For example, several papers show that short-sale constraints directly lead to higher skewness (e.g., Bris et al., 2007; Chang et al., 2007; Xu, 2007). In addition, Conrad et al. (2014) find that their *JACKPOT* measure, which has the best performance in our tests, is strongly associated with arbitrage costs.

In this section, we address the concern outlined above, by adding several measures of arbitrage cost as control variables to our Fama-Macbeth regressions. Similar to our approach in the previous subsection, we also interact those limits to arbitrage proxies with *MIS* and add them alongside our main interaction terms. We expect to observe that our main interactions between skewness and *MIS* do not lose their economic and statistical significance with the addition of the other variables to the regressions. The logic behind this conjecture is that the interactions between skewness and *MIS* capture stocks that are not only difficult to arbitrage, but that are also traded in the wrong direction by investors reacting to skewness. As a result, skewness and *MIS* interactions are likely to predict higher levels of mispricing than simple interactions between *MIS* and proxies for limits to arbitrage.

We follow the previous papers and consider five measures for limits to arbitrage. They include the illiquidity measure of Amihud (2002), the short interest ratio (following Hanson and Sunderam (2014)), the bid-ask spread (motivated by Amihud and Mendelson (1986) and Hasbrouck (2009)), the frequency of zero daily returns devised by Lesmond et al. (1999) and the percentage institutional holding (as in DAvolio (2002)). The construction details of each of the measures are explained in Table A.1.

Panels A to E of Table 7 report the results of running the Fama-Macbeth regressions with the addition of each of the five proxies outlined above. We observe that the coefficients of our main interaction terms between skewness and *MIS* remain almost the same after adding any of the five limits-to-arbitrage proxies and their interactions with *MIS* to the regressions. This finding indicates that the power of the interaction between skewness and anomaly-related mispricing in predicting returns is unlikely to be caused just by the correlation between skewness and proxies for limits to arbitrage. In fact, the interactions between *MIS* and the five limits-to-arbitrage proxies are statistically significant only in a very few cases. In sum, these results indicate that the role of skewness in exacerbating anomaly mispricing goes beyond just highlighting arbitrage costs, which are often associated with skewness.

6 Skewness as a Factor

In the previous sections, we establish that skewness features of stocks that are likely to be mispriced according to anomaly strategies attract investors with skewness preferences and contribute to mispricing. In this section, we build on the approach of Stambaugh and Yuan (2017) and examine whether considering firm-specific skewness in asset pricing models, in the form of a *mispricing factor* rather than a systematic risk factor, improves the performance of the models in capturing anomaly returns. The idea behind a mispricing factor is that mispricing has common sources across stocks; therefore, factors exhibiting these common sources would help explain cross-sectional variations in returns that do not reflect compensation for systematic risks. Considering that skewness has a significant association with the common mispricing-related component of anomaly strategies, a skewness factor is likely to capture at least parts of the commonality in abnormal returns. It is important to note, however, that we are not seeking to devise an asset pricing model here. The purpose of the exercise in this section is just to investigate whether a skewness factor should be considered in future models to enable a better explanation of cross-sectional returns.

We follow the approach of Stambaugh and Yuan (2017) and use our four skewness measures, i.e. *JACKPOT*, *LIDX*, *MAXRET* and *ESKEW*, to construct a skewness factor. That is, we first compute the average decile rank of each stock at the end of every month with respect to the four skewness measures. Next, we independently sort stocks based on their average skewness decile ranks and their market capitalization into three and two portfolios, respectively. We then compute the value-weighted monthly return of each of the 6 ($= 2 \times 3$) intersecting portfolios. Unlike Stambaugh and Yuan (2017), we use the sample median rather than the NYSE median to allocate stocks into size groups. The reason for our different approach is that using NYSE median groups would lead to an extreme difference between the numbers of firms in the two size groups within highly skewed stocks. Lastly, we take the average of the returns of the two size portfolios with the highest skewness tercile rank and deduct it from the average return of the two size portfolios with the lowest tercile rank, aiming to get monthly factor returns. We call this skewness factor *non-skewed minus skewed* (NMS).

We add *NMS* to the following four prominent models: Fama and French (1993) three-factor (*FF3*), Carhart (1997) four-factor (*CAR*), Fama and French (2015) five-factor (*FF5*) and Fama and French (2015) with the addition of momentum (*FF6*). We then compare the performance of the new models with the original ones in capturing the eleven anomaly strategies that are used to construct our anomaly mispricing variable (MIS). As described in section 3.1, the anomalies include accruals, asset growth, composite equity issues, distress, gross profitability, investment-to-assets, momentum, net operating assets, net stock issues, O-score, and return on assets. We evaluate the performance of the models by comparing the long-short abnormal returns of each anomaly strategy with respect to different models. The return on the long-short portfolio is computed as the difference between the value-weighted monthly return on stocks ranked in the bottom decile, and the return on those in the top decile of each anomaly variable. We then regress the time-series of long-short portfolio returns on various factors to estimate for the abnormal returns, as captured by the intercept alpha.

Panels A and B of Table 8 respectively present the alphas and t-statistics of the eleven anomaly strategies produced using various models. The results indicate that adding the NMS factor shrinks the anomaly strategy alphas in the majority of cases. The exceptions are accruals, composite equity issuance and investment-to-assets anomalies, for which the hedge alphas in some cases increase with the addition of the NMS factor. The most significant cases of improvement come from distress and o-score anomalies. Adding the NMS factor reduces the distress anomaly alphas by 0.24% to 0.72% and the o-score alphas by 0.1 to 0.29%. Models with the NMS factor also produce t-statistics that are between 1.11 and 2.6 lower for the distress anomaly, and between 0.98 to 2.2 lower for the o-score anomaly.

To better compare the models with each other, we present a set of summarizing performance measures for each model in Panel C of Table 8. In particular, we follow Stambaugh and Yuan (2017) and compute the average absolute alpha, average absolute t-statistic of alpha and the Gibbons et al. (1989) statistics (GRS) testing the null hypothesis that the intercept terms of all anomaly strategies are collectively equal to zero. Consistent across all these three performance measures, models with the NMS factor perform better than their peers that do not have the NMS factor. For example, the three-factor model (*FF3*) with the addition of NMS produces a 0.2% lower average alpha and the average t-statistics and GRS statistics that are lower by 1.04 and 3.16, respectively. Comparing the performance of models with the same number of factors also indicates that those with the NMS factor perform relatively better.*FF3* with the addition of NMS, for instance, generates an average alpha that is almost the same as *CAR* but has t- and GRS statistics that are lower by 0.17 and 1.02. The best model among all turns out to be the five-factor model with momentum (*FF6*) and the NMS factor. This model produces an average alpha of 0.5%, an average t-statistic of 2.929 and a GRS statistic of 6.471. For comparison, the corresponding figures for *FF3* are 1%, 5.033 and 7.269.

In sum, we find that the NMS factor helps capture parts of the commonality in mispricing that is linked to skewness. The NMS factor is particularly useful for explaining distress-related anomalies, which are shown to be driven by skewed stocks (e.g., Conrad et al., 2014). Future studies can build on these findings and could produce more refined factors, capturing the pricing effect of skewness.

7 Conclusion

This paper examines whether the preference for skewness can act as a common driver of cross-sectional mispricing patterns identified by anomaly strategies. Using a composite mispricing measure based on eleven strategies, we show that anomaly mispricing is significantly more prevalent among stocks with higher levels of cross-sectional skewness. This result is consistent across a wide range of skewness measures commonly used in the literature. Skewness exacerbates anomaly mispricing predominantly through an increase in overpricing among short-leg stocks. Returns of long-leg stocks, on the other hand, do not significantly change with the level of skewness.

We attribute the effect of skewness on anomalies to the proclivity of a group of investors to hold positively-skewed positions. The portfolio holdings from a large U.S. brokerage house suggest that investors with a history of holding positively-skewed positions are considerably more likely to overweight stocks that anomaly strategies predict will underperform, relative to those that will outperform. Investors that overweight underperforming stocks relative to outperforming ones also possess characteristics that have been previously linked to investor sophistication and a preference for skewness.

We do not aim to fully explain market anomalies in this study. There are numerous underlying mechanisms, not all related to mispricing, that are responsible for each individual anomaly. Rather, our intention is to explore mispricing-related commonalities across a range of strategies and to show that the preference for skewness plays an important role here. In this sense, our work is related to papers that look for common drivers of anomalies such as Stambaugh et al. (2012), who highlight the role of investor sentiment. While investor sentiment can elegantly explain time-series variations in the performance of anomalies, our story explains variations in the cross-section. For example, we can, at least partly, explain why some stocks in the short-legs of anomalies are more overpriced than others.

As the main takeaway, we document that pricing implications of skewness extend beyond individual cases of cross-sectional mispricing investigated by the previous papers. Considering that stocks with the most extreme fundamental characteristics are also the most skewed in the cross-section, skewness should be taken into account in some form to be able to better explain expected returns. The problem, however, is that the effect of skewness is mostly in the form of mispricing, which is unlikely to be captured by a systematic risk factor. In this case, we propose that a factor capturing skewness-related mispricing commonalities can be useful in asset pricing models.

References

Amihud, Yakov, 2002, Illiquidity and stock returns: cross-section and time-series effects, *Journal of Financial Markets* 5, 31–56.

Amihud, Yakov, and Haim Mendelson, 1986, Asset pricing and the bid-ask spread, *Journal of Financial Economics* 17, 223–249.

Avramov, Doron, Tarun Chordia, Gergana Jostova, and Alexander Philipov, 2013, Anomalies and financial distress, *Journal of Financial Economics* 108, 139–159.

Bakshi, Gurdip, Nikunj Kapadia, and Dilip Madan, 2003, Stock return characteristics, skew laws, and the differential pricing of individual equity options, *Review of Financial Studies* 16, 101–143.

Bali, Turan G, Nusret Cakici, and Robert F Whitelaw, 2011, Maxing out: Stocks as lotteries and the cross-section of expected returns, *Journal of Financial Economics* 99, 427–446.

Barberis, Nicholas, 2013, The psychology of tail events: Progress and challenges, *The American Economic Review* 103, 611–616.

Barberis, Nicholas, and Ming Huang, 2008, Stocks as lotteries: The implications of probability weighting for security prices, *The American Economic Review* 98, 2066–2100.

Barberis, Nicholas, Abhiroop Mukherjee, and Baolian Wang, 2016, Prospect theory and stock returns: An empirical test, *Review of Financial Studies* 29, 3068–3107.

Boyer, Brian, Todd Mitton, and Keith Vorkink, 2010, Expected idiosyncratic skewness, *Review of Financial Studies* 23, 169–202.

Boyer, Brian H, and Keith Vorkink, 2014, Stock options as lotteries, *The Journal of Finance* 69, 1485–1527.

Bris, Arturo, William N Goetzmann, and Ning Zhu, 2007, Efficiency and the bear: Short sales and markets around the world, *The Journal of Finance* 62, 1029–1079.

Brunnermeier, Markus K., Christian Gollier, and Jonathan A. Parker, 2007, Optimal beliefs, asset prices, and the preference for skewed returns, *The American Economic Review* 97, 159–165.

Campbell, John Y., Jens Hilscher, and J. A. N. Szilagyi, 2008, In search of distress risk, *The Journal of Finance* 63, 2899–2939.

Cao, H Henry, Joshua D Coval, and David Hirshleifer, 2002, Sidelined investors, trading-generated news, and security returns, *Review of Financial Studies* 15, 615–648.

Carhart, Mark M, 1997, On persistence in mutual fund performance, *The Journal of Finance* 52, 57–82.

Chang, Eric C, Joseph W Cheng, and Yinghui Yu, 2007, Shortsales constraints and price discovery: Evidence from the hong kong market, *The Journal of Finance* 62, 2097–2121.

Chen, Joseph, Harrison Hong, and Jeremy C Stein, 2001, Forecasting crashes: Trading volume, past returns, and conditional skewness in stock prices, *Journal of Financial Economics* 61, 345–381.

Chordia, Tarun, Avanidhar Subrahmanyam, and Qing Tong, 2014, Have capital market anomalies attenuated in the recent era of high liquidity and trading activity?, *Journal of Accounting and Economics* 58, 41–58.

Conine, Thomas E, and Maurry J Tamarkin, 1981, On diversification given asymmetry in returns, *The Journal of Finance* 36, 1143–1155.

Conrad, Jennifer, Robert F Dittmar, and Eric Ghysels, 2013, Ex ante skewness and expected stock returns, *The Journal of Finance* 68, 85–124.

Conrad, Jennifer, Nishad Kapadia, and Yuhang Xing, 2014, Death and jackpot: Why do individual investors hold overpriced stocks?, *Journal of Financial Economics* 113, 455–475.

Cooper, Michael J, Huseyin Gulen, and Michael J Schill, 2008, Asset growth and the crosssection of stock returns, *The Journal of Finance* 63, 1609–1651.

Daniel, Kent, and Sheridan Titman, 2006, Market reactions to tangible and intangible information, *The Journal of Finance* 61, 1605–1643.

DAvolio, Gene, 2002, The market for borrowing stock, *Journal of Financial Economics* 66, 271–306.

Del Viva, Luca, Eero Kasanen, and Lenos Trigeorgis, 2017, Real options, idiosyncratic skewness, and diversification, *Journal of Financial and Quantitative Analysis* 52, 215–241.

Dittmar, Robert F, 2002, Nonlinear pricing kernels, kurtosis preference, and evidence from the cross section of equity returns, *The Journal of Finance* 57, 369–403.

Fama, Eugene F, 1970, Efficient capital markets: A review of theory and empirical work, *The journal of Finance* 25, 383–417.

Fama, Eugene F, and Kenneth R French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.

Fama, Eugene F, and Kenneth R French, 2006, Profitability, investment and average returns, *Journal of Financial Economics* 82, 491–518.

Fama, Eugene F, and Kenneth R French, 2008, Dissecting anomalies, *The Journal of Finance* 63, 1653–1678.

Fama, Eugene F, and Kenneth R French, 2015, A five-factor asset pricing model, *Journal of Financial Economics* 116, 1–22.

Fama, Eugene F, and James D MacBeth, 1973, Risk, return, and equilibrium: Empirical tests, *The Journal of Political Economy* 607–636.

Gibbons, Michael R, Stephen A Ross, and Jay Shanken, 1989, A test of the efficiency of a given portfolio, *Econometrica: Journal of the Econometric Society* 1121–1152.

Goetzmann, William N, and Alok Kumar, 2008, Equity portfolio diversification, *Review of Finance* 12, 433–463.

Green, T Clifton, and Byoung-Hyoun Hwang, 2012, Initial public offerings as lotteries: Skewness preference and first-day returns, *Management Science* 58, 432–444.

Hanson, Samuel G, and Adi Sunderam, 2014, The growth and limits of arbitrage: Evidence from short interest, *Review of Financial Studies* 27, 1238–1286.

Harvey, Campbell R, John C Liechty, Merrill W Liechty, and Peter Mller, 2010, Portfolio selection with higher moments, *Quantitative Finance* 10, 469–485.

Harvey, Campbell R., Yan Liu, and Heqing Zhu, 2016, and the cross-section of expected returns, *Review of Financial Studies* 29, 5–68.

Harvey, Campbell R, and Akhtar Siddique, 2000, Conditional skewness in asset pricing tests, *The Journal of Finance* 55, 1263–1295.

Hasbrouck, Joel, 2009, Trading costs and returns for u.s. equities: Estimating effective costs from daily data, *The Journal of Finance* 64, 1445–1477.

Hirshleifer, David, Kewei Hou, Siew Hong Teoh, and Yinglei Zhang, 2004, Do investors overvalue firms with bloated balance sheets?, *Journal of Accounting and Economics* 38, 297–331.

Hirshleifer, David, Siew Hong Teoh, and Jeff Jiewei Yu, 2011, Short arbitrage, return asymmetry, and the accrual anomaly, *Review of Financial Studies* 24, 2429–2461.

Ivkovi, Zoran, and Scott Weisbenner, 2005, Local does as local is: Information content of the geography of individual investors' common stock investments, *The Journal of Finance* 60, 267–306.

Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, *The Journal of Finance* 48, 65–91.

Kausar, Asad, Alok Kumar, and Richard J Taffler, 2015, Why the going-concern accounting anomaly: gambling in the market?, *Available at SSRN 2249029* .

Korniotis, George M, and Alok Kumar, 2013, Do portfolio distortions reflect superior information or psychological biases?, *Journal of Financial and Quantitative Analysis* 48, 1–45.

Kraus, Alan, and Robert H Litzenberger, 1976, Skewness preference and the valuation of risk assets, *The Journal of Finance* 31, 1085–1100.

Kumar, Alok, 2009, Who gambles in the stock market?, *The Journal of Finance* 64, 1889–1933.

Kumar, Alok, Jeremy K. Page, and Oliver G. Spalt, 2011, Religious beliefs, gambling attitudes, and financial market outcomes, *Journal of Financial Economics* 102, 671–708.

Kumar, Alok, Jeremy K Page, and Oliver G Spalt, 2016, Gambling and comovement, *Journal of Financial and Quantitative Analysis* 51, 85–111.

Lesmond, David A, Joseph P Ogden, and Charles A Trzcinka, 1999, A new estimate of transaction costs, *Review of Financial Studies* 12, 1113–1141.

Loughran, Tim, and Jay R Ritter, 1995, The new issues puzzle, *The Journal of Finance* 50, 23–51.

McLean, R David, and Jeffrey Pontiff, 2016, Does academic research destroy stock return predictability?, *The Journal of Finance* 71, 5–32.

Miller, Edward M, 1977, Risk, uncertainty, and divergence of opinion, *The Journal of Finance* 32, 1151–1168.

Mitton, Todd, and Keith Vorkink, 2007, Equilibrium underdiversification and the preference for skewness, *Review of Financial Studies* 20, 1255–1288.

Nagel, Stefan, 2005, Short sales, institutional investors and the cross-section of stock returns, *Journal of Financial Economics* 78, 277–309.

Newey, Whitney K., and Kenneth D. West, 1987, A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica* 55, 703–708.

Novy-Marx, Robert, 2013, The other side of value: The gross profitability premium, *Journal of Financial Economics* 108, 1–28.

Ohlson, James A., 1980, Financial ratios and the probabilistic prediction of bankruptcy, *Journal of Accounting Research* 18, 109–131.

Ritter, Jay R, 1991, The longrun performance of initial public offerings, *The Journal of Finance* 46, 3–27.

Sloan, Richard G, 1996, Do stock prices fully reflect information in accruals and cash flows about future earnings?, *The Accounting Review* 71, 289–315.

Stambaugh, Robert F, Jianfeng Yu, and Yu Yuan, 2012, The short of it: Investor sentiment and anomalies, *Journal of Financial Economics* 104, 288–302.

Stambaugh, Robert F, Jianfeng Yu, and Yu Yuan, 2014, The long of it: Odds that investor sentiment spuriously predicts anomaly returns, *Journal of Financial Economics* 114, 613–619.

Stambaugh, Robert F, Jianfeng Yu, and Yu Yuan, 2015, Arbitrage asymmetry and the idiosyncratic volatility puzzle, *The Journal of Finance* 70, 1903–1948.

Stambaugh, Robert F., and Yu Yuan, 2017, Mispricing factors, *Review of Financial Studies* forthcoming.

Titman, Sheridan, Kuo-Chiang Wei, and Feixue Xie, 2004, Capital investments and stock returns, *Journal of Financial and Quantitative Analysis* 39, 677–700.

Tversky, Amos, and Daniel Kahneman, 1992, Advances in prospect theory: Cumulative representation of uncertainty, *Journal of Risk and Uncertainty* 5, 297–323.

Xu, Jianguo, 2007, Price convexity and skewness, *The Journal of Finance* 62, 2521–2552.

Table 1: **Summary Statistics**

This table reports average characteristics of MIS quintiles in Panels A and B and the monthly value-weighted abnormal returns of quintiles based on MIS and the four skewness measures of JACKPOT, LIDX, MAXRET and ESKEW in Panel C. MIS is a combined measure of mispricing based on 11 prominent anomaly strategies following Stambaugh et al. (2015). Higher (lower) values of MIS indicate a higher likelihood for the stock to be overpriced (underpriced). MIS and all other variables are defined in Table A.1. Quintile portfolios are formed by sorting stocks at the end of every month into five groups. The t-statistics for the difference between values of quintiles one and five (5 -1) in Panels A and B are based on Newey-West heteroskedasticity- and autocorrelation-consistent standard errors using a lag of 36. The three-, four- and five-factor models used to adjust returns in Panel C correspond to the models of Fama and French (1993), Carhart (1997) and Fama and French (2015), respectively. The sample excludes penny stocks and covers January 1963 to December 2015, except for sorts based on ESKEW which start in January 1988.

	All sample	MIS portfolios					
		1	2	3	4	5	5 - 1
Panel A: Key Statistics of MIS Portfolios							
ME ($ Billion)	1.56	3.5	1.88	1.14	0.78	0.51	-2.99 (-3.61)
PRICE ($)	21.16	29.17	24.4	20.43	17.81	13.99	-15.18 (-8.04)
VOLATILITY (%)	3.05	2.5	2.78	3.03	3.27	3.68	1.19 (7.83)
IVOL (%)	2.95	2.37	2.67	2.95	3.19	3.6	1.23 (6.98)
RET[-12,-2] (%)	3.13	18.41	10.67	4.08	-3.07	-14.45	-32.86 (-11.13)
TURNOVER (%)	9.39	8.87	8.83	8.98	9.67	10.63	1.76 (3.54)
SHORTRATIO	2.14	1.82	1.96	2.12	2.41	2.8	0.98 (5.38)
ILLIQ (10ˆ6)	4.28	2.91	4.22	5.1	4.92	4.26	1.35 (7.59)
LEVERAGE	0.24	0.13	0.19	0.25	0.29	0.33	0.2 (15.52)
B/M	0.84	0.67	0.81	0.9	0.92	0.9	0.23 (5.66)
RHOLDING (%)	0.1	0.08	0.09	0.1	0.11	0.11	0.03 (4.37)
IHOLDING (%)	30.71	36.89	34	32.04	28.02	22.61	-14.28 (-7.93)
Panel B: Skewness Characteristics of MIS Portfolios							
ESKEW	0.78	0.62	0.7	0.77	0.84	0.96	0.33 (5.48)
JACKPOT (%)	2	1.3	1.63	1.98	2.24	2.82	1.52 (4.36)
LIDX	0.49	0.42	0.45	0.49	0.51	0.57	0.15 (8.17)
MAXRET (%)	6.87	5.49	6.18	6.83	7.42	8.45	2.97 (7.23)
OS	-0.28	-0.32	-0.28	-0.25	-0.24	-0.21	0.11 (6.86)
ISKEWNESS	0.18	0.17	0.18	0.18	0.19	0.2	0.03 (2.24)
SKEWNESS	0.25	0.23	0.24	0.25	0.26	0.28	0.05 (2.55)

Table 1 (Continued)

Panel C: Abnormal Returns of MIS and Skewness Measures							
Variable	Model	1	2	3	4	5	5 - 1
MIS	3-factor	0.29***	0.07*	-0.07	-0.22***	-0.8***	-1.09***
		(6.66)	(1.77)	(-1.24)	(-3.57)	(-8.3)	(-8.9)
	4-factor	0.2***	0.08*	-0.05	-0.11*	-0.56***	-0.76***
		(4.87)	(1.76)	(-0.82)	(-1.78)	(-6.31)	(-6.92)
	5-factor	0.18***	0.05	0	-0.08	-0.45***	-0.63***
		(4.46)	(1.2)	(0.08)	(-1.26)	(-5.32)	(-5.99)
JACKPOT	3-factor	0.08***	0.02	-0.09	-0.51***	-0.97***	-1.05***
		(3.47)	(0.29)	(-1.24)	(-4.23)	(-5.39)	(-5.5)
	4-factor	0.05**	0.07	-0.03	-0.34***	-0.65***	-0.7***
		(2.16)	(1.31)	(-0.35)	(-2.82)	(-3.73)	(-3.8)
	5-factor	0.01	0.17***	0.15**	-0.08	-0.35**	-0.37**
		(0.62)	(3.17)	(2.36)	(-0.73)	(-2.29)	(-2.27)
LIDX	3-factor	0.11***	-0.02	-0.09	-0.32***	-0.99***	-1.09***
		(4.13)	(-0.32)	(-1.17)	(-3.13)	(-6.45)	(-6.77)
	4-factor	0.08***	0	0.01	-0.14	-0.66***	-0.74***
		(2.97)	(0.08)	(0.07)	(-1.36)	(-4.55)	(-4.84)
	5-factor	0.07***	0.07	0.14**	0	-0.57***	-0.64***
		(3.07)	(1.34)	(1.99)	(-0.02)	(-4.09)	(-4.46)
MAXRET	3-factor	0.1**	0.03	0.08	-0.1	-0.61***	-0.7***
		(2.03)	(0.6)	(1.38)	(-1.07)	(-4.92)	(-4.68)
	4-factor	0.08	0.06	0.12**	-0.04	-0.47***	-0.55***
		(1.56)	(1.09)	(1.97)	(-0.44)	(-3.81)	(-3.62)
	5-factor	0.01	0.06	0.18***	0.12	-0.24**	-0.25*
		(0.2)	(1.29)	(2.84)	(1.35)	(-2.17)	(-1.86)
ESKEW	3-factor	0.1**	0.11*	-0.09	-0.25**	-0.62***	-0.72***
		(2.55)	(1.73)	(-0.83)	(-2.1)	(-4.21)	(-4.46)
	4-factor	0.08**	0.1	-0.01	-0.13	-0.44***	-0.52***
		(2.06)	(1.52)	(-0.09)	(-1.07)	(-2.96)	(-3.22)
	5-factor	0.09**	0.14**	0.1	0	-0.25*	-0.34**
		(2.3)	(2.29)	(0.88)	(-0.02)	(-1.87)	(-2.32)

Table 2: Double Sorts

Panel A reports benchmark adjusted returns for double sorted portfolios based on MIS and one of the four skewness measures of JACKPOT, LIDX, MAXRET and ESKEW. All variables are defined in Table A.1. The portfolios are formed by independently sorting stocks at the end of every month with respect to each variable into five portfolios. We then compute the value-weighted returns of the 25 intersecting portfolios for the following month and regress the time series of returns on the four factors of Carhart (1997). The regression intercept is the abnormal return estimate reported in the table below. Panel B presents the average number of stocks in each of the 25 portfolios. The sample excludes penny stocks and covers January 1963 to December 2015, except for sorts based on ESKEW which start in January 1988.

		Most Underpriced	2	3	4	Most Overpriced	Most Overpriced - Most Underpriced
	Low	0.19***	0.02	-0.11*	-0.11	-0.16	-0.35***
		(4.23)	(0.4)	(-1.74)	(-1.58)	(-1.51)	(-2.89)
	2	0.37***	0.37***	0.17*	-0.19*	-0.68***	-1.05***
		(4.54)	(4.56)	(1.68)	(-1.88)	(-5.62)	(-7.2)
	3	0.42***	0.48***	0.08	-0.09	-0.92***	-1.34***
JACKPOT		(3.99)	(4.21)	(0.72)	(-0.82)	(-6.83)	(-7.85)
	4	0.72***	0.35**	0.07	-0.1	-1.11***	-1.83***
		(4.94)	(2.45)	(0.49)	(-0.65)	(-6.81)	(-9.71)
	High	0.5**	0.45**	-0.21	-0.29	-1.55***	-2.06***
		(2.33)	(2.36)	(-1.05)	(-1.42)	(-7.73)	(-8.15)
	High -	0.31	0.43**	-0.09	-0.18	-1.4***	-1.71***
	Low	(1.4)	(2.14)	(-0.43)	(-0.8)	(-6.03)	(-6.32)
	Low	0.22***	0.06	-0.04	-0.06	-0.35***	-0.56***
		(4.47)	(1.17)	(-0.6)	(-0.77)	(-3.3)	(-4.65)
	2	0.21**	0.05	-0.01	-0.17*	-0.34***	-0.55***
		(2.52)	(0.67)	(-0.14)	(-1.79)	(-2.73)	(-3.54)
	3	0.51***	0.35***	0.13	-0.2	-0.75***	-1.27***
LIDX		(4.2)	(3.12)	(1.14)	(-1.65)	(-5.77)	(-6.88)
	4	0.43***	0.52***	0.05	-0.04	-1.06***	-1.5***
		(3.18)	(4.06)	(0.44)	(-0.3)	(-6.68)	(-7.52)
	High	0.47**	0.15	-0.23	-0.4**	-1.43***	-1.9***
		(2.4)	(0.82)	(-1.23)	(-2.03)	(-7.48)	(-8.27)
	High -	0.25	0.09	-0.18	-0.34	-1.08***	-1.37***
	Low	(1.24)	(0.46)	(-0.91)	(-1.58)	(-5.01)	(-5.47)
	Low	0.2***	0.1	0	0.04	-0.15	-0.34**
		(2.68)	(1.36)	(-0.02)	(0.42)	(-1.28)	(-2.56)
	2	0.21***	0.14*	0.06	-0.11	-0.34***	-0.54***
		(2.65)	(1.7)	(0.6)	(-1.19)	(-2.98)	(-3.91)
	3	0.49***	0.14	-0.05	-0.04	-0.62***	-1.11***
MAXRET		(4.98)	(1.39)	(-0.46)	(-0.35)	(-4.9)	(-6.89)
	4	0.54***	0.14	0.03	-0.34**	-0.8***	-1.34***
		(3.64)	(1.02)	(0.24)	(-2.44)	(-5.49)	(-6.68)
	High	0.2	-0.08	-0.37**	-0.39**	-1.51***	-1.7***
		(1.1)	(-0.44)	(-2.02)	(-2.21)	(-8.61)	(-7.62)
	High -	0	-0.17	-0.37*	-0.43**	-1.37***	-1.37***
	Low	(-0.02)	(-0.86)	(-1.72)	(-2.12)	(-6.19)	(-5.36)

Table 2 (Continued)

		Most Underpriced	2	3	4	Most Overpriced	Most Overpriced - Most Underpriced
ESKEW	Low	0.31***	0.03	-0.05	-0.09	-0.32**	-0.62***
		(4.57)	(0.46)	(-0.53)	(-1)	(-2.54)	(-4.32)
	2	0.22**	0.15*	0.11	-0.01	-0.51***	-0.73***
		(2.11)	(1.66)	(1.1)	(-0.09)	(-3.98)	(-4.53)
	3	0.32**	0.18	0.09	-0.11	-0.86***	-1.18***
		(2.34)	(1.3)	(0.67)	(-0.8)	(-5.24)	(-5.69)
	4	0.57***	0.35**	-0.1	-0.06	-1***	-1.58***
		(4.01)	(2.19)	(-0.64)	(-0.38)	(-6.11)	(-8.28)
	High	0.58***	0.35**	0.22	-0.24	-1.3***	-1.88***
		(3.45)	(2.21)	(1.22)	(-1.25)	(-5.98)	(-7.78)
	High - Low	0.28	0.32*	0.27	-0.16	-0.98***	-1.22***
		(1.53)	(1.83)	(1.26)	(-0.71)	(-3.89)	(-4.56)

Panel B: Number of Stocks

		Most Underpriced	2	3	4	Most Overpriced
JACKPOT	Low	209	172	135	106	68
	2	154	144	132	118	86
	3	112	116	122	124	119
	4	92	106	120	134	157
	High	65	95	124	150	202
LIDX	Low	196	163	131	106	66
	2	154	141	130	120	94
	3	121	123	123	125	123
	4	89	105	120	133	158
	High	63	93	120	140	182
MAXRET	Low	176	146	124	104	78
	2	156	143	130	117	96
	3	126	130	129	128	120
	4	97	112	124	135	150
	High	69	94	117	139	181
ESKEW	Low	190	160	133	115	83
	2	168	151	135	118	90
	3	121	126	129	132	132
	4	102	114	124	135	153
	High	74	104	128	146	181

Table 3: Baseline Fama-Macbeth Regressions

This table presents the estimates from monthly Fama-MacBeth cross-sectional regressions. At the end of each month t, we use a set of independent variables including stock characteristics as well as our skewness and mispricing measures to predict the stock returns for month $t+1$. Our primary independent variable is the interaction between each of the four skewness measures of JACKPOT, LIDX, MAXRET and ESKEW and the anomaly mispricing variable, MIS. We control for the market value, the book-to-market ratio, the previous-month returns and the past 12-month returns skipping the last month. All variables are defined in Table A.1. All independent variables in our regressions are standardized to have a mean of zero and a standard deviation of one and are winsorized at their 0.5 and 99.5 percentile levels. Standard errors are adjusted using the Newey and West (1987) approach. Panel A reports the baseline regression results and Panel B presents the results based on alternative samples or data filters. For brevity, we only report the interaction coefficients in Panel B. The sample excludes penny stocks and covers January 1963 to December 2015, except for regression that include ESKEW which start in January 1988.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Panel A: Baseline Estimates								
Intercept	0.01***	0.01***	0.01***	0.01***	0.01***	0.009***	0.01***	0.01***	0.009***
	(4.33)	(3.98)	(4.35)	(4.11)	(3.89)	(3.83)	(4.29)	(4.11)	(3.6)
MIS	-0.005***					-0.005***	-0.004***	-0.004***	-0.005***
	(-11.72)					(-12.37)	(-13.69)	(-11.74)	(-12.25)
JACKPOT		-0.004***				-0.001			
		(-4.16)				(-1.56)			
LIDX			-0.002**				0		
			(-2.06)				(-0.44)		
MAXRET				-0.003***				-0.002***	
				(-5.14)				(-3.39)	
ESKEW					-0.002***				-0.002**
					(-2.6)				(-2.03)
MIS × JACKPOT						-0.003***			
						(-6.12)			
MIS × LIDX							-0.002***		
							(-7.53)		
MIS × MAXRET								-0.002***	
								(-7.6)	
MIS × ESKEW									-0.001***
									(-3.95)
Log(ME)	-0.002**	-0.002***	-0.002***	-0.002**	-0.001*	-0.002***	-0.002***	-0.002***	-0.002**
	‘(-2.26)	(-2.67)	(-3.5)	(-2.55)	(-1.72)	(-3.18)	(-3.12)	(-3.18)	(-2.44)
Log(B/M)	0.003***	0.004***	0.004***	0.003***	0.004***	0.003***	0.003***	0.003***	0.003***
	(5.29)	(6.01)	(5.98)	(5.83)	(6.14)	(5.06)	(4.95)	(4.96)	(5.14)
RET[-12,-2]	0.004***	0.006***	0.006***	0.006***	0.005***	0.004***	0.004***	0.004***	0.003***
	(4.56)	(5.89)	(6.56)	(6.25)	(5.35)	(4.07)	(4.54)	(4.5)	(3.47)
RET[-1,0]	-0.007***	-0.007***	-0.007***	-0.006***	-0.007***	-0.007***	-0.007***	-0.006***	-0.007***
	(-11.47)	(-11.01)	(-11.01)	(-8.06)	(-10.06)	(-11.86)	(-12.02)	(-9.39)	(-11.09)
Average Number of Observations	3033	3146	3082	3083	3200	3072	3032	3033	3153
Average Adjusted R^2	0.042	0.042	0.046	0.045	0.039	0.047	0.048	0.047	0.044

Table 3 (Continued)

Panel B: Robustness Tests								
Test	MIS × JACKPOT	Avg N	MIS × LIDX	Avg N	MIS × MAXRET	Avg N	MIS × ESKEW	Avg N
Baseline	-0.003***	3072	-0.002***	3032	-0.002***	3033	-0.001***	3153
	(-6.12)		(-7.53)		(-7.6)		(-3.95)	
Basic Robustness Checks								
(1) No Winsorization	-0.002***	3072	-0.002***	3032	-0.002***	3033	-0.001***	3153
	(-4.37)		(-7.66)		(-6.85)		(-3.91)	
(2) Exclude Price ≤ 5	-0.003***	2385	-0.002***	2355	-0.002***	2356	-0.002***	2433
	(-8.14)		(-8.33)		(-7.37)		(-5.82)	
(3) Exclude Micro-Cap Stocks	-0.009***	1351	-0.002***	1335	-0.002***	1336	-0.002***	1385
	(-5.49)		(-6.92)		(-6.04)		(-4.55)	
(4) Exclude Mega-Cap Stocks	-0.003***	2811	-0.002***	2773	-0.002***	2775	-0.001***	2889
	(-6)		(-8.03)		(-7.41)		(-4.12)	
(5) Exclude NASDAQ Stocks	-0.002***	1549	-0.002***	1531	-0.001***	1532	-0.001***	1582
	(-4.81)		(-6.71)		(-4.95)		(-4.22)	
Subperiods								
(6) Recession Periods	-0.005***	1731	-0.002**	1730	-0.003***	1731	-0.001	1647
	(-2.67)		(-2.56)		(-3.83)		(-1.5)	
(7) Expansion Periods	-0.003***	2782	-0.001***	2745	-0.002***	2746	-0.001***	2858
	(-5.39)		(-6.7)		(-6.5)		(-2.96)	
(8) 1962 - 1990	-0.001***	2658	-0.001***	2594	-0.001***	2596	N/A	
	(-3.18)		(-3.01)		(-3.35)			
(10) 1991-2015	-0.004***	3526	-0.003***	3526	-0.003***	3526	-0.004***	3456
	(-5.79)		(-7.53)		(-8.38)		(-4.55)	

Table 4: Option-Based Skewness Tests

This tables presents double sorting and Fama-Macbeth regression results based on the option-based idiosyncratic skewness measure (OS) of Conrad et al. (2013). The double sorting and regression methodologies are the same as those described in Tables 2 and 3, respectively. All variables are defined in Table A.1. The sample period covers January 1996 to December 2015, as the option price data for older periods are not available on the Optionmetrics database.

Panel A: Double Sorts

OS quintile	Most Underpriced	Most Overpriced	Most Overpriced - Most Underpriced
Low	0.21	0.28	0.1
	(1.22)	(0.43)	(0.14)
2	0	-1.86***	-1.7***
	(0.02)	(-3.43)	(-2.99)
3	0.44*	-1.72***	-2.04***
	(1.89)	(-2.82)	(-2.95)
4	0.08	-0.82	-0.99*
	(0.27)	(-1.49)	(-1.65)
High	0.52	-1.66***	-2.13***
	(1.04)	(-2.9)	(-2.98)
High - Low	0.31	-1.55**	-2.06**
	(0.58)	(-2.04)	(-2.23)

Panel B: Fama-Macbeth Estimates

	(1)	(2)
Intercept	-0.001	0.005
	(-0.16)	(0.61)
MIS		-0.003**
		(-2.31)
OS	0	-0.001
	(-0.59)	(-1.43)
MIS × OS		-0.003**
		(-2.29)
Log(ME)	0.003	0
	(1.22)	(0.08)
Log(B/M)	0.001	0.001
	(0.39)	(0.71)
RET[-12,-2]	0.003	0.002
	(1.3)	(0.79)
RET[-1,0]	0.002	0.002
	(1.27)	(1.27)
Average Number of Observations	279	278
Average Adjusted R^2	0.10	0.11

Table 5: Individual Investor Portfolio Weight Regressions

This table presents estimates from Fama-Macbeth regressions, where the dependent variables are the raw weight (columns (1) to (4)) and the excess weight (columns (5) to (8)) allocated to overpriced stocks relative to undepriced ones in each investor portfolio at the end of every month. Overpriced (underpriced) stocks are defined as those in the fifth (first) quintile of MIS. The raw and the excess relative weights are defined as $W_{i,t}^{overpriced} - W_{i,t}^{underpriced}$ and $EW^{overpriced} - EW^{underpriced} = [(W_{i,t}^{overpriced} - W_{mkt,t}^{overpriced}) - (W_{i,t}^{underpriced} - W_{mkt,t}^{underpriced})]$, respectively. $W_{i,t}^{overpriced}$ is the raw weight allocated to overpriced stocks in portfolio i at the end of month t, $W_{i,t}^{underpriced}$ is the raw weight allocated to underpriced stocks in portfolio i at the end of month t, $W_{mkt,t}^{overpriced}$ is the raw weight allocated to overpriced stocks in the market portfolio at the end of month t and $W_{mkt,t}^{underpriced}$ is the raw weight allocated to underpriced stocks in the market portfolio at the end of month t. In Panel A, our main independent variables are the average portfolio weight an investor allocated to stocks with skewness levels above the sample median over the past 12 months. We use four different skewness measures of JACKPOT, LIDX, MAXRET and ESKEW to compute this weight. In Panel B, we estimate the same models but modify our measures of past weight on skewed stocks to exclude all stocks that are allocated to MIS quintiles 1 or 5. We include a wide range of socioeconomic and portfolio characteristics control variables in both Panels. For brevity, we do not report the control variable coefficients in Panel B. All variables are defined in Table A.1. We standardize all independent variables in our regressions to have a mean of zero and a standard deviation of one and winsorize them at their 0.5 and 99.5 percentile levels. Standard errors are adjusted for heteroscedasticity and autocorrelation using the Newey and West (1987) approach. The sample period is January 1991 to December 1996.

Panel A: Baseline Estimates								
	$W^{overpriced} - W^{underpriced}$				$EW^{overpriced} - EW^{underpriced}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	-0.317***	-0.319***	-0.317***	-0.313***	-0.075***	-0.076***	-0.075***	-0.313***
	(-9.57)	(-9.97)	(-10.34)	(-10.96)	(-4.63)	(-4.74)	(-4.59)	(-10.96)
$W_{JACKPOT}$	0.142***				0.107***			
	(20.45)				(16.61)			
W_{LIDX}		0.17***				0.129***		
		(20.19)				(23.05)		
W_{MAXRET}			0.184***				0.139***	
			(21.09)				(20.67)	
W_{ESKEW}				0.116***				0.087***
				(17.45)				(20.63)
Portfolio α	-0.004	-0.006	-0.008	0	-0.005	-0.006	-0.008	-0.003
	(-0.13)	(-0.24)	(-0.27)	(-0.01)	(-0.2)	(-0.31)	(-0.34)	(-0.09)
Portfolio Return	-0.153***	-0.161***	-0.167***	-0.158***	-0.121***	-0.127***	-0.131***	-0.124***
	(-4.65)	(-5.83)	(-5.3)	(-4.59)	(-4.74)	(-5.9)	(-5.41)	(-4.7)
Portfolio Variance	0.183***	0.154***	0.132***	0.217***	0.148***	0.125***	0.109***	0.173***
	(8.22)	(9.94)	(7.42)	(9.43)	(8.73)	(10.55)	(8.03)	(10.07)
Local Weight	-0.012***	-0.014***	-0.022***	-0.008**	-0.01***	-0.011***	-0.018***	-0.007**
	(-2.84)	(-4.24)	(-4.79)	(-2.23)	(-2.74)	(-3.85)	(-4.35)	(-2.24)
Industry	-0.118***	-0.118***	-0.119***	-0.121***	-0.122***	-0.122***	-0.122***	-0.124***
Concentration	(-17.95)	(-21.09)	(-21.05)	(-19.13)	(-20.45)	(-23.35)	(-23.27)	(-21.61)
Diversification	0.013***	0.009***	0.007***	0.017***	0.013***	0.011***	0.009***	0.016***
	(5.31)	(4.38)	(3.56)	(5.89)	(6.77)	(5.72)	(5.37)	(7.01)
Ln(Portolio Size)	-0.013**	-0.001	-0.005	-0.014**	-0.001	0.008*	0.005	-0.002
	(-2.02)	(-0.14)	(-0.98)	(-2.33)	(-0.25)	(1.7)	(1.06)	(-0.35)
Age (Years)	0.015***	0.015***	0.021***	0.012***	0.012***	0.011***	0.016***	0.009***
	(7.26)	(7.43)	(10.59)	(4.76)	(7.07)	(6.87)	(10.09)	(4.65)
Male Dummy	0.009***	0.008***	0.006***	0.01***	0.007***	0.006***	0.005***	0.007***
	(8.83)	(6.25)	(5.75)	(8.19)	(9.52)	(7.12)	(5.92)	(8.99)

Table 5 (Continued)

Panel A (Continued):								
	$W^{overpriced} - W^{underpriced}$				$EW^{overpriced} - EW^{underpriced}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Married Dummy	-0.01***	-0.01***	-0.009***	-0.011***	-0.007***	-0.007***	-0.006***	-0.008***
	(-4.98)	(-4.71)	(-4.44)	(-6)	(-4.22)	(-3.85)	(-3.72)	(-5.06)
Tenant Dummy	0.005**	0.006***	0.005***	0.006***	0.003**	0.004***	0.003***	0.004***
	(2.64)	(3.2)	(3.1)	(3.33)	(2.35)	(2.9)	(2.7)	(3.07)
CPRATIO	0.005***	0.004***	0.004**	0.006***	0.004**	0.003**	0.003*	0.005***
	(3.2)	(2.78)	(2.12)	(4.34)	(2.64)	(2.31)	(1.82)	(3.6)
Ln(Population)	-0.012***	-0.011***	-0.012***	-0.013***	-0.01***	-0.009***	-0.01***	-0.011***
	(-3.65)	(-3.02)	(-2.95)	(-3.75)	(-4.25)	(-3.49)	(-3.43)	(-4.26)
Income Equality	-0.024***	-0.027***	-0.035***	-0.023***	-0.02***	-0.022***	-0.029***	-0.02***
(%)	(-4.48)	(-6.26)	(-6.7)	(-4.21)	(-4.86)	(-6.64)	(-6.61)	(-4.46)
Ln(Household	-0.034***	-0.038***	-0.044***	-0.034***	-0.028***	-0.031***	-0.036***	-0.028***
Income)	(-12.22)	(-13.57)	(-24.58)	(-14.28)	(-14.1)	(-14.62)	(-28.5)	(-15.99)
Minority (%)	0.004	0.001	0.001	0.003	0.003	0.001	0.001	0.003
	(1.05)	(0.19)	(0.18)	(0.86)	(0.94)	(0.22)	(0.22)	(0.79)
Rural (%)	-0.003	-0.004*	-0.003	-0.003*	-0.003	-0.004*	-0.003	-0.003*
	(-1.46)	(-1.93)	(-1.21)	(-1.94)	(-1.66)	(-2)	(-1.38)	(-1.96)
Education (%)	-0.006*	-0.005**	-0.011***	-0.005	-0.004*	-0.004*	-0.008***	-0.003
	(-1.91)	(-2.04)	(-3.99)	(-1.64)	(-1.86)	(-1.87)	(-3.78)	(-1.42)
Average Number of Observations	6477	6477	6477	6477	6477	6477	6477	6477
Average Adjusted R^2	0.248	0.267	0.272	0.234	0.245	0.261	0.266	0.233

Panel B: Skewness Weights Excluding Overpriced and Underpriced Stocks								
	$W^{overpriced} - W^{underpriced}$				$EW^{overpriced} - EW^{underpriced}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$W_{JACKPOT}$	0.076***				0.056***			
	(15.88)				(13.6)			
W_{LIDX}		0.113***				0.085***		
		(21.44)				(21.31)		
W_{MAXRET}			0.104***				0.077***	
			(8.77)				(8.33)	
W_{ESKEW}				0.073***				0.055***
				(8.51)				(8.14)

Table 6: Fama-Macbeth Regressions Controlling for Coskewness

This table presents Fama-Macbeth regression estimates after controlling for the effect of coskewness. We take the regression specifications in Table 3 and add a measure of coskewness and its interaction with MIS to all regressions. In Panel A, we define coskewness (COSKEW) following the original definition of Harvey and Siddique (2000). In Panel B, we adopt Harvey and Siddique's (2000) alternative measure of coskewness defined as the regression coefficient on a squared market factor. All variables are defined in Table A.1. We standardize all independent variables in our regressions to have a mean of zero and a standard deviation of one and winsorize them at their 0.5 and 99.5 percentile levels. Standard errors are adjusted for heteroscedasticity and autocorrelation using the Newey and West (1987) approach. The sample excludes penny stocks and covers January 1963 to December 2015, except for regression that include ESKEW which start in January 1988.

	(1)	(2)	(3)	(4)	(5)
Panel A: Coskewness Based on the Original Harvey and Siddique (2000) Definition (COSKEW)					
Intercept	0.011***	0.01***	0.01***	0.01***	0.009***
	(4.7)	(3.9)	(4.32)	(4.13)	(3.69)
MIS		-0.004***	-0.004***	-0.004***	-0.004***
		(-10.53)	(-12.96)	(-11.18)	(-11.17)
JACKPOT		-0.001			
		(-1.12)			
LIDX			0		
			(-0.16)		
MAXRET				-0.002**	
				(-2.55)	
ESKEW					-0.001
					(-1.4)
COSKEW	0	0	0*	0	0
	(-1.2)	(-1.21)	(-1.77)	(-1.28)	(-1.52)
MIS × JACKPOT		-0.002***			
		(-3.6)			
MIS × LIDX			-0.002***		
			(-6.62)		
MIS × MAXRET				-0.002***	
				(-6.35)	
MIS × ESKEW					-0.001***
					(-3.85)
MIS × COSKEW		0	0	0	0
		(-0.24)	(-0.68)	(-0.29)	(-0.81)
Log(ME)	-0.001	-0.002***	-0.002***	-0.002***	-0.001**
	(-1.47)	(-2.98)	(-2.71)	(-2.98)	(-1.98)
Log(B/M)	0.003***	0.003***	0.003***	0.003***	0.003***
	(5.21)	(4.84)	(4.62)	(4.66)	(4.92)
RET[-12,-2]	0.005***	0.003***	0.003***	0.003***	0.003***
	(5.22)	(3.48)	(3.71)	(3.69)	(3.11)
RET[-1,0]	-0.007***	-0.008***	-0.008***	-0.007***	-0.007***
	(-11.34)	(-12.24)	(-12.42)	(-10.04)	(-11.69)
Average Number of Observations	2173	2154	2154	2154	2198
Average Adjusted R^2	0.043	0.052	0.053	0.052	0.048

Table 6 (Continued)

Panel B: Coskewness Defined as the Coefficient on the Squared Market Factor (β_{m^2})					
β_{m^2}	-0.001	0	-0.001	0	-0.001
	(-0.53)	(-0.55)	(-0.72)	(-0.4)	(-0.6)
MIS × JACKPOT		-0.003***			
		(-6.05)			
MIS × LIDX			-0.002***		
			(-7.65)		
MIS × MAXRET				-0.002***	
				(-7.2)	
MIS × ESKEW					-0.001***
					(-3.96)
MIS × β_{m^2}		0	0	0	0
		(0.15)	(-0.34)	(-0.16)	(-0.19)
Average Number of Observations	3084	3072	3032	3033	3153
Average Adjusted R^2	0.041	0.048	0.05	0.048	0.045

Table 7: Fama-Macbeth Regressions Controlling for Limits to Arbitrage

This table presents Fama-Macbeth regression estimates after controlling for limits to arbitrage. We take the regression specifications in Table 3 and add five proxies for limits to arbitrage and their interactions with MIS to each specification, separately. Panels A to E report the results based on each of the five proxies. ILLIQ is the illiquidity measure of Amihud (2002), SHORTINT is the short interest ratio following Hanson and Sunderam (2014), BIDASK is the bid-ask spread, %ZEROS is the frequency of zero daily returns devised by Lesmond et al. (1999) and IHOLDING is the percentage institutional holding. The construction details of all variables are explained in Table A.1. For brevity, we only report the coefficients on the interaction terms and the proxies for limits to arbitrage. All independent variables in the regressions are standardized to have a mean of zero and a standard deviation of one and are winsorized at their 0.5 and 99.5 percentile levels. Standard errors are adjusted for heteroscedasticity and autocorrelation using the Newey and West (1987) approach. The sample excludes penny stocks and covers January 1963 to December 2015, except for regression that include ESKEW which start in January 1988 and those including SHORTINT and IHOLDING which due to data availability start from January 1973 and January 1980, respectively.

	(1)	(2)	(3)	(4)
	Panel A: ILLIQ			
ILLIQ	0.003***	0.003***	0.003***	0.002***
	(3.37)	(2.94)	(3.12)	(2.71)
MIS × JACKPOT	-0.004***			
	(-5.82)			
MIS × LIDX		-0.002***		
		(-8.96)		
MIS × MAXRET			-0.003***	
			(-10.5)	
MIS × ESKEW				-0.002***
				(-5.01)
MIS × ILLIQ	0.002***	0.002***	0.002***	0.002***
	(3.99)	(3.51)	(2.94)	(2.9)
Average Number of Observations	3097	3096	3097	3047
Average Adjusted R^2	0.049	0.051	0.049	0.048
	Panel B: SHORTINT			
SHORTINT	-0.002	-0.002	-0.001	-0.002
	(-1.13)	(-1.09)	(-0.95)	(-1.22)
MIS × JACKPOT	-0.004***			
	(-4.2)			
MIS × LIDX		-0.002***		
		(-6.76)		
MIS × MAXRET			-0.002***	
			(-5.67)	
MIS × ESKEW				-0.002***
				(-4.61)
MIS × SHORTINT	-0.002*	-0.002*	-0.002	-0.002**
	(-1.74)	(-1.76)	(-1.19)	(-2.11)
Average Number of Observations	1629	1629	1629	1597
Average Adjusted R^2	0.054	0.053	0.052	0.052

Table 7 (Continued)

Panel C: BIDASK				
BIDASK	0.003	0.003*	0.004**	0.004*
	(1.63)	(1.67)	(2.11)	(1.85)
MIS × JACKPOT	-0.004***			
	(-3.19)			
MIS × LIDX		-0.003***		
		(-6.98)		
MIS × MAXRET			-0.003***	
			(-5.62)	
MIS × ESKEW				-0.003***
				(-5.68)
MIS × BIDASK	0	0.002*	0	0.002
	(0.43)	(1.67)	(-0.16)	(1.34)
Average Number of Observations	2860	2859	2860	2810
Average Adjusted R^2	0.043	0.044	0.042	0.041
Panel D: %ZEROS				
%ZEROS	-0.001	-0.001	-0.001	-0.002
	(-0.54)	(-0.36)	(-0.65)	(-0.74)
MIS × JACKPOT	-0.004***			
	(-6.96)			
MIS × LIDX		-0.002***		
		(-9.44)		
MIS × MAXRET			-0.002***	
			(-10.88)	
MIS × ESKEW				-0.002***
				(-6.18)
MIS × %ZEROS	0	0.002**	0	0.001
	(0.55)	(2.18)	(-0.28)	(1.55)
Average Number of Observations	3370	3368	3370	3252
Average Adjusted R^2	0.047	0.049	0.047	0.046
Panel E: IHOLDING				
IHOLDING	-0.048	-0.049	-0.053	-0.039
	(-1.34)	(-1.35)	(-1.4)	(-1.29)
MIS × JACKPOT	-0.003***			
	(-5.38)			
MIS × LIDX		-0.002***		
		(-7.41)		
MIS × MAXRET			-0.002***	
			(-8.76)	
MIS × ESKEW				-0.001***
				(-3.28)
MIS × IHOLDING	0.092	0.095	0.096	0.068
	(1.4)	(1.46)	(1.5)	(1.46)
Average Number of Observations	3487	3486	3487	3392
Average Adjusted R^2	0.038	0.039	0.038	0.037

Table 8: **Ability of a Skewness Factor to Capture Anomaly Alphas**

Panels A and B present the alphas and the t-statistics of 11 anomaly strategies based on various asset pricing models. In Panel C we present a set of summarizing performance measures for each model including the average absolute alpha, average absolute t-statistic of alpha, the Gibbons et al. (1989) statistics (GRS) and the p-value corresponding to the GRS statistics. We devise a skewness factor, denoted NMS, and add it to the following four prominent models: Fama and French (1993) three-factor (FF3), Carhart (1997) four-factor (CAR), Fama and French (2015) five-factor (FF5) and Fama and French (2015) with the addition of momentum (FF6). We construct NMS in four steps. First, we compute the average decile rank of each stock at the end of every month with respect to the four skewness measures of JACKPOT, LIDX, MAXRET and ESKEW. Next, we independently sort stocks based on their average skewness decile ranks and their market capitalization into three and two portfolios, respectively. We then compute the value-weighted monthly return of each of the 6 intersecting portfolios. Lastly, we take the average of the returns of the two size portfolios with the highest skewness trecile rank and deduct it from the average return of the two size portfolios with the lowest trecile rank to get monthly factor returns. The sample excludes penny stocks and covers January 1963 to December 2015, except for distress and return-on-assets anomalies which due to data availability start from January 1973.

Anomaly	FF3	FF3 + NMS	CAR	CAR + NMS	FF5	FF5 + NMS	FF6	FF6 + NMS
				Panel A: Alphas				
Accruals	0.009	0.011	0.007	0.010	0.009	0.011	0.008	0.010
Asset Growth	0.004	0.003	0.004	0.003	0.001	0.001	0.002	0.001
Composite Equity Issues	0.004	0.005	0.004	0.005	0.005	0.006	0.005	0.005
Distress	0.019	0.012	0.010	0.005	0.012	0.008	0.005	0.003
Gross Profitability	0.008	0.005	0.007	0.004	0.001	0.001	0.001	0.001
Investment-to-Assets	0.006	0.006	0.005	0.006	0.005	0.005	0.004	0.005
Momentum	0.022	0.020	0.006	0.007	0.019	0.018	0.006	0.007
Net Operating Assets	0.009	0.009	0.008	0.009	0.009	0.009	0.008	0.008
Net Stock Issues	0.008	0.006	0.008	0.006	0.004	0.003	0.004	0.004
O-Score	0.009	0.006	0.008	0.005	0.006	0.005	0.005	0.004
Return on Assets	0.012	0.008	0.010	0.007	0.006	0.005	0.005	0.005

Table 8 (Continued)

Anomaly	FF3	FF3 + NMS	CAR	CAR + NMS	FF5	FF5 + NMS	FF6	FF6 + NMS
				Panel B: t-Statistics				
Accruals	4.467	5.221	3.802	4.688	4.676	5.195	4.150	4.760
Asset Growth	2.632	1.941	2.665	2.002	0.720	0.496	1.090	0.807
Composite Equity Issues	2.726	3.357	2.603	3.234	3.769	3.898	3.579	3.740
Distress	6.241	3.637	3.986	2.044	4.170	2.536	2.320	1.210
Gross Profitability	4.285	2.587	3.575	2.104	0.596	0.706	0.363	0.512
Investment-to-Assets	4.633	4.537	3.891	3.974	4.001	3.941	3.528	3.559
Momentum	6.886	5.710	4.253	4.144	5.773	5.044	4.214	4.155
Net Operating Assets	6.090	5.612	5.420	5.120	6.000	5.515	5.498	5.124
Net Stock Issues	5.915	4.114	5.884	4.184	3.217	2.622	3.620	2.975
O-Score	5.865	3.664	5.146	3.196	4.510	3.414	4.037	3.057
Return on Assets	5.618	3.504	4.621	2.933	3.439	2.748	2.773	2.320
				Panel C: Model Performance				
Average $\|\alpha\|$	0.010	0.008	0.007	0.006	0.007	0.006	0.005	0.005
Average $\|t\|$	5.033	3.989	4.168	3.420	3.715	3.283	3.197	2.929
GRS	10.436	7.269	8.293	6.701	7.852	6.524	6.870	6.471
p(GRS)	0	1.44E-11	1.91E-13	1.60E-10	1.24E-12	3.40E-10	7.86E-11	4.25E-10

Table A.1: Variable Description

This table defines the main variables used in the empirical analysis.

Variable Name	Source	Description
		Panel A: Skewness and Anomaly Variables
β_{m^2}	CRSP	This is computed following Harvey and Siddique (2000) by estimating the following model: $$R_{i,t} - R_{f,t} = \alpha_i + \beta_{m,i}(R_{m,t} - R_{f,t}) + \beta_{m^2,i}(R_{m,t} - R_{f,t})^2 + \epsilon_{i,t}$$ where $R_{i,t}$ is the return on stock i on day t, $R_{m,t}$ is the market return on day t and $R_{f,t}$ is the risk-free rate on day t. We estimate the above regression using daily returns for the most recent month.
COSKEW	CRSP	Harvey and Siddique (2000) use this as their main measure of coskewness computed as follows: $$COSKEW_{i,t} = \frac{E[\epsilon_{i,t}\epsilon_{m,t}^2]}{\sqrt{E[\epsilon_{i,t}^2]}E[\epsilon_{m,t}^2]}$$ where $\epsilon_{i,t} = R_{i,t} - R_{f,t} - \alpha_i - \beta_i(R_{m,t} - R_{f,t})$, $R_{i,t}$ is the return on stock i on month t, $R_{m,t}$ is the market return on month t and $R_{f,t}$ is the risk-free rate on month t. We estimate the above regression using monthly returns for the past 60 months.
ESKEW	CRSP	Following Boyer et al. (2010), this is defined by running a cross-sectional regression at the end of every month using the most recent five years of data to predict the daily idiosyncratic skewness of stocks estimated over the following five years. Variables used in the regression include the historical estimates of daily idiosyncratic volatility and skewness relative to the Fama-French three-factor model over the past 60 months, momentum as the cumulative returns over months $t-12$ through $t-1$, turnover as the average daily turnover in month $t-1$, small-size and medium-size market capitalisation dummies (based on sorts of firms by market capitalisation into three groups of small, medium and large), industry dummy based on the Fama-French 17 industries and NASDAQ dummy. After estimating the model at the end of every month t, we use the parameters together with the most recent data to get out-of-sample expected idiosyncratic skewness estimates for months $t+61$ through $t+120$. Our estimates start in 1988 because detailed data on the trading volume of NASDAQ stocks become available in the 1983.

Table A.1: (Continued)

Variable Name	Source	Description
		Panel A (Continued): Skewness and Anomaly Variables
JACKPOT	CRSP and Compustat	Conrad et al. (2014) compute this by running a logit model at the end of June of every year to predict the out-of-sample probability of a stock generating a log return greater than 100% in the next 12 months. Variables used in the logit regression are the stock's (log) return over the last 12 months, volatility and skewness of daily log returns over the past three months, de-trended stock turnover [(6-month volume/shares outstanding) − (18-month volume/shares outstanding)], and log market capitalisation. The model is estimated following a rolling window approach using data from the past 10 years. Unlike Conrad et al. (2014) that use the data from the past 20 years, we only require 10 years of historical data for each rolling window estimation. Considering that Compustat Fundamentals databased starts in 1950, a shorter estimation window enables us to start our parameter estimates from 1963. After estimating the logit model at the end of June of year t, the estimated parameters are used together with the most recently available data to estimate a jackpot score for every stock from July of year t to the end of June of year $t+1$.
LIDX	CRSP	Following Kumar et al. (2016), this is defined as the sum of the vigintile allocation of stocks with respect to price, idiosyncratic volatility and idiosyncratic skewness divided by 60. Vigintiles are defined such that stocks with the lowest price, the highest idiosyncratic skewness and the highest idiosyncratic volatility are allocated to the highest corresponding vigintile groups. All stocks in the sample are sorted at the end of each month based on the three characteristics to compute the lottery index for the following month. Price is the monthly closing price. Idiosyncratic volatility is defined as the standard deviation of the residuals from fitting the four-factor model of Carhart (1997) on the past six months daily return data. Idiosyncratic skewness refers to the skewness of residuals obtained from a two-factor model estimated using the past six months daily return data, with the two factors being the market factor and its square.

Table A.1: (Continued)

Variable Name	Source	Description
		Panel A (Continued): Skewness and Anomaly Variables
MAXRET	CRSP	Bali et al. (2011) define this as the maximum daily return in the previous month.
MIS	CRSP and Compustat	Following Stambaugh et al. (2015), MIS is the average of decile ranks of a stock with respect to 11 prominent anomalies. Sorting for each anomaly is performed at the end of every month with deciles 1 and 10 including stocks that each anomaly strategy predicts will outperform and underperform in the following month, respectively. Unlike Stambaugh et al. (2015), we determine our decile cutoffs using our whole sample and not just NYSE stocks. We require at least 5 non-missing anomaly decile ranks to compute MIS for a stock. The 11 anomaly strategies considered are accruals (Sloan, 1996), asset growth (Cooper et al., 2008), composite equity issues (Daniel and Titman, 2006), distress (Campbell et al., 2008), gross pro tability (Novy-Marx, 2013), investment-to-assets (Titman et al., 2004), momentum (Jegadeesh and Titman, 1993), net operating assets (Hirshleifer et al., 2004), net stock issues (Ritter, 1991; Loughran and Ritter, 1995), O-score (Ohlson, 1980), and return on assets (Fama and French, 2006). We follow the detailed description of Stambaugh et al. (2012, 2015) together with the corresponding anomaly literature to replicate each strategy.
ISKEWNESS	CRSP	Skewness of residuals obtained from running the the four-factor model of Carhart (1997) on daily returns for the most recent month.
OS	Optionmetrics	This is defined following Conrad et al. (2013) and Bakshi et al. (2003) as the third moment of the risk-neutral density function of a security constructed using a set of out-of-the-money option prices with different strike price on that security. Our sample of out-of-the-money calls and puts include securities that have expiration dates that are closest to 0.250 years (3 months). We choose this time to maturity because the measure based on options with 3 months to maturity has the strongest return predictability in Conrad et al. (2013). Our estimation technique and option data filters closely follow those stated in Conrad et al. (2013).
SKEWNESS	CRSP	Skewness of daily returns for the most recent month.

Table A.1: (Continued)

Variable Name	Source	Description
		Panel B: All Other Control Variables
%ZEROS	CRSP	Devised by Lesmond et al. (1999) as the percentage of daily returns of each stock that are equal to zero. We measure this using the past 12 months of daily returns for each firm.
B/M	CRSP and Compustat	Ratio of the book-value to the market capitalization of the firm.
BIDASK	CRSP	The average daily bid-ask spread over the past 12 months.
IHOLDING	Thomson Reuters	The fraction of a stock's outstanding shares held by institutional investors. We obtain the stock's institutional holdings by aggregating the positions of its institutional investors. If the Thomson Reuters database does not have data on a particular stock, we set the stock's institutional holdings to zero.
ILLIQ	CRSP	Annual average of the daily ratio of absolute stock return to daily dollar trading volume following Amihud (2002).
IVOL	CRSP	Volatility of residuals obtained from running the the four-factor model of Carhart (1997) on daily returns for the most recent month.
LEVERAGE	CRSP and Compustat	The sum of total debt in current liabilities plus total long-term debt, all divided by total assets.
ME	CRSP	Price times shares outstanding.
PRICE	CRSP	Monthly closing price.
RET[-1,0]	CRSP	Buy-and-hold return over the previous month.
RET[-12,-2]	CRSP	The prior years monthly-compounded buy-and-hold return skipping the last month.
RHOLDING	Brokerage	Percentage of total shares outstanding owned by individuals in the brokerage sample.
SHORTRATIO	Compustat	Average ratio of short interest to shares outstanding over the past 12 months.
TURNOVER	CRSP	Total trading volume over the last month divided by shares outstanding.
VOLATILITY	CRSP	Volatility of daily returns for the most recent month.

Table A.1: (Continued)

Variable Name	Source	Description
		Panel C: Variables Used in the Individual Holdings Regressions
Age (Years)	Brokerage	The portfolio holder's age.
CPRATIO	ARDA	Ratio of Catholic population to Protestant population in the portfolio holder's county.
Diversification	Brokerage and CRSP	Portfolio variance divided by the average variance of all stocks in the portfolio.
Education	1990 Census	Proportion of residents in the portfolio holder's county with a Bachelor's or higher educational degree.
Income Equality	1990 Census	Ratio of the number of households in the lowest annual income group (less than \$10,000) to those in the highest annual income group (\$150,000 or more) in the portfolio holder's county.
Industry Concentration	Brokerage and CRSP	Largest weight allocated to one of the 48 Fama-French industries.
Ln(Household Income)	1990 Census	Natural log of annual household income in the portfolio holder's county.
Ln(Population)	1990 Census	Natural log of the portfolio holder's home county population.
Ln(Portolio Size)	Brokerage	Natural log of the size of the portfolio.
Local Weight	Brokerage	Portfolio weight allocated to stocks located in the portfolio holder's home state.
Male Dummy	Brokerage	Set to one if the portfolio holder is a male.
Married Dummy	Brokerage	Set to one if the portfolio holder is married.
Minority	1990 Census	Proportion of the population that is not white in the portfolio holder's county.
Portfolio Return	Brokerage and CRSP	Monthly-compounded portfolio returns over the past 12 months.

Table A.1: (Continued)

Variable Name	Source	Description
Panel C (Continued): Variables Used in the Individual Holdings Regressions		
Portfolio Variance	Brokerage and CRSP	Variance of the portfolio estimated using the past 12 months of returns.
Portfolio α	Brokerage and CRSP	Intercept of the regression of monthly portfolio returns on the four-factors of Carhart (1997) estimated using the past 12 months of data.
Rural	1990 Census	Proportion of the population that lives in rural areas in the portfolio holder's county.
Tenant Dummy	Brokerage	Set to one if the portfolio holder lives in a rental property.
W_{ESKEW}	Brokerage	Average monthly weight allocated to stocks with ESKEW values above the cross-sectional median over the past 12 months.
$W_{JACKPOT}$	Brokerage	Average monthly weight allocated to stocks with JACKPOT values above the cross-sectional median over the past 12 months.
W_{LIDX}	Brokerage	Average monthly weight allocated to stocks with LIDX values above the cross-sectional median over the past 12 months.
W_{MAXRET}	Brokerage	Average monthly weight allocated to stocks with MAXRET values above the cross-sectional median over the past 12 months.