Mispricing, Market Anomalies, and Investor Behaviour

by

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Declarations

I declare the following:

– This thesis has not been submitted for a degree to any other university.

– Chapter 2, entitled *"The Other Side of Lottery: The Profitability Premium"*, is co-authored with Dr. Asad Kausar and Professor Richard J. Taffler.

– Chapter 3, entitled *"Skewness Preference and Market Anomalies"*, is co-authored with Professor Alok Kumar and Professor Richard J. Taffler.

– Chapter 4, entitled *"Do Geography and Industry Predict Mispricing?"*, is an independent paper, but has benefited immensely from the feedback from Professor Alok Kumar and Professor Richard J. Taffler.

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Abstract

The thesis explores various sources of commonality in market mispricing and their underlying drivers and effects. In this context, mispricing is defined and measured by looking at market anomalies, patterns in prices not explained by conventional asset pricing models. There has not been a consensus in the literature regarding the reason(s) why market anomalies appear. Therefore, my investigation of the underlying drivers that link the phenomenon to mispricing can contribute to our understanding in this area. In my three main chapters, I consider two main sources of common mispricing in the market: investors preference for skewness and heterogeneous behaviours of investors in different states and industries.

In Chapters 2 and 3, I focus on investors preference for skewness. There is an emerging line of behavioural finance research showing that there is a group of investors in the market that have a preference to hold positively-skewed positions at the expense of under-diversification. This preference then leads to stocks with higher levels of skewness to be overpriced and generate lower market returns. In particular I demonstrate how the preference for skewness can play a bigger role in explaining market anomalies.

I begin by looking at the profitability premium in Chapter 2. I find that less profitable firms in the cross-section exhibit higher measures of skewness than their more profitable counterparts. Because of this, investors with a preference for skewness are attracted towards less profitable firms and away from more profitable ones, inter alia contributing to the profitability premium. In Chapter 3, I take a more holistic approach and consider the common mispricing-related component of 11 prominent market anoma-

lies. I show that the anomaly strategies, to the extent that are related to mispricing, are driven by the preference for skewness. I also introduce a factor that captures skewness-related mispricing and improves the performance of conventional asset pricing models in explaining anomalies.

Finally, in Chapter 4. I document a phenomenon not studied before. That is, stocks in specific states and industries have higher levels of mispricing in terms of anomalous market behaviour. The most mispriced states do not necessarily stay mispriced for longer that 12 months, on average. However, the most mispriced industries continue to be mispriced even after 60 months. I show that state-level mispricing is likely due to heterogeneous investor sentiment and noise trading across states. Industry-level mispricing, on the other hand, is linked to earnings forecast errors made by analysts. I believe such a novel perspective on market pricing is completely original to the literature.

Chapter 1

Introduction

Market anomalies are cross-sectional patterns in average stock returns that have not been explained by exposure to systematic risk factors in asset pricing models (Fama and French, 2008). Each pattern is attributable to a specific variable that predicts future returns without capturing an established source of systematic risk. This contradicts the Efficient Market Hypothesis (Fama, 1970), which states that any cross-sectional predictability should represent a source of systematic risk. In spite of the longstanding challenge to asset pricing theory posed by anomalies, no consensus has yet been reached as to what causes so-called anomaly variables to be priced (Fama, 2014).

Recent developments, however, have shed light on various aspects of market anomalies. First, anomalies are significantly more pronounced among stocks with greater arbitrage risks and costs (e.g., Nagel, 2005; Stambaugh et al., 2015). In particular, a large part of the problem is generated by stocks that anomaly variables predict will underperform (e.g., Hirshleifer et al., 2011; Stambaugh et al., 2012; Avramov et al., 2013). Miller (1977) argues that this predictability will endure as short-selling impediments make it highly costly for arbitragers to adjust overpricing compared with underpricing. Second, greater arbitrage activity – due to either lower transaction costs or more informed market participants – has led to a decay in the performance of anomalies (e.g.,

Hanson and Sunderam, 2014; Chordia et al., 2014; McLean and Pontiff, 2016).

Lastly, there is evidence that anomalies have common underlying drivers based on the behaviors of their investor clienteles. For example, Stambaugh et al. (2012, 2014) argue that investor sentiment explains much of the common variation in anomalies in the equity market. This is because investors tend to become over-optimistic in periods of high sentiment, leading to overpricing in the market. However, this effect does not occur in the bond market due to the different characteristics of its investor clientele (Chordia et al., 2017).

The points above indicate that anomalies at least partly reflect market mispricing and, to the extent that this is the case, have commonalities. My studies in this thesis build on recent advances in behavioral finance and present new common factors that generate mispricing and thus anomalies.

I begin my thesis by considering preference for skewness as a common driver of anomalies. The behavioral literature shows that investors at the aggregate level are particularly interested in positively skewed, or lottery-like, stocks. Investors are willing to buy these stocks despite holding under-diversified positions (see Mitton and Vorkink, 2007; Brunnermeier et al., 2007). This phenomenon is shown to produce mispricing in the market in the presence of limits to arbitrage (see, e.g., Mitton and Vorkink, 2007; Kumar, 2009; Boyer et al., 2010; Bali et al., 2011; Conrad et al., 2014).

In Chapter 2, I investigate preference for skewness as a driver of the mispricing that leads to the profitability premium. This is based on the work of Novy-Marx (2013) and Ball et al. (2015) showing that firms more profitable in the cross-section outperform their less profitable peers. My main conjecture is that the positive skewness, or lottery-like features, of less profitable firms attract investors with speculative proclivities toward such stocks and away from more profitable ones. This behavior might translate into a systematic overvaluation of less profitable firms relative to more profitable ones, giving rise to the profitability premium.

Using a sample of US firms, I show that less profitable firms are more positively skewed, or lottery-like. I employ various measures of lottery characteristics to ensure that this finding is not due to noisy measurement of skewness. The profitability premium is also considerably larger and more significant among more lottery-like stocks. Similarly, more lottery-like stocks tend to be significantly more overvalued when they are relatively unprofitable. Overall, I find that investors' preference for lottery-like payoffs can at least partly explain the profitability premium.

Chapter 3 extends my investigation of investor preference for skewness and shows that this is a common driver of mispricing across a wide range of market anomalies. Specifically, I find that skewness-loving investors overweight overpriced stocks in their portfolios, which contributes to these anomalies. Using a combined measure of mispricing based on eleven prominent anomaly strategies, I demonstrate that stocks with higher skewness are significantly more mispriced than those with lower skewness. In particular, positively skewed stocks are more overpriced in the short portfolios of long-short trading strategies that are used to exploit anomalies. In contrast, underpricing in long portfolios does not vary with skewness. Finally, I construct a new factor that captures skewness-related mispricing and observe that it improves the performance of conventional asset pricing models in explaining the abnormal returns of anomalies.

In Chapter 4, I move to another growing area of behavioral finance and look at industry and geography as characteristics that can contribute to anomalies. Geography and industry are attributes shown to attract common investor clienteles (e.g., Coval and Moskowitz, 1999; Kacperczyk et al., 2005). There is also evidence demonstrating that commonality in investor clientele for firms in the same geographic region results in their biases and behaviors being reflected in prices (Kumar et al., 2013). I conjecture that in the presence of limits to arbitrage, the behaviors of investor clienteles that concentrate on specific regions or industries may exacerbate anomalies within these groups.

Following this argument, I show that the mispricing levels of a firm's geographic

or industrial peers predict how mispriced the firm will be in future. I apply the combined measure of mispricing that I use in Chapter 3 and find that states and industries in which anomalies perform better will continue to have more predictable stock returns. The mispricing levels of industrial peers are stronger predictors of future firm mispricing that those of geographic peers, but the effect of each group is not absorbed by the other. Finally, I show that geography and industry lead to mispricing for different reasons. Geographic mispricing is linked to variations in local investor sentiment, whereas industrial mispricing is related to misinformation generated by analysts.

Overall, this thesis contributes to the asset pricing literature on market anomalies. In particular, I highlight further that there are other common factors that can generate market mispricing and exacerbate anomalies. My findings also add to the behavioral finance literature that looks at investors' preference for skewness, investor clientele effects, and geographic and industrial attributes. I show that these behavioral phenomena may have asset pricing implications beyond what is already documented in the literature. They not only help us better understand the shortcomings of asset pricing theory, but also provide novel insights for devising trading strategies.

Chapter 2

The Other Side of Lottery: The Profitability Premium

2.1 Introduction

More profitable firms tend to generate higher average returns than their less profitable peers in the cross-section. This phenomenon is commonly referred to as the profitability premium and has attracted considerable academic attention since the early work of Ball and Brown (1968). Over the years, various measures of firm profitability have been proposed, almost all having significant predictive power for future stock returns. Famous examples of profitability measures include net income before extraordinary items (Ball and Brown, 1968), return on equity (Haugen and Baker, 1996), return on assets (Chen et al., 2011), and gross profitability (Novy-Marx, 2013). The gross profitability measure has also recently been subject to various refinements leading to even more robust measures of operating profitability (Ball et al., 2015) and cash profitability (Ball et al., 2015). Developments in this field have been so significant that almost all recent major asset pricing factor models include some variant of profitability as an explanatory factor (e.g., Chen et al., 2011; Hou et al., 2014; Fama and French, 2015,

2018).

The assumption behind using profitability as a factor is that the profitability characteristic is linked to some form of systematic risk. In favor of this argument, Ball et al. (2015) show that operating profitability can reliably predict returns at least four years before they occur. The authors argue that this evidence is consistent with a rational risk-based explanation for the profitability premium as other behavioral explanations can normally only justify the return predictability in the short-run. However, Wang and Yu (2013) cast doubt on a solely risk-based story showing that the profitability characteristic has a better return predictability than the loading on a mimicking factor. In addition, they find that the profitability premium is not significant among firms that are easy to arbitrage. Wang and Yu (2013) further argue that investor under-reaction can act as the main cause of the profitability premium. I contribute to this discussion by providing a new behavioral explanation suggesting that an opposite reaction to profitability information based on a group of investors' preferences for positively skewed or lottery-like payoffs can help explain the profitability premium.

Firms with the highest and the lowest profitability levels in the cross-section, which are the major drivers of the profitability premium, are fundamentally different. Less profitable firms are on average smaller, more leveraged and have cheaper, more illiquid and more volatile shares (Wang and Yu, 2013). These characteristics highlight the possibility of such stocks being positively skewed or *lottery-like* (Kumar, 2009; Conrad et al., 2014). The term lottery-like represents cheap bets with a small probability of a large payoff (Kumar, 2009). Shares possessing such features are significantly over-priced in the cross-section (Kumar, 2009; Boyer et al., 2010; Bali et al., 2011). This is because a lottery-like payoff particularly appeals to the so-called prospect theory investors who tend to over-weight the tails of the return distribution (Barberis and Huang, 2008). That is, in a market with only a fraction of investors behaving according to the prospect theory of Kahneman and Tversky (1979), firms with (without) the lottery-like features become

under- (over-) priced (Barberis et al., 2016). In fact, Kumar (2009) shows that the main investor clientele for lottery-like stocks are small (retail), unsophisticated, and from low socio-economic backgrounds. Therefore, the possible under-reaction of the market to profitability information may instead be largely driven by the aforementioned preference simply attracting a host of speculative investors toward less profitable firms and away from the profitable ones.

Specifically, I test whether the preference for lottery-like features can contribute to the mispricing of profitability information in the market. The main conjecture is that less profitable firms are more likely to possess lottery-like features in the cross-section, making them attractive gambling objects for the investor clientele who tends to favor such features. Therefore, the degree to which a less-profitable stock possesses lottery-like features can predict its level of overpricing in the market. The effect of lottery-like features on more profitable firms, however, is relatively more complex. Although more profitable firms are expected to be, on average, less-lottery like and, therefore, less attractive for lottery investors, such firms would be unlikely to attract lottery investors as much as less-profitable firms even if they were highly lottery-like. This is because profitable stocks usually perform well in the market and investors of booming stocks are less likely to demonstrate gambling propensities (Thaler and Johnson, 1990; An et al., 2018) or to show interest in the lottery-like features. In other words, the mispricing levels of profitable firms are not linked to their lottery-like features, because these firms are less likely to trigger the lottery preference in investors. Consequently, the overall profitability premium is expected to be stronger among the more lottery-like stocks. I would also expect the pricing implications of the lottery features to be more (less) pronounced among less (more) profitable firms.

Using a sample of all NYSE, AMEX, and NASDAQ stocks from January 1972 to December 2015 that meet my selection criteria, I find results that are consistent with the main propositions outlined above. I observe that there is a negative association between

profitability and the level of the lottery-like features. This relationship is consistent across the three profitability proxies used in Ball et al. (2015), i.e. gross profitability, income before extraordinary items, and operating profitability, and four different prominent proxies of the lottery-like features including the jackpot score (Conrad et al., 2014), the lottery index (Kumar et al., 2016), the maximum daily return (Bali et al., 2011)), and the expected idiosyncratic skewness (Boyer et al., 2010).

I test for the role of the lottery preference in driving the profitability premium by sorting stocks independently based on the profitability and the lottery variables. The main prediction is that less profitable firms should have lower returns among the stocks with higher lottery measures, and the overall profitability premium (long on the more profitable stocks and short on the less profitable ones) should be stronger among the lottery-like stocks. I also expect the lottery premium to be stronger for less profitable firms. My empirical double-sorting results strongly support these predictions using various lottery and profitability measures. Conditional profitability strategies based on the lottery variables (i.e. replicating the profitability strategies just for the most lottery-like stocks) generate significantly higher returns than unconditional strategies. For example, the double sorts on the JACKPOT show that high-JACKPOT stocks generate abnormal monthly hedge returns for the strategies based on gross profitability, income before extraordinary items, and operating profitability equal to 2.06%, 1.93%, and 2.38%, while the same profitability strategies generate unconditional hedge abnormal returns of 0.51%, 0.66%, and 0.81%, respectively. A similar pattern can also be observed for the lottery premiums. For example, the JACKPOT strategy generates hedge JACKPOT abnormal returns between 0.93% and 1.36% among the least profitable firms, whereas the unconditional JACKPOT strategy yields only 0.7% abnormal monthly hedge returns. Altogether, the findings indicate that the profitability premiums can be, at least party, attributable to investors' preference for the lottery-like features of less-profitable firms and their aversion to buying and holding on to the profitable firms.

To gather further support, I investigate the relationship between my variables using the Fama and MacBeth (1973) regression framework. This time, I test my key conjecture by adding a lottery and a profitability variable and an interaction between the two in the regressions. The estimated interaction coefficients test my key conjecture that the profitability premium is strongest when the stock has lottery-like characteristics. Again, the results provide corroborating evidence for my predications. A 1-standard-deviation increase in the lottery measures improves the relationship between profitability and returns by approximately 0.1% to 0.8%, depending on the measure. The interaction results are also economically meaningful. For instance, a conditional strategy based on both the gross profitability and the JACKPOT measures outperforms an unconditional strategy by approximately 50%. Overall, the findings sharply highlight the role of the lottery-like features in generating the profitability premium. Nevertheless, I should note that my behavioral factor is not the only driving force; the profitability variables can still significantly predict returns after controlling for the lottery-like measures and their interactions with profitability.

My findings contribute to various streams of literature in finance. First, I build on the pervious accounting and finance literature investigating the profitability premium (e.g., Novy-Marx, 2013; Ball et al., 2015, 2016) and provide a new behavioral explanation for the phenomenon. Considering that a consensus has not yet been reached as to why the profitability information is priced (Ball et al., 2015) and that profitability is now a well-established asset-pricing factor (Fama and French, 2015), my results can help researchers better understand the underlying sources of the profitability premium. In line with the findings of Wang and Yu (2013), I conclude that mispricing is at least partly responsible for the premium. Unlike, Wang and Yu (2013), however, my evidence is not in favor of an inattentive under-reaction to the profitability information, but rather is consistent with an opposite or an intentionally-delayed reaction due to the lottery preference. I also contribute to the behavioral finance literature that investigates the implications of

the lottery preference in asset pricing (e.g., Barberis and Huang, 2008; Kumar, 2009; Boyer et al., 2010; Bali et al., 2011). Several recent studies have accomplished solving asset pricing puzzles by referring them to the preference for lottery-like assets (Lemmon and Ni, 2008; Boyer and Vorkink, 2014; Conrad et al., 2014; Kausar et al., 2015). My results further highlight the importance of such behavior, implying that it may be an important determinant of how markets react to adverse news more generally.

The remainder of this paper is organized as follows: Section 2.2 provides the background and my testable hypotheses. Section 2.3 describes the sample, the variable construction procedure and the single sorting results for various lottery and profitability strategies used in the paper. Section 2.4 outlines the main results including the double sort and the regressions, and Section 2.5 concludes.

2.2 Background and Hypotheses

Evidence on the pricing implications of profitability information goes back to the early work of Ball and Brown (1968), showing that net income before extraordinary items predicts cross-sectional returns. Ever since, a number of papers have documented similar findings (e.g., Haugen and Baker, 1996; Griffin and Lemmon, 2002; Cohen et al., 2002; Fama and French, 2006, 2008); however, there is no clear explanation for the phenomenon. Recently, Novy-Marx (2013) attracted more attention to the issue by introducing a more refined measure, gross profitability, which he claimed is less prone to the accounting noise often undermining the bottom-line net income. Ball et al. (2015) built on this study and demonstrated that the predicative powers of gross profitability and net income before extraordinary items are actually not significantly different when both measures are deflated by total assets. However, one can still devise a more refined profitability measure to achieve extra return predictability by deducting only the noisy income statement items between gross profits and net income. Following this notion,

Ball et al. (2015) proposed the operating profitability measure, which beats the previous two measures in predicting cross-sectional returns.

There are two main camps of thought on the possible causes of the profitability effect. The first group adopts a rational explanation for the phenomenon by linking the profitability premium to systematic risk. This has led to profitability being accepted as a major factor in recent asset pricing models (e.g., Chen et al., 2011; Hou et al., 2014; Fama and French, 2015, 2018). In fact, adding a profitability factor significantly improves the performance of contemporary factor models in capturing cross-sectional abnormal returns attributable to various anomalies (Ball et al., 2015; Novy-Marx, 2013). Fama and French (2015) justify the profitability factor by linking it to expected future earnings in the context of Miller and Modigliani (1961). Nevertheless, there is no well-established justification for profitability representing (or being associated with) a source of systematic risk, apart from the evidence from Ball et al. (2015), showing that it has long-term return predictability. In fact, Ball et al. (2015) themselves indicate that the evidence in favor of the rational explanation is not conclusive.

The second camp of research links the profitability premium to mispricing, mainly in behavioral contexts. The dominant argument here is that investors do not pay attention to profitability information, leading to a systematic under-reaction (e.g., Cohen et al., 2002; Wang and Yu, 2013; Daniel and Titman, 2016). In a comprehensive study, Wang and Yu (2013) found no link between the profitability premium and the traditional sources of macro risk. Furthermore, they showed that the profitability characteristic has a better return predictability than the loading on a mimicking factor, suggesting that risk plays only a marginal role in explaining the premium. More importantly, Wang and Yu (2013) found that the profitability premium is not statistically significant among firms that are easy to arbitrage, again contrary to the rational explanation. On the other hand, firms with more inattentive investors based on the measure of Hong and Stein (1999) demonstrated a stronger effect. Altogether, the findings highlight the role

of mispricing in explaining the puzzle.

Recent developments in behavioral finance have established that investors show a strong preference for the right tail of return distributions, i.e. positively skewed or lottery-like payoffs (e.g., Barberis and Huang, 2008; Kumar, 2009; Boyer et al., 2010; Bali et al., 2011). Similarly, investors do not show interest and systematically tilt away from stocks that are less likely to generate lottery-like payoffs (Barberis et al., 2016). In asset pricing terms, this immediately translates into the over- (under-) pricing of positively (negatively) skewed payoffs, as modelled by Barberis and Huang (2008) and Brunnermeier et al. (2007). This preference for the lottery-like features is particularly pronounced among retail investors at the aggregate level. These investors are willing to buy stocks with lottery-like features in spite of the fact that such investments are often not justified by rational models of risk and return (Goetzmann and Kumar, 2008; Kumar, 2009; Kumar et al., 2011).

Kumar et al. (2016) recently demonstrated that these gambling-like trades are a significant source of co-movement in stock returns, in particular among stocks that are considered attractive gambling objects and when local investors have a higher propensity to gamble. A number of studies have also attempted to explain market anomalies using the lottery preference. For example, Kausar et al. (2015) showed that stocks with going-concern issues have the lottery-like characteristics and that retail investors are responsible for most of their trades, leading to a market under-reaction to the going-concern announcements. Conrad et al. (2014) linked the distress anomaly to the overvaluation of stocks with high jackpot probabilities. Other examples of anomalies attributed to the lottery preference include the post-earnings announcement drift (Jiao, 2017), IPO first-day returns (Aissia, 2014), and option mispricing (Lemmon and Ni, 2008; Boyer and Vorkink, 2014). As far as profitability is concerned, less profitable firms are, on average, overpriced, whereas profitable firms are undervalued. Therefore, in order for the preference for the lottery-like payoffs to act as an explanation for the mispricing,

one would expect the lottery-like features to be more prevalent among less-profitable firms. This means that the lottery-like features would, on average, attract investors who favor such features to buy less-profitable firms, or to not sell them when they become unprofitable, and this prevents the price from being adjusted. Similarly, profitable firms would be perceived as more unfavorable by some investors simply because they do not have appealing lottery-like payoffs, contributing to their underpricing.

The more lottery-like a stock with low profitability is, the more overpriced it will likely become. This is because when an investment is loss-making, which is typically the case for a firm with low levels of profitability, its loss-averse investors will become risk-seeking and will have a stronger tendency to gamble to break even (Thaler and Johnson, 1990). Therefore, investors are more likely to hold on to less-profitable firms with the lottery-like features. For profitable firms, however, the relationship between the lottery-like features and mispricing is less evident as the loss-aversion tendencies of investors are not triggered. In this case, on one hand, the lottery-like features would attract investors with gambling preferences in spite of how profitable the firm is because of the reasons discussed above. On the other hand, investors of profitable firms are usually more risk-averse as they are more likely to be in the gain regions of their value functions, according to the framework of Kahneman and Tversky (1979). Therefore, these investors might avoid buying the lottery-like firms as such firms often have higher idiosyncratic volatility and significant liquidity concerns (Kumar, 2009). Such risks would not only deter arbitragers from holding on to the lottery-like stocks and adjusting the underpricing related to profitability, but might also override the gambling preferences of less-sophisticated investors. An et al. (2018) studied this effect in the context of past gains and losses and found that the negative relationship between the lottery-like characteristics and abnormal returns becomes reversed following prior capital gains. This means that the lottery-like characteristics completely lose their attractiveness for firms that are doing well. These arguments constitute my testable hypotheses:

H1: *More (less) profitable firms are less (more) likely to possess the lottery-like features.*

H2: *Lottery-like features increase the profitability premium (abnormal return of buying more profitable stocks and selling less-profitable ones) by generating overpricing in less-profitable stocks.*

2.3 Sample and Data

The sample consists of all NYSE, AMEX, and NASDAQ firms with available data from the Center for Research in Security Prices (CRSP) daily and monthly stock return files and Compustat Fundamentals Quarterly files for the period January 1972 to December 2015 (the period for which quarterly data are available). In addition, quarterly data on institutional stock holdings from the Thomson Reuters (formerly CDA/Spectrum) are incorporated. Following Ball et al. (2015), all firms with negative book equity or belonging to the financial sector ($6000 \leq SIC \leq 6999$) are excluded from the sample. Due to microstructure-related issues discussed in Macey et al. (2008), all monthly and daily CRSP observations are required to have a share price greater than or equal to $1. In case of missing returns, delisting returns are used if available. Also, for shareholders' equity, missing values are replaced with the value of common equity, if available, or total assets minus total liabilities. If still missing, the Davis et al. (2000) book values of equity from Professor Kenneth French's data library.[1]

2.3.1 Definition of Main Variables

Three profitability measures of income before extraordinary items (Compustat IBQ), gross profits [total revenues (Compustat REVTQ) minus cost of goods sold (Compustat COGSQ)], and operating profits [gross profits minus selling, general, and administrative

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

expenses (Compustat XSGAQ) plus research and development expenses (XRDQ)] are considered in this study, following Ball et al. (2015). All three measures are deflated by the total book value of assets (Compustat ATQ). This choice is motivated by the finding of Ball et al. (2015) that showed profit measures deflated by the book value of total assets provide better return predictability than those deflated by other frequently used alternatives such as the book and the market value of equity. Unlike Ball et al. (2015), however, I use quarterly data instead of annual data for all accounting variables throughout this study. This is in order to capture the most current publicly available information in the tests.

Following the behavioral finance literature, four major measures of return skewness (or lottery-like payoff) are adopted:

Jackpot score (JACKPOT): Conrad et al. (2014) used 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 [(six-month volume/shares outstanding) − (18-month volume/shares outstanding)], and log market capitalization. The model is estimated following a rolling window approach using the data from the past 20 years. For my sample, this starts in July 1952 to get the parameters used in 1972. 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 $t + 1$.

Lottery index (LIDX): Following Kumar et al. (2016), the lottery index is defined as the sum of the vigintile allocation of stocks with respect to price, idiosyncratic volatility, and idiosyncratic skewness divided by 60. 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 (Kumar, 2009).

Maximum daily return (MAXRET): Bali et al. (2011) define this as the maximum daily return in the previous month.

Expected idiosyncratic skewness (ESKEW): 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 capitalization dummies (based on sorts of firms by market capitalization into three groups of small, medium and large), industry dummy based on the Fama-French 17 industries, and the NASDAQ dummy. After estimating the model at the end of every month t, the parameters are used together with the most recent data to get out-of-sample expected idiosyncratic skewness estimates for months $t+61$ through $t+120$.

2.3.2 Summary Statistics

Panel A of Table 2.1 provides a summary of the properties of quintile portfolios based on the three profitability measures. Following Novy-Marx (2013), quintiles are created by sorting firms at the beginning of every month based on the most recent quarterly profitability data available at the end of the previous month (following a firm's report date of quarterly earnings, Compustat item RDQ). The results demonstrate that firms'

size and share price, on average, increase with the level of profitability. That is, more profitable firms are relatively larger and have higher share prices. Also, more profitable firms tend to have significantly lower leverage ratios compared to their less profitable counterparts. These patterns are consistent across the three profitability measures. The differences in the average age of profitable and non-profitable firms, however, are not consistent across the three measures. Less-profitable firms based on gross profitability are, on average, older than the profitable firms, while this relationship is reversed once other profitability measures are considered.

Less-profitable firms also tend to have, on average, higher total and idiosyncratic volatility levels, and lower liquidity, according to the Amihud (2002) measure. This is consistent with the previous papers showing that less-profitable firms are considerably more volatile and face significant shorting barriers (e.g., Wang and Yu, 2013). As a result, one would also expect institutions to be less interested in holding less-profitable firms than more-profitable firms. The data clearly backs up this argument; however, institutions still tend to hold, on average, approximately 20% of the total market capitalization of the less-profitable firms, which is not a negligible figure. Moreover, profitable firms have significantly higher past 12-month returns and abnormal turnover ratios [based on the measure of Chen et al. (2001)]. I will later explain that both of these attributes are consistent with the model of Hong and Stein (2003), showing that stocks with higher abnormal turnover and past returns tend to become negatively skewed. Similarly, less-profitable firms have lower past returns and abnormal turnovers, which would cause them to become positively skewed.

2.3.3 Profitability Anomaly and Single Sorts

In this section I present the results of preforming single sorts based on the profitability and the lottery variables. This is to show that the variables have pricing implications beyond what is captured by the systematic risk factors. Table 2.2 presents the monthly

value weighted abnormal returns of the quintiles of the three profitability and the four lottery measures. Three risk adjustment models from Fama and French (1993), Carhart (1997), and Fama and French (2015) are used to achieve abnormal returns. For comparison purposes, the profitability strategies are replicated using both the annual and the quarterly data. The quarterly strategies are based on sorting stocks at the beginning of every month for which returns are measured, using the most recent quarterly announcement data. Annual strategies are replicated following the methodology of Ball et al. (2015). That is, first, all stocks are sorted at the end of every June using the most recent annual data released in the previous calendar year. Then, the portfolio returns are measured from July until the end of June of the next year. The lottery strategies are based on monthly sorts of stocks using the four variables explained in the previous section.

Panels A and B of Table 2.2 report the results for the profitability strategies. The three- and the four-factor hedge (buying quintile 5 and selling quintile 1) portfolio alphas are statistically significant at the 5% level for all of the annual and quarterly profitability strategies. Consistent with the findings of Ball et al. (2015), the gross profitability strategy actually tends to generate the lowest abnormal hedge returns among the three profitability strategies. Moreover, in almost all cases, the quarterly strategies generate more statistically and economically significant hedge returns than the annual strategies, which is consistent with the findings of Novy-Marx (2013). The hedge returns tend be driven mostly by the short leg, except those based on the gross profitability measure. In fact, in most cases, the short leg is more than twice as large as the long leg for the quarterly data.

Interestingly, the hedge alphas based on the five-factor model, which includes a profitability factor, are also all statistically significant apart from the one based on the annual income before extraordinary items. This is in line with the findings of Wang and Yu (2013), showing that the abnormal returns are not all attributable to systematic

risk and could be mispricing-related. Nevertheless, the factor used in the Fama and French (2015) model is based on operating profitability to assets, which is different from the three measures used here. Fama and French (2018) show that the choice of the profitability factor can make a significant difference in the magnitude of alphas. In other words, a better profitability factor could capture the abnormal returns currently left unexplained by the five-factor model.

Panel C of Table 2.2 presents the replication results for the four return skewness (lottery) measures. The three- and the four-factor hedge alphas show that the lottery index (LIDX) of Kumar et al. (2016) generates the highest abnormal returns. This is followed by the jackpot score (JACKPOT) of Conrad et al. (2014), the maximum returns (MAXRET) of Bali et al. (2011), and the expected idiosyncratic skewness (ESKEW) of Boyer and Vorkink (2014), in that order. The LIDX is still in the lead with the five-factor model; however, ESKEW seems to beat the other two measures this time. Nevertheless, all measures are statistically and economically significant. As the returns to these strategies are mostly driven by the extreme cases, one would expect the hedge returns to be significantly larger once deciles are used instead of quintiles. However, since the tests in the rest of this paper are mostly based on quintile sorts, the deciles sorting results are not reported.

2.4 Results

This section presents the main empirical results. First, I investigate how various skewness (lottery) measures vary with profitability and can attract investors based on the different natures of profitable and non-profitable firms. Next, the role of skewness is examined in determining the profitability premiums through regressions and double sorts.

2.4.1 4.1. Are Less-profitable Firms More Lottery-like?

In this section, I compare how various return skewness or lottery-like payoff measures change across the profitability quintiles. Panel B of Table 2.1 presents the average values of the four skewness measures outlined in Subsection 2.3.1 for the quarterly quintiles based on the three profitability proxies. Increase in all four lottery proxies indicates a more positively skewed or lottery-like return distribution. Consistent across all measures, the propensity for a stock to have a lottery-like payoff distribution increases as it becomes less profitable. The difference between the lottery scores of the profitable (quintile 5) and non-profitable (quintile 1) firms are all statistically significant at the 1% level. These differences seem to be significantly larger for the sorts based on operating profitability and income before extraordinary items. Moreover, in almost all cases, there seems to be a jump in value from quintile 1 to 2, suggesting a considerable concentration of the lottery-like features in quintile 1, which consists of the least-profitable firms. The results so far provide supporting evidence for the first hypothesis. That is, the lottery measures, on average, decrease with profitability. This predicts that less-sophisticated investors should, on average, be more attracted to less-profitable firms than profitable firms.

Although explaining why less (more) profitable firms are more likely to have positively (negatively) skewed returns is beyond the scope of this study, one can still reasonably speculate based on the characteristics observed so far. Less-profitable firms are on average smaller, more volatile, and have significantly lower past returns and turnover. All of these characteristics are documented by Chen et al. (2001) to relate to positive skewness. Now, it is not clear whether such characteristics are caused by low profitability itself or by some other unknown variable. However, the argument of Chen et al. (2001) still holds here; firms generally have strong tendencies to hide bad information and this particularly becomes a problem when bad news is more frequent and the firm faces less external scrutiny due to its small size. The market already knows

this, therefore, takes a pessimistic view of these firms. Consequently, the market would only be surprised once positive news comes out, as there always is a continuous and slow stream of previously hidden bad news. The sudden positive reaction of the market to occasional positive news leads to a positively skewed or lottery-like returns distribution.

For profitable firms, on the other hand, the story is slightly more complex. These firms are large and have significant past returns and turnover. Hong and Stein (2003) show that high past abnormal turnover is a proxy for significant difference in opinion among investors. In a world with shorting constraints, this would mean that, ordinarily, only the buying activity of bullish investors is reflected in prices, leading to high average returns. However, when there is very bad news about the firm, some of the previously bearish investors may enter the market and buy if they believe that the news is not credible or that the market has over-reacted. This way, the stock price would change much more in response to bad news than to good news, leading to a negative skewness.

2.4.2 Double Sorts

As shown previously, profitability tends to have a negative relationship with the lottery proxies. I now examine how the return predictability of the three profitability measures relies on the stock's lottery characteristics. This is done by independently sorting stocks at the end of every month into five profitability and five lottery groups and then looking at the value-weighted returns of the intersecting portfolios for the following month. Tables 2.3 to 2.6 present the double sorting results based on the JACKPOT, the LIDX, the MAXRET, and the ESKEW, respectively. The results include value-weighted raw and abnormal returns based on the four-factor model (Carhart, 1997).

Consistent across Tables 2.3, 2.4, 2.5, and 2.6, the profitability premiums (buying the more profitable quintile and selling the least profitable one) based on the three strategies increase monotonically with the lottery measures. That is, conditional profitability strategies based on the lottery variables generate significantly higher returns than uncon-

ditional strategies. Taking the double sorts on the JACKPOT in Table 2.3, for example, high-JACKPOT stocks (quintile 5) generate abnormal monthly hedge returns for the strategies based on gross profitability, income before extraordinary items and operating profitability equal to 2.06%, 1.93%, and 2.38%, respectively. This is while the same profitability strategies generate unconditional hedge abnormal returns of 0.51%, 0.66%, and 0.81%, respectively (reported in Table 2.2). Low-JACKPOT stocks also tend to yield statistically significant profitability premia, but the abnormal hedge returns are about five times smaller than those of the high-JACKPOT stocks.

A similar pattern can also be observed for the lottery premia. That is, the previously documented abnormal returns attributable to the strategy of shorting high-lottery stocks and buying low-lottery stocks seem to be mostly driven by the lowest-profitability stocks. For example, the JACKPOT double sorts in Table 2.3 report hedge JACKPOT abnormal returns between 0.93% and 1.36%. This compares with an unconditional JACKPOT strategy that yields only 0.7% abnormal monthly hedge returns. For profitable firms, on the other hand, the lottery premiums are not statistically significant or even negative in a few cases. This interesting observation is similar to the finding of An et al. (2018), that the lottery strategy returns become reversed following capital gains. In fact, the abnormal hedge returns of the high-profitability quintiles increase monotonically with the lottery measures in most cases. The differences in returns between the extreme quintiles, however, are statistically significant only in a few instances. Actually, in contrast to the abnormal returns of the least-profitable stocks, which almost completely vanish in the low-lottery quintiles, the most-profitable stocks generate positive and significant abnormal returns both in the high- and in the low-lottery groups. This is in line with my prediction regarding the two countervailing forces driving the abnormal returns of the profitable firms.

Altogether, the findings highlight a positive relationship between the profitability premiums and the lottery characteristics measured using different proxies. This is in line

with my second hypothesis suggesting that the profitability premia can be attributable to investors' preference for the lottery-like features of less-profitable firms and their aversion to buying and holding on to the profitable firms.

2.4.3 Fama Macbeth Regressions

The results in the previous subsection provide corroborating evidence for my second hypothesis by demonstrating a simple and intuitive relationship between profitability and the lottery-like feature. However, double sorting does not immediately allow us to compare the magnitude and the significance of the relationship across my measures. Also, one cannot explicitly control for other variables in a sorting methodology. To address these issues, I ran a series of Fama and MacBeth (1973) regressions. The effect of the lottery features on the relationship between profitability and return was investigated through running regressions separately within the lottery quintiles and using interaction terms, which are reported in the sections below. Following the main profitability studies (e.g., Novy-Marx, 2013; Ball et al., 2015), I use four main control variables in all regressions including the natural logarithms of the market value of equity and the book-to-market ratio, the previous month return and the return for the past 12 months excluding the past month. The regressions are estimated using quarterly profitability and monthly lottery variables, explained in Subsection 2.3.1, from January 1972 to December 2015. All independent variables are standardized to have a mean of zero and a standard deviation of one in the pooled distribution across the whole sample. To eliminate outliers, all explanatory variables are winsorized at their 5th and 95th percentiles.

2.4.3.1 Regressions by Quintile

Table 2.7 presents the Fama-Macbeth regression coefficients estimated separately for the three profitability measures. For illustration purposes, the sample used for estimation was broken down into five quintiles based on the lottery proxies. That is, the regressions

are estimated separately within each lottery quintile. The regression models contain only one profitability variable and the four control variables mentioned above (for more details, please see the description in Table 2.7). Only the profitability coefficients are reported in the table. The estimated coefficients indicate that the three profitability variables tend to have highly statistically significant predicting powers for the future returns. This relationship is robust in all of the lottery quintile sub-samples. However, the coefficients increase monotonically as one moves from the low-lottery to the high-lottery sub-samples. This is in line with my previous findings that the predictive power of profitability is driven mostly by the high-lottery stocks. Nevertheless, the sub-sample results in this subsection are for illustration only and I do not seek to draw any statistical inference about the conditional effect of the lottery characteristics.

Consistent with the sorting results, the operating profitability (OP) measure has generally the largest and the most significant coefficients. A 1-standard-deviation increase in the OP is, on average, associated with an approximate 1% to 4% increase in the future monthly returns, depending on the lottery sub-sample. After OP, income before extraordinary items (IB) has the strongest coefficients. Gross profitability (GP), although the weakest among the three measures, still has significant statistical power with the coefficients ranging from 0.3% to 1%. The division into lottery sub-samples seems to carve out the most drastic spread in the coefficients for the OP measure. The difference between the OP coefficients in the high- and the low-lottery sub-samples exceeds 1% in all cases.

I have repeated the same regression exercise for the four lottery measures, this time estimated separately within five profitability sub-samples. Table 2.8 presents the estimated Fama-Macbeth coefficients of the four lottery measures. The LIDX generally tends to have the largest coefficients, followed by JACKPOT, MAXRET, and ESKEW. In line with the sorting results, the return predictabilities of all four lottery variables appear to be stronger for the less-profitable firms. Also, the spreads between the lottery

coefficients of the highest- and the lowest-profitability firms are larger for JACKPOT and ESKEW. In fact, for these two measures, the lottery variables do not have any statistically significant power to predict the returns of the profitable stocks. Altogether, the results of this subsection provide supporting evidence for my predictions. In the next subsection, I will use the Fama-Macbeth regression framework to test my second hypothesis in a more rigorous way.

2.4.3.2 Regressions with Interaction Term

To identify and test the role of the lottery-like features in generating the profitability premium, I again estimated a series of Fama-Macbeth regressions for my various proxies. However, this time, I add both a lottery and a profitability variable and an interaction between the two ($lottery \times profitability$) in every regression. The estimates of this interaction term test my key conjecture that the profitability premium is strongest when a stock has the lottery-like characteristics. At the same time, the individual profitability and lottery explanatory variables capture the direct effects of the two variables.

Table 2.9 presents the baseline regression results. The table includes 12 subsections for different combinations of my profitability and lottery variables. The 12 interaction terms, except one for the interaction between IB and ESKEW, are all highly statistically significant and positive. This indicates that the profitability premium is strongest for stocks that have high-lottery features. A 1-standard-deviation increase in the lottery measures improves the relationship between profitability and returns by approximately 0.1% to 0.8%, depending on the measure. The positive interaction terms also mean that the lottery features are better linked to the future returns once a firm is less profitable. Among the profitability measures, the OP tends to have a stronger interaction with the lottery measures. For the lottery measures, on the other hand, JACKPOT generates larger and more significant interaction coefficients. For the rest of the measures, the results are slightly mixed and not directly comparable.

The odd columns (1, 3, 5, and 7) in Table 2.9 provide estimation results for the same regression models without interaction terms. It is interesting to observe that the profitability effect tends to absorb the lottery effect of the LIDX and the ESKEW once both variables are included in the regressions. This is demonstrated by insignificant coefficients of the two measures once a profitability measure is added in the regressions. Considering that all of the lottery measures have a very significant return predictability, the fact that the profitability variables can account for their role highlights how closely the lottery and profitability are related to one another. Interestingly, some of these insignificant coefficients become significant again once an interaction term is added. This suggests that the lack of significance issue may be due partly to the estimated lottery variables capturing the omitted interaction effects.

The interaction results are also economically meaningful. For example, looking at column 2 of Panel A, which includes the GP and the JACKPOT, the interaction term is almost half of the size of the GP and the JACKPOT coefficients. This means that a conditional strategy based on both the GP and the JACKPOT outperforms an unconditional strategy by approximately 50%. However, this was a relatively extreme case, as for the rest of the measures the interaction coefficients range from 20% to 60% of the profitability coefficients. Collectively, the results in this section provide strong evidence for my second hypothesis.

2.4.3.3 Robustness Check

In this subsection, I investigate whether the effect of the lottery-like features on the profitability premium can be captured by other firm characteristics. In particular, I consider four major stock variables including the market value of equity, book-to-market ratio, and past short-term and long-term returns. I also incorporate two prominent proxies for liquidity and arbitrage costs including the illiquidity measure of Amihud (2002) and the institutional ownership ratio. These variables control for any liquidity

concerns that may be captured by our lottery measures. The construction details of all these variables are explained in Table 2.1.

To investigate whether any of the six variables stated above drives the results, I add all these variables together with their interactions with the profitability measures to the regression models of Table 2.9. By doing this, I can check whether the new interaction terms can absorb the coefficients on the interactions between lottery and profitability.

I present the results of this robustness test in Table 2.10. All the interactions between the lottery and the profitability measures remain highly statistically and economically significant after controlling for the new variables. The only exception is the interaction between IB and ESKEW, which is not statistically significant even in the original model in Table 2.9. Most of the new interaction coefficients are not statistically significant, expect those including illiquidity and institutional ownership. This finding indicates that liquidity and arbitrage costs play a role in generating the profitability premium. However, these variables still cannot capture the effect of the lottery-like features.

Taken together, the robustness check results indicate that the role of the lottery-like features in generating the profitability premium is unlikely to be related to other stock characteristics unrelated to investors' preference for lottery-like assets. Importantly, I show that the lottery-like features do not indirectly capture liquidity or arbitrage costs, which could be a major concern.

2.5 Conclusion and Discussion

Accounting and finance literature have long reported the power of firm profitability in predicting future stock returns (e.g., Haugen and Baker, 1996; Griffin and Lemmon, 2002; Cohen et al., 2002; Fama and French, 2006, 2008). That is, more profitable firms

outperform less profitable ones in the cross-section of stock returns. Recent more refined profitability measures (e.g., Novy-Marx, 2013; Ball et al., 2015, 2016) are, in fact, so robust that they have been used to construct new factors in the latest asset-pricing models (e.g., Chen et al., 2001; Hou et al., 2014; Fama and French, 2015, 2018). Adding a profitability factor significantly improves the performance of previous factor models in capturing cross-sectional abnormal returns generated by various anomaly strategies (Novy-Marx, 2013; Fama and French, 2016). Nevertheless, the literature has not yet explicitly defined why there is a premium attributable to profitability. In a recent study, Wang and Yu (2013) find corroborating evidence for mispricing due to information uncertainty and investor inattention as the main driver of the profitability premium. In this paper, I propose a novel behavioral explanation and link the return predictability of profitability information to investors' preference for lottery-like payoffs. Motivated by the recent behavioral studies (e.g., Barberis and Huang, 2008; Kumar, 2009; Boyer et al., 2010; Bali et al., 2011), my story is that the lottery-like features of less profitable firms attract investors with the lottery preferences toward less profitable firms and away from more profitable ones, leading to a mispricing.

I address the research question in two main steps. First, I explore whether less profitable firms have higher measures of lottery-like features than more profitable ones. At this stage, I expect to observe that less-profitable firms are more lottery-like leading to them becoming overpriced. Similarly, more profitable firms are not expected to have high lottery measures. Considering that profitability can significantly predict the future four years of returns (Ball et al., 2015), I would anticipate less-profitable firms in the cross-section to continue to be relatively more lottery-like, remaining attractive investment options for the lottery investors. In the second step, I explore the effect of the lottery-like features on the profitability premium. In particular, I test whether the profitability premium is stronger among more lottery-like stocks and, similarly, whether the lottery premium is more pronounced among less profitable stocks. My expectation is that the

profitability premium is larger and more significant among the more lottery-like stocks. Also, since my proposition relies on a two-way relationship between profitability and the lottery-like features, I predict that the lottery premium is larger among the less profitable stocks.

I use a sample of all NYSE, AMEX, and NASDAQ firms with available data from the CRSP daily and monthly stock return files and Compustat Fundamentals Quarterly files for the period January 1972 to December 2015. Following Ball et al. (2015), I use three profitability proxies of gross profitability, income before extraordinary items and operating profitability. Also, I use four of the most prominent proxies of the lottery-like features including the jackpot score (Conrad et al., 2014), the lottery index (Kumar et al., 2016), the maximum daily return (Bali et al., 2011)), and the expected idiosyncratic skewness (Boyer et al., 2010). The results indicate that there is a negative relationship between the lottery tendencies of a stock using my four measures and that stock's profitability level. In other words, less profitable firms are, on average, more lottery-like than more profitable ones. This relationship is also consistent for at least a four-year event period around the announcement.

I test my second hypothesis using double-sorting and Fama and MacBeth (1973) regression methodologies. The results from the both methods indicate that an interaction between the lottery-like features and profitability has a significant power in predicting future returns, beyond what is captured by the individual effects of the two variables. In other words, the profitability premium is stronger and more significant among the more lottery-like stocks and it is more robust among the less-profitable stocks. These findings are in line with my main conjecture that the profitability premium is at least partly attributable to investors' preference for lottery-like assets. However, my explanation, clearly, does not explain the whole profitability premium as the least lottery-like stocks still demonstrate marginally significant profitability premiums in some cases. In other words, not all of the mispricing, if in fact the whole phenomenon can be categorized

as such, is driven by the lottery-like stocks. In fact, the positive abnormal returns generated by the most profitable stocks are highly significant in all my lottery sub-samples. Therefore, my theory leaves a large part of the premium that is driven by the profitable stocks unexplained. The reason is that I do not explicitly justify positive returns (underpricing) but rather focus on the negative ones (overpricing). I also do not explicitly investigate the underlying trades that lead to, or exacerbate, the mispricing. I therefore build on the previous papers in this area (e.g., Kumar, 2009; Kausar et al., 2015) and argue that unsophisticated retail investors, who are found to be the main trading clientele of lottery-like assets, trade stocks in a direction that is the opposite to what the stocks' profitability levels indicate they should be traded.

My study contributes to the finance and accounting literature investigating the profitability premium (e.g., Novy-Marx, 2013; Ball et al., 2015, 2016). My study provides a novel explanation for the profitability premium showing that the mispricing due to the preference of a group of investors for the lottery-like assets is at least partly causing the phenomenon. I also contribute to the behavioral finance literature looking at the lottery preference in asset pricing (e.g., Barberis and Huang, 2008; Kumar, 2009; Boyer et al., 2010; Bali et al., 2011). My findings suggest that investors' preference for lottery-like assets can play a bigger role in explaining how markets react to adverse news more generally.

Table 2.1: Summary Statistics

This table provides a summary of the properties of quintile portfolios based on the three profitability measures. Following Novy-Marx (2013), quintiles are created by sorting firms at the beginning of every month based on the most recent quarterly profitability data available at the end of the previous month (following a firm's report date of quarterly earnings, Compustat item RDQ). The sample consists of all NYSE, AMEX and NASDAQ firms with available data from the CRSP daily and monthly stock return files and Compustat Fundamentals Quarterly files for the period January 1972 to December 2015. Firms with negative book equities, share prices lower than 1$ or financial sector classifications ($6000 \leq SIC \leq 6999$) are excluded from the sample. The three profitability measures considered are gross profits (GP), income before extraordinary items (IB), and operating profits (OP). All three profitability measures are deflated by the book value of total assets. $JACKPOT$ is defined by Conrad et al. (2014) as the out-of-sample probability of a stock generating a log return greater than 100% in the next twelve 12 months, estimated using a logit model. $LIDX$ is the lottery index of Kumar et al. (2016) defined as the sum of the vigintile allocation of stocks with respect to price, idiosyncratic volatility and idiosyncratic skewness divided by 60. $MAXRET$ is the maximum daily return in the previous month following Bali et al. (2011). $ESKEW$ is the expected idiosyncratic skewness defined following Boyer et al. (2010) 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. The key profitability and lottery variables are explained in more detail in Subsection 2.3.1. *Size* is the market capitalization in millions. *Age* is the time (in years) since appearance on CRSP. *Price* is the monthly closing price. *Vol* is the standard deviation of daily returns over the past three months. *I.Vol* is the idiosyncratic volatility 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. Turn is the monthly turnover. *A.Turn* is defined by Chen et al. (2001) as detrended stock turnover computed as average past six-month turnover minus average past 18-month turnover. *Illiq* is the illiquidity measure of Amihud (2002), calculated as the annual average of the daily ratio of absolute stock return to its daily dollar trading volume, all scaled by $10^{-}6$. *Past Ret* is log return over the past year. *I.Hold* is the sum of the quarterly institutional holdings by aggregating the positions of different institutions from the Thomson Reuters database. The t-statistics are calculated based on the Newey-West adjusted standard errors with lag of 36 for firm characteristics.

	GP						IB						OP					
	1	2	3	4	5	5 - 1 (t-stat)	1	2	3	4	5	5 - 1 (t-stat)	1	2	3	4	5	5 - 1 (t-stat)
Panel A: Summary Statistics																		
Size	1,244	1,989	2,042	2,200	1,701	457 (3.30)	311	913	1,849	2,498	3,562	3,251 (3.72)	371	1,085	1,727	2,549	3,389	3,017 (4.02)
Age	17.96	18.67	18.05	16.69	15.07	-2.89 (-3.78)	12.67	17.67	20.23	19.38	16.32	3.65 (3.64)	13.79	17.66	18.56	18.12	15.75	1.96 (3.61)
Price	14.44	19.39	19.39	20.16	18.78	4.33 (4.11)	7.08	13.64	19.88	23.89	26.89	19.8 (8.00)	8.41	15.06	19.66	22.98	25.16	16.76 (8.98)
Vol	3.53	3.12	3.13	3.16	3.29	-0.24 (-2.90)	4.48	3.29	2.78	2.70	2.90	-1.58 (-10.64)	4.28	3.30	2.98	2.89	3.03	-1.25 (-9.85)
I.Vol	3.39	2.92	2.94	2.99	3.16	-0.23 (-2.99)	4.38	3.14	2.60	2.51	2.70	-1.68 (-10.98)	4.19	3.13	2.80	2.69	2.82	-1.36 (-10.27)
Turn	11.11	10.21	10.09	10.58	11.82	0.71 (1.25)	11.78	9.59	9.23	10.13	12.96	1.18 (1.39)	10.69	9.52	9.74	10.62	13.78	3.09 (3.35)
A.Turn	0.27	0.05	0.07	0.19	0.52	0.25 (1.81)	0.13	-0.09	0.07	0.26	0.72	0.59 (2.02)	-0.01	-0.03	0.10	0.27	0.69	0.69 (2.4)
Illiq	4.30	3.66	3.49	3.56	4.15	-0.15 (-0.21)	7.46	4.43	2.75	2.13	2.11	-5.34 (-4.44)	7.75	4.54	3.26	2.47	2.20	-5.55 (-5.82)
Lev	0.27	0.28	0.24	0.21	0.17	-0.09 (-7.83)	0.24	0.29	0.27	0.22	0.16	-0.08 (-4.82)	0.21	0.26	0.26	0.23	0.18	-0.03 (-2.84)
Past Ret	-6.03	-0.06	3.72	7.92	12.67	18.7 (9.03)	-19.66	-3.91	7.08	13.42	20.87	40.53 (13.5)	-17.02	-2.35	5.94	11.51	19.19	36.21 (9.95)
I.Hold	24.32	33.18	34.07	33.29	30.92	6.59 (7.50)	19.50	30.38	34.07	36.54	34.97	15.47 (7.04)	20.94	31.3	35.15	36.34	35.64	14.7 (7.40)
Panel B: Skewness (Lottery) Measures																		
LIDX	0.54	0.49	0.49	0.49	0.51	-0.03 (-3.90)	0.66	0.53	0.45	0.43	0.44	-0.22 (-20.49)	0.64	0.53	0.48	0.45	0.46	-0.18 (-18.67)
JACKPOT	2.50	1.83	1.82	1.84	1.98	-0.51 (-3.65)	3.80	2.06	1.41	1.25	1.35	-2.45 (-7.44)	3.61	2.09	1.62	1.43	1.43	-2.19 (-7.22)
MAXRET	7.97	6.86	6.91	7.02	7.38	-0.59 (-2.89)	10.26	7.26	6.07	5.91	6.42	-3.84 (-8.92)	9.78	7.27	6.55	6.35	6.71	-3.07 (-8.32)
ESKEW	82.26	71.69	71.62	71.32	75.01	-7.25 (-2.53)	109.75	80.06	63.99	58.82	58.91	-50.83 (-7.72)	107.53	80.08	68.97	62.79	60.52	-47.00 (-7.47)

Table 2.2: Quintile Portfolio Analysis

This table presents the monthly value-weighted abnormal returns of the quintiles of the three profitability and the four lottery measures. Three risk adjustment models of Fama and French (1993), Carhart (1997), and Fama and French (2015) are used to achieve abnormal returns. The profitability strategies are replicated using both the annual and the quarterly data. The quarterly strategies are based on sorting stocks at the beginning of every month for which returns are measured, using the most recent quarterly announcement data. For the annual strategies, first all stocks are sorted at the end of every June using the most recent annual data released in the previous calendar year. Then, the portfolio returns are measured from July until the end of June of the next year. The profitability measures include gross profits (GP), income before extraordinary items (IB), and operating profits (OP). All three profitability measures are deflated by the book value of total assets. The lottery strategies are based on monthly sorts of stocks using the four variables explained in Subsection 2.3.1. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Anomaly	Quintile	Three Factor α	Four Factor α	Five Factor α
Panel A: Quarterly Profitability Measures				
GP	Low	-0.249***	-0.197**	-0.030
		(-3.00)	(-2.33)	(-0.40)
	2	-0.170**	-0.137*	-0.181**
		(-2.21)	(-1.75)	(-2.27)
	3	0.019	0.054	-0.035
		(0.27)	(0.76)	(-0.49)
	4	0.118*	0.154**	0.110
		(1.70)	(2.17)	(1.55)
	High	0.367***	0.318***	0.231***
		(4.49)	(3.83)	(2.87)
	High-Low	0.616***	0.515***	0.261**
		(4.85)	(4.01)	(2.33)
IB	Low	-0.670***	-0.471***	-0.164
		(-4.34)	(-3.08)	(-1.37)
	2	-0.356***	-0.172*	-0.06
		(-3.37)	(-1.70)	(-0.66)
	3	-0.024	0.040	0.012
		(-0.38)	(0.64)	(0.18)
	4	0.094	0.097	-0.027
		(1.60)	(1.61)	(-0.47)
	High	0.255***	0.196***	0.167***
		(4.19)	(3.19)	(2.83)
	High-Low	0.925***	0.666***	0.331**
		(5.10)	(3.74)	(2.43)
OP	Low	-0.775***	-0.560***	-0.312**
		(-5.2)	(-3.83)	(-2.45)
	2	-0.315***	-0.154*	-0.122
		(-3.63)	(-1.86)	(-1.45)
	3	-0.102	-0.052	-0.141**
		(-1.48)	(-0.74)	(-1.97)
	4	0.074	0.092	-0.038
		(1.16)	(1.41)	(-0.60)
	High	0.306***	0.256***	0.255***
		(4.81)	(3.98)	(3.94)
	High-Low	1.081***	0.816***	0.568***
		(6.25)	(4.83)	(3.81)

Table 2.2: Quintile Portfolio Analysis (Continued)

Anomaly	Quintile	Three Factor α	Four Factor α	Five Factor α
Panel B: Annual Profitability Measures				
GP	Low	-0.192***	-0.189***	-0.031
		(-4.15)	(-3.98)	(-0.76)
	2	-0.155***	-0.134***	-0.156***
		(-3.52)	(-2.98)	(-3.46)
	3	0.056	0.058	0.037
		(1.45)	(1.46)	(0.94)
	4	0.078*	0.153***	0.060
		(1.94)	(3.85)	(1.47)
	High	0.360***	0.308***	0.250***
		(7.39)	(6.23)	(5.41)
	High-Low	0.552***	0.497***	0.281***
		(4.92)	(4.33)	(2.90)
IB	Low	-0.231**	-0.174*	0.172**
		(-2.47)	(-1.83)	(2.40)
	2	-0.226***	-0.155***	-0.046
		(-4.16)	(-2.83)	(-1.03)
	3	0.006	0.006	0.005
		(0.19)	(0.16)	(0.14)
	4	0.026	0.017	-0.057*
		(0.82)	(0.52)	(-1.80)
	High	0.185***	0.182***	0.135***
		(5.89)	(5.66)	(4.60)
	High-Low	0.416***	0.357**	-0.036
		(2.81)	(2.36)	(-0.34)
OP	Low	-0.539***	-0.477***	-0.02
		(-4.67)	(-4.04)	(-0.21)
	2	-0.188***	-0.087	-0.062
		(-2.95)	(-1.36)	(-1.02)
	3	0.025	0.020	-0.035
		(0.54)	(0.42)	(-0.73)
	4	0.061	0.101**	0.029
		(1.45)	(2.37)	(0.67)
	High	0.310***	0.290***	0.301***
		(6.95)	(6.36)	(6.66)
	High-Low	0.849***	0.767***	0.321**
		(4.77)	(4.22)	(2.18)
Panel C: Lottery Measures				
JACKPOT	Low	0.080***	0.049**	0.012
		(3.44)	(2.13)	(0.56)
	2	0.015	0.074	0.166***
		(0.28)	(1.34)	(3.18)
	3	-0.048	0.012	0.202***
		(-0.63)	(0.15)	(3.06)
	4	-0.514***	-0.337***	-0.078
		(-4.23)	(-2.81)	(-0.74)
	High	-0.948***	-0.652***	-0.332**
		(-5.23)	(-3.68)	(-2.14)
	Low-High	1.028***	0.701***	0.344**
		(5.35)	(3.75)	(2.12)

Table 2.2: Quintile Portfolio Analysis (Continued)

Anomaly	Quintile	Three Factor α	Four Factor α	Five Factor α
Panel C: Lottery Measures (Continued)				
LIDX	Low	0.115***	0.084***	0.072***
		(4.85)	(3.53)	(3.12)
	2	-0.008	0.012	0.075
		(-0.16)	(0.23)	(1.49)
	3	-0.092	-0.007	0.113*
		(-1.24)	(-0.09)	(1.68)
	4	-0.330***	-0.146	0.022
		(-3.2)	(-1.46)	(0.24)
	High	-1.007***	-0.701***	-0.586***
		(-6.63)	(-4.85)	(-4.29)
	Low-High	1.123***	0.785***	0.658***
		(7.01)	(5.19)	(4.66)
MAXRET	Low	0.109**	0.086*	0.004
		(2.33)	(1.79)	(0.09)
	2	0.072	0.096*	0.074
		(1.51)	(1.96)	(1.50)
	3	0.085	0.125*	0.167***
		(1.35)	(1.96)	(2.62)
	4	-0.091	-0.033	0.155*
		(-0.99)	(-0.35)	(1.79)
	High	-0.628***	-0.501***	-0.227**
		(-5.04)	(-3.99)	(-2.06)
	Low-High	0.737***	0.587***	0.231*
		(4.82)	(3.81)	(1.72)
ESKEW	Low	0.093**	0.076*	0.083**
		(2.42)	(1.95)	(2.16)
	2	0.131**	0.117*	0.166***
		(2.04)	(1.77)	(2.72)
	3	-0.108	-0.018	0.077
		(-0.94)	(-0.15)	(0.69)
	4	-0.249**	-0.136	-0.004
		(-2.07)	(-1.12)	(-0.04)
	High	-0.636***	-0.457***	-0.281**
		(-4.34)	(-3.15)	(-2.10)
	Low-High	0.729***	0.534***	0.364**
		(4.55)	(3.36)	(2.51)

Table 2.3: Double Sorts by JACKPOT and Profitability

This table presents the double sorting results based on the jackpot score ($JACKPOT$) and the three profitability measures. The profitability measures include gross profits (GP), income before extraordinary items (IB), and operating profits (OP). All three profitability measures are deflated by the book value of total assets. The jackpot measure is explained in Subsection 2.3.1. The results include value-weighted raw and abnormal returns based on the four-factor model (Carhart, 1997). Sorting is performed by independently sorting stocks at the end of every month into five profitability and five lottery groups and then looking at the value-weighted returns of the intersecting portfolios for the following month. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

		JACKPOT					
		Low	2	3	4	High	Low - High
Panel A: Raw Returns							
GP	Low	0.882	0.833	0.722	0.338	-0.515	1.397
	2	0.907	0.907	0.833	0.330	0.09	0.824
	3	0.948	0.929	0.989	0.814	0.545	0.417
	4	0.966	1.064	1.167	0.908	0.845	0.131
	High	1.171	1.269	1.623	1.348	1.464	-0.317
	High - Low	0.289	0.436	0.901	0.992	2.043	
IB	Low	0.755	0.684	0.643	0.127	-0.240	0.983
	2	0.821	0.95	0.793	0.630	0.089	0.712
	3	0.944	1.069	1.080	0.922	1.151	-0.216
	4	1.010	1.075	1.291	0.912	1.188	-0.164
	High	1.077	1.153	1.394	1.224	1.721	-0.648
	High - Low	0.321	0.469	0.729	1.098	1.975	
OP	Low	0.581	0.473	0.609	0.051	-0.571	1.151
	2	0.822	0.767	0.622	0.607	0.202	0.621
	3	0.887	0.985	1.129	0.818	1.164	-0.256
	4	0.986	1.061	1.122	1.032	1.444	-0.445
	High	1.095	1.191	1.529	1.193	1.819	-0.721
	High - Low	0.514	0.718	0.919	1.125	2.385	
Panel B: Four Factor Alphas							
GP	Low	-0.061	-0.251*	-0.380**	-0.633***	-1.377***	1.316***
		(-0.68)	(-1.82)	(-1.97)	(-3.06)	(-5.42)	(4.85)
	2	-0.118	-0.154	-0.200	-0.567***	-0.792***	0.68**
		(-1.35)	(-1.32)	(-1.22)	(-2.76)	(-2.77)	(2.18)
	3	0.064	-0.083	0.027	-0.098	-0.414*	0.483*
		(0.78)	(-0.71)	(0.18)	(-0.56)	(-1.66)	(1.75)
	4	0.159*	0.158	0.146	0.044	-0.043	0.214
		(1.90)	(1.53)	(1.11)	(0.23)	(-0.18)	(0.82)
	High	0.294***	0.355***	0.608***	0.330*	0.654***	-0.368
		(3.00)	(3.04)	(4.20)	(1.76)	(2.62)	(-1.28)
	High - Low	0.355***	0.606***	0.988***	0.951***	2.067***	
		(2.63)	(3.28)	(4.29)	(3.93)	(7.35)	
IB	Low	-0.247	-0.231	-0.351*	-0.836***	-1.130***	0.935***
		(-1.17)	(-1.27)	(-1.84)	(-3.97)	(-4.55)	(2.99)
	2	-0.136	-0.089	-0.249	-0.271	-0.802***	0.662***
		(-1.38)	(-0.74)	(-1.56)	(-1.36)	(-3.36)	(2.70)
	3	0.025	0.113	0.054	-0.142	0.130	-0.104
		(0.38)	(1.10)	(0.42)	(-0.86)	(0.58)	(-0.44)
	4	0.098	0.034	0.214	0.038	0.360	-0.258
		(1.41)	(0.37)	(1.47)	(0.23)	(1.45)	(-0.94)
	High	0.196***	0.251**	0.394***	0.272	0.772***	-0.582*
		(2.71)	(2.40)	(2.90)	(1.37)	(2.62)	(-1.87)
	High - Low	0.440**	0.489**	0.742***	1.108***	1.931***	
		(2.02)	(2.38)	(3.23)	(4.48)	(6.08)	

Table 2.3: Double Sorts by JACKPOT and Profitability (Continued)

		JACKPOT					
		Low	2	3	4	High	Low - High
Panel B: Four Factor Alphas (Continued)							
OP	Low	-0.272*	-0.48***	-0.412**	-0.847***	-1.442***	1.17***
		(-1.75)	(-2.59)	(-2.05)	(-3.93)	(-5.91)	(4.13)
	2	-0.091	-0.266**	-0.393**	-0.337*	-0.666***	0.562**
		(-1.04)	(-2.22)	(-2.44)	(-1.67)	(-2.63)	(2.06)
	3	-0.064	-0.116	0.039	-0.137	0.259	-0.300
		(-0.80)	(-1.09)	(0.28)	(-0.75)	(0.89)	(-0.95)
	4	0.061	0.122	0.152	0.184	0.451*	-0.376
		(0.80)	(1.06)	(1.09)	(1.02)	(1.69)	(-1.31)
	High	0.219***	0.284**	0.512***	0.293	0.937***	-0.713**
		(2.94)	(2.55)	(3.44)	(1.38)	(3.20)	(-2.29)
	High - Low	0.491***	0.764***	0.924***	1.128***	2.384***	
		(2.76)	(3.73)	(3.76)	(4.22)	(7.36)	

Table 2.4: Double Sorts by LIDX and Profitability

This table presents the double sorting results based on the lottery index (*LIDX*) and the three profitability measures. The profitability measures include gross profits (*GP*), income before extraordinary items (*IB*), and operating profits (*OP*). All three profitability measures are deflated by the book value of total assets. The lottery index measure is explained in Subsection 2.3.1. The results include value-weighted raw and abnormal returns based on the four-factor model (Carhart, 1997). Sorting is performed by independently sorting stocks at the end of every month into five profitability and five lottery groups and then looking at the value-weighted returns of the intersecting portfolios for the following month. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Double Sorts by LIDX and Profitability

		LIDX					
		Low	2	3	4	High	Low - High
Panel A: Raw Returns							
GP	Low	0.827	0.793	0.746	0.409	-0.209	1.029
	2	0.923	0.819	0.880	0.657	0.253	0.672
	3	0.924	0.940	1.042	0.944	0.595	0.330
	4	0.945	1.042	1.149	1.300	0.775	0.178
	High	1.097	1.406	1.631	1.776	1.333	-0.232
	High - Low	0.273	0.613	0.885	1.367	1.534	
IB	Low	0.864	0.831	0.43	0.282	-0.094	0.933
	2	0.813	0.749	0.808	0.709	0.293	0.542
	3	0.922	0.958	1.330	1.107	1.09	-0.172
	4	1.003	1.056	1.179	1.514	1.250	-0.276
	High	1.035	1.141	1.351	1.601	1.515	-0.481
	High - Low	0.187	0.322	0.921	1.319	1.591	
OP	Low	0.562	0.44	0.39	0.076	-0.524	1.078
	2	0.830	0.767	0.631	0.740	0.312	0.518
	3	0.930	0.795	1.160	0.913	1.036	-0.100
	4	0.988	1.040	0.987	1.470	1.368	-0.388
	High	1.037	1.282	1.609	1.758	2.007	-0.969
	High - Low	0.477	0.843	1.219	1.682	2.524	
Panel B: Four Factor Alphas							
GP	Low	-0.036	-0.209	-0.285*	-0.651***	-1.235***	1.204***
		(-0.37)	(-1.49)	(-1.77)	(-3.14)	(-5.14)	(4.71)
	2	-0.071	-0.230**	-0.188	-0.339*	-0.641***	0.571**
		(-0.75)	(-1.98)	(-1.28)	(-1.77)	(-2.64)	(2.16)
	3	0.049	0.003	0.101	-0.055	-0.331	0.380
		(0.55)	(0.02)	(0.70)	(-0.36)	(-1.36)	(1.45)
	4	0.167*	0.090	0.269**	0.345**	-0.260	0.437*
		(1.88)	(0.72)	(1.97)	(2.06)	(-1.27)	(1.94)
	High	0.259**	0.450***	0.708***	0.788***	0.222	0.041
		(2.57)	(3.63)	(4.9)	(4.75)	(0.98)	(0.16)
	High - Low	0.299**	0.659***	0.994***	1.439***	1.462***	
		(2.05)	(3.49)	(4.97)	(6.09)	(5.44)	
IB	Low	0.035	-0.178	-0.455**	-0.805***	-1.005***	1.074***
		(0.16)	(-0.82)	(-2.34)	(-3.73)	(-4.39)	(3.84)
	2	-0.061	-0.180	-0.258*	-0.321*	-0.730***	0.687***
		(-0.53)	(-1.35)	(-1.74)	(-1.78)	(-3.49)	(2.9)
	3	0.038	-0.030	0.310**	0.134	-0.078	0.124
		(0.5)	(-0.29)	(2.44)	(0.87)	(-0.36)	(0.52)
	4	0.105	0.005	0.199	0.517***	0.144	-0.041
		(1.5)	(0.05)	(1.52)	(3.03)	(0.67)	(-0.18)
	High	0.181**	0.203*	0.424***	0.553***	0.382*	-0.202
		(2.55)	(1.86)	(2.98)	(3.16)	(1.69)	(-0.84)
	High - Low	0.160	0.382	0.878***	1.358***	1.379***	
		(0.69)	(1.63)	(3.76)	(5.26)	(5.37)	

Table 2.4: Double Sorts by LIDX and Profitability (Continued)

		LIDX					
		Low	2	3	4	High	Low - High
Panel B: Four Factor Alphas (Continued)							
OP	Low	-0.208	-0.486**	-0.482**	-1.015***	-1.444***	1.24***
		(-1.17)	(-2.53)	(-2.36)	(-4.78)	(-6.33)	(4.59)
	2	-0.021	-0.163	-0.433***	-0.270	-0.72***	0.699***
		(-0.21)	(-1.29)	(-2.86)	(-1.51)	(-2.96)	(2.65)
	3	0.005	-0.268**	0.143	-0.068	-0.122	0.132
		(0.06)	(-2.48)	(1.04)	(-0.42)	(-0.50)	(0.51)
	4	0.088	0.019	0.034	0.522***	0.411*	-0.313
		(1.09)	(0.18)	(0.23)	(3.01)	(1.69)	(-1.19)
	High	0.193**	0.344***	0.665***	0.757***	0.859***	-0.664**
		(2.45)	(2.71)	(4.19)	(3.71)	(3.45)	(-2.56)
	High - Low	0.403**	0.830***	1.147***	1.772***	2.307***	
		(2.02)	(3.77)	(4.71)	(6.58)	(8.24)	

Table 2.5: Double Sorts by MAXRET and Profitability

This table presents the double sorting results based on the maximum daily return (*MAXRET*) and the three profitability measures. The profitability measures include gross profits (*GP*), income before extraordinary items (*IB*), and operating profits (*OP*). All three profitability measures are deflated by the book value of total assets. The maximum daily return measure is explained in Subsection 2.3.1. The results include value-weighted raw and abnormal returns based on the four-factor model (Carhart, 1997). Sorting is performed by independently sorting stocks at the end of every month into five profitability and five lottery groups and then looking at the value-weighted returns of the intersecting portfolios for the following month. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

		MAXRET					
		Low	2	3	4	High	Low - High
Panel A: Raw Returns							
GP	Low	0.989	0.731	0.918	0.376	-0.06	1.049
	2	1.127	0.886	0.893	0.755	0.331	0.797
	3	1.194	0.963	0.779	0.985	0.601	0.593
	4	1.046	1.096	1.117	0.923	0.787	0.259
	High	1.128	1.282	1.229	1.650	1.139	0.000
	High - Low	0.139	0.550	0.323	1.256	1.197	
IB	Low	1.061	0.940	0.699	0.395	-0.331	1.396
	2	1.036	0.865	0.902	0.607	0.286	0.750
	3	0.861	1.043	0.993	1.035	0.814	0.047
	4	1.076	1.025	1.001	0.96	1.042	0.041
	High	1.164	1.136	1.162	1.331	1.056	0.108
	High - Low	0.098	0.196	0.442	0.936	1.387	
OP	Low	0.981	0.453	0.421	0.185	-0.541	1.522
	2	1.055	0.814	0.705	0.560	0.24	0.812
	3	1.051	0.874	0.893	0.834	0.770	0.281
	4	1.124	1.102	0.888	0.900	0.963	0.160
	High	1.062	1.181	1.203	1.519	1.025	0.045
	High - Low	0.081	0.750	0.782	1.321	1.564	
Panel B: Four Factor Alphas							
GP	Low	0.110	-0.251**	-0.144	-0.690***	-0.994***	1.105***
		(0.97)	(-2.24)	(-0.93)	(-3.74)	(-4.19)	(4.31)
	2	0.191	-0.177*	-0.123	-0.219	-0.659***	0.871***
		(1.59)	(-1.70)	(-0.94)	(-1.25)	(-2.95)	(3.34)
	3	0.256**	0.106	-0.154	0.068	-0.322	0.578**
		(2.04)	(0.87)	(-1.18)	(0.37)	(-1.55)	(2.31)
	4	0.190	0.300**	0.259**	-0.059	-0.129	0.319
		(1.64)	(2.40)	(2.01)	(-0.37)	(-0.62)	(1.23)
	High	0.314**	0.394***	0.352***	0.718***	0.241	0.086
		(2.40)	(3.28)	(2.70)	(4.17)	(1.17)	(0.33)
	High - Low	0.203	0.644***	0.508***	1.381***	1.243***	
		(1.18)	(3.83)	(2.60)	(5.52)	(4.51)	
IB	Low	0.088	0.012	-0.219	-0.524**	-1.315***	1.412***
		(0.44)	(0.06)	(-1.15)	(-2.52)	(-5.84)	(4.99)
	2	0.123	-0.131	-0.038	-0.404**	-0.703***	0.826***
		(1.05)	(-1.02)	(-0.27)	(-2.35)	(-3.06)	(3.20)
	3	-0.049	0.087	0.021	0.027	-0.157	0.127
		(-0.52)	(0.87)	(0.17)	(0.18)	(-0.83)	(0.58)
	4	0.205**	0.044	0.051	-0.039	0.055	0.157
		(2.34)	(0.46)	(0.44)	(-0.25)	(0.28)	(0.71)
	High	0.287***	0.341***	0.232*	0.400**	0.127	0.160
		(2.75)	(3.20)	(1.79)	(2.45)	(0.59)	(0.61)
	High - Low	0.199	0.328	0.433*	0.924***	1.442***	
		(0.90)	(1.43)	(1.95)	(3.73)	(5.34)	

Table 2.5: Double Sorts by MAXRET and Profitability (Continued)

		MAXRET					
		Low	2	3	4	High	Low - High
Panel B: Four Factor Alphas (Continued)							
OP	Low	0.096	-0.472***	-0.444**	-0.713***	-1.446***	1.543***
		(0.61)	(-2.64)	(-2.2)	(-3.46)	(-5.87)	(5.14)
	2	0.211*	-0.187	-0.242*	-0.362*	-0.771***	0.99***
		(1.78)	(-1.64)	(-1.81)	(-1.94)	(-3.61)	(3.81)
	3	0.084	-0.106	-0.114	-0.201	-0.109	0.193
		(0.73)	(-1.06)	(-0.93)	(-1.25)	(-0.51)	(0.78)
	4	0.179	0.199*	-0.031	-0.058	-0.023	0.220
		(1.61)	(1.79)	(-0.25)	(-0.38)	(-0.10)	(0.80)
	High	0.229**	0.359***	0.274**	0.613***	0.120	0.119
		(2.06)	(3.04)	(1.98)	(3.42)	(0.53)	(0.44)
	High - Low	0.133	0.832***	0.719***	1.332***	1.574***	
		(0.68)	(3.95)	(3.04)	(5.19)	(5.18)	

Table 2.6: Double Sorts by ESKEW and Profitability

This table presents the double sorting results based on the expected idiosyncratic skewness (*ESKEW*) and the three profitability measures. The profitability measures include gross profits (*GP*), income before extraordinary items (*IB*), and operating profits (*OP*). All three profitability measures are deflated by the book value of total assets. The expected idiosyncratic skewness measure is explained in Subsection 2.3.1. The results include value-weighted raw and abnormal returns based on the four-factor model (Carhart, 1997). Sorting is performed by independently sorting stocks at the end of every month into five profitability and five lottery groups and then looking at the value-weighted returns of the intersecting portfolios for the following month. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

		ESKEW					
		Low	2	3	4	High	Low - High
Panel A: Raw Returns							
GP	Low	0.828	0.872	0.488	0.213	0.033	0.809
	2	0.845	0.900	0.860	0.733	0.411	0.428
	3	0.847	1.175	0.974	1.093	0.826	0.011
	4	1.054	1.039	0.927	1.176	1.006	0.029
	High	1.258	1.163	1.484	1.528	1.817	-0.559
	High - Low	0.440	0.292	0.977	1.315	1.784	
IB	Low	1.049	0.426	0.453	0.075	-0.260	1.365
	2	0.764	0.870	0.797	0.801	0.647	0.088
	3	0.903	1.042	1.011	1.384	1.400	-0.472
	4	0.979	1.236	1.222	1.284	1.829	-0.856
	High	1.139	1.036	1.010	1.426	1.872	-0.743
	High - Low	0.054	0.610	0.557	1.350	2.118	
OP	Low	0.500	0.580	0.028	-0.099	-0.346	0.865
	2	0.800	0.757	0.742	0.838	0.383	0.404
	3	0.916	1.048	1.010	1.108	1.265	-0.344
	4	0.982	0.985	1.163	1.458	1.713	-0.731
	High	1.160	1.161	1.191	1.370	2.121	-0.955
	High - Low	0.661	0.581	1.148	1.469	2.468	
Panel B: Four Factor Alphas							
GP	Low	-0.073	-0.102	-0.579***	-0.625***	-0.916***	0.872***
		(-0.67)	(-0.79)	(-3.05)	(-3.01)	(-3.76)	(-3.39)
	2	-0.140	-0.131	-0.073	-0.190	-0.495**	0.370
		(-1.39)	(-1.05)	(-0.44)	(-1.01)	(-2.21)	(-1.50)
	3	-0.070	0.321***	0.194	0.039	-0.033	-0.038
		(-0.75)	(2.89)	(1.24)	(0.23)	(-0.16)	(0.16)
	4	0.284***	0.112	0.300**	-0.109	0.089	0.185
		(2.94)	(0.82)	(2.08)	(-0.6)	(0.43)	(-0.82)
	High	0.387***	0.31**	0.586***	0.761***	0.570***	-0.182
		(3.53)	(2.43)	(3.81)	(3.86)	(2.65)	(0.73)
	High - Low	0.472***	0.413**	1.136***	1.397***	1.486***	
		(3.00)	(2.24)	(4.78)	(5.31)	(5.53)	
IB	Low	-0.094	-0.429**	-0.536**	-0.955***	-1.111***	1.041***
		(-0.43)	(-2.18)	(-2.35)	(-4.66)	(-4.82)	(-3.49)
	2	-0.122	-0.115	-0.153	-0.315*	-0.382*	0.242
		(-1.09)	(-0.83)	(-0.91)	(-1.65)	(-1.73)	(-1.01)
	3	-0.013	0.126	0.099	0.243	0.354*	-0.339
		(-0.15)	(1.23)	(0.69)	(1.28)	(1.88)	(1.63)
	4	0.068	0.358***	0.255*	0.299*	0.623***	-0.564**
		(0.85)	(3.47)	(1.75)	(1.87)	(2.85)	(2.35)
	High	0.304***	0.098	0.234	0.544***	0.675***	-0.383
		(3.44)	(0.88)	(1.43)	(2.92)	(2.67)	(1.44)
	High - Low	0.374	0.528**	0.769***	1.499***	1.781***	
		(1.60)	(2.33)	(2.78)	(5.91)	(6.36)	

Table 2.6: Double Sorts by ESKEW and Profitability (Continued)

		ESKEW					
		Low	2	3	4	High	Low - High
Panel B: Four Factor Alphas (Continued)							
OP	Low	-0.251	-0.362*	-0.891***	-1.12***	-1.216***	0.985***
		(-1.32)	(-1.9)	(-4.13)	(-5.48)	(-5.23)	(-3.57)
	2	-0.096	-0.179	-0.205	-0.077	-0.586***	0.485**
		(-0.87)	(-1.35)	(-1.39)	(-0.40)	(-2.88)	(-2.09)
	3	-0.045	0.128	-0.076	0.153	0.155	-0.196
		(-0.47)	(1.13)	(-0.51)	(0.91)	(0.77)	(0.84)
	4	0.033	0.151	0.419***	0.406**	0.816***	-0.782***
		(0.36)	(1.35)	(2.6)	(2.25)	(3.18)	(2.88)
	High	0.338***	0.267**	0.474***	0.424**	0.834***	-0.489*
		(3.32)	(2.12)	(2.63)	(2.00)	(3.17)	(1.74)
	High - Low	0.589***	0.629***	1.342***	1.556***	2.05***	
		(2.84)	(2.67)	(4.6)	(5.9)	(7.13)	

Table 2.7: Fama-Macbeth Regressions by Lottery Quintile

This table presents the Fama-Macbeth regression coefficients estimated separately for the three profitability measures. The profitability measures include gross profits (GP), income before extraordinary items (IB), and operating profits (OP). All three profitability measures are deflated by the book value of total assets. The sample used for estimation is broken down into quintiles based on the lottery proxies. That is, the regressions are estimated separately within each lottery quintile. The lottery measures are explained in Subsection 2.3.1. The regression models contain only one profitability variable and four control variables: $R_{i,t} = \beta_0 + \beta_1 profitability_{i,t-1} + \beta_2 logme_{i,t-1} + \beta_3 logbm_{i,t-1} + \beta_4 ret[-12,2]_{i,t-1} + \beta_5 ret[-1,0]_{i,t-1} + \epsilon_{i,t}$, where $logme$ is the natural logarithm of the market value of equity, $logbm$ is the natural logarithm of the book-to-market ratio, $ret[-1,0]$ is the prior 1-month return, and $ret[-12,2)]$ is the prior year's return skipping the last month. Only the profitability coefficients (β_1) are reported in the table. The sample period is from January 1972 to December 2015. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Lottery Variable	Lottery Quintile	GP	IB	OP
JACKPOT	Low	0.004***	0.007***	0.016***
		(5.04)	(6.98)	(9.07)
	2	0.004***	0.007***	0.022***
		(5.78)	(8.72)	(11.64)
	3	0.006***	0.009***	0.023***
		(7.76)	(8.29)	(13.33)
	4	0.008***	0.010***	0.031***
		(9.58)	(8.87)	(15.16)
	High	0.010***	0.011***	0.037***
		(10.14)	(10.69)	(16.04)
LIDX	Low	0.003***	0.006***	0.015***
		(5.09)	(8.27)	(9.96)
	2	0.005***	0.008***	0.022***
		(6.16)	(9.16)	(11.36)
	3	0.006***	0.008***	0.026***
		(7.95)	(9.43)	(13.22)
	4	0.009***	0.011***	0.034***
		(9.78)	(9.6)	(16.04)
	High	0.010***	0.010***	0.038***
		(9.11)	(8.49)	(14.02)
MAXRET	Low	0.005***	0.010***	0.025***
		(7.05)	(10.96)	(14.48)
	2	0.006***	0.008***	0.024***
		(7.97)	(9.71)	(13.31)
	3	0.006***	0.007***	0.025***
		(7.97)	(8.49)	(12.27)
	4	0.007***	0.008***	0.028***
		(7.23)	(7.91)	(13.20)
	High	0.010***	0.011***	0.037***
		(9.86)	(9.40)	(14.90)
ESKEW	Low	0.004***	0.007***	0.015***
		(5.30)	(7.34)	(7.85)
	2	0.006***	0.009***	0.023***
		(7.69)	(8.67)	(10.58)
	3	0.006***	0.008***	0.028***
		(7.68)	(8.07)	(12.92)
	4	0.008***	0.011***	0.036***
		(10.15)	(10.85)	(17.34)
	High	0.010***	0.012***	0.042***
		(9.98)	(10.26)	(15.20)

Table 2.8: Fama-Macbeth Regressions by Profitability Quintile

This table presents the Fama-Macbeth regression coefficients estimated separately for the four lottery proxies. The lottery proxies are explained in Subsection 2.3.1. The sample used for estimation is broken down into quintiles based on the profitability proxies. That is, the regressions are estimated separately within each profitability quintile. The profitability measures include gross profits (GP), income before extraordinary items (IB), and operating profits (OP). All three profitability measures are deflated by the book value of total assets. The regression models contain only one lottery variable and four control variables: $R_{i,t} = \beta_0 + \beta_1 lottery_{i,t-1} + \beta_2 logme_{i,t-1} + \beta_3 logbm_{i,t-1} + \beta_4 ret[-12,2]_{i,t-1} + \beta_5 ret[-1,0]_{i,t-1} + \epsilon_{i,t}$, where $logme$ is the natural logarithm of the market value of equity, $logbm$ is the natural logarithm of the book-to-market ratio, $ret[-1,0]$ is the prior 1-month return, and $ret[-12,2)]$ is the prior year's return skipping the last month. Only the lottery coefficients (β_1) are reported in the table. The sample period is from January 1972 to December 2015. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Lottery Variable	Profitability Quintile	GP	IB	OP
JACKPOT	Low	-0.006***	-0.005***	-0.005***
		(-3.20)	(-3.72)	(-3.35)
	2	-0.008***	-0.003*	-0.004***
		(-4.90)	(-1.84)	(-2.80)
	3	-0.005***	0.000	-0.000
		(-3.70)	(0.01)	(-0.19)
	4	-0.005***	-0.001	-0.003*
		(-3.82)	(-0.64)	(-1.80)
	High	-0.004***	-0.005**	-0.004**
		(-2.79)	(-2.48)	(-2.29)
LIDX	Low	-0.014***	-0.013**	-0.013**
		(-2.88)	(-2.54)	(-2.57)
	2	-0.012***	-0.003	-0.010**
		(-2.88)	(-0.68)	(-2.16)
	3	-0.006	0.002	0.000
		(-1.45)	(0.58)	(0.00)
	4	-0.004	0.005	0.000
		(-0.93)	(1.51)	(-0.01)
	High	0.002	-0.001	0.003
		(0.44)	(-0.17)	(0.75)
MAXRET	Low	-0.005***	-0.005***	-0.005***
		(-5.75)	(-6.60)	(-6.43)
	2	-0.004***	-0.003***	-0.004***
		(-5.43)	(-3.73)	(-4.74)
	3	-0.003***	-0.001	-0.002***
		(-4.27)	(-1.45)	(-3.08)
	4	-0.003***	-0.001*	-0.002**
		(-4.46)	(-1.67)	(-2.28)
	High	-0.002***	-0.003***	-0.002**
		(-2.95)	(-3.35)	(-2.46)
ESKEW	Low	-0.0022***	-0.004***	-0.0042***
		(-2.55)	(-2.84)	(-2.88)
	2	-0.002	0.001	-0.001
		(-1.53)	(0.91)	(-0.84)
	3	0.002	0.002**	0.000
		(1.29)	(2.10)	(0.21)
	4	-0.001	0.002	0.000
		(-1.21)	(1.64)	(0.53)
	High	-0.001	-0.001	-0.000
		(-0.86)	(-1.01)	(-0.04)

Table 2.9: Fama-Macbeth Regression with Interactions

This table presents the results of running the following Fama-Macbeth regression model for the sample period January 1972 to December 2015: $R_{i,t} = \beta_0 + \beta_1 profitability_{i,t-1} + \beta_2 lottery_{i,t-1} + \beta_3 profitability_{i,t-1} \times lottery_{i,t-1} + \beta_4 logme_{i,t-1} + \beta_5 logbm_{i,t-1} + \beta_6 ret[-12,2]_{i,t-1} + \beta_7 ret[-1,0]_{i,t-1} + \epsilon_{i,t}$ The profitability measures include gross profits (GP), income before extraordinary items (IB), and operating profits (OP). All three profitability measures are deflated by the book value of total assets. The lottery measures are explained in Subsection 2.3.1. *logme* is the natural logarithm of the market value of equity, *logbm* is the natural logarithm of the book-to-market ratio, $ret[-1,0]$ is the prior 1-month return, and $ret[-12,2)]$ is the prior year's return skipping the last month.

	JACKPOT		LIDX		MAXRET		ESKEW	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Gross Profitablity (GP)								
GP	0.007***	0.008***	0.007***	0.007***	0.007***	0.007***	0.007***	0.007***
	(10.65)	(10.39)	(10.76)	(10.65)	(10.44)	(10.58)	(11.40)	(11.63)
lottery	-0.006***	-0.006***	-0.002**	-0.002**	-0.004***	-0.004***	-0.001	-0.001
	(-4.84)	(-4.95)	(-1.97)	(-2.09)	(-6)	(-5.65)	(-1.27)	(-1.29)
GP × lottery		0.003***		0.002***		0.002***		0.002***
		(4.01)		(5.80)		(5.20)		(3.33)
logme	-0.002***	-0.002***	-0.001**	-0.001**	-0.001**	-0.001**	-0.001	-0.001
	(-3.38)	(-3.39)	(-2.01)	(-2.03)	(-1.99)	(-2.03)	(-1.13)	(-1.15)
logbm	0.004***	0.003***	0.004***	0.004***	0.004***	0.003***	0.004***	0.004***
	(6.5)	(6.26)	(6.91)	(6.5)	(6.37)	(6.17)	(6.96)	(6.76)
ret[-12,2)]	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***
	(3.42)	(3.43)	(4.00)	(3.99)	(3.75)	(3.76)	(3.72)	(3.74)
ret[-1,0]	-0.007***	-0.007***	-0.007***	-0.007***	-0.006***	-0.006***	-0.007***	-0.007***
	(-10.61)	(-10.61)	(-10.6)	(-10.61)	(-7.94)	(-7.96)	(-10.41)	(-10.44)
Panel B: Income Before Extraordinary Items (IB)								
IB	0.009***	0.010***	0.009***	0.009***	0.009***	0.009***	0.009***	0.009***
	(13.75)	(12.76)	(14.25)	(13.69)	(13.04)	(12.49)	(13.89)	(10.8)
lottery	-0.004***	-0.004***	-0.000	-0.000	-0.003***	-0.003***	-0.000	-0.000
	(-3.33)	(-3.38)	(-0.73)	(-0.99)	(-4.90)	(-4.93)	(-0.62)	(-0.55)
IB × lottery		0.003***		0.001**		0.002***		0.000
		(2.69)		(2.17)		(2.91)		(0.84)
logme	-0.003***	-0.003***	-0.002***	-0.002***	-0.003***	-0.003***	-0.002***	-0.002**
	(-4.37)	(-4.06)	(-3.04)	(-2.93)	(-3.68)	(-3.53)	(-2.66)	(-2.52)
logbm	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***
	(7.05)	(6.92)	(7.33)	(7.09)	(6.89)	(6.74)	(7.19)	(7.01)
ret[-12,2)]	0.003**	0.003**	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***
	(2.56)	(2.54)	(2.92)	(2.89)	(2.81)	(2.79)	(2.73)	(2.75)
ret[-1,0]	-0.007***	-0.007***	-0.007***	-0.007***	-0.006***	-0.006***	-0.007***	-0.007***
	(-10.96)	(-11.05)	(-10.98)	(-11.03)	(-8.69)	(-8.76)	(-10.83)	(-10.96)

Table 2.9: Fama-Macbeth Regression with Interactions (Continued)

	JACKPOT		LIDX		MAXRET		ESKEW	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel C: Operating Profitability (OP)								
OP	0.029***	0.030***	0.029***	0.028***	0.029***	0.028***	0.030***	0.030***
	(18.93)	(15.75)	(19.51)	(18.78)	(18.24)	(17.54)	(19.64)	(17.76)
lottery	-0.004***	-0.004***	-0.000	-0.002**	-0.003***	-0.004***	-0.001	-0.002*
	(-3.59)	(-3.88)	(-1.17)	(-1.97)	(-5.40)	(-5.76)	(-1.23)	(-1.90)
OP × lottery		0.008***		0.006***		0.006***		0.008***
		(3.21)		(5.86)		(5.54)		(5.67)
logme	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***	-0.003***
	(-4.75)	(-4.3)	(-3.69)	(-3.54)	(-4.21)	(-4.08)	(-3.11)	(-3.02)
logbm	0.004***	0.004***	0.005***	0.004***	0.004***	0.004***	0.005***	0.004***
	(8.40)	(8.16)	(8.63)	(8.09)	(8.15)	(7.83)	(8.82)	(8.34)
ret[-12,2)]	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***
	(2.73)	(2.74)	(3.05)	(3.00)	(2.83)	(2.81)	(2.87)	(2.90)
ret[-1,0]	-0.007***	-0.007***	-0.007***	-0.007***	-0.006***	-0.006***	-0.007***	-0.007***
	(-10.99)	(-11.00)	(-10.97)	(-10.99)	(-8.53)	(-8.58)	(-10.88)	(-10.91)

Table 2.10: Fama-Macbeth Interactions Horserace

This table presents the Fama-Macbeth regression estimates after controlling for a range of stock characteristics. We take the regression specifications in Table 2.9 and add six proxies for stock performance and their interactions with the profitability measures to each specification, separately. The lottery and profitability measures are explained in Subsection 2.3.1. *logme* is the natural logarithm of the market value of equity, *logbm* is the natural logarithm of the book-to-market ratio, $ret[-1,0]$ is the prior 1-month return, and $ret[-12,2)]$ is the prior year's return skipping the last month. *Illiq* is the illiquidity measure of Amihud (2002), calculated as the annual average of the daily ratio of absolute stock return to its daily dollar trading volume, all scaled by $10^{-}6$. *I.Hold* is the sum of the quarterly institutional holdings by aggregating the positions of different institutions from the Thomson Reuters database. For brevity, we only report the coefficients on the interaction terms. The sample period is from January 1980 to December 2015.

	JACKPOT	LIDX	MAXRET	ESKEW
	(1)	(2)	(3)	(4)
Panel A: Gross Profitablity (GP)				
GP × lottery	0.002***	0.002***	0.001***	0.002***
	(2.65)	(4.63)	(4.11)	(2.56)
GP × logme	0.000	0.001	0.000	0.000
	(0.76)	(1.61)	(0.13)	(-0.24)
GP × logbm	0.000*	0.000	-0.001	0.000
	(1.68)	(1.50)	(-1.00)	(0.93)
GP × ret[-12,2)]	0.000	-0.001	0.000	-0.001
	(-0.66)	(-0.88)	(-1.35)	(-1.59)
GP × ret[-1,0]	0.001	0.000	0.000	0.000
	(1.16)	(0.78)	(0.66)	(1.59)
GP × Illiq	0.001***	0.000	0.000	-0.001
	(3.05)	(-0.16)	(-0.33)	(-0.66)
GP × I.Hold	-0.002**	-0.002	-0.001*	-0.002*
	(-2.22)	(-1.47)	(-1.72)	(-1.92)
Panel B: Income Before Extraordinary Items (IB)				
IB × lottery	0.002***	0.001**	0.002**	0.001
	(2.58)	(2.06)	(2.27)	(0.64)
IB × logme	0.000	-0.001*	-0.001	-0.001
	(-0.39)	(-1.85)	(-1.23)	(-0.80)
IB × logbm	0.001	0.000	0.000	0.000
	(1.25)	(0.90)	(0.99)	(0.82)
IB × ret[-12,2)]	0.001	0.001	0.001	0.001
	(1.01)	(1.54)	(1.09)	(1.48)
IB × ret[-1,0]	0.002	0.002	0.002	0.002
	(4.82)	(0.91)	(0.68)	(1.61)
IB × Illiq	0.002***	0.001***	0.001***	0.001***
	(4.01)	(4.66)	(4.39)	(4.21)
IB × I.Hold	0.002***	-0.002**	-0.001**	-0.002***
	(4.01)	(-2.21)	(-2.12)	(-2.69)
Panel C: Operating Profitability (OP)				
OP × lottery	0.006***	0.005***	0.005***	0.007***
	(2.56)	(3.23)	(3.54)	(3.63)
OP × logme	-0.001	-0.001	-0.001*	-0.001
	(-1.36)	(-1.30)	(-1.73)	(-0.90)
OP × logbm	0.001	0.001	0.001	0.001
	(1.16)	(0.99)	(1.15)	(1.02)
OP × ret[-12,2)]	0.001*	0.001	0.001	0.001
	(1.82)	(1.02)	(0.85)	(1.02)
OP × ret[-1,0]	0.003	0.001	0.002	-0.006
	(0.89)	(1.02)	(1.24)	(-0.85)
OP × Illiq	0.003**	0.003**	0.003*	0.002**
	(2.16)	(2.15)	(1.91)	(2.31)
OP × I.Hold	-0.005***	-0.004***	-0.004***	-0.004***
	(-4.00)	(-3.91)	(-3.62)	(-4.21)

Chapter 3

Skewness Preference and Market Anomalies

3.1 Introduction

Stocks with positively skewed or lottery-like return distributions generate lower returns in the cross section (see, e.g., 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 hold positively skewed positions. Theoretical papers commonly refer to this behavior as "the preference for skewness" and attempt to explain it by using more advanced utility functions (e.g., Mitton and Vorkink, 2007; Brunnermeier et al., 2007; Barberis and Huang, 2008).

Recent papers have used the preference for skewness to explain a number of long-standing puzzles in asset pricing. Examples include initial public offering (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, I investigate whether the preference for skewness has broader implications in generating mispricing patterns in the market. In particular, I determine whether the common mispricing-related component of market anomalies is associated

with investor preference for skewness.

Market anomalies are patterns in the cross section of stock returns that are not explained by existing asset pricing models. In particular, stocks with certain characteristics generate returns that are not commensurate with their level of risk. It is often difficult to determine whether anomalies are indications of imperfect risk models or signs of market mispricing.[1]

Recent studies provide evidence showing that anomalies, at least partly, reflect mispricing. For example, Nagel (2005) and Stambaugh et al. (2015), among others, demonstrate that anomalies are significantly more prevalent among stocks with greater arbitrage risks and costs. In addition, most abnormal anomaly returns are attributable to underperforming, or overpriced, stocks. These stocks need to be sold short, but many investors are reluctant or unable to do so (see, e.g., Hirshleifer et al., 2011; Stambaugh et al., 2012; Avramov et al., 2013).

Mispricing, to the extent that it is the underlying driver of market anomalies, exhibits commonalities across stocks. Stambaugh et al. (2012), for example, find a common time-varying component across a wide range of anomalies is strongly related to investor sentiment. I conjecture that the common mispricing-related component of anomalies can be, at least partly, explained by the pricing implications of preference for skewness.

I motivate the potential link between the two phenomena by building on the observation of Harvey and Siddique (2000), who claim that stocks that anomaly strategies predict will underperform, commonly referred to as "Short-leg stocks", are often those with the highest levels of skewness in the cross section. [2] In contrast, stocks predicted by anomaly strategies to outperform, referred to as "Long-leg stocks", have the lowest levels of cross-sectional skewness.

my conjecture is that investors with a preference for skewness will be attracted to Short-leg stocks, but not Long-leg stocks. In the presence of limits to arbitrage, such behavior would contribute to the cross-sectional mispricing predicted by anomaly

[1] This argument began with 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 and of the models themselves.

[2] Higher levels of skewness throughout this paper refer to more positive, or less-negative, skewness values.

variables.

To measure the common mispricing-related component of anomalies, I adopt the approach of Stambaugh et al. (2015). This measure is constructed by taking the average of each stock's decile ranks for 11 anomaly variables. The anomalies I consider 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, 2016).

I also consider prominent skewness measures used in the recent empirical asset pricing literature. These 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 options-based idiosyncratic skewness (Conrad et al., 2013).

I test two main hypotheses by combining the pricing implications of return skewness with the findings of Stambaugh et al. (2012, 2014) for the commonality of mispricing across anomalies. The first hypothesis is that the performance of anomalies, to the extent that it is related to mispricing, would be stronger among stocks with higher skewness. This follows from my previously mentioned argument that skewness features attract investors with a preference for such features and thereby exacerbate anomalies.

I find strong support for this prediction using all five skewness measures. my measure of anomaly-based mispricing generates between 1.22% and 1.71% greater Long-Short monthly abnormal returns among stocks in the highest skewness quintiles compared to those in the lowest skewness quintiles. In a regression framework, I find that a 1-standard-deviation increase in skewness adds between 30% and 60%, depending on the measure of skewness used, to anomaly return predictability.

My second hypothesis states that the effect of skewness on anomalies will 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, because they are underpriced, which is easier for arbitrageurs to adjust.

My findings indicate that Short-leg stocks with high levels of skewness generate 3 to 9 times larger negative abnormal returns, whereas returns of Long-leg stocks do not significantly change with the level of skewness. I 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 mostly driven 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 is underpricing in extreme anomaly portfolios.

My two hypotheses predict that investors with a preference for skewness will invest disproportionately more in Short-leg stocks, rather than among Long-leg stocks. Specifically, I examine whether investors with a preference for skewness actually trade in a direction opposite of what anomaly strategies suggest. I test this by looking at the portfolio holdings data of a sample of retail investors obtained from a large U.S. discount brokerage house for the period 1991 to 1996.

My results strongly support this prediction. 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% greater weight in excess of the market weight) to Short-leg stocks relative to Long-leg ones. I 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. I find that this ratio is associated with a higher portfolio weight on Short-leg stocks in investors' portfolios.

I investigate two alternative explanations for my results. First, I test whether the

relation between skewness and anomaly returns is due to a missing systematic coskewness factor in the asset pricing model, rather than a mispricing effect generated by the preference for skewness. This proposition is based on Harvey and Siddique (2000), who show that extreme anomaly returns are partly explained by the loading on a coskewness factor. Second, I investigate whether my skewness measures indirectly reflect arbitrage costs instead of features that attract investors who like skewness. This test is motivated by previous studies documenting a close association between skewness and limits to arbitrage (e.g., Bris et al., 2007; Chang et al., 2007; Xu, 2007). I find that my 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, I build on the evidence in Stambaugh and Yuan (2016) and examine whether skewness present in asset pricing models improves the models performance in capturing anomaly returns. Specifically, Stambaugh and Yuan (2016) 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. I follow the approach of Stambaugh and Yuan (2016) and construct a skewness factor by combining four skewness measures: jackpot probability, lottery index, maximum daily return, and expected idiosyncratic skewness.

I find that adding this factor to models significantly enhances overall performance in explaining anomalies. my skewness factor is particularly useful for explaining anomalies that are mostly driven by skewed stocks, such as those related to financial distress.

These findings relate to the stream of papers, 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), which investigate the mispricing-related component of market anomalies. I contribute to this stream by providing a new explanation for commonality in mispricing across anomalies.

Aside from Harvey and Siddique (2000), I am not aware of any other paper that has studied the pricing implications of skewness as a common contributing factor to a wide range of market anomalies. My approach is different than that of Harvey and

Siddique (2000), who suggest 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. In my case, I attribute the role of skewness in predicting returns to the mispricing effect of trades initiated by investors who have a preference for skewness. In fact, my findings indicate that exposure to a coskewness factor cannot explain the link between my various firm-level skewness measures and anomaly returns.

The remainder of the paper is organized as follows. Subsection 3.2 briefly discusses the evidence on anomalies and skewness and develops my hypotheses. Section 3.3 summarizes the data and my main variables. Section 3.4 presents the main empirical results. Section 3.5 examines two alternative explanations for my main results. Section 3.6 builds upon the implications of my findings and constructs a skewness factor. Section 3.7 concludes.

3.2 Background and Testable Hypotheses

I begin this section by reviewing the relevant literature on the preference for skewness and its link to market anomalies. I then develop two testable hypotheses exploring whether the mispricing-related component of anomalies is driven by investors' preference for holding positively skewed assets.

3.2.1 Skewness, Mispricing, and Market Anomalies

Much of the early work on return skewness argues that only coskewness, defined as the portion of an asset's skewness 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 will only care about skewness as a measure of undiversifiable downside risk (Harvey et al., 2010) and that idiosyncratic, or firm-level, return skewness will be irrelevant for investment decisions. However, recent empirical findings indicate that idiosyncratic skewness is negatively related to future returns even more strongly than is coskewness (e.g., Kumar, 2009; Boyer et al., 2010; Bali et al., 2011).

More recent theoretical papers justify the pricing role of idiosyncratic skewness by

arguing that a group of investors in the market have a preference for holding positively skewed positions at the expense of underdiversification (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, in doing so, generate lower returns in the market.

Barberis and Huang (2008) develop a model to demonstrate that the cumulative prospect theory of Tversky and Kahneman (1992) can explain why investors might have a preference for holding 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 to positively skewed stocks and that such stocks are overvalued internationally. Nevertheless, not all investors behave according to cumulative prospect theory. Preference for skewness is mainly prevalent among retail investors, in particular, to those who are less sophisticated and tend to exhibit a strong propensity to gamble in nonfinancial settings (Kumar, 2009).

A number of papers build on the role of skewness in explaining 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 introduce a factor to capture systematic coskewness and show that adding it to the capital asset pricing model (CAPM) can significantly improve the performance of the model in explaining market anomalies. Essentially, Harvey and Siddique (2000) attribute market anomalies to the failure of pricing kernels to capture systematic skewness.

In contrast, recent studies suggest that skewness has a mispricing effect that contributes to individual 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 and lead to the overpricing (underpricing) of more (less) positively skewed

stocks (for a review, see Barberis, 2013). The resultant mispricing will persist, because it is too risky or costly for other investors who 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 evidence indicating that anomalies are more pronounced among stocks with higher arbitrage risk (e.g., Nagel, 2005; Stambaugh et al., 2015) and that an increase in arbitrage activity leads to a decay in anomaly strategy returns (e.g., Hanson and Sunderam, 2014; Chordia et al., 2014; McLean and Pontiff, 2016). Also, the profitability of anomaly strategies is largely generated 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 largely prevails because short-selling impediments make it more difficult to adjust overpricing compared with underpricing. Stambaugh et al. (2012, 2014) follow this line of reasoning and uncover a common mispricing component across major anomaly strategies that is strongly related to investors sentiment. In the next subsection, I build on the literature reviewed above to form a series of testable hypotheses.

3.2.2 Main Testable Hypotheses

I 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 my argument is the observation that stocks in the short (long) leg of anomaly strategy portfolios that generate the greatest abnormal returns often have the highest (lowest) levels of skewness in the cross section. This relation 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). For example, Xu (2007) introduces a theoretical model and shows that when short-selling is difficult or costly, investors react more to positive information than to negative information. This is because reacting to negative information requires short-selling the stock, which is costly and difficult. Consequently, stocks will have more extreme positive returns than extreme negative returns, leading to positive skewness. We know that anomaly strategy returns are mostly generated by stocks in the Short-leg, 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 leads to the three main testable predictions outlined below:

> **H1:** *Cross-sectional return predictability of anomalies would be stronger among stocks with higher skewness, to the extent that predictability is related to mispricing.*

This first hypothesis follows from the literature reviewed in the previous subsection showing that high skewness features appeal to a host of investors that have a preference for positive skewness. I 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 are those in the long legs. Therefore, investors with a preference for skewness are generally more likely to be attracted to the short leg, not the long leg, thereby contributing to the anomaly. However, because of short-selling impediments, there is asymmetry in the mispricing effect of investors preference for skewness on short- and Long-leg stock returns. This leads to my second hypothesis:

> **H2:** *The Short legs of anomaly strategies would generate lower returns among stocks with higher skewness compared with those with lower skewness. Re-*

turns of the Long legs, however, would not be affected by different levels of skewness.

My second hypothesis suggests that the effect of skewness on anomalies is driven by the underperformance of overpriced stocks with high levels of skewness. I 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 due to an increase in overpricing in the short leg. On the other hand, the effect of the preference for skewness should be limited on the long leg because the stocks in that group are underpriced, which is easier for arbitragers to adjust.

3.3 Data and Measures

My main tests are based on a conventional sample of all common (share code 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 from January 1963 to December 2015. I exclude all firms with negative book equity, or those belonging to the financial sector ($6000 \leq SIC \leq 6999$) or those with a share price below \$1.[3] In the case of missing returns, I use delisting returns.

To construct my main skewness and anomaly variables, I use accounting data from Compustat Fundamentals Annual and Quarterly files and option price data from OptionMetrics. My factor returns and risk-free rates come from Professor Kenneth French's data library.[4] In addition, I use the end-of-month portfolio positions of a sample of retail investors from a major U.S. discount brokerage house covering the time period from 1991 to 1996. Lastly, for robustness tests, I obtain short interest data from Compustat and quarterly data on institutional stock holdings from Thomson Reuters. Table 3.A presents the definitions and sources of all variables.

[3] I consider other share price cutoffs in the robustness tests and show that my results do not depend on the price filter.

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

3.3.1 Skewness and Anomaly-Based Mispricing Measures

In this section, I briefly introduce my main skewness and anomaly-based mispricing variables. Table 3.A presents further details about the construction of the variables. My main tests employ four prominent (firm-level) skewness measures commonly used in the literature: jackpot probability (*JACKPOT*), lottery index (*LIDX*), maximum daily return (*MAXRET*), and expected idiosyncratic skewness (*ESKEW*). *JACKPOT* is based on Conrad et al. (2014) and is defined as the out-of-sample probability of a stock generating a log return greater than 100% during the next 12 months. *LIDX* is an index originally introduced in Kumar et al. (2016) and ranks 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 the stock's maximum 1-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).

In addition, to provide evidence based on option prices, I use the options-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 nonparametric *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, *OS* is only available for a small subset of stocks with traded options, and, thus, I do not use it in all of my tests. Finally, I use the coskewness (*COSKEW*) measure of Harvey and Siddique (2000) in my robustness tests to distinguish my preference for skewness story from the argument that skewness relates to the stochastic discount factor.

I consider the 11 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 my story is based on the common mispricing component across all of the anomalies, I 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 11 anomaly variables. Decile ranks are defined at the end of every month. The 1st and the 10th deciles consist of stocks that each anomaly strategy predicts will 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, I 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, 2016).

Panel C of Table 3.1 presents the performance of *MIS* and the four key skewness measures (i.e., *JACKPOT*, *LIDX*, *MAXRET*, and *ESKEW*) in predicting future returns. I sort stocks into quintiles at the end of every month based on the five variables. Then I measure the value-weighted return of each quintile group, together with the return of the hedge portfolio (going long in quintile 5 and short in quintile 1) in the following month. To adjust the returns for risk, I 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, which seems to be partly captured by the five-factor model, and is only significant at the 10% level. The *MIS* hedge portfolio 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), I find that the overwhelming majority of hedge *MIS* returns come from the short leg. With all three factor models, the short *MIS* portfolio (quintile 5) generates alphas that are more than 2 times larger than those of the long portfolio (quintile 1).

3.3.2 Summary Statistics: Characteristics of Mispriced Stocks

To have a better understanding of stocks with different levels of mispricing, I present the mean cross-sectional characteristics of *MIS* quintiles in Panel A of Table 3.1. Quintile rankings are determined monthly by sorting stocks based on their end-of-month *MIS* value. I measure the characteristics at the end of the month in which I define the quintiles.

I find that the Short-leg (quintile 5) firms, on average, are smaller (lower market capitalization), are more volatile, and have cheaper shares with poorer past return performance, when compared to firms in the Long-leg (quintile 1). 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 stocks by holding more of the shares of Long-leg stocks. On the other hand, my brokerage sample suggests that retail (individual) investors place a higher weight on Short-leg stocks.

Part of my story relies on the conjecture that stocks in the Short leg have higher skewness, which then attracts investors with a preference for skewness, thereby contributing to overpricing. I test this assertion by comparing the mean skewness measures across the *MIS* quintiles. Together with my four main skewness proxies, I also look at coskewness (*COSKEW*), options-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 3.A).

Panel B of Table 3.1 presents the results. The average values of all seven skewness measures monotonically increase from *MIS* quintiles 1 to 5. In all cases, a simple t-test indicates that the difference between the skewness values of quintiles 1 and 5 is statistically significant at the 5% level. Altogether, I find results similar to those reported in Harvey and Siddique (2000) and Conrad et al. (2014), who find that skewness increases by moving from the long to the short legs of anomaly strategies. However, I must be careful in generalizing my argument because the pattern of skewness that I observe is based on an average measure across anomalies, that is, *MIS*, and not on each individual anomaly.

It is beyond the scope of this study to determine why skewness increases from the Long to the Short leg. Still, I can speculate about possible causes based on the previous literature and the portfolio characteristics in Panel A of Table 3.1. A first possible explanation might be that stocks in the Short leg become more skewed because of their poor past returns performance. Several studies show that low (high) past average returns lead to higher (lower) skewness because of 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 because of their underperformance, as captured by a higher average short ratio in Panel A of Table 3.1. 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 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, thereby leading to higher skewness. The average characteristics in Panel A of Table 3.1 indicate that firms in the short side are not only more volatile but they also have a higher leverage ratio, which can explain their higher skewness.

3.4 Empirical Results

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

3.4.1 Skewness and Anomalies

3.4.1.1 Double Sorts

I test my first and second hypotheses (*H1* and *H2*) by analyzing the performance of portfolios double sorted on my combined anomaly variable, that is, *MIS*, and each of my four main skewness measures, that is, *JACKPOT*, *LIDX*, *MAXRET*, and *ESKEW*. Portfolios are formed by independently sorting stocks into quintiles based on each of the

two variables at the end of every month. I then compute the value-weighted returns of the 25 portfolios over the following month and regress these on the four Carhart (1997) factors to generate abnormal returns.[5] The sample excludes penny stocks and covers January 1963 to December 2015, except for sorts based on *ESKEW*, which start in January 1988.

Panel A of Table 3.2 presents the monthly abnormal returns of the double-sorted portfolios. As expected, the magnitude of mispricing as captured by *MIS* spreads (most overpriced - most underpriced) monotonically increases 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 and 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, and high *JACKPOT* stocks generate a *MIS* spread of -2.06%, which is about 6 times larger than the -0.35% spread of low *JACKPOT* stocks. My findings so far are in line with my first hypothesis (*H1*) that mispricing is concentrated among stocks with higher levels of skewness.

Panel A of Table 3.2 also shows that the differences in *MIS* spreads across the skewness quintiles mostly come from changes in 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 3 to 9 times larger negative abnormal returns. More interesting is that negative abnormal returns are not statistically significant for overpriced stocks in the 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

[5] I find similar results if I adjust returns using the five-factor model of Fama and French (2015). These results are available on request.

literature that anomaly spreads are mostly driven by Short-leg stocks heavily depends on the level of skewness. These results support my second hypothesis (*H2*), which looks at whether the effect of skewness on anomaly returns mostly comes from the short side.

To examine the relative distribution of firms across the most mispriced groups, I compute the average number of observations in each of the double-sorted portfolios. Results, presented in Panel B of Table 3.1, 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 the 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 my summary statistics in Panel B of Table 3.1 showing that overpriced firms are more likely to have higher levels of skewness compared with underpriced ones.

Taken together, my double-sorting results are consistent with my main conjecture, which posits that the mispricing-related component of anomalies is largely driven 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.

3.4.1.2 Fama-Macbeth Regression Estimates

To further investigate the relation between skewness and anomalies, I run a series of Fama and MacBeth (1973) regressions. Specifically, at the end of each month t, I use a set of independent variables, including stock characteristics, and my skewness and mispricing measures to predict stock returns in month $t + 1$. The main variable of interest is the interaction between each of the skewness measures and the anomaly variable, *MIS*. In all regressions, I control for market value, the book-to-market ratio, and past returns for the previous month and for the prior 12 months but skipping the last month. To facilitate my interpretation, I standardize all variables in the regressions to have a mean of zero and a standard deviation of 1. Also, all variables are winsorized at the 0.5 and 99.5 percentiles, to ensure that extreme values do not affect my results.

I test my first hypothesis (*H1*) again using Fama-Macbeth regressions. I hypoth-

esize that the anomaly premium is higher for stocks with greater levels of skewness, so I expect to find that the interaction between the skewness measures and the anomaly variable has a negative sign. Panel A of Table 3.3 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 interaction terms and test whether MIS and my skewness variables are individually linked to future returns. Each of the five main variables is statistically significant at the 5% level. As can be seen, the *MIS* coefficient is larger and more significant than that of any of the individual skewness measures. A 1-standard-deviation increase in *MIS* is associated with a 0.5% decline (t-statistic of -11.72) in the following month's return, after controlling for major firm characteristics. Among the skewness measures, $JACKPOT$ is the strongest return predictor with a coefficient of -0.004 (t-statistic 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, I am essentially testing my main premise that the interaction between skewness and the anomaly variables 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 3 suggested by Harvey et al. (2016).[6] A 1-standard-deviation increase in skewness adds between 0.1% and 0.3% to the predictive power of *MIS* on a monthly basis. These figures amount to between 30% and 60% 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 wholly generated by stocks that are likely to be mispriced, as suggested by the combined anomaly measure.

To ensure that my regression results are not sensitive to my data filters or are driven by specific parts of the sample, I run a series of robustness tests. For brevity, I only report the coefficients on my main variables of interest, which are the interaction terms in Panel B of Table 3.3. Altogether, my estimates are robust. Skipping winsorization and excluding firms with a share price lower than $5 have negligible effects on the interaction

[6] Harvey et al. (2016) argue that because of potential data-mining issues, a t-statistic of 3 is a more appropriate significance cutoff for Fama-Macbeth regressions than is the usual cutoff of 2.

coefficients. An interesting observation is that my results become slightly stronger once I drop micro-cap stocks. Excluding mega-cap stocks, however, has a limited effect on the coefficients. Following Fama and French (2008), I define micro- and mega-cap stocks as those with market capitalizations below the 20th and above the 80th percentiles of NYSE market capitalization, respectively. In addition, I try removing NASDAQ stocks from my sample. In this case, although the coefficients remain highly significant, their magnitudes shrink slightly in some cases.

I also consider looking at different time periods in the sample. First, I divide the whole sample into recession and expansion periods, based on the NBER Recession Indicator,[7] and estimate the interaction coefficients separately for each subsample. This is to see whether the effect of skewness on mispricing is particular to recession times when the market is highly volatile. The results, reported in rows (6) and (7) of Panel B of Table 3.3, indicate that the interaction coefficients remain significant in both the recession and the expansion period. The exception, however, is the $ESKEW \times MIS$ coefficient, which is only significant for expansion periods, probably because the $ESKEW$ data start in 1988, so estimates fail to capture the recessions in the 1970s and the 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.

Last, I divide my sample into two parts: the first involves the period between 1962 and 1990 and the second between 1991 and 2015. The aim is to see whether results change over time. I observe that the coefficients are much larger for the second subsample. This observation is also interesting, because 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 evidence to corroborate my first hypothesis and show that skewness increases the level of mispricing predicted by the anomaly strategies.

In Panel C of Table 3.3, I test my second hypothesis (*H2*) again by checking whether skewness contributes to anomalies by exacerbating overpricing, while not affecting underpricing significantly. Since an interaction term between *MIS* and the skewness

[7]The data are taken from the Federal Reserve Bank of St. Louis website (https://fred.stlouisfed.org/series/USREC).

variables cannot directly capture this effect, I run the Fama-Macbeth specification in column (1) of Panel A within subsamples of *MIS* and the four skewness variables. This specification only includes *MIS* and firm controls as independent variables. I construct the subsamples by sorting stocks independently at the beginning of each month into two *MIS* and two skewness portfolios using medians as breakpoints. I then estimate the regression model within each of the four intersecting subsamples, separately. I repeat this exercise for each of my four skewness measures.

My second hypothesis predicts that mispricing levels (*MIS* coefficients) of overpriced stocks, which are in the above-median *MIS* group, are significantly different between the subsamples of high and low skewness. On the other hand, mispricing levels of underpriced stocks, which are in the below-median *MIS* group, do not significantly differ between the high- and the low-skewness groups. In line with this prediction, the results in Panel C of Table 3.3 show that the *MIS* coefficients of overpriced stocks are between 0.2% and 0.4% more negative in high-skewness subsamples compared to low-skewness ones. These differences are all statistically significant. Among underpriced stocks, however, there are not any statistically significant differences in *MIS* coefficients between high and low skewness subsamples. These findings provide further corroborating evidence for my second hypothesis (*H2*).

3.4.1.3 Evidence from Option-Based Skewness Measures

In the previous sections, I incorporate four prominent measures of firm skewness to test whether they affect the mispricing associated with anomaly strategies, as captured by the *MIS* measure. All four of my skewness variables yield results that are in line with my predictions; however, they are all noisy proxies for investors' perceptions about future return skewness. To make sure that my results reflect the role of skewness in predicting returns, and not an unrelated effect captured by the skewness measures, I repeat my main tests with a skewness measure constructed using option prices. In particular, I use the options-based idiosyncratic skewness measure of Bakshi et al. (2003) and Conrad et al. (2013). This options-based measure offers us information regarding expected future return skewness, without being subject to hindsight bias and without

requiring a parametric model for estimation (Conrad et al., 2013). However, I cannot use this measure in all my tests because option prices are available only for a small subset of firms in my sample.

Table 3.4, Panels A and B, respectively, present the results for double sorting and the Fama-Macbeth regressions using the options-based idiosyncratic skewness measure (OS). I essentially repeat the exercises in sections 4.1 and 4.2 but use the new measure. OS is constructed following the methodology of Conrad et al. (2013), as explained in Table 3.A. The sample period covering OS starts from 1996, because option price data for earlier years are not available in the OptionMetrics database.

The double-sorting results in Panel A of Table 3.4 suggest a pattern similar to what I observed before. That is, the spread between the most overpriced and the most underpriced stocks is largest among stocks in the high-OS quintile. As OS increases, MIS spreads do not grow with a clear monotonic pattern; however, there is a 2.06% difference between the monthly abnormal returns (t-statistic 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. Again, these observations support my first and second hypotheses.

The Fama-Macbeth regression results in Panel B of Table 3.4 are also in line with my first hypothesis. In specification (1), I find that OS by itself cannot significantly predict returns. Conrad et al. (2013) argue that, because of the limited number of firms with available option data, the relation between OS and returns cannot be reliably estimated. Nevertheless, my tests do not require me to have a reliable estimate for the premium associated with OS. I am instead interested to see whether OS exacerbates the mispricing captured by MIS. In specification (2), I test this conjecture by adding an interaction term between OS and MIS to the model.

The coefficient of the interaction term is -0.003 (t-statistics of -2.29), indicating that a 1-standard-deviation increase in OS increases the return predictability of MIS by 0.3%. This estimate is also economically significant. Considering that the MIS coefficient is also equal to -0.003, the interaction coefficient suggests that a 1-standard-deviation increase in OS doubles the premium associated with MIS. Altogether, regressions and

double-sorting tests based on the options-based skewness measure support my previous results about the effect of skewness on the anomaly-based mispricing.

3.4.2 Do Skewness-Loving Investors Hold the Wrong Stocks?

My results so far suggest that the common mispricing-related component of anomaly strategies is strongly concentrated among stocks with higher levels of skewness. Moreover, I show that this relation is mostly driven by the exacerbating effect of skewness on the prices of stocks that anomaly strategies suggest are overpriced. In this subsection, I examine the mechanism through which investors with skewness proclivities affect market anomalies. I expect to find that investors with such preferences invest disproportionately more in Short-leg stocks compared with 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 and place a relatively higher weight on stocks with higher levels of skewness. Stocks in the short legs of anomalies are more positively skewed than are those in the long legs. Therefore, all else being equal, Short-leg stocks should be relatively more attractive to investors with skewness preferences.

I test this prediction using the portfolio holdings data of a sample of retail investors obtained from a large U.S. discount brokerage house for the period 1991 to 1996. The reason for using data for retail investors is that previous papers show that such investors are more likely to have a preference for skewness (Kumar, 2009). My 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.

Raw and 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. Underpriced and overpriced stocks are

defined as those in the 1st and 5th quintiles of *MIS*, respectively.

I regress my relative weight measures on a series of variables capturing investors' preference for skewness, as well as controlling for socioeconomic and portfolio characteristics. I estimate regressions for each month and then compute the time-series averages of the coefficients using the Fama-Macbeth framework. Because preference for skewness is not directly measurable, I adopt an indirect proxy by computing the average portfolio weight each investor allocated to stocks with high levels of positive skewness in the past. I define stocks with high levels of positive skewness as those having skewness measures above the monthly cross-sectional median. At the end of every month t, I take the average of the weight each portfolio holder allocated to stocks with high levels of positive skewness over the previous 12 months ending in t-1. 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 four proxies: *JACKPOT*, *LIDX*, *MAXRET*, and *ESKEW*. I also incorporate the Catholic-to-Protestant ratio (*CPRATIO*) used in Kumar et al. (2011) and Kumar et al. (2016) as a measure of the 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 are 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. Table 3.A presents details about the construction of all variables, including the socioeconomic and portfolio characteristics controls. I standardize all independent variables to have a mean of zero and a standard deviation of 1 and also winsorize them at the 0.5 and 99.5 percentiles.

Panel A of Table 3.5 presents the baseline results. Columns (1) to (4) show that investors who overweighted stocks with high levels of skewness in the past year by 1 standard deviation of the cross-sectional distribution allocate between 11.6% and 18.4% higher raw weight to overpriced stocks, relative to underpriced ones. Excess weight regression estimates (columns (5) to (8)) provide a clearer picture because they are based on weights adjusted for benchmark (market) weights. A 1-standard-deviation

increase in an investor's past weight on high-skewness stocks predicts between 8.7% and 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 a 1-standard-deviation increase in regional *CPRATIO* is associated with between 0.4% and 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 3.5 are also worth noting, because they further highlight the characteristics of the clientele of investors who place higher weights on stocks 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 on a specific industry or geographical location. The latter finding is in line with Ivkovi and Weisbenner (2005), who show that local investors have more knowledge about local stocks and are less likely to buy local stocks that perform poorly.

Investors who 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, 2013a) or a preference for skewness (e.g., Mitton and Vorkink, 2007; Kumar, 2009).

A possible concern with my results in Panel A of Table 3.5 is that I use the same stocks in each portfolio to compute the weights on both mispriced and high-skewess stocks. Even though all my independent variables are lagged by 1 month, most investors do not change their positions regularly. Therefore, the relation between the weights on skewed and overpriced stocks may just reflect the correlation between the skewness

measures and my mispricing indicator, *MIS*. In other words, an investor may overweight stocks with high levels of *MIS* (i.e., overpriced) for reasons other than a 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, I adjust my measures of past weight on high-skewness stocks by excluding all stocks in *MIS* quintile 1 or 5. Essentially, I compute the average weight an investor allocated to skewed stocks by excluding those that are mispriced according to *MIS*.

Panel B of Table 3.5 presents the results based on my alternative measures of weight on high-skewness stocks. I use the same regression specification used in Panel A. For brevity, control variable coefficients are not reported in the table, because they all remain almost intact from the previous regressions. The main results remain both statistically and economically significant with the new weight measures. A 1-standard-deviation increase in an investor's past weight on high-skewness stocks that are not in the extreme *MIS* quintiles predicts between 7.3% and 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% and 8.5%.

In short, the findings in this section support my prediction that investors with skewness preferences invest disproportionately more in Short-leg stocks compared with Long-leg ones and exacerbate market anomalies. Specifically, investors who 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 who overweight underperforming stocks relative to outperforming ones are also likely to come from Catholic regions, where the propensity to gamble is strong. Lastly, I observe that such investors possess other characteristics that have been previously linked to investors sophistication and possession of the preference for skewness and other behavioral biases.

3.5 Robustness Tests

I argued in the previous section that the effect of skewness on anomalies is driven by the preference of a group of investors to hold positively skewed assets. In this section,

I test two alternative explanations for my results. In particular, I consider skewness as a measure of systematic tail risk, as captured by coskewness, and an indirect proxy for factors deterring arbitragers.

3.5.1 Role of Coskewness in Anomalies

Harvey and Siddique (2000) argue that part of the reason anomaly strategies exist is because asset pricing models do not account for the downside tail risk captured by skewness. 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 subsection, I 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 their alternative measure, defined as the loading on a squared market return factor added to the CAPM. I include both variants of coskewness in my tests. I estimate the former measure using monthly returns data for the past 60 months and the latter measure using daily returns for the past month. Table 3.A provides further details on the construction of the variables.

Panel A of Table 3.6 reports the results of my baseline Fama-Macbeth regressions with the addition of the original coskewness measure of Harvey and Siddique (2000) as a control variable. I also consider an interaction term between coskewness and *MIS* to capture any possible effect coskewness might have on the coefficients of my skewness interaction terms. The results indicate that controlling for coskewness has almost no impact on my previous interaction coefficients. The interaction term between coskewness and *MIS* does not enter any of my regressions significantly and has negligible coefficients

in all cases. The coskewness term does not have a statistically significant coefficient, even in the column (1) specification, where none of the other main variables are included in the regression. Barberis et al. (2016) report similar results for the insignificance of coskewness in Fama-Macbeth regressions.

I 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, I only report the main coefficients of interest in Panel B of Table 3.6. 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.

3.5.2 Skewness as a Proxy for Limits to Arbitrage

Part of my story regarding the role of skewness in generating anomalies 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 who have a preference for skewness (Barberis and Huang, 2008). However, a possible concern of my findings is that my skewness measures might 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 anomalies 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 my tests, is strongly associated with arbitrage costs.

In this section, I address the concern outlined above by adding several measures of arbitrage cost as control variables to my Fama-Macbeth regressions. Similar to my approach in the previous subsection, I also interact these limits-to-arbitrage proxies with

MIS and add them alongside my main interaction terms. I expect to observe that my 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 compared with simple interactions between *MIS* and proxies for limits to arbitrage.

I follow 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 suggested by Lesmond et al. (1999), and the percentage institutional holding (like in DAvolio (2002)). Table 3.A presents the construction details for each measure.

Panels A to E of Table 3.7 report the results of running the Fama-Macbeth regressions with the addition of each of the five proxies outlined above. I observe that the coefficients of my 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 strength of the interaction between skewness and anomaly-related mispricing in predicting returns is only due to 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 in only a few cases. In sum, these results indicate that the role of skewness in exacerbating anomalies goes beyond just capturing arbitrage costs, which are often associated with skewness.

3.6 Skewness as a Factor

In the previous sections, I established that skewness features of stocks that are likely to be mispriced according to anomaly strategies attract investors with skewness preferences and thereby contribute to mispricing. In this section, I build on the approach of

Stambaugh and Yuan (2016) and examine whether firm-specific skewness in asset pricing models in the form of a *mispricing factor*, rather than a systematic risk factor, improves their ability to capture anomaly returns.

The idea behind constructing a mispricing factor is that mispricing has common drivers across stocks; therefore, factors exhibiting these common sources will help explain cross-sectional variations in returns that do not reflect compensation for systematic risk. 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 part of the commonality in abnormal returns. It is important to note, however, that I am not seeking to develop an asset pricing model here. The purpose of the exercise in this section is to investigate whether a skewness factor should be considered in future models to enable a better explanation of cross-sectional returns.

I follow the approach of Stambaugh and Yuan (2016) and use my four skewness measures—*JACKPOT*, *LIDX*, *MAXRET*, and *ESKEW*—to construct a skewness factor. That is, I first compute the average decile rank of each stock at the end of each month with respect to the four skewness measures. Next, I independently sort stocks based on their average skewness decile ranks and their market capitalization into three and two portfolios, respectively. I then compute the value-weighted monthly return of each of the six ($= 2 \times 3$) intersecting portfolios.

Unlike Stambaugh and Yuan (2016), I use the sample median rather than the NYSE median to allocate stocks into size groups. The reason for my 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.

Last, I 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, to derive monthly factor returns. I call this skewness factor *nonskewed minus skewed* (*NMS*).

I 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*). I

then compare the performance of the new models with the original ones in capturing the 11 anomaly strategies used to construct my anomaly variable (*MIS*). As described in Subsection 3.3.1, 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.

I 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. I then regress the time series of Long-Short portfolio returns on different systematic risk factors to estimate for the abnormal returns, as captured by the intercept alpha.

Table 3.8, Panels A and B, respectively, present the alphas and t-statistics of the 11 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 the 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 between 1.11 and 2.6 lower for the distress anomaly and between 0.98 and 2.2 lower for the O-score anomaly.

To better compare the models with each other, I present a set of summarizing performance measures for each model in Panel C of Table 3.8. In particular, I follow Stambaugh and Yuan (2016) and compute the average absolute alpha, the 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 do 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 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-statistics and GRS statistics that are lower by 0.17 and 1.02. The best model among them all is the five-factor model with momentum (*FF6*) and the *NMS* factor. This model produces an average alpha of 0.4%, 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.

Overall, I find that the *NMS* factor helps capture part 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 produce more refined factors capturing the pricing effects of skewness.

3.7 Summary and Conclusion

This study examines whether investor preference for skewness can act as a common driver of cross-sectional mispricing patterns identified by various anomaly strategies. Using a composite mispricing measure based on 11 strategies, I demonstrate that anomalies are 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 predominantly exacerbates anomalies through an increase in overpricing among stocks in the Short portfolio. Returns among stocks in the Long portfolio, on the other hand, do not significantly change with the level of skewness.

I attribute the effect of skewness on anomalies to the proclivity of a group of investors to hold positively skewed positions. Portfolio holdings from a large U.S. retail 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 who overweight

underperforming stocks relative to outperforming ones also possess characteristics that have been previously linked to investor sophistication and a preference for skewness.

My results do not fully explain various market anomalies. Numerous underlying mechanisms—though not all related to mispricing— are likely to drive each individual anomaly. I demonstrate mispricing-related commonalities across a range of strategies and show that the preference for skewness plays an important role here. In this sense, my work is related to papers that look for common drivers of anomalies. Stambaugh et al. (2012), for example, highlights the role of investor sentiment. While investor sentiment can explain time-series variations in the performance of anomalies, my story explains variations in the cross section. For example, I can, at least partly, explain why some stocks in the Short legs of anomaly portfolios are more overpriced than others.

As the main takeaway, I document that pricing implications of skewness extend beyond the individual cases of cross-sectional mispricing investigated in 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 asset pricing models, to better explain expected returns. The effect of skewness is mostly observed in the form of mispricing, which is unlikely to be captured by a systematic risk factor. I suggest that a factor that captures skewness-related mispricing commonalities can be useful in asset pricing models.

Table 3.1: Summary Statistics

This table reports the 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). Table 3.A defines MIS and all other variables. Quintile portfolios are formed by sorting stocks into five groups at the end of every month. The t-statistics for the difference between the values of quintiles 1 and 5 (5 - 1) in Panels A and B are based on Newey-West heteroscedasticity- 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 the sorts based on ESKEW, which start in January 1988. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	All Sample	MIS Portfolios					
		1	2	3	4	5	5 - 1
Panel A: Key Statistics of MIS Portfolios							
ME ($ Billion)	1.56	3.50	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	2.50	2.78	3.03	3.27	3.68	1.19 (7.83)
IVOL (%)	2.95	2.37	2.67	2.95	3.19	3.60	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	2.80	0.98 (5.38)
ILLIQ (10^6)	4.28	2.91	4.22	5.10	4.92	4.26	1.35 (7.59)
LEVERAGE	0.24	0.13	0.19	0.25	0.29	0.33	0.20 (15.52)
B/M	0.84	0.67	0.81	0.90	0.92	0.90	0.23 (5.66)
RHOLDING (%)	0.10	0.08	0.09	0.10	0.11	0.11	0.03 (4.37)
IHOLDING (%)	30.71	36.89	34.00	32.04	28.02	22.61	-14.28 (-7.93)
Panel B: Skewness Characteristics of MIS Portfolios							
ESKEW	0.78	0.62	0.70	0.77	0.84	0.96	0.33 (5.48)
JACKPOT (%)	2.00	1.30	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	0.20	0.03 (2.24)
SKEWNESS	0.25	0.23	0.24	0.25	0.26	0.28	0.05 (2.55)

Table 3.1: (Continued)

Panel C: Abnormal Returns of MIS and Skewness Measures							
Variable	Model	1	2	3	4	5	5 - 1
	3-Factor	0.29***	0.07*	-0.07	-0.22***	-0.80***	-1.09***
		(6.66)	(1.77)	(-1.24)	(-3.57)	(-8.30)	(-8.90)
MIS	4-Factor	0.20***	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	0.00	-0.08	-0.45***	-0.63***
		(4.46)	(1.20)	(0.08)	(-1.26)	(-5.32)	(-5.99)
	3-Factor	0.08***	0.02	-0.09	-0.51***	-0.97***	-1.05***
		(3.47)	(0.29)	(-1.24)	(-4.23)	(-5.39)	(-5.50)
JACKPOT	4-Factor	0.05**	0.07	-0.03	-0.34***	-0.65***	-0.70***
		(2.16)	(1.31)	(-0.35)	(-2.82)	(-3.73)	(-3.80)
	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)
	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)
LIDX	4-Factor	0.08***	0.00	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**	0.00	-0.57***	-0.64***
		(3.07)	(1.34)	(1.99)	(-0.02)	(-4.09)	(-4.46)
	3-Factor	0.10**	0.03	0.08	-0.10	-0.61***	-0.70***
		(2.03)	(0.60)	(1.38)	(-1.07)	(-4.92)	(-4.68)
MAXRET	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*
		(0.20)	(1.29)	(2.84)	(1.35)	(-2.17)	(-1.86)
	3-Factor	0.10**	0.11*	-0.09	-0.25**	-0.62***	-0.72***
		(2.55)	(1.73)	(-0.83)	(-2.10)	(-4.21)	(-4.46)
ESKEW	4-Factor	0.08**	0.10	-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**	0.10	0.00	-0.25*	-0.34**
		(2.30)	(2.29)	(0.88)	(-0.02)	(-1.87)	(-2.32)

Table 3.2: 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. Table 3.A defines all the variables. The portfolios are formed by independently sorting stocks into five portfolios at the end of every month with respect to each variable. I 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. Panel B presents the average number of stocks in each portfolio. The sample excludes penny stocks and covers January 1963 to December 2015, except for sorts based on ESKEW, which start in January 1988. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

		Most Underpriced	2	3	4	Most Overpriced	Most Overpriced - Most Underpriced
Panel A: Abnormal Returns of Double-Sorted Portfolios							
JACKPOT	Low	0.19***	0.02	-0.11*	-0.11	-0.16	-0.35***
		(4.23)	(0.40)	(-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)	(-7.20)
	3	0.42***	0.48***	0.08	-0.09	-0.92***	-1.34***
		(3.99)	(4.21)	(0.72)	(-0.82)	(-6.83)	(-7.85)
	4	0.72***	0.35**	0.07	-0.10	-1.11***	-1.83***
		(4.94)	(2.45)	(0.49)	(-0.65)	(-6.81)	(-9.71)
	High	0.50**	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	-1.40***	-1.71***
	Low	(1.40)	(2.14)	(-0.43)	(-0.80)	(-6.03)	(-6.32)
LIDX	Low	0.22***	0.06	-0.04	-0.06	-0.35***	-0.56***
		(4.47)	(1.17)	(-0.60)	(-0.77)	(-3.30)	(-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	-0.20	-0.75***	-1.27***
		(4.20)	(3.12)	(1.14)	(-1.65)	(-5.77)	(-6.88)
	4	0.43***	0.52***	0.05	-0.04	-1.06***	-1.50***
		(3.18)	(4.06)	(0.44)	(-0.30)	(-6.68)	(-7.52)
	High	0.47**	0.15	-0.23	-0.40**	-1.43***	-1.90***
		(2.40)	(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)
MAXRET	Low	0.20***	0.10	0.00	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)	(1.70)	(0.60)	(-1.19)	(-2.98)	(-3.91)
	3	0.49***	0.14	-0.05	-0.04	-0.62***	-1.11***
		(4.98)	(1.39)	(-0.46)	(-0.35)	(-4.90)	(-6.89)
	4	0.54***	0.14	0.03	-0.34**	-0.80***	-1.34***
		(3.64)	(1.02)	(0.24)	(-2.44)	(-5.49)	(-6.68)
	High	0.20	-0.08	-0.37**	-0.39**	-1.51***	-1.70***
		(1.10)	(-0.44)	(-2.02)	(-2.21)	(-8.61)	(-7.62)
	High -	0.00	-0.17	-0.37*	-0.43**	-1.37***	-1.37***
	Low	(-0.02)	(-0.86)	(-1.72)	(-2.12)	(-6.19)	(-5.36)

Table 3.2: (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)	(-1.00)	(-2.54)	(-4.32)
	2	0.22**	0.15*	0.11	-0.01	-0.51***	-0.73***
		(2.11)	(1.66)	(1.10)	(-0.09)	(-3.98)	(-4.53)
	3	0.32**	0.18	0.09	-0.11	-0.86***	-1.18***
		(2.34)	(1.30)	(0.67)	(-0.80)	(-5.24)	(-5.69)
	4	0.57***	0.35**	-0.10	-0.06	-1.00***	-1.58***
		(4.01)	(2.19)	(-0.64)	(-0.38)	(-6.11)	(-8.28)
	High	0.58***	0.35**	0.22	-0.24	-1.30***	-1.88***
		(3.45)	(2.21)	(1.22)	(-1.25)	(-5.98)	(-7.78)
	High -	0.28	0.32*	0.27	-0.16	-0.98***	-1.22***
	Low	(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 3.3: Baseline Fama-Macbeth Regressions

This table presents estimates from the monthly Fama-MacBeth cross-sectional regressions. At the end of each month t, I use a set of independent variables including stock characteristics and my skewness and mispricing measures to predict the stock returns for month $t+1$. My primary independent variable is the interaction between each of the four skewness measures of JACKPOT, LIDX, MAXRET, and ESKEW and the combined anomaly variable, MIS. Table 3.A defines all the variables. All independent variables in my regressions are standardized to have a mean of zero and a standard deviation of 1 and are winsorized at the 0.5 and 99.5 percentiles. Standard errors are adjusted using the Newey and West (1987) approach. Panel A reports the baseline regression results. Panel B presents the results based on alternative samples or data filters. Panel C provides the results of estimating the specification in column (1) of Panel A within subsamples of MIS and the four skewness measures, separately. The subsamples are defined using medians of the variables as breakpoints. For brevity, I only report the interaction coefficients and the MIS coefficients in Panels B and C, respectively. The sample excludes penny stocks and covers January 1963 to December 2015, except for the regression that includes ESKEW, which starts in January 1988. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
					Panel A: Baseline Estimates				
Intercept	0.010***	0.010***	0.010***	0.010***	0.010***	0.009***	0.010***	0.010***	0.009***
	(4.33)	(3.98)	(4.35)	(4.11)	(3.89)	(3.83)	(4.29)	(4.11)	(3.60)
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**				0.000		
			(-2.06)				(-0.44)		
MAXRET				-0.003***				-0.002***	
				(-5.14)				(-3.39)	
ESKEW					-0.002***				-0.002**
					(-2.60)				(-2.03)
MIS × JACKPOT						-0.003***			
						(-6.12)			
MIS × LIDX							-0.002***		
							(-7.53)		
MIS × MAXRET								-0.002***	
								(-7.60)	
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)	(-3.50)	(-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)	(4.50)	(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	3,033	3,146	3,082	3,083	3,200	3,072	3,032	3,033	3,153
Average Adjusted R^2	0.042	0.042	0.046	0.045	0.039	0.047	0.048	0.047	0.044

Table 3.3: (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***	3,072	-0.002***	3,032	-0.002***	3,033	-0.001***	3,153
	(-6.12)		(-7.53)		(-7.60)		(-3.95)	
Basic Robustness Checks								
(1) No Winsorization	-0.002***	3,072	-0.002***	3,032	-0.002***	3,033	-0.001***	3,153
	(-4.37)		(-7.66)		(-6.85)		(-3.91)	
(2) Excludes Price ≤ 5	-0.003***	2,385	-0.002***	2,355	-0.002***	2,356	-0.002***	2,433
	(-8.14)		(-8.33)		(-7.37)		(-5.82)	
(3) Excludes Micro-Cap Stocks	-0.009***	1,351	-0.002***	1,335	-0.002***	1,336	-0.002***	1,385
	(-5.49)		(-6.92)		(-6.04)		(-4.55)	
(4) Excludes Mega-Cap Stocks	-0.003***	2,811	-0.002***	2,773	-0.002***	2,775	-0.001***	2,889
	(-6.00)		(-8.03)		(-7.41)		(-4.12)	
(5) Excludes NASDAQ Stocks	-0.002***	1,549	-0.002***	1,531	-0.001***	1,532	-0.001***	1,582
	(-4.81)		(-6.71)		(-4.95)		(-4.22)	
Subperiods								
(6) Recession Periods	-0.005***	1,731	-0.002**	1,730	-0.003***	1,731	-0.001	1,647
	(-2.67)		(-2.56)		(-3.83)		(-1.50)	
(7) Expansion Periods	-0.003***	2,782	-0.001***	2,745	-0.002***	2,746	-0.001***	2,858
	(-5.39)		(-6.70)		(-6.50)		(-2.96)	
(8) 1962–1990	-0.001***	2,658	-0.001***	2594	-0.001***	2,596	—	
	(-3.18)		(-3.01)		(-3.35)			
(10) 1991–2015	-0.004***	3,526	-0.003***	3,526	-0.003***	3,526	-0.004***	3,456
	(-5.79)		(-7.53)		(-8.38)		(-4.55)	

Table 3.3: (Continued)

Panel C: Regressions Results (MIS Coefficients) by Subsample			
	Below Median MIS (Underpriced)	Above Median MIS (Overpriced)	Above Median MIS - Below Median MIS (Overpriced - Underpriced)
Below Median JACKPOT	-0.000**	-0.002***	-0.002***
	(-2.17)	(-7.79)	(-7.61)
Above Median JACKPOT	-0.001***	-0.006***	-0.005***
	(-3.60)	(-14.77)	(-10.16)
Above Median - Below Median	-0.001	-0.004***	-0.003***
	(-1.61)	(-8.32)	(-5.88)
Below Median LIDX	-0.001***	-0.003***	-0.002***
	(-3.14)	(-7.19)	(-3.81)
Above Median LIDX	-0.001***	-0.006***	-0.005***
	(-3.43)	(-14.66)	(-9.95)
Above Median - Below Median	-0.000	-0.003***	-0.003***
	(-0.06)	(-5.13)	(-5.11)
Below Median MAXRET	-0.001***	-0.003***	-0.002***
	(-2.85)	(-8.97)	(-4.13)
Above Median MAXRET	-0.001***	-0.006***	-0.005***
	(-3.65)	(-14.26)	(-9.96)
Above Median - Below Median	-0.000	-0.003***	-0.003***
	(-0.01)	(-5.58)	(-5.56)
Below Median ESKEW	-0.001***	-0.004***	-0.003***
	(-3.89)	(-9.49)	(-6.08)
Above Median ESKEW	-0.001***	-0.006***	-0.005***
	(-2.86)	(-14.20)	(-9.12)
Above Median - Below Median	-0.000	-0.002***	-0.002***
	(-0.02)	(-3.35)	(-3.35)

Table 3.4: Options-Based Skewness Tests

This tables presents double sorting and Fama-Macbeth regression results based on the options-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. Table 3.A defines all the variables. The sample period covers January 1996 to December 2015, as the option price data for older periods are not available in the OptionMetrics database. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Double Sorts

OS Quintile	Most Underpriced	Most Overpriced	Most Overpriced - Most Underpriced
Low	0.21	0.28	0.10
	(1.22)	(0.43)	(0.14)
2	0.00	-1.86***	-1.70***
	(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)	(-2.90)	(-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	0.000	-0.001
	(-0.59)	(-1.43)
MIS × OS		-0.003**
		(-2.29)
log(ME)	0.003	0.000
	(1.22)	(0.08)
log(B/M)	0.001	0.001
	(0.39)	(0.71)
RET[-12,-2]	0.003	0.002
	(1.30)	(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 3.5: Individual Investor Portfolio Weight Regressions

This table presents estimates from the 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, my 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. I use four different skewness measures of JACKPOT, LIDX, MAXRET, and ESKEW to compute this weight. In Panel B, I estimate the same models but modify my measures of past weight on skewed stocks to exclude all stocks allocated to MIS quintile 1 or 5. I include a wide range of socioeconomic and portfolio characteristics control variables in both panels. For brevity, I do not report the control variable coefficients in Panel B. Table 3.A defines all the variables. I standardize all independent variables in my regressions to have a mean of zero and a standard deviation of 1 and winsorize them at the 0.5 and 99.5 percentiles. Standard errors are adjusted for heteroscedasticity and autocorrelation using the Newey and West (1987) approach. The sample period is January 1991 to December 1996. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

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}		0.170***				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	0.000	-0.005	-0.006	-0.008	-0.003
	(-0.13)	(-0.24)	(-0.27)	(-0.01)	(-0.20)	(-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)	(-5.30)	(-4.59)	(-4.74)	(-5.90)	(-5.41)	(-4.70)
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)	(1.70)	(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 3.5: (Continued)

Panel A (Continued):								
	$W^{overpriced} - W^{underpriced}$				$EW^{overpriced} - EW^{underpriced}$			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Married Dummy	-0.010***	-0.010***	-0.009***	-0.011***	-0.007***	-0.007***	-0.006***	-0.008***
	(-4.98)	(-4.71)	(-4.44)	(-6.00)	(-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)	(3.20)	(3.10)	(3.33)	(2.35)	(2.90)	(2.70)	(3.07)
CPRATIO	0.005***	0.004***	0.004**	0.006***	0.004**	0.003**	0.003*	0.005***
	(3.20)	(2.78)	(2.12)	(4.34)	(2.64)	(2.31)	(1.82)	(3.60)
ln(Population)	-0.012***	-0.011***	-0.012***	-0.013***	-0.010***	-0.009***	-0.010***	-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***	-0.020***	-0.022***	-0.029***	-0.02***
(%)	(-4.48)	(-6.26)	(-6.70)	(-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)	(-2.00)	(-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	6,477	6,477	6,477	6,477	6,477	6,477
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 3.6: Fama-Macbeth Regressions Controlling for Coskewness

This table presents the Fama-Macbeth regression estimates after controlling for the effect of coskewness. I take the regression specifications in Table 3.3 and add a measure of coskewness and its interaction with MIS to all regressions. In Panel A, I define coskewness (COSKEW) following the original Harvey and Siddique (2000) definition. In Panel B, I adopt Harvey and Siddique's (2000) alternative measure of coskewness, which is defined as the regression coefficient on a squared market factor. Table 3.A defines all the variables. I standardize all independent variables in my regressions to have a mean of zero and a standard deviation of 1 and winsorize them at the 0.5 and 99.5 percentiles. 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 the regression that includes ESKEW, which starts in January 1988. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
Panel A: Coskewness Based on the Original Harvey and Siddique (2000) Definition (COSKEW)					
Intercept	0.011***	0.010***	0.010***	0.010***	0.009***
	(4.70)	(3.90)	(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			0.000		
			(-0.16)		
MAXRET				-0.002**	
				(-2.55)	
ESKEW					-0.001
					(-1.40)
COSKEW	0.000	0.000	0.000*	0.000	0.000
	(-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		0.000	0.000	0.000	0.000
		(-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	2,173	2,154	2,154	2,154	2,198
Average Adjusted R^2	0.043	0.052	0.053	0.052	0.048

Table 3.6: (Continued)

Panel B: Coskewness Defined as the Coefficient on the Squared Market Factor (β_{m^2})					
β_{m^2}	-0.001	0.000	-0.001	0.000	-0.001
	(-0.53)	(-0.55)	(-0.72)	(-0.40)	(-0.60)
MIS × JACKPOT		-0.003***			
		(-6.05)			
MIS × LIDX			-0.002***		
			(-7.65)		
MIS × MAXRET				-0.002***	
				(-7.20)	
MIS × ESKEW					-0.001***
					(-3.96)
MIS × β_{m^2}		0.000	0.000	0.000	0.000
		(0.15)	(-0.34)	(-0.16)	(-0.19)
Average Number of Observations	3,084	3,072	3,032	3,033	3,153
Average Adjusted R^2	0.041	0.048	0.05	0.048	0.045

Table 3.7: Fama-Macbeth Regressions Controlling for Limits to Arbitrage

This table presents the Fama-Macbeth regression estimates after controlling for limits to arbitrage. I take the regression specifications in Table 3.3 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. Table 3.A explains the construction details for all variables. For brevity, I 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 1 and are winsorized at the 0.5 and 99.5 percentiles. 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 the regression that includes ESKEW, which starts in January 1988, and those including SHORTINT and IHOLDING, which because of data availability start in January 1973 and in January 1980, respectively. *, **, and *** denote significance at the 10%, 5%, and 1% levels, 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)	(2.90)
Average Number of Observations	3,097	3,096	3,097	3,047
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***			
	(-4.20)			
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	1,629	1,629	1,629	1,597
Average Adjusted R^2	0.054	0.053	0.052	0.052

Table 3.7: (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	0.000	0.002*	0.000	0.002
	(0.43)	(1.67)	(-0.16)	(1.34)
Average Number of Observations	2,860	2,859	2,860	2,810
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	0.000	0.002**	0.000	0.001
	(0.55)	(2.18)	(-0.28)	(1.55)
Average Number of Observations	3,370	3,368	3,370	3,252
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)	(-1.40)	(-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
	(1.40)	(1.46)	(1.50)	(1.46)
Average Number of Observations	3,487	3,486	3,487	3,392
Average Adjusted R^2	0.038	0.039	0.038	0.037

Table 3.8: 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, I present a set of summarizing performance measures for each model, including the average absolute alpha, the average absolute t-statistic of alpha, the Gibbons et al. (1989) statistics (GRS), and the p-value corresponding to the GRS statistics. I 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). I construct *NMS* in four steps. First, I 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, I independently sort stocks based on their average skewness decile ranks and their market capitalization into three and two portfolios, respectively. I then compute the value-weighted monthly return of each of the six intersecting portfolios. Lastly, I 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 obtain the monthly factor returns. The sample excludes penny stocks and covers January 1963 to December 2015, except for distress and return-on-assets anomalies, which because of data availability start in January 1973. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

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 3.8: (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	0.004
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)	0.00×10^{-14}	1.44×10^{-11}	1.91×10^{-13}	1.60×10^{-10}	1.24×10^{-12}	3.40×10^{-10}	7.86×10^{-11}	4.25×10^{-10}

Table 3.A: Variable Descriptions

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. I 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. I 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 5 years of data to predict the daily idiosyncratic skewness of stocks estimated over the following 5 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- and medium-sized market capitalization dummies (based on sorts of firms by market capitalization into three groups of small, medium, and large), an industry dummy based on the Fama-French 17 industries, and a NASDAQ dummy. After estimating the model at the end of every month t, I use the parameters together with the most recent data to get out-of-sample expected idiosyncratic skewness estimates for months $t+61$ through $t+120$. My estimates start in 1988 because detailed data on the trading volume of NASDAQ stocks become available in 1983.

Table 3.A: (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 for 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 3 months, detrended stock turnover ([6-month volume/shares outstanding] − [18-month volume/shares outstanding]), and log market capitalization. The model is estimated following a rolling-window approach using data from the past 10 years. Unlike Conrad et al. (2014), who use data from the past 20 years, I only require 10 years of historical data for each rolling-window estimation. Considering that the Compustat Fundamentals database started in 1950, a shorter estimation window enables me to start my 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) to the daily return data for the past 6 months. Idiosyncratic skewness refers to the skewness of residuals obtained from a two-factor model estimated using daily return data for the past 6 months, with the two factors being the market factor and its square.

Table 3.A: (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. Deciles 1 and 10 include stocks that each anomaly strategy predicts will outperform and underperform the most in the following month, respectively. Unlike Stambaugh et al. (2015), I determine my decile cutoffs using my whole sample, not just NYSE stocks. I require at least five 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 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). I 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 four-factor model of Carhart (1997) on daily returns for the most recent month.
OS	OptionMetrics	This follows Conrad et al. (2013) and Bakshi et al. (2003) and is defined 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. My sample of out-of-the-money calls and puts include securities that have expiration dates close to 0.250 years (3 months). I 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). My estimation technique and option data filters closely follow those used in Conrad et al. (2013).
SKEWNESS	CRSP	Skewness of daily returns for the most recent month.

Table 3.A: (Continued)

Variable Name	Source	Description
		Panel B: All Other Control Variables
%ZEROS	CRSP	This was devised by Lesmond et al. (1999) as the percentage of daily returns of each stock equal to zero. I measure this using the past 12 months of daily returns for each firm.
B/M	CRSP and Compustat	This is the ratio of the book value to the market capitalization of the firm.
BIDASK	CRSP	This is 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. I 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, I set the stock's institutional holdings to zero.
ILLIQ	CRSP	This is the 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 four-factor model of Carhart (1997) on daily returns for the most recent month.
LEVERAGE	CRSP and Compustat	This is the sum of total debt from 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 3.A: (Continued)

Variable Name	Source	Description
	Panel C: Variables Used in the Individual Holdings Regressions	
Age (Years)	Brokerage	The portfolio holder's age.
CPRATIO	ARDA	This is the 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	This is the proportion of residents in the portfolio holder's county with a Bachelor's degree or higher.
Income Equality	1990 Census	This is the 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	This is the natural log of annual household income in the portfolio holder's county.
ln(Population)	1990 Census	This is the natural log of the portfolio holder's home county population.
ln(Portolio Size)	Brokerage	This is the 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	This is equal to 1 if the portfolio holder is a male.
Married Dummy	Brokerage	This is equal to 1 if the portfolio holder is married.
Minority	1990 Census	This is the 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 3.A: (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	This is the intercept of the regression of monthly portfolio returns for Carharts (1997) four factors estimated using the past 12 months of data.
Rural	1990 Census	This is the proportion of the population that lives in rural areas in the portfolio holder's county.
Tenant Dummy	Brokerage	This is equal to 1 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.

Chapter 4

Do Geography and Industry Predict Mispricing?

4.1 Introduction

Firms with similar attributes can attract common investor clienteles and experience common variations in discount rates. Parsons et al. (2017), for example, argue that firm scrutiny by common investors or analysts is in fact crucial for the incorporation of all information into prices, and focus on industry and geography as two key firm attributes to show that a lack of scrutiny by the same group of investors can lead to a delayed reaction to peer information. However, commonality in investor clienteles can also cause prices to reflect their biases and behaviors (Kumar et al., 2013). This can result in firms with a specific common set of investors becoming mispriced. Industry and geography are particularly interesting firm attributes for which to investigate this effect because they have been widely shown to attract common market participants (e.g., Coval and Moskowitz, 1999; Kacperczyk et al., 2005).

In this study, I explore whether a firm's industry and geography contain information about its susceptibility to mispricing. In this context, mispricing is defined as the predictability of a firm's returns with respect to market anomalies. Market anomalies are cross-sectional patterns in stock returns that are not explained by asset pricing models. In many cases, such patterns take the form of certain stock characteristics that

predict future stock returns in the cross section without capturing an apparent source of systematic risk. Several studies suggest that anomalies at least partly reflect mispricing; for example, Nagel (2005) and Stambaugh et al. (2015) demonstrate that anomalies are considerably more pronounced among stocks facing significant arbitrage risks and costs. Furthermore, overpricing is more prevalent than underpricing in market anomalies because many investors are reluctant or unable to short-sell in order to adjust overpricing (Hirshleifer et al., 2011; Stambaugh et al., 2012; Avramov et al., 2013).

If there is a clientele effect that leads to mispricing in specific regions or industries, this should be persistent, and therefore, groups of firms that experience relatively higher levels of mispricing are likely to continue to be mispriced in the future. An empirical explanation of this phenomenon entails dividing the whole cross section of stock returns into smaller geographic and industrial cross sections and investigating the performance of anomalies within each one. My expectation is that I will be able to predict how well anomalies perform in the future for each stock based on their past performance within that stock's geographical region or industry.

I follow Stambaugh et al. (2015) and measure the common mispricing-related component of anomalies, taking the average of each stock's decile ranks with respect to 11 anomaly variables. I consider the following anomalies: 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 and offers an ex-ante measure of mispricing for each stock (see Stambaugh et al., 2015; Stambaugh and Yuan, 2016).

The main hypothesis of this paper explores whether geographic and industrial mispricing exists. In particular, I examine whether the mispricing levels of a firm's geographic or industrial peers can predict its mispricing in the future. This follows my argument above that firms in the same region or industry are affected by the behaviors of their common investors, meaning that these firms are exposed to the same forces that

can generate common mispricing.

I test my hypothesis in two ways and find strong support for it in all cases. First, I construct hedge portfolios (going long stocks in the highest quintile short those in the lowest quintile) based on my anomaly-based mispricing variable. I find that hedge abnormal returns are 0.346% higher for stocks headquartered in those states that had the highest abnormal returns over the previous year. The corresponding figure for stocks belonging to industries with the highest past abnormal returns is 0.348%. Second, I look at the return predictability at the firm level by only considering each firm's peers in my calculations of geographic or industrial mispricing. An increase of 1 standard deviation in the state-level mispricing of peer firms measured over the previous 12 months increases the return predictability of the firm by 0.045% on a monthly basis, while the corresponding figure for industry-level mispricing is 0.062%. Both results are highly statistically significant.

Both industrial and geographic mispricing variables remain economically and statistically significant in a setting where they are considered at the same time; in other words, they are complementing effects, in that neither captures the other. I also show that these results are robust to a series of basic tests, including an examination of subsamples and the use of alternative data filters. In addition, I control for a wide range of proxies for limits to arbitrage, and conclude that my measures of geographic and industrial mispricing are not only capturing illiquidity or trading costs. Nevertheless, one could still cast doubt on the results by arguing that any other arbitrary way of grouping stocks would lead to the same findings. To address this, I run a simulation exercise in which I randomly assign firms to other states and industries and estimate results accordingly. In so doing, I show that I find outcomes with magnitudes larger than or equal to mine in less than 1% of simulated cases.

In the second part of the paper, I explore the potential drivers of geographic or industrial mispricing. I begin by considering the role played by analysts. Specifically, I build on Engelberg et al. (2017) and argue that analyst forecast errors can potentially generate biased expectations, leading to mispricing. Therefore, firms in the most mispriced industries or regions may be those that are valued incorrectly by analysts.

However, analysts are more likely to be clustered by industry than geography (Parsons et al., 2017); therefore, I expect to observe a stronger role for analysts in generating industrial than geographic mispricing. My results indicate that industry-level mispricing is only significant for the subset of stocks with high analyst forecast errors in the most recent period. Although a similar result is observed for state-level mispricing, it is significantly weaker.

In addition, I investigate the role of local sentiment and risk aversion as a second potential driver of geographic mispricing. Following Korniotis and Kumar (2013b) and Kumar et al. (2013), I argue that local investor demand shocks can affect the prices of local stocks. Baker et al. (2012) shows that market anomalies perform better in countries with higher levels of sentiment. Original to the literature, I conjecture that heterogeneous investor sentiment levels across US states leads to different levels of mispricing for stocks in different regions. To measure local sentiment, I replicate the sentiment measure of Baker et al. (2012) across US states and, as a proxy for local risk aversion, I use the state macroeconomic index of Korniotis and Kumar (2013b). My results indicate that state-level mispricing is driven by those states experiencing economic expansion, or those with higher levels of investor sentiment.

To the best of my knowledge, this is the first study to investigate differences in the return predictability of market anomalies across different regions and industries. My study relates to two main strands of finance literature. First, I contribute to the literature on market anomalies (e.g., Nagel (2005); Stambaugh et al. (2012, 2015); Avramov et al. (2013); Hanson and Sunderam (2014); Chordia et al. (2014); McLean and Pontiff (2016); Chordia et al. (2017)) by showing that anomalies perform differently for firms in different states and industries; thus, refining anomaly strategies by geography or industry can improve their performance. Second, this study contributes to the literature by highlighting the importance of geography and industry in asset pricing (e.g., Moskowitz and Grinblatt (1999); Hou and Robinson (2006); Kumar et al. (2013); Korniotis and Kumar (2013b); Parsons et al. (2017)). I add to this vein of literature by showing that geography and industry not only affect discount rates, but also have the potential to generate return predictability.

The remainder of the paper is organized as follows. Section 4.2 briefly reviews the literature and develops the hypothesis; Section 4.3 summarizes the data and the main variables; Section 4.4 presents the main empirical results; Section 4.5 includes a series of robustness checks; and Section 4.6 concludes this paper.

4.2 Background and Hypotheses

I begin this section by summarizing the literature on the role of geography and industry in asset pricing. I then develop my main testable hypothesis to explore whether geography and industry can predict mispricing.

4.2.1 Related Literature

A large body of literature documents how firms' geographical locations can affect their stock returns. Pirinsky and Wang (2006) show that the stock returns of firms headquartered in the same geographical area comove with each other, and further argue that this comovement is not related to economic fundamentals, but is rather linked to the trading patterns of local investors. Bernile et al. (2017) extend these findings, and show that firms headquartered in different but economically connected states also experience excess stock comovement. Various papers attribute this excess comovement to local bias, which induces local investors to take larger positions in local stocks. For example, Bernile et al. (2015) suggest that institutional investors overweigh firms whose 10-K frequently mentions the investors' state. On the other hand, Kumar et al. (2013) show that retail trades cause comovement in local stocks, whereas institutional trades actually mitigate the issue.[1]

Local bias leads to the incorporation of the behaviors and preferences of local investors into the prices of local stocks. Becker et al. (2011) provide evidence indicating that firms located in regions with higher fractions of seniors experience stronger demand for dividends, leading to larger stock price falls on ex-dividend days. Hong et al. (2008) and Korniotis and Kumar (2013b) highlight that local risk tolerance affects the returns of local stocks. Specifically, Korniotis and Kumar (2013b) argue that U.S. state-level

[1]Other studies that document the localization of investors' trading activity include Coval and Moskowitz (1999, 2001), Loughran and Schultz (2004, 2005), and Shive (2012).

heterogeneity in economic conditions leads to variations in investor risk tolerance across states, and that this heterogeneous risk tolerance results in variations in the cross section of stock returns. Moreover, although Korniotis and Kumar (2013b) attribute some mispricing to geographical differences in stock returns, other studies provide risk-based explanations. For example, Garcia and Norli (2012) and Tuzel and Zhang (2017) show that there are various geographical sources of systematic risk that can lead firms in specific regions to experience higher expected returns.

There have been similar findings relating to the effect of firms' industries on stock returns. Moskowitz and Grinblatt (1999) find a lead-lag relationship between the returns of a stock and those of its industrial peers, while Parsons et al. (2017) argue that this relationship arises because the stock price movements of industry peers contain information about a firm's future earnings. However, since analysts are often clustered by industry, they are likely to communicate industry-related information and thus eliminate industry momentum. Parsons et al. (2017) provide evidence for this argument by showing that industry momentum is concentrated in small stocks with lower analyst following.

Industry is also shown to affect returns due to long-term shifts in consumption patterns. DellaVigna and Pollet (2007) document that demographic changes bring about forecastable changes in profits in various industries, and that this information is not incorporated into stock returns. Hou and Robinson (2006) prove that more concentrated industries generate lower returns because they have lower levels of risk in terms of innovation and technological progress. Moreover, institutional investors are aware of these predictable patterns in industries' stock returns. For example, Kacperczyk et al. (2005) find that mutual fund managers deviate from well-diversified portfolios and concentrate their investments in specific industries; their choice of industry is often related to their informational advantage because those with more concentrated positions demonstrate better performance.

The literature clearly shows a strong link between geography and industry, and expected returns. However, a missing piece of the puzzle concerns the question of whether a firm's geography and industry affect its levels of mispricing. Market anomalies are often used to characterize mispricing because there is indirect evidence that anomalies appear,

at least partly, due to some form of market friction. Nagel (2005) and Stambaugh et al. (2015), among others, find that anomalies are stronger among stocks with a higher arbitrage risk; in fact, increases in arbitrage activity can mitigate anomaly-strategy returns (e.g., Hanson and Sunderam, 2014; Chordia et al., 2014; McLean and Pontiff, 2016). In addition, the profitability of anomaly strategies is mostly generated by overpriced stocks (e.g., Hirshleifer et al., 2011; Stambaugh et al., 2012; Avramov et al., 2013). Miller (1977) argues that this is because short-selling impediments make it harder to adjust overpricing than underpricing. Stambaugh et al. (2012, 2014) build on these findings, indicating both that there is a common mispricing component across anomalies and that this component is strongly related to investor sentiment. In the next subsection, I form my main testable hypothesis based on the literature reviewed above.

4.2.2 Main Testable Hypothesis

In this paper, I examine whether the geography or industry of a firm can predict its predisposition to mispricing; in other words, I look at whether firms in geographic regions or industries with higher levels of cross-sectional mispricing will be more mispriced in the future. Following the literature reviewed in the previous subsection, we can expect a strong clientele effect for firms in certain regions and industries; in other words, firms are likely to share common investors with their geographic or industrial peers.

According to Parsons et al. (2017), scrutiny by a common set of investors or analysts affects how information is incorporated into prices. I argue that mistakes or biases among these common market participants can generate mispricing in the stocks of firms in specific regions or industries. This being so, I expect to observe that this mispricing – measured by market anomalies – is predictable by looking at a firm's geographic or industrial levels of mispricing. This leads to my primary hypothesis:

> **H1:** *Firms in regions or industries experiencing higher levels of cross-sectional mispricing are more likely to be mispriced in future periods, compared to their peers in less mispriced regions or industries.*

4.3 Data

My sample includes all common (share code 10 or 11) NYSE, AMEX, and NASDAQ stocks with available data in the Center for Research in Security Prices (CRSP) monthly stock return files in the period from July 1963 to December 2017. I exclude all firms with negative book equity, those belonging to the financial sector ($6000 \leq SIC \leq 6999$), and those with a share price below \$1.[2] In the case of missing returns, I use delisting returns.

The anomaly variables use accounting data from Compustat Fundamentals Annual and Quarterly files. For analyst earnings forecasts and coverage measures, I use the Institutional Brokers' Estimate System (IBES) database. The Baker and Wurgler (2006) US-wide sentiment data are taken from Professor Jeffery Wurgler's website.[3] I construct a state-wide sentiment series following the methodology of Baker et al. (2012) and, in doing so, collect the IPO offer date, offer price, and zip code data from Thomson Reuters Securities Data Corporation (SDC). All other attributes, including the IPO closing price for the first day, stock turnover, and stock returns, are drawn from CRSP daily and monthly files. Lastly, I collect short-interest data from Compustat and quarterly data on institutional stock holdings from Thomson Reuters. Table 4.A.1 presents the definitions and sources of all variables.

Firms in this paper are classified geographically by the states in which their headquarters are located; this state-level classification method is chosen to maintain consistency with previous studies, e.g. Parsons et al. (2017) and Korniotis and Kumar (2013b). Firm headquarters state data are obtained from the Compustat Fundamentals Annual database. Although Compustat only reports current firm headquarters location, according to Parsons et al. (2017), this measurement error has a limited effect. I also assign firms to the Fama-French 48 industry classifications using their SIC codes. This number of industry classifications is chosen to ensure that there are similar numbers of industry and state groups, which facilitates direct comparison between the two categories.

[2] I consider other share price cutoffs in the robustness tests, and thereby show that my results do not depend on the price filter.

[3] See http://people.stern.nyu.edu/jwurgler/.

4.3.1 Mispricing Measures

In this section, I briefly introduce my firm-, state-, and industry-level mispricing variables. Further details regarding the construction of the variables are presented in Table 4.A.1. To construct the main measure of mispricing for each firm, i.e. *MIS*, I combine information from the 11 prominent anomaly strategies analyzed in Stambaugh et al. (2012, 2014, 2015). These 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). Specifically, I compute the common mispricing component across all the anomalies following Stambaugh et al. (2015). *MIS* is constructed by taking the average of each stock's decile ranks with respect to the 11 anomaly variables. Decile ranks are defined at the end of every month, with the first and 10th deciles consisting of stocks that each anomaly strategy predicts are going to underperform and outperform the most in the following month, respectively. Anomalies may not be wholly related to mispricing; therefore *MIS* is a less noisy measure of mispricing than considering across all the anomalies separately. This is because, by taking the average of the anomaly decile ranks, we diversify any anomaly-specific effect, and are thus left with a mispricing component that is common across all the strategies (see Stambaugh et al., 2015; Stambaugh and Yuan, 2016).

State- and industry-level mispricing variables essentially capture the performance of the firm-level mispricing variable, *MIS*, in predicting returns within each state or industry group. A larger state or industry mispricing measure indicates greater return predictability, and ultimately higher anomaly profits for stocks in that group. To construct these measures, I estimate the following Fama and MacBeth (1973) regression for each state or industry group g:

$$R_{i,\tau} = \beta_{0_g} + \beta_{1_g} MIS_{i,\tau-1} + \sum_{n=1}^{N} \beta_{n+1_g} Control_{n_{i,\tau-1}} + \epsilon_{i,\tau} \tag{4.1}$$

where, $R_{i,\tau}$ is the monthly return for firm i in month τ, $MIS_{i,\tau-1}$ is the monthly firm mispricing measure for firm i in month $\tau-1$, and $Control_{n_{i,\tau-1}}$ is a monthly firm control variable. The estimated β_{1_g} coefficient is the measure of state or industry mispricing for each stock in the state or industry group g. In order to look for the out-of-sample performance of the mispricing measures, I estimate the state and industry mispricing measures at the end of each month t by running the model in Equation 4.1, using the past T months of data ending in month $t-1$. I call the resulting state (geographic) mispricing variable *GM[t-T,t-1]* and the industry mispricing variable *IM[t-T,t-1]*. Moreover, since each stock is itself included in the estimations for that stock's state and industry mispricing variables, the estimates may capture the stock's past performance, rather than the state or industry effects. To address this, I construct two alternative measures that exclude each stock itself, and use the rest of the sample to estimate the state or industry mispricing measures for that stock. I call these alternative state and industry mispricing measures *GMX[t-T,t-1]* and *IMX[t-T,t-1]*, respectively.

4.3.2 Descriptive Statistics: What Are the Characteristics of Mispriced States or Industries?

Table 4.1 presents the characteristics of firms in each state and industry group averaged over the whole sample period. I follow Korniotis and Kumar (2013b) and Parsons et al. (2017) and require each group to have at least 5 nonmissing observations for at least 1 month. Since some groups do not meet this criteria due to missing *MIS* values, I exclude them from the sample altogether. I also exclude month groups with less than 5 nonmissing observations; however, I compute the average number of observations, i.e. *N*, in Table 4.1 before excluding these firm months.

States and industries in Table 4.1 are sorted by their group mispricing measures, i.e. *GM* and *IM*, estimated using the whole sample. That is, I run the regression in Equation 4.1 using all firm-months for each state and industry group. Higher *GM* and *IM* suggest more mispricing on average. I also report *MIS* α for each state or industry. This is computed as the intercept of the four factor model of Carhart (1997) for the time-series of monthly hedge (long minus short) *MIS* portfolio returns. Monthly hedge

MIS portfolio returns for each state or industry group are defined as the monthly average returns of stocks in that group with *MIS* values above the cross-sectional median at the beginning of each month, minus the average returns of those with *MIS* values below the cross-sectional median. The median *MIS* is based on the whole cross section and not each individual state or industry.

There are no visible trends in firm characteristics as one moves from the least mispriced states or industries to the most mispriced ones. As shown in Panel A of Table 4.1, the least mispriced states are Kentucky, New Mexico, and Montana. In these states, GM is negative, meaning that *MIS* predicts lower average future returns in contrast to what the anomalies suggest. By contrast, South Dakota, Tennessee, and the District of Columbia are the most mispriced regions. The average number of observations (N), firm size (ME), share price ($PRICE$), and the other characteristics of the most and least mispriced states are not substantially different.

The results presented in Panel B of Table 4.1 are very similar to those in Panel A; that is, the most and the least mispriced groups do not have visibly different firm characteristics. The figures fluctuate noticeably from one industry to another, but do not follow a specific trend. The least mispriced industries are Coal, Shipping Containers, and Tobacco Products, while the most mispriced ones are Recreation, Candy and Soda, and Other (uncategorized firms). Overall, average firm characteristics indicate that there is no fundamental difference between firms in various states or industries that can explain the heterogeneity in mispricing.

4.4 Empirical Results

In this section, I present the main empirical findings of this paper. I begin by testing whether mispricing is persistent and predictable across different geographic and industrial groups (*H1*). I then examine whether analyst errors, along with local sentiment and risk aversion induced by changes in local macroeconomic conditions can help to explain the geographic and industrial heterogeneity in mispricing.

4.4.1 Geographic and Industrial Mispricing

4.4.1.1 Is Mispricing Persistent in States or Industries?

I test my primary hypothesis (*H1*) by analyzing whether mispriced states or industries continue to be mispriced in future periods; in other words, I investigate whether one can predict future stock mispricing levels by taking mispricing of the stock's industrial or geographic peers into account. Given the persistence of state-level and industry-level mispricing, one should be able to predict the performance of anomaly strategies based on *MIS* for firms in each state or industry using their past performance within that state or industry. In order to test this prediction, I double-sort stocks based on their current *MIS* and past *MIS* performance in the state or industry to which they belong.

My double sorting procedure entails four steps. First, I construct hedge *MIS* portfolios for firms in each state and industry. Hedge *MIS* portfolio returns for each state or industry group are defined as the average returns of stocks in that group that have *MIS* values above the cross-sectional median, minus the average returns of those with *MIS* values below the cross-sectional median. I use the median *MIS* based on the whole cross section, rather than on each individual state or industry, in order to ensure the portfolios will be comparable across states and industries. Second, for each month t, I regress the time-series of hedge *MIS* portfolio returns for each state or industry from months $t - T$ to $t - 1$ on the four factors of Carhart (1997). The intercept (α) of the regression is my measure of past mispricing in each state or industry. Third, I independently sort stocks each month into 5 portfolios based on their *MIS* and 5 portfolios based on their past state or industry *MIS* α. I then compute the average 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 intercepts are the abnormal return estimates for the 25 portfolios.

The doubles sorting results are reported in Table 4.2. Panels A and B present the results for state-level and industry-level mispricing portfolios, respectively. The past *MIS* α estimates in these panels use the observations from the previous 12 months ($T = 12$). The results in Panel A indicate that hedge *MIS* abnormal returns are 0.346% higher for stocks headquartered in states that had the highest hedge *MIS* abnormal returns

over the previous year compared to those in states with the lowest hedge *MIS* abnormal returns. Similarly, in Panel B, stocks belonging to industries with the highest past hedge *MIS* abnormal returns generate *MIS* strategy abnormal returns that are 0.348% larger compared to those of industries with the lowest past hedge *MIS* abnormal returns.[4]

In Panels C and D of Table 4.2, I consider alternative past *MIS* α estimates based on longer time windows, namely over the past 24 ($T = 24$) and past 60 ($T = 60$) months. Interestingly, there are no differences in *MIS* abnormal returns for firms in state or industry groups with the highest and the lowest past two-year or five-year hedge *MIS* abnormal returns. This indicates that state-level or industry-level mispricing fades away after a year. Korniotis and Kumar (2013b) report similar findings regarding the dissipation of state-level mispricing after 12 months.

Overall, the double sorting results provide corroborating evidence for my primary hypothesis (*H1*); that is, stocks belonging to the most mispriced states or industries, as captured by the *MIS* strategy, continue to be more mispriced in the cross section. In the next subsection, I further elaborate on this result by conducting my tests at the firm level rather than using portfolios.

4.4.1.2 Firm-Level Return Predictability

In the previous subsection, I test my primary hypothesis (*H1*) using a double sorting approach and find evidence in line with my predictions. However, double sorting has two major shortcomings stemming from its portfolio-based approach. First, past and future state-level and industry-level portfolios could contain the same set of stocks. This means that the persistence in state-level and industry-level mispricing could be due to the persistence in mispricing levels of each individual firm, rather than the common mispricing level in firms' states or industries. Second, double sorting does not allow firm characteristics to be controlled for, or for state and industry effects to be compared.

I address the challenges above by complementing my tests with a firm-level regression approach. If there is any persistence in mispricing within states or industries, I expect to observe that the combined mispricing measure (*MIS*) is a stronger predictor

[4]Considering that the double sorting approach does not control for time and state / industry fixed effects, I also test the persistence in hedge portfolio returns using panel regressions with fixed effects and find similar returns. These results are presented in Appendix Table 4.A.2.

of future returns in states or industries that experienced higher return predictability in the past. I test this conjecture by adding past geographic and industrial peer mispricing measures, i.e. *GMX[t-T,t-1]* and *IMX[t-T,t-1]*, and their interactions with (*MIS*) to the Fama-MacBeth regression in Equation 4.1. The coefficients of interest are those on the interaction terms. I estimate *GMX[t-T,t-1]* and *IMX[t-T,t-1]* using various time periods (T): namely, 1, 3, 6, 12, 24, and 60 months.

Panels A and B of Table 4.3 present estimation results for states and industries, respectively. As presented in the first columns of both tables, 1 standard deviation increase in *MIS* before controlling for past state or industry mispricing is associated with 0.446% (t-statistic of 11) higher future monthly returns. After adding *GMX[t-T,t-1]* or *IMX[t-T,t-1]* and the interaction terms, the *MIS* coefficients remain almost the same in all specifications in both panels.

In Panel A, the *MIS* × *GMX[t-T,t-1]* interaction coefficients start from 0.024% (t-statistic of 1.81) for the estimation window of 1 month (T=1), peak at 0.045% (t-statistic of 3.2) for the estimation period of 12 months (T=12), and become weaker and insignificant for longer estimation periods. The result based on the 12-month estimation window is both statistically and economically significant. A 1-standard-deviation increase in the state mispricing measured over the past 12 months increases the return predictability of *MIS* by 0.045%, which amounts to around 10% of the coefficient of *MIS*. This result is also statistically significant, as the t-statistic of 3.2 is larger than the target threshold figure of 3 suggested by Harvey et al. (2016).[5]

The results based on industry groups presented in Panel B are slightly different to those in Panel A. First, in all the 6 specifications, the *MIS* × *IMX[t-T,t-1]* coefficients are statistically significant at the 5% level. Second, the estimation window of 1 month (T=1) generates the largest interaction coefficient of 0.07% (t-statistic of 4.19). After this point, the interaction coefficients become smaller and less significant as the estimation window expands. These results are also economically significant; taking the 12-month estimation specification (T=12) again, for example, a 1-standard-deviation increase in the industry-level mispricing measured over the past 12 months increases the return predictability of

[5]Harvey et al. (2016) argue that because of potential data-mining issues, a t-statistic of 3 is a more appropriate significance cutoff for Fama-MacBeth regressions than the usual cutoff of 2.

MIS by 0.062% (t-statistic of 3.76).

It is interesting to observe that both *GMX[t-T,t-1]* and *IMX[t-T,t-1]* have negative coefficients in all specifications. This indicates that a stock is more likely to be overpriced in states or industries in which returns are more predictable. A plausible explanation for this observation could be that, if overpricing is the prevalent form of mispricing, then firms in more mispriced states or industries are more likely to be overpriced than underpriced. I investigate this further in subsection 4.4.2.

In Panel C of Table 4.3, I repeat the tests in Panels A and B, but with alternative state- and industry-level mispricing measures, i.e. *GM[t-T,t-1]* and *IM[t-T,t-1]*, respectively. The only difference is that *GM[t-T,t-1]* and *IM[t-T,t-1]* do not exclude the firm for which mispricing is measured from the estimates of past state or industry mispricing; that is, I include all firms in a state or industry when estimating the model in Equation 4.1. Results based on these alternative measures are slightly stronger and more robust than those in Panels A and B. For example, the *MIS* × *GM[t-T,t-1]* coefficient for the 12-month estimation period (T=12) increases to 0.052% (t-statistic of 3.47) from 0.045% in Panel A. Similarly, the *MIS* × *IM[t-T,t-1]* coefficient for the same specification is 0.076% (t-statistic of 4.1), which is larger than the 0.07% interaction coefficient in Panel B.

Overall, the results in Table 4.3 again support my primary hypothesis (*H1*). The combined anomaly variable (*MIS*) generates larger future returns in states and industries in which there is a history of return predictability. In other words, the mispricing levels of a firm's geographic and industrial peers can predict its likelihood of being mispriced in the future.

4.4.1.3 State-Level vs. Industry-Level Mispricing

In the previous subsections, I established that the level of mispricing in a firm's state or industry offers relevant information about its general susceptibility to mispricing. Nevertheless, one might ask how the effects of state and industry mispricing compare to each other. One possible concern is that there may be a considerable overlap between states and industries, so that state- and industry-level mispricing may be highly correlated.

In order to address these issues, I include both the industry- and state-level interaction terms in the regression model. In so doing, I am essentially examining the effect of one variable while controlling for the other.

Results presented in Panel A of Table 4.4 indicate that both the *MIS* × *GMX[t-T,t-1]* and *MIS* × *IMX[t-T,t-1]* interaction coefficients remain almost the same as before when they are added in one regression. For example, the coefficients for the estimation period of 12 months (T=12) are 0.04% (t-statistic of 2.96) and 0.061% (t-statistic of 3.65) for *MIS* × *GMX[t-T,t-1]* and *MIS* × *IMX[t-T,t-1]*, respectively. The corresponding figures in Panels A and B of Table 4.3, where the interaction terms are estimated in separate regressions, are 0.045% (t-statistic of 3.2) and 0.062% (t-statistic of 3.76), respectively. The results of the other specifications and those based on *GM[t-T,t-1]* and *IM[t-T,t-1]* in Panel B of Table 4.4 are also very close to the original estimates in Table 4.3.

These findings indicate that state- and industry-level mispricing variables do not explain each other: both interaction terms remain robust after controlling for the other. In other words, past state and industry mispricing can predict future mispricing levels of a stock independent of each other. This is in line with our predictions regarding the two group effects having different causes.

4.4.2 The Role of Analysts

In this subsection, I examine the role of analyst earnings forecasts in generating state- and industry-level mispricing. Following Parsons et al. (2017), analysts are clustered by industry, and are therefore crucial in helping industry-related information be incorporated into prices. If analysts make errors, however, it is likely that firms within the same industry will not be properly distinguished and priced. I expect to observe that firms experiencing greater levels of analyst earnings forecast errors are more likely to be affected by industrial mispricing. Moreover, since analysts are not clustered by geography (Parsons et al., 2017), I do not expect to find a similar effect for geographic mispricing. Nevertheless, analysts errors can affect mispricing in general (Engelberg et al., 2017); therefore, even geographic mispricing should be stronger for stocks with greater analyst

forecast errors. However, this result is likely to be weaker compared to that for industrial mispricing.

I begin by looking at the analyst-related characteristics of quintile portfolios based on state- and industry-level mispricing variables. As in the previous sections, I take *GMX[t-12,t-1]* and *IMX[t-12,t-1]* as my main variable specifications. Quintiles are formed by sorting stocks based on each of these variables separately into 5 groups. I then look at the average characteristics of each portfolio measured at the end of the previous month. These characteristics include absolute earnings forecast error (*AFE*), signed forecast error (*FE*), forecast dispersion (*DISPERSION*), and no analyst coverage indicator (*NOCOVERAGE*). The construction details of all variables are explained in Table 4.A.1.

Panels A and B of Table 4.5 present the average characteristics for the *GMX[t-12,t-1]* and *IMX[t-12,t-1]* quintiles, respectively. The figures indicate that both *AFE* and *FE* increase with state- and industry-level mispricing. However, the differences between the *AFE* and *FE* figures of *IMX[t-12,t-1]* quintiles 1 and 5 are much larger than those for *GMX[t-12,t-1]*. For instance, the *5 - 1* average *AFE* figure for *IMX[t-12,t-1]* is 0.099 (t-statistic of 4.46), whereas the comparable figure for *GMX[t-12,t-1]* is 0.052 (t-statistic of 4.61). In addition, the difference between the average *FE* of *GMX[t-12,t-1]* for quintiles 1 and 5 is not statistically significant. This indicates that firms in the most mispriced industries have significantly higher earnings forecast errors, and that their forecasts tend to be over-optimistic rather than over-pessimistic. Firms in the most mispriced states, on the other hand, face moderately higher analyst forecast errors, but their forecasts are not necessarily over-optimistic.

Firms in higher *IMX[t-12,t-1]* quintiles also have higher levels of dispersion in earnings forecasts (*DISPERSION*), with the difference between the first and fifth quintiles being highly statistically significant. Although a similar pattern exists for *GMX[t-12,t-1]* quintiles, the difference between the values of the extreme quintiles is only statistically significant at the 5% level. Lastly, the highest *GMX[t-12,t-1]* and *IMX[t-12,t-1]* quintiles have a larger proportion of stocks with no analyst coverage. Overall, the results indicate that the most mispriced states and industries include firms with more noisy, bi-

ased, and dispersed earnings forecasts, and that this is more the case for mispriced industries than mispriced states.

After establishing that there is a relationship between analyst forecast errors and state- and industry-level mispricing, I divide my sample into two parts based on *AFE* and estimate the regressions in Panels A and B of Table 4.3 for each subsample. I use the *AFE* cross-sectional median as the break point for the two subsamples. My expectation is that firms facing higher analyst forecast errors have higher degrees of state- and industry-level mispricing. This effect should be particularly strong for industry-level mispricing.

The results in Panels A and B of Table 4.6 indicate that the *MIS* × *GMX[t-12,t-1]* and *MIS* × *IMX[t-12,t-1]* interaction coefficients are only statistically significant for the subsample of high *AFE* stocks. However, the differences between the interaction coefficients of the high and the low *AFE* subsamples are only just statistically significant for *MIS* × *IMX[t-12,t-1]* in Panel B. The difference in figures are 0.055% (t-statistic of 1.26) and 0.098% (t-statistic of 1.96) for *MIS* × *GMX[t-12,t-1]* and *MIS* × *IMX[t-12,t-1]*, respectively. These results are in line with my earlier prediction that industry-level mispricing is particularly driven by stocks that are subject to analyst forecast errors. Moreover, although a similar result is observed for state-level mispricing, it is significantly less robust, which is also in line with my earlier prediction.

4.4.3 Sentiment and Local Risk Aversion

In this subsection, I consider heterogeneous state-wide sentiment and risk aversion as another possible explanation for state-wide mispricing. I build on Korniotis and Kumar (2013b) and Kumar et al. (2013) to argue that shocks to local investor demand can affect the prices of local stocks. Baker et al. (2012) examine this idea across different countries and finds a link between measures of local sentiment and local return predictability or mispricing. I also expect to find that geographic mispricing is more pronounced in regions facing greater levels of investor sentiment or lower risk aversion. Before testing this prediction, however, I examine the effect of national sentiment in generating mispricing. To do this, I use the sentiment proxy of Baker and Wurgler (2006), and assess

whether changes in national sentiment affect state- and industry-wide mispricing. From Stambaugh et al. (2015), we already know that sentiment affects firm-level mispricing; however, it is not immediately clear whether geographic and industrial mispricing are also affected by national sentiment.

In a similar fashion to the methodology of Subsection 4.4.3, I divide my sample into two parts, based on the time-series median of national sentiment (*NSENT*) measure of Baker and Wurgler (2006). I then estimate the regressions in Panels A and B of Table 4.3 for each subsample. Just as before, my emphasis is on the *MIS* × *GMX[t-12,t-1]* and *MIS* × *IMX[t-12,t-1]* interaction coefficients. The results presented in Panels A and B of Table 4.7 indicate that the two interaction coefficients are only statistically significant at the 1% level in periods of high *NSENT*, while the magnitudes of the interaction coefficients in high *NSENT* periods are twice those in low *NSENT* periods. Nevertheless, the differences in the interaction coefficients of the two subsamples are not statistically significant, even at the 5% level. This indicates that one cannot reliably conclude that national sentiment affects state- or industry-level mispricing.

After gaining some insight into the role of national sentiment, I focus on local, i.e. state-wide, variations in sentiment. I use two main proxies for local sentiment. First, I follow the country-wide sentiment methodology of Baker et al. (2012) and construct a sentiment index for each state (*SSENT*). This is computed by taking the first principal component of volatility premium, number of IPOs, average first-day returns of IPOs, and turnover for each state. Second, I use the state macroeconomic activity index (*SEA*) of Korniotis and Kumar (2013b). This is defined as taking the standardized values of state income growth and housing collateral, subtracting the standardized value of relative unemployment, and dividing by 3. Korniotis and Kumar (2013b) show that this measure captures the dynamics in local investors' risk aversion, and can predict mispricing in local stocks. Table 4.A.1 provides further details about the construction of these variables.

I also examine the effect of *SEA* and *SSENT* on state-level mispricing by dividing the sample into two subsamples, using the cross-sectional median of each variable as the breaking point. I then estimate the *MIS* × *GMX[t-12,t-1]* interaction coefficient, as I

did for Tables 4.6 and 4.7. Results are presented in Table 4.8. Panels A and B show that the interaction coefficients are only statistically significant in subsamples of high *SEA* or *SSENT*. Differences in the interaction coefficients of the two subsamples are also statistically significant at the 5% level. Periods of high *SEA* and high *SSENT* generate 0.075% (t-statistic of 1.94) and 0.050% (t-statistic of 2.09) higher *MIS* × *GMX[t-12,t-1]* interaction coefficients, respectively. In summary, these results support my prediction and suggest that state-level mispricing can be driven by states experiencing economic expansion or higher levels of investor sentiment.

4.5 Robustness Checks

4.5.1 Basic Robustness Checks and Controlling for Limits to Arbitrage

This subsection examines the robustness of my main results, as presented in Table 4.3, using several additional tests. Results from these robustness tests are summarized in Table 4.9. I only focus on the coefficients in Panel A of Table 4.3, and the specifications based on the estimation period of 12 months (T=12); that is, I use *GMX[t-12,t-1]* and *IMX[t-12,t-1]* as the main state- and industry-level mispricing variables. I choose 12 months as the estimation period here because it provides the most collectively robust specification for the state- and industry-level mispricing variables. In the interests of brevity, I only report the estimates for the interaction terms, i.e. *MIS* × *GMX[t-12,t-1]* and *MIS* × *IMX[t-12,t-1]*, which are my main variables of interest.

The results in Panel A of Table 4.9 indicate that the interaction coefficient estimates are robust for the sample, excluding stocks cheaper than $5, the largest and smallest quantiles of stocks, and the expansion and recession subsamples, defined using the NBER Recession Indicator.[6] Although excluding stocks cheaper than $5 slightly reduces the magnitude of the argued estimates, their statistical and economic significance remain. In addition, the interaction coefficients tend to be larger and more significant for the quintile consisting of the smallest stocks based on market capitalization, compared to the quintile of large stocks. This is in line with Parsons et al. (2017), who

[6]The data are taken from the Federal Reserve Bank of St. Louis website (https://fred.stlouisfed.org/series/USREC).

argues that the smallest stocks are more likely to be affected by geographic or industrial mispricing effects because they are scrutinized by the market to a lesser degree. Lastly, the interaction coefficient estimates are larger but less significant for recession periods. While this is an interesting observation, it would be beyond the scope of this study to justify.

When using the midpoint, i.e. year 1990, to break the sample into two parts, the *MIS* × *IMX[t-12,t-1]* loses its statistical significance in the subsample 1963-1990. However, *MIS* × *GMX[t-12,t-1]* remains statistically significant in both subsamples, albeit smaller in magnitude during the period 1963-1990. The weaker results for the first 27 years could be due to the lower number of observations in each group, which leads to lower statistical power in all tests. Nevertheless, this is an interesting observation because it indicates that the main findings of the paper may actually be stronger in recent years, despite the increase in arbitrage activity.

Another concern regarding the results in Table 4.3 is that the state- and industry-level mispricing variables may simply act as a proxy for liquidity or arbitrage costs. It is well documented that market anomalies, and mispricing in general, are more prevalent among stocks that are harder to arbitrage (see, e.g., Nagel, 2005; Hirshleifer et al., 2011; Stambaugh et al., 2012; Avramov et al., 2013; Stambaugh et al., 2015). This being so, most mispriced states or industries could continue to be mispriced because they happen to include stocks that face significant limits to arbitrage, rather than necessarily being exposed to forces related to their geographic or industrial identity.

Accordingly, I control for the effects of limits to arbitrage by adding five commonly used proxies and their interactions with *MIS* to the regression in Table 4.3. The five measures include the illiquidity measure of Amihud (2002), short interest ratio (following Hanson and Sunderam (2014)), idiosyncratic volatility (motivated by Stambaugh et al. (2015)), institutional holdings (following Nagel (2005)), and market capitalization. The results in Panel B of Table 4.9 indicate that none of these proxies, nor their interactions with *MIS*, absorb the coefficients of *MIS* × *GMX[t-12,t-1]* and *MIS* × *IMX[t-12,t-1]*. These two main interaction coefficients remain statistically and economically significant in all cases, which means that the ability of state or industry affiliations to predict future

mispricing is not due to the concentration of illiquid stocks in specific groups.

4.5.2 Robustness Simulations

In the previous subsection, I showed that the main results in Table 4.3 are robust to a range of simple robustness tests and controls for limits to arbitrage. However, this does not fully address all identification concerns regarding the state- and the industry-level mispricing variables. One could argue that these two variables predict future mispricing simply for spurious reasons; after all, some firms tend to be more mispriced than others, and will continue to be that way, while specific state or industry groups could be more mispriced simply because they randomly include the most mispriced firms, regardless of the characteristics of the state or industry. In other words, it might be possible to observe the same pattern in my data after repeating the exercise for any other method of grouping firms that is not necessarily linked to firms' geography or industry.

I address the challenge outlined above by randomizing the state and industry allocations of all firms in the sample. To do so, I randomly allocate firms in the sample to other state and industry groups, then re-run my tests. I require all my pseudo-state and -industry groups to include the same number of firms as the original groups in order to ensure that the sample groups are as statistically comparable as possible. Specifically, I simulate 10,000 iterations based on these pseudo-state and -industry allocations for the 12-month specifications (T=12) in Panel C of Table 4.3. I focus on the *GM* and *IM* variables because they are better predictors of future mispricing, and are more likely to lead to spurious findings. If I find that the *MIS* × *GM[t-12,t-1]* and *MIS* × *IM[t-12,t-1]* coefficients are not statistically and economically meaningful in a significant proportion of the simulated estimates, I can safely argue in favor of the existence of state and industry effects.

Table 4.10 summarizes my simulation results. The 99th percentiles (*P99*) of the distributions of simulated *MIS* × *GM[t-12,t-1]* and *MIS* × *IM[t-12,t-1]* coefficients are 0.040% (t-statistic of 2.92) and 0.041% (t-statistic of 2.88), respectively. In comparison, the baseline estimates from Panel C of Table 4.3 are 0.045% (t-statistic of 3.20) and 0.062% (t-statistic of 3.76), respectively. This means that less than 1% of simulation

runs lead to estimates that are as statistically and economically significant as the baseline result. The *MIS* × *IM[t-12,t-1]* coefficient tends to be slightly more robust than that of *MIS* × *GM[t-12,t-1]* because it has a larger gap with the 99th percentile threshold. I also plot the histogram of simulations in Figure 4.1. Again, it is visually evident that the actual coefficients (subfigures (a) and (c)) and t-statistics (subfigures (b) and (d)) are far to the right of the 1% threshold.

In summary, my simulation results indicate that the probability of any random groups of stocks yielding the same results as those presented in Table 4.3 is less than 1%. The GM[t-12,t-1] and IM[t-12,t-1] for which the simulations are performed generate the strongest collective results for both state- and industry-level mispricing. They also include each firm itself in the past state and industry mispricing estimates, and are thus more prone to autocorrelation or spuriosity compared to GMX[t-12,t-1] and IMX[t-12,t-1]. Despite this, however, the fact that results based on even these variables specifically are highly unlikely to be achieved with random groups supports my main contention regarding the role of geographic and industrial forces in mispricing.

4.6 Conclusion

This study investigates whether the geographic or industry characteristics of a firm can affect its mispricing, as captured by market anomalies. Using a composite mispricing measure based on 11 anomaly strategies, I show that states or industries experiencing higher levels of cross-sectional mispricing are more likely to have mispriced firms in future periods.

These findings are robust to several different specifications, treatments, and controls, and have potentially important practical implications. For example, my results indicate that anomaly strategies could be refined by considering the performance of the firm's regional or geographic peers, while geographic and industrial mispricing are independent of each other, and provide complementary information about a firm's future mispricing. This being so, both should be taken into account at the same time in order to fully exploit the observed phenomenon.

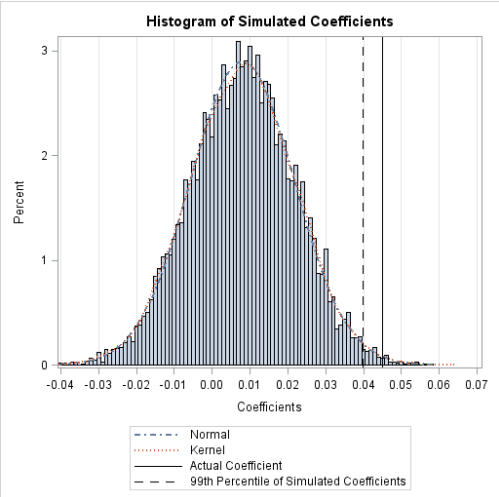
In summary, I argue that geography and industry predict mispricing consistent

with common behaviors or biases of clienteles of investors or analysts who concentrate on firms in a certain region or industry. However, I provide evidence that the mechanism through which these clienteles generate mispricing differs geographically and by industry. For industries, analysts tend to play a significant role because they are clustered by industry, and are thus crucial in distinguishing between industrial peers (Parsons et al., 2017); consequently, their lack of ability to value stocks within an industry can lead to mispricing for all stocks in the group. On the other hand, for geographical regions, the common investor clientele is likely to be local investors who possess a local bias. Therefore any shift in local sentiment or risk aversion can affect the prices of local stocks and lead to mispricing, as documented by previous papers (e.g., Stambaugh et al., 2012; Baker et al., 2012)

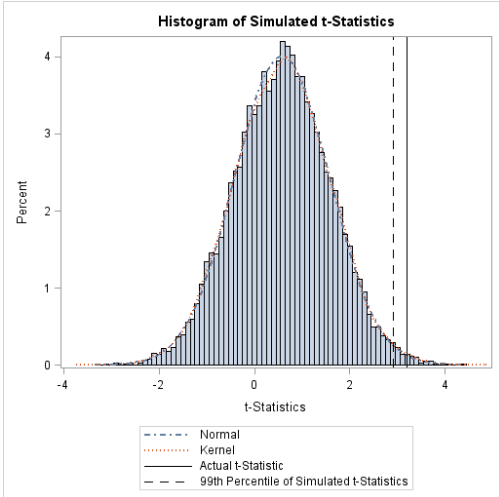
The main objective of this study is to highlight the role of geography and industry in stock mispricing. This study represents an initial attempt in the literature to provide an explanation for this phenomenon. Investigating other channels that could potentially explain the results obtained in this study would be a fruitful avenue of future research. Further work should also explore the profitability of trading strategies based on firm geography and industry.

Figure 4.1: Histograms of Simulated Coefficients

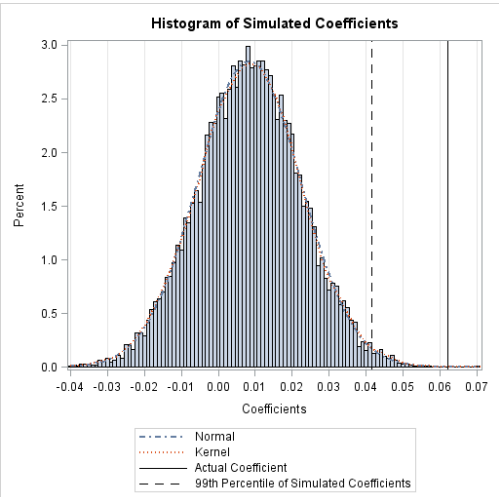
The subfigures below present the histograms of simulated coefficients and their t-statistics as summarized in Table 4.5. Subfigure (a) presents the histogram of simulated MIS × GM[t-12,t-1] coefficients. Subfigure (b) presents the histogram of simulated MIS × GM[t-12,t-1] t-statistics. Subfigure (c) presents the histogram of simulated MIS × IM[t-12,t-1] coefficients. Subfigure (d) presents the histogram of simulated MIS × IM[t-12,t-1] t-statistics. All subfigures include the normal and the kernel distribution curves together with lines marking the 99th percentiles of simulations and the actual estimates.



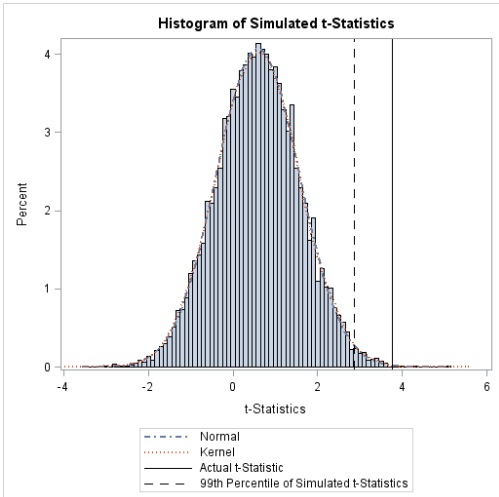
(a) *MIS* × *GM[t-12,t-1]* Coefficients



(b) *MIS* × *GM[t-12,t-1]* t-statistics



(c) *MIS* × *IM[t-12,t-1]* Coefficients



(d) *MIS* × *IM[t-12,t-1]* t-statistics

Table 4.1: Descriptive Statistics

This table reports the average characteristics of firms in each state and industry. The states in Panel A and industries in Panel B are sorted from the least to the most mispriced, based on their GM and IM values, estimated using the whole sample. MIS α is the abnormal return (intercept of the four factor model of Carhart (1997)) of the hedge (long minus short) MIS portfolio of firms in each state or industry. Hedge MIS returns for each state or industry group are defined as the average returns of stocks in that group that have MIS values above the cross-sectional median minus the average returns of those with MIS values below the cross-sectional median. The median MIS is based on the whole cross section and not each individual state or industry. The definition of state and industry for each firm are the same as those used in GM and IM variables defined in Table 4.A.1. N is the average number of firms in each group, before excluding the firm-groups with lower than 5 observations. GM, IM, and all other variables are defined in Table 4.A.1. The sample excludes penny stocks and covers the period from July 1963 to December 2017, except for the IHOLD variable, which starts in January 1980.

Panel A: States

#	State	GM	MIS α	N	PRICE	ME	B/M	VOL	IVOL	TURN	ILLIQ	IHOLD
1	Kentucky	-3.861	0.848	17	24.520	1,046	0.861	2.458	2.282	0.087	2.633	44.183
2	New Mexico	-3.541	0.152	5	15.510	630	0.938	2.951	2.764	0.104	4.322	41.190
3	Montana	-2.365	0.245	2	17.999	340	0.604	2.853	2.624	0.072	1.057	25.575
4	Delaware	-1.515	0.159	12	24.946	3,248	0.932	2.619	2.436	0.065	2.564	35.501
5	West Virginia	-1.367	0.662	3	10.131	143	1.177	3.218	3.085	0.068	10.246	31.380
6	North Dakota	0.000	-0.690	2	24.280	854	0.907	2.082	1.898	0.106	2.915	35.459
7	Indiana	0.100	0.440	38	26.535	1,553	0.950	2.643	2.445	0.083	3.725	43.234
8	South Carolina	0.186	0.549	16	21.743	659	0.935	2.688	2.466	0.076	3.588	42.203
9	Missouri	0.197	0.392	54	26.777	1,801	0.873	2.430	2.219	0.092	1.845	42.847
10	Winsconsin	0.225	0.237	50	24.632	944	0.824	2.390	2.189	0.071	2.722	44.188
11	Alabama	0.260	0.536	16	21.922	690	0.843	2.654	2.470	0.095	5.300	40.875
12	Arkansas	0.271	0.239	13	21.967	6,931	0.948	2.643	2.440	0.085	4.253	40.750
13	Mississippi	0.289	0.886	5	16.671	304	0.884	2.996	2.811	0.132	9.083	41.765
14	Washington	0.294	0.422	45	22.573	3,953	0.763	2.920	2.703	0.110	2.393	37.695
15	Oklahoma	0.311	0.685	25	19.876	1,357	0.813	3.221	2.977	0.098	6.079	37.044
16	Texas	0.359	0.550	288	21.767	1,645	0.828	3.028	2.782	0.103	3.912	41.951
17	Nevada	0.360	0.268	24	20.733	1,008	0.728	3.148	2.935	0.105	4.224	29.689
18	Arizona	0.374	0.751	42	19.832	997	0.777	3.084	2.854	0.120	4.157	43.239
19	Pennsylvania	0.375	0.469	138	23.029	1,186	0.846	2.757	2.540	0.091	4.348	43.448
20	Connecticut	0.394	0.617	81	26.637	1,630	0.797	2.800	2.575	0.087	3.789	44.753
21	Illinois	0.415	0.475	156	25.971	2,520	0.860	2.572	2.355	0.086	2.769	46.338
22	New York	0.417	0.634	277	20.878	2,640	0.894	3.097	2.906	0.092	6.595	35.835
23	Minnesota	0.418	0.506	90	22.835	1,325	0.724	2.876	2.699	0.088	4.273	37.380
24	Colorado	0.425	1.026	70	16.695	769	0.782	3.344	3.130	0.107	6.424	35.930
25	North Carolina	0.430	0.548	64	22.366	1,403	0.932	2.686	2.489	0.092	3.316	42.243
26	Ohio	0.439	0.645	126	24.705	1,848	0.924	2.544	2.339	0.084	2.852	44.297
27	Iowa	0.444	0.700	17	21.696	675	0.892	2.491	2.301	0.071	2.731	37.654
28	Massachusetts	0.445	0.555	157	19.732	1,608	0.780	3.259	3.024	0.107	4.265	40.125
29	Virginia	0.450	0.716	79	31.942	1,955	0.810	2.756	2.544	0.095	2.599	41.743
30	Georgia	0.458	0.720	81	21.597	2,376	0.840	2.873	2.666	0.086	4.272	47.348
31	New Jersey	0.472	0.696	154	19.708	2,551	0.805	3.164	2.985	0.095	6.181	35.872
32	Oregon	0.484	0.539	28	20.227	1,006	0.813	2.945	2.722	0.093	6.409	42.984
33	Michingan	0.488	0.691	82	22.193	2,058	0.922	2.646	2.427	0.084	3.469	41.953
34	California	0.508	0.763	432	19.033	1,800	0.714	3.386	3.135	0.129	3.859	39.398
35	Maryland	0.513	0.346	46	20.342	973	0.83	3.179	2.979	0.112	4.281	36.762
36	Florida	0.567	0.874	123	17.822	671	0.845	3.277	3.086	0.094	5.180	34.718
37	Idaho	0.623	0.252	9	22.417	1,496	0.662	2.859	2.623	0.122	0.804	42.113
38	Utah	0.684	1.212	24	17.676	392	0.764	3.208	3.034	0.093	3.577	34.022
39	Rhode Island	0.808	0.787	11	22.801	2,864	0.858	2.704	2.522	0.075	2.471	42.605
40	Hawaii	2.506	0.810	6	18.728	423	0.819	2.403	2.275	0.051	2.374	23.527
41	New Hampshire	2.645	-0.029	15	19.802	316	0.752	2.881	2.644	0.081	2.819	38.477
42	Kansas	2.945	0.175	18	62.339	1,054	0.911	2.857	2.694	0.097	4.462	34.534

Table 4.1: Descriptive Statistics (Continued)

Panel A: States (Continued)												
#	State	GM	MIS α	N	PRICE	ME	B/M	VOL	IVOL	TURN	ILLIQ	IHOLD
43	Nebraska	3.019	1.098	9	25.826	2,078	0.711	2.665	2.489	0.081	2.147	35.539
44	Louisiana	3.554	0.839	17	21.940	1,381	1.005	2.775	2.533	0.107	3.659	43.684
45	Vermont	3.976	1.620	5	18.213	822	0.793	3.133	2.936	0.099	4.548	30.755
46	Maine	5.091	0.917	5	23.363	718	0.931	2.381	2.290	0.050	7.905	30.215
47	District of Columbia	9.152	0.239	7	24.183	2,333	0.902	2.562	2.379	0.105	2.330	48.584
48	Tennessee	10.821	0.324	42	24.357	1,314	0.830	2.519	2.325	0.086	2.019	46.485
49	South Dakota	70.306	1.223	5	21.323	407	0.712	2.270	2.077	0.080	0.836	40.752
Panel B: Industries												
#	Industry	IM	MIS α	N	PRICE	ME	B/M	VOL	IVOL	TURN	ILLIQ	IHOLD
1	Coal	-0.997	-1.715	6	26.100	944	1.119	2.901	2.552	0.187	0.870	44.387
2	Shipping Containers	-0.251	0.703	22	27.168	1,527	0.817	2.489	2.291	0.072	3.310	47.688
3	Tobacco Products	-0.189	2.741	7	38.291	15,490	0.658	1.974	1.809	0.067	1.291	43.064
4	Non-Metallic and Industrial Metal Mining	0.073	2.392	17	21.373	1,327	0.839	3.148	2.885	0.111	1.869	32.363
5	Agriculture	0.108	3.019	11	20.256	360	0.874	2.801	2.650	0.066	3.548	34.503
6	Defense	0.187	1.302	7	28.230	2,510	0.719	2.659	2.461	0.134	2.695	45.356
7	Precious Metals	0.209	1.133	10	16.495	2,129	0.522	3.613	3.413	0.151	2.137	31.921
8	Textiles	0.253	1.620	34	17.821	355	1.374	2.874	2.707	0.058	6.648	39.271
9	Food Products	0.254	1.453	65	38.428	2,018	0.853	2.411	2.279	0.070	3.179	34.643
10	Utilities	0.260	1.840	142	28.589	2,499	0.973	1.465	1.325	0.057	0.437	33.980
11	Rubber and Plastic Products	0.270	1.484	31	16.838	657	0.898	3.011	2.844	0.070	6.687	36.586
12	Restaraunts, Hotels, Motels	0.300	1.652	71	21.473	1,453	0.801	2.937	2.743	0.098	5.030	41.045
13	Business Supplies	0.302	2.232	39	26.170	1,463	0.887	2.301	2.078	0.063	3.381	47.509
14	Printing and Publishing	0.306	1.295	39	33.595	1,279	0.777	2.401	2.206	0.068	2.160	46.119
15	Pharmaceutical Products	0.306	1.043	127	24.877	2,931	0.410	3.295	3.066	0.115	1.972	35.810
16	Aircraft	0.306	1.088	22	29.977	3,986	0.799	2.738	2.500	0.075	4.364	45.182
17	Measuring and Control Equipment	0.310	0.593	72	20.420	952	0.686	3.248	3.021	0.087	6.345	37.651
18	Retail	0.327	1.206	192	21.747	2,234	0.980	2.822	2.629	0.110	3.938	44.587
19	Construction	0.332	1.886	41	24.199	590	1.049	3.151	2.891	0.119	5.969	42.468
20	Petroleum and Natural	0.335	1.007	129	26.081	2,503	0.786	3.104	2.802	0.114	4.509	40.250
21	Gas Construction Materials	0.353	1.992	105	23.010	860	0.955	2.600	2.394	0.072	4.507	40.728
22	Beer & Liquor	0.371	2.547	13	28.793	1,767	1.052	2.473	2.334	0.068	2.867	35.929
23	Electronic Equipment	0.382	1.642	177	17.128	1,526	0.709	3.518	3.227	0.134	5.875	39.575
24	Steel Works Etc	0.386	1.135	61	22.858	1,211	1.144	2.686	2.401	0.113	2.534	48.140
25	Personal Services	0.387	0.774	37	16.420	471	0.889	3.042	2.867	0.088	6.721	44.851
26	Communication	0.394	0.810	74	27.017	4,110	0.775	2.804	2.564	0.100	2.156	41.210
27	Electrical Equipment	0.401	1.344	79	17.985	1,205	0.734	3.313	3.096	0.099	5.506	35.838
28	Machinery	0.410	1.635	128	23.352	1,650	0.835	2.793	2.548	0.085	4.106	44.150
29	Computers	0.413	1.961	104	27.063	3,364	0.655	3.454	3.168	0.132	3.798	39.560
30	Wholesale	0.432	1.304	138	18.371	797	0.945	3.113	2.929	0.087	7.444	43.619
31	Apparel	0.494	2.198	53	20.192	1,086	1.008	2.861	2.683	0.096	6.175	42.421
32	Entertainment	0.496	2.743	42	17.578	1,483	0.839	3.276	3.086	0.102	8.028	33.788

Table 4.1: Descriptive Statistics (Continued)

Panel B: Industries (Continued)												
#	Industry	IM	MIS α	N	PRICE	ME	B/M	VOL	IVOL	TURN	ILLIQ	IHOLD
33	Consumer Goods	0.513	2.170	81	25.827	3,383	0.816	2.679	2.491	0.078	4.484	40.672
34	Chemicals	0.517	1.848	70	29.270	2,220	0.732	2.585	2.348	0.082	2.518	48.300
35	Transportation	0.534	1.870	81	24.828	1,634	1.176	2.805	2.560	0.109	2.809	44.823
36	Business Services	0.547	2.013	321	18.770	1,381	0.668	3.373	3.150	0.108	4.862	39.008
37	Medical Equipment	0.569	1.844	88	23.561	1,070	0.482	3.261	3.072	0.101	2.624	35.691
38	Automobiles and Trucks	0.576	2.359	56	23.342	1,889	0.942	2.697	2.424	0.089	3.393	48.636
39	Shipbuilding, Railroad Equipment	0.592	0.490	7	29.430	1,455	1.025	2.612	2.364	0.090	1.514	48.843
40	Healthcare	0.609	1.657	64	15.653	845	0.713	3.509	3.314	0.112	4.584	39.691
41	Fabricated Products	0.611	0.513	14	17.986	315	0.988	2.792	2.582	0.064	3.821	36.877
42	Candy & Soda	0.728	0.801	11	31.888	12,425	0.606	2.050	1.885	0.055	2.074	37.102
43	Other	0.743	1.552	15	17.271	1,691	0.773	3.220	3.031	0.079	1.959	38.649
44	Recreation	0.878	2.842	33	16.184	516	0.966	3.289	3.105	0.081	5.892	33.044

Table 4.2: Persistence of Abnormal Returns by Geography and Industry

This table presents benchmark adjusted returns for double-sorted portfolios based on MIS (defined in Table 4.A.1) and past MIS abnormal returns (α) within each firm's state or industry. The portfolios are formed by sorting stocks independently into five portfolios at the end of every month with respect to each variable. I then compute the average 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. Past MIS abnormal returns (α) are computed by regressing past hedge MIS returns of firms headquartered in each state or industry on the time series of returns on the four factors of Carhart (1997). Hedge MIS returns for each state or industry group are defined as the average returns of stocks in that group that have MIS values above the cross-sectional median minus the average returns of those with MIS values below the cross-sectional median. The median MIS is based on the whole cross section and not each individual state or industry. The definitions of state and industry are the same as those used in GM and IM variables defined in Table 4.A.1. In Panel A, past MIS α for month t is computed using observations from months $t-12$ to $t-1$; in Panel B, we use observations from months $t-24$ to $t-1$ or months $t-60$ to $t-1$. The sample excludes penny stocks and covers the period from July 1963 to December 2017. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Persistence of Geographic Mispricing Measured Over the Past-Year						
	Low Past MIS α	2	3	4	High Past MIS α	High - Low
Low MIS	-0.587***	-0.743***	-0.656***	-0.489***	-0.793***	-0.206*
	(-5.26)	(-6.01)	(-5.36)	(-3.59)	(-6.26)	(-1.89)
2	-0.006	0.024	0.090	0.055	0.102	0.107
	(-0.07)	(0.26)	(0.93)	(0.56)	(1.19)	(1.18)
3	0.204***	0.243***	0.245***	0.275***	0.260***	0.055
	(2.82)	(3.06)	(2.95)	(3.38)	(3.27)	(0.67)
4	0.438***	0.367***	0.420***	0.411***	0.341***	-0.096
	(6.86)	(5.21)	(5.95)	(5.88)	(5.03)	(-1.28)
High MIS	0.497***	0.510***	0.549***	0.514***	0.637***	0.140*
	(8.02)	(7.32)	(8.56)	(8.01)	(10.28)	(1.95)
High - Low	1.084***	1.253***	1.205***	1.003***	1.429***	0.346***
	(8.74)	(9.14)	(9.36)	(7.00)	(10.78)	(2.79)
Panel B: Persistence of Industrial Mispricing Measured Over the Past-Year						
	Low Past MIS α	2	3	4	High Past MIS α	High - Low
Low MIS	-0.507***	-0.682***	-0.857***	-0.518***	-0.767***	-0.260*
	(-3.85)	(-4.74)	(-6.15)	(-3.78)	(-5.92)	(-1.71)
2	0.129	0.043	0.006	0.305***	-0.155	-0.284**
	(1.22)	(0.43)	(0.05)	(2.71)	(-1.58)	(-2.36)
3	0.264***	0.165*	0.316***	0.422***	0.171**	-0.093
	(2.98)	(1.71)	(3.46)	(4.37)	(2.11)	(-0.83)
4	0.320***	0.324***	0.289***	0.527***	0.370***	0.050
	(4.04)	(3.88)	(3.83)	(6.34)	(4.91)	(0.50)
High MIS	0.399***	0.566***	0.530***	0.687***	0.487***	0.088
	(5.50)	(6.68)	(7.38)	(9.19)	(7.09)	(1.00)
High - Low	0.906***	1.248***	1.387***	1.206***	1.253***	0.348**
	(8.51)	(8.67)	(9.85)	(8.68)	(10.44)	(3.18)

Table 4.2: Persistence of Abnormal Returns by Geography and Industry (Continued)

Panel C: Persistence of Geographic Mispricing Measured Over the Past Two and Five Years						
	T=24			T=60		
	1	5	5 - 1	1	5	5 - 1
Low MIS	-0.495***	-0.625***	-0.130	-0.573***	-0.699***	-0.126
	(-3.63)	(-4.79)	(-0.83)	(-4.60)	(-5.77)	(-1.21)
High MIS	0.382***	0.509***	0.127	0.555***	0.541***	-0.015
	(5.26)	(6.92)	(1.36)	(9.53)	(8.86)	(-0.22)
High - Low	0.877***	1.134***	0.256	1.128***	1.239***	0.111
	(5.87)	(8.07)	(1.51)	(8.33)	(9.54)	(0.98)

Panel D: Persistence of Industrial Mispricing Measured Over the Past Two and Five Years						
	T=24			T=60		
	1	5	5 - 1	1	5	5 - 1
Low MIS	-0.544***	-0.687***	-0.143	-0.605***	-0.698***	-0.093
	(-4.70)	(-5.68)	(-1.43)	(-4.52)	(-5.19)	(-0.54)
High MIS	0.506***	0.590***	0.084	0.454***	0.547***	0.093
	(8.32)	(9.11)	(1.18)	(6.60)	(7.07)	(0.99)
High - Low	1.050***	1.277***	0.227*	1.059***	1.245***	0.186
	(8.20)	(10.15)	(1.92)	(7.53)	(9.13)	(1.13)

Table 4.3: Firm-Level Return Predictability Based on Geography and Industry

This table presents estimates from the monthly Fama-MacBeth cross-sectional regressions. At the end of each month t, I use a set of independent variables including stock characteristics and my mispricing measures to predict the stock returns for month $t+1$. My primary independent variable is the interaction between the combined anomaly variable, MIS, and GMX[t-T,t-1] or IMX[t-T,t-1]. For each stock, GMX[t-T,t-1] and IMX[t-T,t-1] measure the past return predictability of MIS from month $t-T$ to $t-1$ within that stock's state and industry peers, respectively. Table 4.A.1 defines all the variables. All independent variables in my regressions are standardized to have a mean of zero and a standard deviation of 1, and are winsorized at the 0.5 and 99.5 percentiles. Standard errors are adjusted using the Newey and West (1987) approach. Panels A and B report the baseline regression results based on GMX[t-T,t-1] and IMX[t-T,t-1], respectively. Panel C presents the results based on alternative measures of past state and industry mispricing, i.e. GM[t-T,t-1] and IM[t-T,t-1], which include the dependent-variable firm itself to estimate the past return predictability of each state and industry. For brevity, I exclude the intercept and the control variable estimates in Panel C. The sample excludes penny stocks and covers the period from July 1963 to December 2017. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Firm-Level Return Predictability Based on Past Geographic Mispricing

	Only MIS	T=1	T=3	T=6	T=12	T=24	T=60
Intercept	0.998***	1.002***	0.999***	0.996***	0.995***	0.990***	0.987***
	(4.33)	(4.36)	(4.34)	(4.32)	(4.32)	(4.30)	(4.30)
GMX[t-T,t-1]		-0.049***	-0.029*	-0.035**	-0.033**	-0.03*	-0.035**
		(-3.38)	(-1.85)	(-2.34)	(-2.18)	(-1.96)	(-2.15)
MIS	0.446***	0.443***	0.438***	0.443***	0.442***	0.447***	0.439***
	(11.00)	(11.03)	(10.59)	(10.65)	(10.84)	(10.85)	(10.78)
MIS × GMX[t-T,t-1]		0.024*	0.014	0.042***	0.045***	0.027*	0.014
		(1.81)	(0.96)	(3.06)	(3.20)	(1.94)	(1.00)
log(ME)	-0.199**	-0.194**	-0.195**	-0.195**	-0.195**	-0.194**	-0.195**
	(-2.43)	(-2.39)	(-2.39)	(-2.39)	(-2.39)	(-2.39)	(-2.40)
log(B/M)	0.321***	0.318***	0.319***	0.318***	0.318***	0.319***	0.319***
	(5.27)	(5.22)	(5.24)	(5.22)	(5.22)	(5.24)	(5.25)
RET[-12,-2]	0.361***	0.356***	0.355***	0.354***	0.353***	0.355***	0.356***
	(4.50)	(4.46)	(4.45)	(4.43)	(4.42)	(4.45)	(4.46)
RET[-1,0]	-0.633***	-0.638***	-0.639***	-0.639***	-0.639***	-0.638***	-0.638***
	(-10.97)	(-11.10)	(-11.09)	(-11.10)	(-11.10)	(-11.06)	(-11.06)
Average Adjusted R^2	4.23%	4.27%	4.28%	4.28%	4.29%	4.29%	4.28%
Average Observations	2,852	2,812	2,813	2,814	2,815	2,816	2,819

Table 4.3: Firm-Level Return Predictability Based on Geography and Industry (Continued)

Panel B: Firm-Level Return Predictability Based on Past Industrial Mispricing							
	Only MIS	T=1	T=3	T=6	T=12	T=24	T=60
Intercept	0.998***	0.992***	0.989***	1.004***	1.001***	0.998***	0.996***
	(4.33)	(4.35)	(4.35)	(4.41)	(4.39)	(4.37)	(4.36)
IMX[t-T,t-1]		-0.126***	-0.107***	-0.110***	-0.094***	-0.071***	-0.071***
		(-4.93)	(-3.99)	(-4.10)	(-3.41)	(-2.62)	(-2.92)
MIS	0.446***	0.427***	0.428***	0.427***	0.427***	0.429***	0.425***
	(11.00)	(11.20)	(11.09)	(11.10)	(11.22)	(11.19)	(11.08)
MIS × IMX[t-T,t-1]		0.07***	0.067***	0.06***	0.062***	0.044***	0.038**
		(4.19)	(3.85)	(3.65)	(3.76)	(2.74)	(2.51)
log(ME)	-0.199**	-0.182**	-0.180**	-0.184**	-0.185**	-0.187**	-0.186**
	(-2.43)	(-2.25)	(-2.22)	(-2.27)	(-2.27)	(-2.30)	(-2.29)
log(B/M)	0.321***	0.321***	0.320***	0.321***	0.322***	0.322***	0.317***
	(5.27)	(5.33)	(5.33)	(5.31)	(5.31)	(5.31)	(5.21)
RET[-12,-2]	0.361***	0.344***	0.339***	0.338***	0.337***	0.341***	0.343***
	(4.50)	(4.23)	(4.19)	(4.20)	(4.20)	(4.24)	(4.24)
RET[-1,0]	-0.633***	-0.647***	-0.646***	-0.646***	-0.645***	-0.643***	-0.641***
	(-10.97)	(-11.11)	(-11.13)	(-11.13)	(-11.09)	(-11.06)	(-11.03)
Average Adjusted R^2	4.23%	4.45%	4.45%	4.45%	4.44%	4.44%	4.41%
Average Observations	2,852	2,731	2,731	2,732	2,732	2,733	2,734
Panel C: Alternative Past Mispricing Measure (Including the Dependent Variable Firm)							
	Only MIS	T=1	T=3	T=6	T=12	T=24	T=60
GM[t-T,t-1]		-0.054***	-0.027*	-0.035**	-0.042***	-0.029*	-0.034**
		(-3.58)	(-1.72)	(-2.26)	(-2.62)	(-1.80)	(-1.99)
MIS	0.446***	0.442***	0.442***	0.445***	0.456***	0.456***	0.449***
	(11.00)	(11.07)	(10.91)	(10.87)	(11.28)	(11.12)	(10.94)
MIS × GM[t-T,t-1]		0.029**	0.015	0.047***	0.052***	0.026*	0.018
		(2.08)	(1.03)	(3.24)	(3.47)	(1.93)	(1.30)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Average Adjusted R^2	4.23%	4.26%	4.27%	4.26%	4.27%	4.26%	4.26%
Average Observations	2,852	2,840	2,840	2,841	2,841	2,842	2,843
IM[t-T,t-1]		-0.133***	-0.118***	-0.121***	-0.102***	-0.079***	-0.052
		(-5.08)	(-4.21)	(-4.32)	(-3.47)	(-2.59)	(-1.63)
MIS	0.446***	0.426***	0.426***	0.433***	0.44***	0.434***	0.421***
	(11.00)	(11.07)	(11.03)	(11.32)	(11.61)	(10.98)	(10.59)
MIS × IM[t-T,t-1]		0.064***	0.066***	0.059***	0.076***	0.044**	0.017
		(3.60)	(3.50)	(3.29)	(4.10)	(2.55)	(1.00)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Average Adjusted R^2	4.23%	4.44%	4.46%	4.46%	4.45%	4.45%	4.42%
Average Observations	2,852	2,759	2,759	2,759	2,760	2,760	2,760

Table 4.4: Firm-Level Return Predictability Based on Both Geography and Industry

This table presents the Fama-MacBeth regression results based on a model that includes both MIS × GMX[t-T,t-1] and MIS × IMX[t-T,t-1] interactions at the same time. The regression methodology is the same as that described in Table 4.2. Table 4.A.1 defines all the variables. The sample period covers July 1963 to December 2017. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Past Mispricing Excluding the Dependent Variable Firm						
	T=1	T=3	T=6	T=12	T=24	T=60
MIS	0.427***	0.422***	0.426***	0.427***	0.434***	0.423***
	(11.29)	(10.50)	(10.70)	(10.99)	(10.94)	(10.76)
GMX[t-T,t-1]	-0.045***	-0.030*	-0.032**	-0.027*	-0.027*	-0.031*
	(-3.17)	(-1.95)	(-2.20)	(-1.84)	(-1.81)	(-1.94)
IMX[t-T,t-1]	-0.124***	-0.107***	-0.109***	-0.092***	-0.070***	-0.070***
	(-4.86)	(-4.02)	(-4.13)	(-3.38)	(-2.60)	(-2.88)
MIS × GMX[t-T,t-1]	0.024*	0.014	0.043***	0.040***	0.023*	0.011
	(1.76)	(1.05)	(3.20)	(2.96)	(1.69)	(0.71)
MIS × IMX[t-T,t-1]	0.071***	0.070***	0.060***	0.061***	0.041**	0.035**
	(4.27)	(4.02)	(3.67)	(3.65)	(2.51)	(2.30)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Average Adjusted R^2	4.47%	4.48%	4.47%	4.48%	4.47%	4.44%
Average Observations	2,080	2,710	2,711	2,713	2,715	2,718
Panel B: Past Mispricing Including the Dependent Variable Firm						
	T=1	T=3	T=6	T=12	T=24	T=60
MIS	0.425***	0.426***	0.433***	0.449***	0.443***	0.422***
	(11.12)	(10.87)	(11.07)	(11.7)	(10.93)	(10.39)
GM[t-T,t-1]	-0.048***	-0.028*	-0.030*	-0.037**	-0.024	-0.031*
	(-3.21)	(-1.80)	(-1.95)	(-2.38)	(-1.56)	(-1.88)
IM[t-T,t-1]	-0.131***	-0.118***	-0.122***	-0.101***	-0.077**	-0.051
	(-5.02)	(-4.24)	(-4.36)	(-3.48)	(-2.55)	(-1.58)
MIS × GM[t-T,t-1]	0.027*	0.016	0.042***	0.044***	0.020	0.015
	(1.89)	(1.07)	(2.93)	(3.00)	(1.45)	(1.10)
MIS × IM[t-T,t-1]	0.065***	0.068***	0.058***	0.075***	0.044**	0.017
	(3.65)	(3.62)	(3.25)	(4.06)	(2.52)	(0.99)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Average Adjusted R^2	4.46%	4.5%	4.48%	4.48%	4.47%	4.44%
Average Observations	2,744	2,744	2,745	2,746	2,747	2,748

Table 4.5: Analyst Characteristics of GMX[t-12,t-1] and IMX[t-12,t-1] Quintiles

This table reports the average analyst characteristics of quintile portfolios, sorted based on the past geographic (GMX[t-12,t-1]) and industrial (IMX[t-12,t-1]) mispricing variables. The quintiles are formed by sorting all stocks at the end of each month, based on their most recent GMX[t-12,t-1] and IMX[t-12,t-1] values. The characteristics are also reported for the same month, at the end of which the quintiles are formed. AFE is the average absolute analyst forecast error for the most recent quarter scaled by the stock price, FE is the forecast error for the most recent quarter scaled by the stock price, DISPERSION is the average analyst forecast dispersion for the most recent quarter, and NOCOVERAGE is equal to 1 if a stock did not have any analyst coverage over the past 3 months, and 0 otherwise. The construction details of all variables are explained in Table 4.A.1. All variables are winsorized at their 0.1 and 99.9 percentile levels. The t-statistics for the difference between the values of quintiles 1 and 5 (5 - 1) are based on Newey-West heteroscedasticity- and autocorrelation-consistent standard errors using a lag of 12 months. The sample excludes penny stocks and covers January 1990 to December 2017.

Panel A: Quintiles Based on GMX[t-12,t-1]						
	1	2	3	4	5	5 - 1 (t)
AFE	0.596	0.621	0.631	0.64	0.648	0.052 (4.61)
FE	0.070	0.071	0.065	0.069	0.082	0.012 (1.51)
DISPERSION	0.221	0.228	0.228	0.236	0.233	0.012 (1.99)
NOCOVERAGE	36.391	36.326	36.826	37.35	38.144	1.754 (2.52)
Panel B: Quintiles Based on IMX[t-12,t-1]						
	1	2	3	4	5	5 - 1 (t)
AFE	0.589	0.596	0.598	0.616	0.688	0.099 (4.46)
FE	0.066	0.064	0.057	0.056	0.104	0.038 (3.00)
DISPERSION	0.217	0.227	0.229	0.229	0.240	0.024 (2.78)
NOCOVERAGE	36.346	36.819	36.704	36.713	38.177	1.831 (2.93)

Table 4.6: Firm-Level Return Predictability Within Subsamples of Absolute Analyst Forecast Error

This table presents Fama-MacBeth regression estimates for two subsamples of stocks formed based on their absolute forecast errors (AFE). The subsamples are formed by sorting stocks every month, based on their most recent AFE values, into two groups. I then take the regression specifications in Table 4.3 and estimate them for each of the two subsamples. The construction details of all variables are explained in Table 4.A.1. For brevity, I exclude the intercept and control variable estimates. All independent variables in the regressions are standardized to have a mean of zero and a standard deviation of 1, 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 1990 to December 2017.

Panel A: Firm-Level Return Predictability Based on Past Geographic Mispricing			
	Low AFE	High AFE	High - Low
MIS	0.231***	0.612***	0.381***
	(3.37)	(8.05)	(3.70)
GMX[t-12,t-1]	-0.011	0.001	0.012
	(-0.40)	(0.04)	(0.32)
MIS × GMX[t-12,t-1]	0.015	0.070**	0.055
	(0.57)	(2.02)	(1.26)
Controls	Yes	Yes	
Average Adjusted R^2	5.44%	4.05%	
Average Observations	1014	983	
Panel B: Firm-Level Return Predictability Based on Past Industrial Mispricing			
	Low AFE	High AFE	High - Low
MIS	0.191***	0.564***	0.373***
	(2.99)	(7.64)	(3.82)
IMX[t-12,t-1]	-0.018	-0.100	-0.082
	(-0.42)	(-1.61)	(-1.09)
MIS × IMX[t-12,t-1]	0.032	0.13***	0.098**
	(1.03)	(3.33)	(1.96)
Controls	Yes	Yes	
Average Adjusted R^2	5.65%	4.35%	
Average Observations	996	958	

Table 4.7: Firm-Level Return Predictability for Periods of High and Low National Sentiment

This table report Fama-MacBeth regression estimates for two subsamples of stocks formed based on the previous month's sentiment score. The subsamples are formed by dividing the sample into months of high and low sentiment, using the Baker and Wurgler (2006) sentiment score for the previous month. I then take the regression specifications in Table 4.3 and estimate them for each of the two subsamples. The construction details of all variables are explained in Table 4.A.1. For brevity, I exclude the intercept and control variable estimates. All independent variables in the regressions are standardized to have a mean of zero and a standard deviation of 1, 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 1970 to December 2015.

Panel A: Firm-Level Return Predictability Based on Past Geographic Mispricing			
	Low NSENT	High NSENT	High - Low
MIS	0.358***	0.652***	0.294***
	(7.35)	(8.45)	(3.20)
GMX[t-12,t-1]	-0.020	-0.059**	-0.039
	(-0.93)	(-2.21)	(-1.14)
MIS × GMX[t-12,t-1]	0.030	0.079***	0.049
	(1.60)	(3.39)	(1.64)
Controls	Yes	Yes	
Average Adjusted R^2	3.7%	4.47%	
Average Observations	2818	3422	
Panel B: Firm-Level Return Predictability Based on Past Industrial Mispricing			
	Low NSENT	High NSENT	High - Low
MIS	0.346***	0.634***	0.288***
	(7.15)	(9.14)	(3.41)
IMX[t-12,t-1]	-0.078**	-0.153***	-0.075
	(-2.07)	(-3.01)	(-1.19)
MIS × IMX[t-12,t-1]	0.048**	0.113***	0.065*
	(2.05)	(4.00)	(1.77)
Controls	Yes	Yes	
Average Adjusted R^2	3.85%	4.61%	
Average Observations	2707	3369	

Table 4.8: Firm-Level Return Predictability for Periods of High and Low State Sentiment and Economic Activity

This table reports the Fama-MacBeth regression estimates for the subsamples of stocks formed based on the previous month's state sentiment or state macroeconomic activity variables. In Panel A, the subsamples are formed by dividing the sample into two parts, based the state sentiment score for each stock available at the end of the previous month. The subsamples in Panel B are constructed using the most recent quarterly state macroeconomic activity index of Korniotis and Kumar (2013b) available from the previous month. I then take the regression specifications in Table 4.3, and estimate them for each of the two subsamples. The construction details of all variables are explained in Table 4.A.1. For brevity, I exclude the intercept and the control variable estimates. All independent variables in the regressions are standardized to have a mean of zero and a standard deviation of 1, 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 1970 to December 2017 for Panel B. Due to data constraints, for Panel A, the sample covers only 1980 to 2008.

Panel A: Dividing the Sample by State Economic Activity Index (SEA)			
	Low SEA	High SEA	High - Low
MIS	0.530***	0.551***	0.021
	(9.49)	(9.48)	(0.30)
GMX[t-12,t-1]	-0.027	-0.146***	-0.119**
	(-1.14)	(-2.67)	(-2.00)
MIS × GMX[t-12,t-1]	0.030	0.105***	0.075**
	(1.69)	(3.06)	(1.94)
Controls	Yes	Yes	
Average Adjusted R^2	3.59%	3.63%	
Average Observations	1699	1709	
Panel B: Dividing the Sample by State Sentiment (SSENT)			
	Low SSENT	High SSENT	High - Low
MIS	0.471***	0.486***	0.015
	(10.17)	(9.96)	(0.20)
GMX[t-12,t-1]	-0.035	0	0.035
	(-1.48)	(0.01)	(1.48)
MIS × GMX[t-12,t-1]	0.005	0.055**	0.050**
	(1.00)	(2.35)	(2.09)
Controls	Yes	Yes	
Average Adjusted R^2	3.99%	4.17%	
Average Observations	1530	1525	

Table 4.9: Robustness and Control for Limits to Arbitrage

Panel A presents the estimates of MIS × GMX[t-12,t-1] and MIS × IMX[t-12,t-1] interactions from Panels A and B of Table 4.2, based on alternative samples or data filters. Panel B reports the estimates of the interaction terms in Panel A after controlling for limits to arbitrage. I take the regression specifications in Table 4.2 and add five proxies for limits to arbitrage and their interactions with MIS to each specification, separately. ILLIQ is the illiquidity measure of Amihud (2002); SIR is the short interest ratio following Hanson and Sunderam (2014); IVOL is the idiosyncratic volatility; log(ME) is the natural logarithm of market capitalization; and IHOLD is the percentage of institutional holdings. Table 4.A.1 explains the construction details for all variables. For brevity, I only report the interaction coefficients in both panels. All variables are defined in Table 4.A.1. The sample period covers July 1963 to December 2017. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Basic Robustness						
	MIS × GMX[t-12,t-1]			MIS × IMX[t-12,t-1]		
Test	Estimate	(t)	N	Estimate	(t)	N
Baseline	0.045***	(3.20)	2,815	0.062***	(3.76)	2,732
Exclude price < $5	0.035***	(2.69)	2,223	0.054***	(3.39)	2,163
1963-1990	0.039**	(1.99)	2,396	0.025	(1.10)	2,296
1991-2017	0.051**	(2.54)	3,240	0.100***	(4.22)	3,175
Exclude highest size quintile	0.054***	(3.27)	2,221	0.073***	(4.02)	2,145
Exclude lowest size quintile	0.048***	(3.56)	2,283	0.064***	(3.83)	2,220
Expansion periods	0.053***	(3.17)	2,560	0.061***	(3.21)	2,488
Recession periods	0.076**	(2.24)	1,671	0.089**	(1.99)	1,565
Panel B: Controlling for Limits to Arbitrage Variables						
Control for liquidity (ILLIQ)	0.047***	(3.04)	3,127	0.065***	(3.44)	3,043
Control for short interest (SIR)	0.054***	(3.42)	3,191	0.078***	(4.07)	3,101
Control for idiosyncratic volatility (IVOL)	0.034**	(2.46)	2,815	0.054***	(3.44)	2,732
Control for size (log(ME))	0.042***	(2.97)	2,815	0.050***	(3.06)	2,732
Control for institutional holdings (IHOLD)	0.052***	(2.93)	3,263	0.091***	(4.39)	3,199

Table 4.10: Robustness Simulations

This table presents the Fama-MacBeth regression results for MIS × GM[t-12,t-1] and MIS × IM[t-12,t-1] interaction coefficients, based on 10,000 simulated samples of artificial state and industry allocations. The model specification is the same as that in Panel B of Table 4.2. For each simulation, state and industry allocations are shuffled among firms so that each firm has a state and industry that is different from its original ones. Randomization is performed in a way that ensures there are the same number of stocks in each state and industry group as there were originally in that group. The regressions are then estimated based on artificial state and industry allocations to get the estimated coefficients. The results include the original estimates, together with the summary statistics of the coefficients and the t-statistics, based on simulations. Table 4.A.1 defines all the variables. The sample period covers July 1963 to December 2017.

	MIS × GM[t-12,t-1]		MIS × IM[t-12,t-1]	
	Coefficient	t	Coefficient	t
Estimates Based on Sample Data:				
Baseline	0.045	3.20	0.062	3.76
Simulations:				
Mean	0.008	0.58	0.008	0.59
Standard Deviation	0.014	1.00	0.014	0.98
P1	-0.025	-1.72	-0.024	-1.67
P25	-0.001	-0.10	-0.001	-0.07
P50	0.008	0.59	0.008	0.59
P75	0.017	1.26	0.018	1.25
P99	0.040	2.92	0.041	2.88

Table 4.A.1: Variable Descriptions

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

Panel A: Mispricing Variables		
Variable Name	Source	Description
GM[t-T,t-1]	CRSP and Compustat	This is defined in the same way as GMX[t-T,t-1], except stock s is included in the Fama-MacBeth estimation sample.
GMX[t-T,t-1]	CRSP and Compustat	For each stock s and month t, this is defined as the estimated β_{1_g} coefficient from running the following Fama-MacBeth regression: $R_{i,\tau} = \beta_{0_g} + \beta_{1_g} MIS_{i,\tau-1} + \sum_{n=1}^{N} \beta_{n+1_g} Control_{n_{i,\tau-1}} + \epsilon_{i,\tau}$. The model is estimated using monthly data from month $t-T$ to month $t-1$. The sample includes all stocks in stock s's state, except stock s itself. States are defined based on the firm headquarters location, available on Compustat.
IM[t-T,t-1]	CRSP and Compustat	This is defined the same as IMX[t-T,t-1] except that stock s is included in the Fama-MacBeth estimation sample.
IMX[t-T,t-1]	CRSP and Compustat	For each stock s and month t, this is defined as the estimated β_{1_g} coefficient from running the following Fama-MacBeth regression: $R_{i,\tau} = \beta_{0_g} + \beta_{1_g} MIS_{i,\tau-1} + \sum_{n=1}^{N} \beta_{n+1_g} Control_{n_{i,\tau-1}} + \epsilon_{i,\tau}$. The model is estimated using monthly data from month $t-T$ to month $t-1$. The sample includes all stocks in stock s's industry, except stock s itself. Industries are defined based on the FamaFrench 48 industry definitions.
LONG	CRSP and Compustat	Defined as a dummy variable that is equal to 1 if a stock is in MIS quintile 5, and 0 otherwise. MIS quintiles are defined by sorting all stocks in the cross section at the beginning of every month, based on the most recent MIS values available at the end of the previous month.
MIS	CRSP and Compustat	Following Stambaugh et al. (2015), MIS is the average of the decile ranks of a stock, with respect to 11 prominent anomalies. Sorting for each anomaly is performed at the end of every month. Deciles 1 and 10 include stocks that each anomaly strategy predicts will underperform and outperform the most in the following month, respectively. Unlike Stambaugh et al. (2015), I determine the decile cutoffs using my whole sample, not just NYSE stocks. I require at least 5 non-missing anomaly decile ranks to compute the 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 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). I follow the detailed description of Stambaugh et al. (2012, 2015), together with the corresponding anomaly literature, to replicate each strategy.
SHORT	CRSP and Compustat	Defined as a dummy variable that is equal to 1 if a stock is in MIS quintile 1, and 0 otherwise. MIS quintiles are defined by sorting all stocks in the cross section at the beginning of each month, based on the most recent MIS values available at the end of the previous month.

Table 4.A.1: (Continued)

Panel B: Analyst Forecast, Sentiment and Economic Activity Variables		
Variable Name	Source	Description
AFE	IBES and CRSP	Computed as the average of $\|(analystearningsforecast - actualearnings)\|/price$, where price is the stock price at the beginning of the forecast period. The average is computed using all earnings forecasts for the most recent quarter announced over the past 3 months.
NOCOVERAGE	IBES	Equal to 1 if a stock did not have any analyst forecasts during the past 3 months and 0 otherwise.
DISPERSION	IBES	Standard deviation of analyst earnings forecasts for the most recent quarter annouced over the past 3 months.
FE	IBES	Computed as the average of $(analystearningsforecast - actualearnings)/price$, where price is the stock price at the beginning of the forecast period. The average is computed using all earnings forecasts for the most recent quarter annouced over the past 3 months.
NSENT	From Professor Jeffrey Wurgler's website	This is the index of market-wide investor sentiment constructed by Baker and Wurgler (2006).
SEA	From Professor Alok Kumar	Index of macroeconomic activity calculated for each state quarter by adding the standardized values of state income growth and housing collateral, subtracting the standardized value of relative unemployment, and dividing by 3 (see Korniotis and Kumar, 2013).
SSENT	CRSP and Thomson Reuters Securities Data Corporation (SDC)	This is the investor sentiment index for each state, computed by taking the first principal component of four time-series proxies for sentiment, following Baker et al. (2012). The four sentiment proxies are as follows: 1-Volatility premium, defined as the ratio of the value-weighted average market-to-book ratio of stocks in the top 3 state volatility deciles to that of the stocks in the bottom 3 state volatility deciles. Volatility is defined as the standard deviation of CAPM residuals estimated using the past 12 months of returns. 2-The number of IPOs in that state during the previous 12 months. 3-Average first-day returns of IPOs during the past 12 months. 4-State turnover computed as the log of total turnover (total dollar volume of all stocks headquartered in the state over the year, divided by total capitalization at the end of the prior year), detrended with the five-year moving average.

Table 4.A.1: (Continued)

Panel C: Firm Characteristics and Control Variables		
Variable Name	Source	Description
B/M	CRSP and Compustat	This is the ratio of the book value to the market capitalization of the firm.
IHOLD	Thomson Reuters	The fraction of a stock's outstanding shares held by institutional investors. I 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, I set its institutional holdings to zero.
ILLIQ	CRSP	This is the 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 four-factor model of Carhart (1997) on daily returns for the most recent month.
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 year's monthly compounded buy-and-hold return, skipping the last month.
SHORTRATIO	Compustat	Average ratio of short interest to shares outstanding over the past 12 months.
TURN	CRSP	Total trading volume over the last month, divided by shares outstanding.
VOL	CRSP	Volatility of daily returns for the most recent month.

Table 4.A.2: Mispricing Persistence Regressions

This table presents coefficient estimates from panel regressions of monthly hedge MIS portfolio returns for each state and industry on average hedge MIS portfolio returns for that state and industry over the previous 12 months. Hedge MIS returns for each state or industry group are defined as the average returns of stocks in that group that have MIS values above the cross-sectional median minus the average returns of those with MIS values below the cross-sectional median. The median MIS is based on the whole cross section and not each individual state or industry. The definitions of state and industry are the same as those used in GM and IM variables defined in Table 4.A.1. The regressions include fixed effects for time and state or industry. t-statistics are based on standard errors double-clustered by time and state or industry. The sample excludes penny stocks and covers the period from July 1963 to December 2017. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	Dependent Variable	
	State MIS Returns	Industry MIS Returns
Past State MIS Returns	0.445**	
	(2.01)	
Past Industry MIS Returns		0.587**
		(2.08)
R^2	10.62%	12.71%
Time Fixed Effects	YES	YES
State / Industry Fixed Effects	YES	YES

Chapter 5

Conclusion

My thesis explores various channels rooted in investor behavior that can explain puzzling aspects of market mispricing. The foundation of my work is built upon the literature showing market anomalies exhibit commonalities (e.g., Stambaugh et al., 2012, 2015; Jacobs, 2016). In most cases, such commonalities reflect stock mispricing as they are driven mostly by stocks facing barriers to arbitrage. My contribution is to highlight two previously undocumented factors that can shed light on the dynamics of the common mispricing-related component across market anomalies. These are investor preference for skewness and firm geographic and industrial attributes.

In Chapter 2, I show that investor preference for skewness is a more consequential phenomenon in asset pricing than has been reported. Stocks that are predicted to underperform in anomalies are often those with the highest level of positive skewness in the cross section. This feature attracts investors that are willing to pay a premium to hold positively-skewed stocks and leads to underpricing. I apply this idea to the profitability anomaly and observe that less profitable firms are in fact more positively skewed than their more profitable peers. Also, in line with my conjecture, the premium associated with profitability is considerably stronger among more positively-skewed stocks; however, investor preference for skewness cannot fully explain the profitability premium. This is because profitability is unlikely to be priced solely due to market mispricing (Ball et al., 2015). Moreover, the premium associated with it is partly captured by systematic risk factors (Novy-Marx, 2013).

Next, in Chapter 3, in order to focus more on the mispricing-related part of anomalies, I follow Stambaugh et al. (2015) and combine a range of prominent anomalies to capture the common component reflecting mispricing. I find that skewness-loving investors overweight stocks that this measure indicates will underperform. Also, positively-skewed stocks are the predominant set whose returns are predictable using the combined anomaly measure. Therefore, I suggest that investor preference for skewness can, in fact, explain a large part of the mispricing-related aspect of market anomalies.

Finally, in Chapter 4, I explore the implications of a firm's geographic and industrial characteristics. These attributes are likely to attract common investor clienteles and affect a firm's susceptibility to mispricing, as captured by market anomalies. I show that the mispricing levels of a firm's geographic or industrial peers can predict how mispriced the firm will be in the future. This effect is relatively stronger for geography than for industry, however, the two attributes tend to have complementary predictive power.

Geographic persistence in mispricing is concentrated in regions experiencing high levels of investor sentiment. I argue that firms in specific regions are more prone to market anomalies as their investor clienteles are relatively more over-optimistic and, as a result, invest in overpriced stocks. On the other hand, industrial persistence in mispricing is driven by stocks experiencing higher levels of analyst forecast errors. This is in line with the argument that firms in certain industries are more prone to mispricing as analysts covering that industry do a poorer job of distinguishing overpriced and underpriced firms.

My studies contribute to the asset pricing literature on market anomalies. This is primarily by highlighting that exploring investor behavior is crucial for understanding anomalous patterns in stock returns. My research can be further developed in two main ways. First, it would be interesting to explore how relatively sophisticated investors such as short sellers or active funds react to eliminate market anomalies. In particular, it is not clear whether overpriced stocks – which are the primary drivers of mispricing – are impossible to arbitrage or institutions are unable or unwilling to invest in them for other reasons. One could even discover that more sophisticated investors are a part of the problem due to the same behavioral arguments. Second, my findings have

a range of trading implications which might potentially yield profits after transaction costs. Specifically, I speculate that investors trading on anomalies can improve their performance by refining their strategies to take into account skewness, geography, and industry. It would be fruitful to investigate empirically whether such strategies are profitable and, if so, to what extent.

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