Hazard Stocks and Expected Returns

R. Jared DeLisle
Utah State University
jared.delisle@usu.edu

Michael Ferguson
University of Cincinnati
fergusm@ucmail.uc.edu

Haimanot Kassa
Miami University
kassah@miamioh.edu

Abstract

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Keywords: hazard stocks, underreaction, equity returns, tail risk, information uncertainty, limits to arbitrage

JEL Codes: G10, G11, G12

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1. Introduction

Recent studies have documented empirical evidence of investors' preference for lottery stocks (e.g. Kumar (2009) and Bali *et al.* (2011)). Of particular interest, Bali *et al.* (2011) present convincing evidence that stocks that have recently experienced extreme positive returns (as measured by MAX, the maximum daily return during a month) are subsequently characterized by low expected returns.[1] In this paper, we focus on the opposite of lottery stocks, which we call hazard stocks, and examine the relation between hazard stocks and expected returns. Just like lottery stocks are stocks that are prone to experience extreme positive returns, hazard stocks are stocks that are prone to experience extreme negative returns. This parallel between hazard stocks and lottery stocks suggests that the results from lottery stocks could be generalized to hazard stocks. That is, investors pay a premium for lottery stocks but should discount hazard stocks. However, studies about negative corporate events report that bad news is particularly prone to underreaction (e.g. Womack (1996), Hong *et al.* (2000), Chan (2003), and Taffler *et al.* (2004)), suggesting that investors could underreact to hazard stocks. Since these two concepts are in opposition to each other, it is an empirical question to answer which effect dominates.

We follow the literature on lottery stocks (Bali *et al.* 2011) and calculate a proxy for hazard stocks as the minimum daily idiosyncratic return with respect to Fama-French-Carhart four factor model for each stock every month, labeled IMIN. We multiply IMIN by negative one so that higher values represent hazard stocks. We focus on idiosyncratic returns to differentiate the market's reaction to firm-specific information from the reaction to economy-wide shocks. This is especially important in looking at extreme negative returns because they are likely to have a larger systematic

[1] The study reports that a trading strategy that is long stocks in the top decile of MAX in the previous month and short the bottom decile of MAX earns a Fama and French (1993)-Carhart (1997) alpha of -1.18% per month with monthly rebalancing. This evidence is consistent with the existence of investors who have a preference for lottery-like payoffs.

component than positive returns due to the increased correlations that arise in down markets that can mask investors' response to the idiosyncratic portion of an extreme return.[2]

Our main result is that the market underreacts to hazard stocks, and does not discount hazard stocks in a manner that is consistent with lottery stock premiums. Specifically, firms with high IMIN (lowest idiosyncratic returns) have low returns in subsequent months. Portfolios long in low IMIN stocks (small negative extreme returns) and short high IMIN stocks (large negative extreme returns) earn significantly positive abnormal returns of 0.52% per month using value-weighted portfolios and 0.75% per month when using equal-weighted portfolios. We find similar results using Fama and MacBeth (1973) regressions. This underreaction is persistent, forecasting negative abnormal returns for up to 24 months without subsequent reversals. Importantly, these findings remain unchanged when earnings announcement months are removed from the analyses, suggesting the results are not related to post-earnings announcement drift associated with earnings surprises. These results are robust to numerous controls including size, book-to-market, momentum, turnover, lagged returns, idiosyncratic volatility, and MAX.[3]

Overall, we uncover a striking difference between investors preference for lottery stocks and hazard stocks. Investors pay a premium for lottery stocks but don't discount hazard stocks. Instead, the market underreacts to hazard stocks.

The literature offers several potential explanations for underreaction including limited investor attention, structural uncertainty, and limits to arbitrage. Under the limited investor

[2] Szado (2009), Chan *et al.* (2011), Lee *et al.* (2011), and Yang *et al.* (2012) find that returns become more correlated during market downturns, even across asset classes. Ang and Chen (2002) and Ang *et al.* (2006a) find equities tend to have higher CAPM betas when the market has negative returns (especially extreme downside price movements).

[3] We also compute a measure of extreme positive idiosyncratic returns, IMAX, but find that the market does not underreact to IMAX. Rather, consistent with Bali *et al*. (2011), we find that IMAX and subsequent returns are negatively related. The market underreacts to IMIN, but overreacts to (or pays a premium for) IMAX. Because the overreaction to IMAX result is so similar to that reported in Bali *et al*. (2011), we focus the remainder of our attention on the underreaction to IMIN.

attention hypothesis, investors do not process all information as rapidly as it becomes available which results in slow price adjustment (Hirshleifer and Teoh (2003), Peng (2005), Peng and Xiong (2006), Hirshleifer *et al.* (2009)). This may be due to cognitive limitations (e.g., bounded rationality), time availability, or suboptimal behavior (e.g., behavioral biases). Under the structural uncertainty hypothesis (see, for example, Brav and Heaton (2002)), investors are rational but do not have rational expectations because of incomplete information (e.g., they do not know all model parameters with certainty). Here investors appear to underreact to information, but they are in fact resolving their uncertainty ('learning') and updating their prior beliefs via Bayes Rule. Yet another mechanism that would lead to apparent underreaction is that limits to arbitrage prevent investors from arbitraging away the mispricing. If arbitrageurs are impeded from trading misvalued stocks, they cannot quickly exploit mispricing and, thus, prices do not rapidly converge to fundamental values as the market efficiency hypothesis suggests (e.g. Pontiff (1996), Shleifer and Vishny (1997), and Pontiff (2006)). In each of these cases, information is incorporated into prices more slowly than it is revealed.

Consequently, we examine the limited attention, rational learning (resolving uncertainty), and limits to arbitrage explanations for underreaction to IMIN. Following prior literature we proxy firms that receive limited investor attention as characterized by low institutional ownership, small market capitalization, and low analyst following (see, for example, Bali *et al.* (2014)). We use earnings accruals quality (Dechow and Dichev (2002) and Francis *et al.* (2005, 2007)) to proxy for information uncertainty. Lastly, bid-ask spread (Bhardwaj and Brooks (1992) and Lam and Wei (2011)), relative short interest (D'Avolio (2002) and Asquith *et al.* (2005)), and idiosyncratic volatility (Ali *et al.* (2003)) proxy for limits to arbitrage. We then perform two sets of initial tests, and perhaps surprisingly, find support for all three explanations.

First, we divide our sample into quintiles based on the various proxies and investigate the relationship between IMIN and returns across portfolios within a quintile. We find that the negative relation between IMIN and future returns is more pronounced in the portfolios of stocks characterized by lower investor attention, greater information uncertainty, and higher limits to arbitrage. Next, we perform Fama and Macbeth (1973) regression analyses incorporating interaction terms for IMIN and each of the proxies, individually, for investor attention, information uncertainty, and limits to arbitrage. We find that the IMIN effect is amplified by low earnings quality, low investor attention (in two of the three measures), and higher limits to arbitrage (in two of the three measures). This is consistent with the evidence from the portfolio sorts. Thus, our evidence is consistent with all three underreaction explanations.

We attempt to disentangle the attention, information uncertainty, and limited arbitrage explanations. In order to accomplish this, we conduct Fama and MacBeth (1973) regressions that simultaneously include interaction terms with IMIN and proxies for information uncertainty, investor attention, and limits to arbitrage. Only the interaction terms with information uncertainty and limits to arbitrage have the expected sign (i.e., they amplify the IMIN effect) and are statistically significant. Thus, the strongest evidence supports only two of the proposed explanations of underreaction related to IMIN: structural uncertainty and limited arbitrage.

The papers most closely related to ours are Jiang and Zhu (2017) and Atilgan *et al.* (2018). Jiang and Zhu (2017) identify positive and negative stock price jumps as large discontinuous price changes relative to a martingale process and find evidence of symmetric underreaction: stocks with positive (negative) jumps continue to have high (low) returns in the next month. Atilgan *et al*. (2018) use a 12-month Value-at-Risk (VaR) measure as a proxy for left-tail risk and document a significant negative relation between left-tail risk and future returns. Our IMIN measure shares many of the advantages of the approaches employed by Jiang and Zhu (2017) and Atilgan *et al*. (2018) in that we do not have to identify event dates or windows, nor are we limited to public announcements (e.g., Hong *et al.* (2000), Chan (2003), and Taffler *et al.* (2004)). Moreover, not all public announcements are newsworthy; a great deal of information has been anticipated or 'priced in'.

However, the IMIN approach carries some distinct advantages over the jump and VaR approach. First, and perhaps most importantly, since IMIN is an analogous measure to Bali *et al.* (2011) MAX measure, we can compare the return predictability of lottery stocks with hazard stocks (i.e. a symmetric preference for lottery stocks and hazard stocks suggests investors will pay a premium for high MAX stocks but demand a discount for high IMIN stocks). Second, unlike Bali *et al*. (2011), Jiang and Zhu (2017), or Atilgan *et al*. (2018), our IMIN measure for hazard stock is firm specific and thus does not include the potentially large systematic component that the other measures are liable to encompass.[4] Third, we identify more than twice as many extreme price changes for each firm than are identified by the jump approach.

We contribute to the literature on lottery preferences and causes of underreaction to hazard stocks. Specifically, we show that investors underreact to hazard stocks, which is not consistent with the literature on lottery stock premiums. Additionally, the limited literature examining underreaction to hazard stocks and negative information shocks identify limited attention as the basis of underreaction. Contrary to these studies, we rule out limited attention in favor of information uncertainty and limits to arbitrage as the main contributors to the underreaction.

[4] To the extent that extreme price movements primarily reflect firm specific information, then this distinction may not matter that much. But, if that was true, MIN would predict future returns just as well as IMIN. However, Bali *et al.* (2011) report that they find weak evidence that MIN is positively priced (i.e. high MIN is followed by positive returns in the following month); but, after controlling for MAX and other firm characteristics they show MIN has no return predictability. In stark contrast, we document that IMIN has substantial return predictability.

The rest of the paper is organized as follows. Section 2 presents related literature. Section 3 describes our data and presents summary statistics. Section 4 presents the main empirical results on the relation between IMIN and future returns. Section 5 investigates various explanations for the results reported in Section 4 including limited investor attention hypothesis, structural uncertainty (rational learning) hypothesis, and limits to arbitrage hypothesis. It also distinguishes between the three underreaction explanations. Section 6 concludes.

2. Related Literature

There is a growing literature on the relation between lottery stocks and future returns. For example, (Kumar 2009) finds evidence of lottery premiums in the cross-section of equity returns. His classification of lottery stocks includes idiosyncratic volatility, idiosyncratic skewness, and low price. Bali *et al*. (2011) find similar results using the maximum raw daily return in a month (MAX) as the measure of a lottery stock characteristic. They report that a trading strategy that is long stocks in the top decile of MAX in the previous month and short the bottom decile of MAX earns a Fama and French (1993)-Carhart (1997) alpha of -1.18% per month with monthly rebalancing.

The difference between the MAX measure and others is that it focuses on only extreme positive returns to determine lottery stock. If lottery preferences are symmetric (e.g. investors place a premium on lottery stocks and a discount on hazard stocks), then we should observe an opposite effect for minimum returns compared to maximum returns. To this end, Bali *et al*. (2011) use the minimum raw daily return in a month, MIN, as a measure of anti-lottery, or hazard, stocks. In untabulated results, they find that stocks with extreme low returns outperform those with less extreme minimum returns, albeit with smaller magnitudes and weaker statistical significance than the MAX findings. However, unlike MAX, the MIN effect is not robust to subsample analyses and appears to be limited to small, illiquid stocks. Additionally, the MIN effect is absent when controlling for MAX. The main takeaway from Bali *et al*. (2011) is that there is a negative relation between extreme positive price changes and future returns and less so, if any, between extreme negative price changes and future returns.

Studies such as Hirshleifer and Teoh (2003), Peng (2005), Peng and Xiong (2006), and Hirshleifer *et al.* (2011) present theories of limited investor attention that result in price adjustments that are much slower than expected in a classical semistrong-form efficient market. Bolstering these theories, numerous empirical studies link underreaction to information to limited investor attention.[5] Most closely related to our study, Jiang and Zhu (2017) identify stock price jumps (large discontinuous price changes) and use them as a proxy for information shocks. They examine short-term market reactions to these information shocks and find evidence of underreaction: stocks with positive (negative) jumps continue to have high (low) returns in the next month. They also demonstrate these findings are robust to various controls and that limited attention is a contributor to the underreaction. These results conflict with the Bali *et al*. (2011) results of a negative relation between MAX (and, more weakly, MIN) and future returns.

Atilgan *et al*. (2018) also identify underreaction to recent losses, albeit indirectly since they do not overtly estimate price changes. Rather, they compute the Value-at-Risk (VaR) for a firm from the empirical distribution of daily losses over the last year. They use a 1% and 5% lower-tail cutoff as their measure of risk, and find that the higher the magnitude of the VaR measures the lower the future returns, which they call ‘left-tail momentum’. Atilgan *et al*. (2018) note that this

[5] Studies that demonstrate that limited investor attention and under reaction are linked include Bernard and Thomas (1989), Hong and Stein (1999), DellaVigna and Pollet (2009), Hirshleifer *et al.* (2009), Da *et al.* (2011), Hirshleifer *et al.* (2013), and Bali *et al.* (2014).

higher risk/lower return combination appears to violate the basic principles of the CAPM. Furthermore, they show that for stocks that have lower measures of investor attention, this underreaction is highest.

Atilgan *et al*. (2018) find that ‘left-tail momentum’ is strongest when the VaR is high in the previous month. This is similar to our IMIN result. VaR is measured over the last year, IMIN over the last month. In fact, VaR is akin to a MIN over last 12 months. Therefore, their result is likely driven by the underreaction to ‘events’ that we document with IMIN. And, as we establish below, because this effect works with a long lag, their VaR measure picks it up even when the extreme negative return was 12 months ago.

There are important differences, however, in the measures of extreme price changes in this paper (IMIN), Bali *et al*. (2011), Jiang and Zhu (2017), and Atilgan *et al*. (2018). The first major difference across the measures of extreme returns is their exposure to systematic risk. Bali *et al*. (2011) and Atilgan *et al*. (2018) use raw returns to rank stocks by MAX and VaR, respectively, so each return is composed of a systematic and an idiosyncratic component. Likewise, there is no adjustment or filter for market returns in the Jiang and Zhu (2017) model of returns used to identify jumps. Note that by definition IMIN, MIN, and VaR are negative returns. This is significant because studies such as Szado (2009), Chan *et al.* (2011), Lee *et al.* (2011), and Yang *et al.* (2012) find that returns become more correlated during market downturns, even across distinct asset classes. Furthermore, Ang and Chen (2002) and Ang *et al.* (2006a) find equities tend to have higher CAPM betas when the market has negative returns. This is especially true when there are extreme downside price movements. Taken together, these findings imply that negative equity returns (e.g., MIN and VaR) are likely to have a larger systematic component than positive returns (e.g., MAX). Our measures of extreme returns (IMIN and IMAX) combine the best features of the Jiang and

Zhu (2017), Bali *et al*. (2011), and Atilgan *et al*. (2018) measures. Our idiosyncratic measures isolate firm-specific information shocks (i.e., news), unlike the other measures of extreme returns.

In addition, unlike the jumps in Jiang and Zhu (2017), IMIN is identified frequently (i.e., monthly), like MAX and VaR. Jumps in Jiang and Zhu (2017) are relatively rare; Jiang and Zhu (2017) report an average of 4.5 jumps per stock-year, with positive jumps occurring twice as often as negative jumps. Thus, a stock jump effect is only identified, on average, in less than half the months of the year for each stock. IMIN, MAX, and VaR, however, are computed in every month of the sample period. Thus, by construction, IMIN, MAX and VaR are observed roughly two and a half times as often as jumps. Consequently, IMIN, MAX and VaR are likely to be more reflective of the distribution of returns than the relatively infrequent jumps which are likely to be more reflective of information shocks.[6]

Although the previous studies mentioned find evidence of limited attention driving underreaction, it is not the only possible explanation. Imperfect information may also lead to the patterns of apparent under reaction documented above. For example, Lewellen and Shanken (2002) present a model of Bayesian investors with uncertain information about value-relevant parameters. In their model, return predictability arises due to evolution of investors' updated beliefs about these parameters. Supporting this theory, Francis *et al.* (2007) find that the well-known post-earnings-announcement-drift is related to uncertainty induced by low quality earnings accruals.[7] As information comes to the market, investors update their prior beliefs using Bayes Rule. The observed underreaction is due to the investor placing weight on both their prior beliefs

[6] The difference between jumps and MAX and MIN is even more stark when we consider that the average 4.5 jumps per year consists of roughly 3 positive jumps and 1.5 negative jumps. Thus, MAX is observed 4 times as often as a positive jump and MIN is observed 8 times as often as a negative jump.

[7] Accrual quality refers to the degree to which accounting earnings can be mapped into cash flows. In this context, lower quality accruals reduce the precision of information generated about the firm from earnings announcements. See Section III.A below for a fuller explanation.

and the new information. Naturally, this will manifest as a partial adjustment towards the new information and appear to be an under reaction to the signal. The weight placed on the new information is a function of the precision of the new signal (i.e., less weight is placed on noisier signals). The inverse of precision is information uncertainty. The greater the information uncertainty, the less weight placed on the new signal.

Limited arbitrage is yet another mechanism that generates underreaction in financial markets. Arbitrageurs will only engage in trading on mispricing if their proceeds from doing so exceed the associated transaction and holding costs. Therefore, these costs are considered limits to arbitrage. If the limits to arbitrage are considerable, then mispricing will not be rapidly corrected and the price will exhibit a drift rather than a sharp return to fundamental value. This observed underreaction can be attributable to several limits to arbitrage. For example, the bid-ask spread is a transaction costs that inhibits arbitrage activity (Bhardwaj and Brooks (1992) and Lam and Wei (2011)). Short sale constraints is another transaction cost that impedes arbitrageurs with pessimistic views about a stocks outlook from shorting the stock (D'Avolio (2002) and Asquith *et al.* (2005)). Idiosyncratic volatility is an example of a major holding cost that an investor would face when trying to arbitrage mispricing (e.g. Pontiff (1996), Shleifer and Vishny (1997), Ali *et al.* (2003), Mashruwala *et al.* (2006), Pontiff (2006), Au *et al.* (2009), Stambaugh *et al.* (2015), and Cao and Han (2016)). We explore all three explanation of underreaction to IMIN – limited attention, information uncertainty, and limits to arbitrage.

3. Data and Descriptive Statistics

3.1. Data

Stock return and related data is from CRSP, accounting information is from COMPUSTAT, analyst and related data is from IBES and institutional ownership data is from Thomson Reuters 13f. We start with CRSP common equities (share code 10 and 11) that are traded on major exchanges (NYSE, NASDAQ and AMEX) from January 1963 to December 2014. Although the data starts in 1963, our analysis begins in June 1969 due to the need to employ various lags.

IMIN and Related Variables: We compute daily idiosyncratic returns by regressing daily excess returns on the Carhart (1997) 4-factors (MKT, SMB, HML, and UMD) within a month. We require stocks to have at least 15 trading days within a month to be included in our sample. The following proxies are computed from either the daily residual (i.e., idiosyncratic) or raw returns within a month. Our main variable of interest, the monthly measure of idiosyncratic minimum return (IMIN), is the minimum of the residuals from this regression within a month. Similarly, MIN and MAX are, respectively, the minimum and maximum raw returns within a month. IMAX is the maximum idiosyncratic return within a month. IVOL is the idiosyncratic volatility, computed as the standard deviation of the residuals within a month. ISKEW is idiosyncratic skewness, computed as the skewness of the residuals within a month.

We compute monthly BETA from a rolling regression of daily excess return on CRSP value weighted excess returns, looking back up to a year and requiring at least 150 daily return observation to be included in the sample. SIZE is the market capitalization of the firm, computed as the price per share multiplied by shares outstanding and reported in thousands. MOM is momentum and it is computed as the compound return of the previous six monthly returns, skipping the immediately previous month. RET(-1) is reversal or the immediate previous month return or lagged return. TURNOVER is computed as trading volume divided by the float or the number of shares outstanding. Following Fama and French (1993) and Daniel and Titman (1997) we compute the book-to-market ratio (BEME) as the book value of equity (total assets minus total liabilities, plus deferred tax and investment credits, and minus the value of preferred stock, if available) divided by the market value of equity (price per share of common stock multiplied by the number of shares outstanding).

Investor Attention Proxies: Our investor attention measures follow the prior literature and include *SIZE*, *IOR*, and *ANALYSTS*.[8] *SIZE* is defined above. *IOR* is the institutional owner ratio computed from Thomson Reuters 13f filings as the ratio of the number of shares held by institutions to the total number of shares outstanding. *ANALYSTS* is the number of analysts following a particular stock reported by IBES. Naturally, larger firms, firms held primarily held by institutions, and firms with large analyst following indicate greater investor attention.

Information Uncertainty Proxy: Our measure of information uncertainty (IU) is based on a measure of earnings accrual quality developed in Dechow and Dichev (2002). Intuitively, the Dechow and Dichev model views cash flows as fundamental to investor valuations. Consequently, a central task for investors is to map accounting earnings (public information) into cash flows. Low quality (inaccurate or noisy) accruals weakens this mapping and increases IU. Following Francis *et al*. (2005, 2007) we estimate the Dechow and Dichev (2002) measure of earnings accrual quality for firm j (EAQ_j) as

$$EAQ_j = \frac{1}{\sigma_j(\varepsilon)} \tag{1}$$

where ε are the residuals from the following regression:

$$TCA_{j,t} = \beta_0 + \beta_1 CFO_{j,t-1} + \beta_2 CFO_{j,t} + \beta_3 CFO_{j,t+1} + \beta_4 \Delta REV_{j,t} + \beta_5 PPE_{j,t} + \varepsilon_{j,t} \tag{2}$$

[8] See for example, Hirshleifer and Teoh (2003), Peng (2005), and Hirshleifer *et al.* (2013), and Bali *et al.* (2014).

$TCA_{j,t}$ is firm j's total current working capital accruals; $CFO_{j,i}$ is firm j's cash flows from operation in periods $i = t-1$, t, and $t+1$; $PPE_{j,t}$ is the gross value of firm j's property, plant and equipment in year t; and $\Delta REV_{j,t}$ is change in firm j's revenue from year $t-1$ to year t. When the standard deviation of the residuals is high, the mapping between cash flows and accruals is poor, resulting in low EAQ. Information uncertainty for firm j (IU_j) is simply

$$IU_j = \left(EAQ_j\right)^{-1} = \sigma_j\left(\varepsilon_{j,t}\right) \tag{3}$$

Quite naturally, when EAQ is low, IU is high, and vice versa.

Limits to Arbitrage Proxies: Our limits to arbitrage measures also come from prior literature. Following Lam and Wei (2011), bid-ask spread is defined as the difference between the bid and ask price divided by the midpoint between the two. The short interest ratio proxies for short sale constraints. As in Asquith *et al.* (2005), the short interest ratio is defined as the number of outstanding shares sold short divided by the total number of outstanding shares. Asquith *et al.* (2005) show that the short interest ratio and short sale constraints are positively related. Idiosyncratic volatility is defined above.

3.2. Descriptive Statistics

Table 1 presents the summary statistics and correlations for these data. Panel A shows that a typical firm in our sample has a monthly return of 1.1% and idiosyncratic minimum return or IMIN of 3.8%.[9] Panel B shows that IMIN and returns are negatively correlated. This preliminary result suggests firms that experienced a negative idiosyncratic shock have higher valuations and lower future returns. As expected, IMIN is also highly positively correlated with IVOL, MIN and MAX at 88%, 78% and 60%, respectively. To alleviate a potential concern that we might be re-

[9] For ease of interpretation, we multiply IMIN by -1. Thus, a higher IMIN reflects a more negative idiosyncratic minimum return and, thus, hazard stocks.

documenting results associated with IVOL, MIN and MAX in the analysis below, we control for these variables via a dependent bivariate sort procedure and via multivariate regressions. The main results we report are also qualitatively similar when we rank orthogonalize IMIN with these variables (untabulated).

4. Cross-Sectional Relation between Hazard Stocks and Expected Returns

4.1. Univariate Portfolio-Level Analysis

In Table 2, we present equal- and value-weighted average monthly returns and Carhart (1997) four-factor alphas of quintile portfolios formed by idiosyncratic minimum return and idiosyncratic maximum returns, dubbed IMIN and IMAX, respectively. In Panels A and B, we report equal- and value-weighted results for IMIN, and in Panels C and D, we report equal- and value-weighted results for IMAX, respectively.

We find that IMIN is negatively related to future returns. Specifically, Panel A shows that the lowest IMIN quintile portfolio has an average return of 1.23% per month, and the highest IMIN quintile portfolio has an average return of 0.60% per month. The last column labeled "H - L" shows that an investment strategy that is long the highest IMIN quintile portfolio and short the lowest IMIN quintile portfolio earns an economically large and statistically significant average return of -0.63% per month (*t*-statistic = -3.37). Additionally, we find that the return from this strategy is not driven by commonly used risk factors, as the strategy earns an abnormal return of -0.75% per month (*t*-statistic = -7.28), relative to the Carhart (1997) four-factor model. The results in Panel B show that the raw high-minus-low IMIN hedge return diminishes when we form value-weighted portfolios (-0.39%, with *t*-statistic=1.89) suggesting that the return difference attributed to IMIN is, in part, driven by small stocks. However, the value-weighted Carhart (1997) four-factor alpha is still economically large and statistically significant, -0.52% per month with *t*-statistic = -3.78, confirming that the value-weighing scheme does not eliminate the abnormal returns due to IMIN.

The results in both Panels A and B are consistent with the market underreacting to hazard stocks, and does not discount hazard stocks in a manner that is consistent with lottery stock premiums. In untabulated results (available upon request), we remove firm-months in which firms release an earnings announcement and find the results are qualitatively and quantitatively similar to the original results. This suggests post-earnings announcement drift (PEAD) is not driving the results.

We perform a similar portfolio analysis of IMAX. In Panel C, we form equal-weighted portfolios based on IMAX and find very similar results. The average return on the lowest IMAX quintile portfolio is 1.19% per months, and the average return on the highest IMAX quintile portfolio is 0.56% percent per month. The investment strategy that is long the highest IMAX quintile portfolio and short the lowest IMAX quintile portfolio generates a statistically large and economically significant average return of -0.63% per month (*t*-statistic = -3.37), and a Carhart (1997) four-factor of -0.77% per month (*t*-statistic = -7.35) confirming that the return difference on the two portfolios is not due to known risk factors. The results in Panel D show that the raw return diminishes when we form value-weighted portfolios (-0.29%, with *t*-statistic=1.41), suggesting that the return difference attributed to IMAX is also, in part, driven by small stocks. As we found for IMIN, the value-weighing scheme does not eliminate the abnormal returns due to IMAX, as there is an economically large and statistically significant hedge portfolio alpha of -0.47% per month (*t*-statistic = -3.63) on IMAX. The results in both Panels C and D are consistent with investors paying a premium for lottery stocks. We note that this finding is similar to Bali *et* *al*. (2011) who report that MAX and returns are negatively related, and they interpret MAX as a proxy for lottery stocks. As noted in the Introduction, we are primarily interested in understanding hazard stocks and the sources of under reaction; therefore we focus on IMIN throughout the rest of the paper.

4.2. Bivariate Portfolio-Level Analysis

Before we investigate potential explanations for the negative relationship between IMIN and returns, we first confirm that our results are not subsumed by known firm characteristics via a bivariate sort procedure and a Fama and MacBeth (1973) regression. In Table 3, we perform a sequential bivariate sort similar to Ang *et al*. (2006) Table 7. We first sort stocks in our sample into quintiles based on firm characteristics known to explain the cross section of stock returns, and then, within each quintile, we sort firms into quintiles by IMIN. For each of the IMIN-characteristic portfolios, we report the average alpha for the stocks identified by the double sort. Thus, the returns in this table represent the IMIN quintile portfolio returns after controlling for the characteristics.

We find that the high-minus-low IMIN quintile portfolio generates economically large and statistically significant alphas for all of the 11 characteristics we examined – market beta, size, book-to-market, momentum, turnover, reversal, idiosyncratic volatility, idiosyncratic skewness, MIN, MAX and IMAX. The Carhart (1997) four-factor alphas range from -0.20% per month (*t*-statistic = 4.90) for IVOL sorted portfolios to -0.79% per month (*t*-statistic = -7.51) for idiosyncratic skewness sorted portfolios. As such, these results support the notion that the IMIN effect is independent of firm characteristics known to explain the cross-section of returns. Next, we examine this further within a multivariate regression framework.

4.3. Firm-Level Cross-Sectional Regressions

We further examine the relationship between IMIN and returns using Fama and MacBeth (1973) regressions and present the results in Table 4. In column (1), we first run a univariate regression and find that IMIN and future returns are negatively correlated; we get a point estimate of -0.13 (*t*-statistic = -5.01). In column (2), we control for variables commonly used to explain the cross-section of stock returns - beta, size, and book-to-market. In this case, IMIN loads in a qualitatively similar way to the univariate result, with a point estimate of -0.15 (*t*-statistic = -10.93). In column (3), we control for additional firm characteristics that have been found to explain the cross-section of stock returns – momentum, reversal, liquidity, idiosyncratic volatility, idiosyncratic skewness, maximum daily return. The magnitude of the IMIN coefficient is smaller but remains significantly negative. Taken together, the results from Tables 3 and 4 rule out the possibility that IMIN captures firm characteristics that are known to explain the cross-section of stock returns, including the MAX variable of Bali *et al*. (2011) and idiosyncratic volatility of Ang *et al.* (2006b). Again, to rule out the explanation that PEAD is driving the results, we remove firm-months in which firms have earnings announcements and the results (untabulated and available upon request) remain both quantitatively and qualitatively similar to the original results.

Over all, the results thus far show a strong negative correlation between IMIN and future returns, which is not consistent with the results implied by lottery stocks; rather it suggests that investors underreact to hazard stocks.

4.4. Long-run Underreaction to IMIN

In Table 5, we repeat our main univariate portfolio analysis using up to 24 lags of IMIN to examine whether the relationship between IMIN and returns is short- or long-lived. We present the average raw returns in Panel A and the Carhart (1997) four-factor alphas in Panel B. The results from Panel A show that IMIN contains information about future returns for up to nine months, as the magnitude and statistical significance of the high-minus-low IMIN hedge portfolio diminishes from -63 basis points (*t*-statistic = -3.37) at one lag to -29 basis points (*t*-statistic = 1.66) at nine lags. At 12 lags and beyond, the economic magnitude of this strategy is extremely small and not statistical significant. However, the results in Panel B show that the Carhart (1997) four-factor alphas due to IMIN are rather long-lived, to more than 24 months. Notably, we do not find evidence that this underreaction is reversed in the long run, i.e., we do not observe a positive IMIN coefficient at any lag. These results demonstrate that IMIN predicts returns well into the future, for possibly more than two years.

We confirm the robustness of the univariate sort results we reported in Panels A and B of Table 5 by performing a Fama and MacBeth (1973) univariate regression. The results are reported in Panel C of Table 5. Model (1) shows that the contemporaneous relationship between IMIN and returns is also negative, confirming that investors underreact to IMIN. Subsequent regressions show that the relationship between IMIN and returns dissipates slowly, and dies out 9-months later. Studies such as De Bondt and Thaler (1985), Hong and Stein (1999), and Ottaviani and Sørensen (2015) suggest that, following a period of underreaction, investors overreact and there is a price reversal. While we show a continuation of the response to IMIN, there is no evidence of a subsequent reversal. Savor (2012) reports that return momentum follows major price changes accompanied by information releases. On the other hand, he finds that major price changes not accompanied by information releases result in return reversals. The patterns in the panels of Table 5 are more consistent with the notion that the drift is associated with information. This suggests that learning and updating are taking place rather than attention-based underreaction. In the next section we will formally investigate the source of this underreaction.

5. Investigating the Underlying Mechanism of Underreaction

The results presented thus far indicate that investors underreact to IMIN. A natural interpretation of underreaction is that investors are either unable or unwilling to devote sufficient attention to valuing all assets all the time and are, thus, slow to fully incorporate new information into prices. However, as Brav and Heaton (2002) note, there is very little observational distinction between this limited investor attention explanation and structural uncertainty models. In the case of structural uncertainty, investors update their beliefs about the underlying return generating process in accordance with Bayes' Rule. The process of updating beliefs takes time and, therefore, appears to be underreaction to news. Finally, investors may be fully paying attention and armed with complete knowledge of the return generating process but faced with high transactions costs. In this case, their ability to arbitrage away mispricing is limited. This is likely to be more severe for overpricing (see D'Avolio (2002) and Asquith *et. al.* (2005)). We examine each of these explanations in the following sections.

5.1. Limited Investor Attention

We begin by investigating the negative relationship between IMIN and investor attention via a double sort procedure and a Fama and MacBeth (1973) regression. According to Hirshleifer and Teoh (2003), Peng (2005), and Hirshleifer *et al.* (2013), size and analyst coverage proxy for investor attention. Bali *et al.* (2014) also use institutional ownership as an additional measure of investor attention. In Table 6, we perform a sequential bivariate sort, where we first sort stocks in our sample into quintiles based on of these three investor attention proxies separately, and then, within each quintile, we sort firms into quintiles by IMIN.

We find that the high-minus-low IMIN quintile portfolio generates an economically large and statistically significant alpha for 13 of the 15 investor attention portfolios. Importantly, for each of the three attention proxies, the Carhart (1997) four-factor alphas are monotonically increasing as we go from low investor attention to greater investor attention. This provides the first evidence that the under-reaction associated with IMIN is, in part, due to limited investor attention.

We further examine the effect of investor attention on the relationship between IMIN and returns using Fama and MacBeth (1973) regressions and present the results in Table 7. In the first column of each panel, we perform a regression that controls for IMIN, the attention proxy (either institutional ownership, number of following analysts, or firm size), and an interaction term. We find that IMIN and future returns are significantly negatively correlated and that the interaction term is significantly positive. Note that larger values of the attention proxy indicate greater attention, so the positive interaction term indicates that there is less underreaction. In the second column of each panel of Table 7, we control for beta, size, and book-to-market. The interaction of IMIN with investor attention loads in a qualitatively similar way to the results presented in the first column. In the third column of each panel, we control for several additional firm characteristics – momentum, reversal, liquidity, idiosyncratic volatility, idiosyncratic skewness, maximum daily return. The results are again qualitatively similar to the first column of the panel: a negative (positive) relation between IMIN (the interaction term) and returns. Taken together, the results from Tables 6 and 7 suggest that the influence of IMIN on returns is amplified by limited investor attention and that this interaction is not due to investor attention being driven by other firm characteristics that have been found to explain the cross-section of stock returns.

5.2. Information Uncertainty

Similar to the analyses performed with the investor attention proxies, in this section we investigate the relation between IMIN and information uncertainty (IU) via a double sort procedure and a Fama and MacBeth (1973) regression. As detailed in Section 3, we estimate IU following

Francis *et al.* (2007). In Table 8, we show the resulting portfolio four-factor alphas from a sequential double sort, where we first sort stocks in our sample into quintiles based on earnings accruals quality, and then, within each quintile, we sort firms into quintiles by IMIN.

We find that the high-minus-low IMIN quintile portfolio generates four-factor alphas that are economically large and statistically significant at the 1% level for the three highest information uncertainty quintiles. Moreover, the Carhart (1997) four-factor alphas monotonically decrease from -0.12% per month (*t*-statistic = -1.14) to -1.03% per month (*t*-statistic = -6.57) as information uncertainty increases from the first quintile to the fifth quintile.

We further examine the effect of information uncertainty on the relationship between IMIN and returns using Fama and MacBeth (1973) regressions and present the results in Table 9. In the first column, we first perform a regression that controls for IMIN, earnings quality, and an interaction term. We find that IMIN and future returns are negatively correlated and that the interaction term is significantly negative. Recall, larger values of the information uncertainty proxy indicate greater uncertainty, so the negative interaction term indicates that there is more underreaction when IU is higher. As in Table 7, in the second column of Table 9, we control for beta, size, and book-to-market and in the third column we control for additional firm characteristics. The results in columns 2 and 3 are very similar to those in column 1. Taken together, the results from Tables 8 and 9 demonstrate that the influence of IMIN on returns is greater in the presence of greater information uncertainty and that this interaction is not due to information uncertainty being driven by other firm characteristics.

5.3. Limits to Arbitrage

In this section we investigate the relation between IMIN and limits to arbitrage via a double sort procedure and a Fama and MacBeth (1973) regression. Again, as detailed in Section 3, proxies for limits to arbitrage are bid-ask spread, short interest ratio, and idiosyncratic volatility. In Table 10, we show the four-factor portfolio alphas resulting from a sequential bivariate sort, where we first sort stocks in our sample into quintiles based on of these three limits to arbitrage proxies separately, and then, within each quintile, we sort firms into quintiles by IMIN.

We find that the high-minus-low IMIN quintile portfolios generate an economically large and statistically significant (at least at the 5% level) alphas for 13 of the 15 limited arbitrage portfolios. Only the two lowest bid-ask spread quintiles show no statistical difference between portfolios with high and low IMIN. For each of the three limited arbitrage proxies, the Carhart (1997) four-factor alphas generally become more negative as limited arbitrage increases. For example, for portfolios first sorted by idiosyncratic volatility, the lowest IVOL quintile high-minus-low IMIN quintile portfolio's monthly alpha is -53 basis points (*t*-statistic = -4.72) while highest IVOL quintile high-minus-low IMIN quintile portfolio's monthly alpha is -155 basis points (*t*-statistic = 9.89). This evidence supports the hypothesis that the under-reaction associated with IMIN is, at least in part, due to limited investor attention.

Again, we use Fama and MacBeth (1973) regressions to further examine the effect of limits to arbitrage on the relationship between IMIN and returns. Table 11 displays the results. In the first column, we first perform a regression that controls for IMIN, earnings quality, and an interaction term. We find that IMIN and future returns are negatively correlated and that the interaction terms with short interest and idiosyncratic volatility are negative and highly statistically significant (*t*-statistics of -4.383 to -6.032, respectively). There is no evidence that bid-ask spread affects future returns related to IMIN. Recall, larger values of the limits to arbitrage proxies indicate greater limits to arbitrage, so the negative interaction term indicates that there is more underreaction with higher limits to arbitrage. Again, in the second column of each panel we control for beta, size, and book-to-market and in the third column we control for additional firm characteristics. In Panels B and C, the parameter estimates for the interaction of limited arbitrage and IMIN in columns 2 and 3 are very similar to those in column 1 both in magnitude and in statistical significance. Taken together, the results from Tables 10 and 11 demonstrate that the influence of IMIN on returns is greater in the presence of greater limits to arbitrage and that this interaction is not driven by other firm characteristics.

5.4. Information Uncertainty, Limited Investor Attention, or Limits to Arbitrage?

Thus far we show that greater limited investor attention, information uncertainty, and limits to arbitrage appear to magnify the market's underreaction to IMIN. Next, we explore the extent to which each of the explanations subsumes the others. Since the seven proxies for limited investor attention, information uncertainty, and limits to arbitrage are likely highly correlated, we create measures that consolidate the proxies for each explanation. First, we follow Stambaugh et al. (2015) and create an aggregate rank for limited investor attention (from size, institutional ownership, and number of analyst), for information uncertainty (from earnings accruals quality measure following Francis *et al*., 2005, 2007), and for limits to arbitrage (from bid-ask spread, idiosyncratic volatility, and short interest ratio) as a sum of the ranks of each proxy. Then, we create an indicator for low attention $ATTN\_low$ if the aggregate attention ranking is in the lowest quintile. Similarly, we create indicators for high information uncertainty IU_high and separately for high limits to arbitrage $LIMIT2ARB\_high$ if the overall information uncertainty and limits to arbitrage rankings are in the highest quintile.

We again employ Fama and MacBeth (1973) regressions; this time to discern the relative importance of each explanation of the IMIN underreaction. The results are presented in Table 12. In the first column, we perform a regression that controls for IMIN, *ATTN_low*, *IU_high,* and

LIMIT2ARB_high. We find that IMIN and future returns are significantly negatively correlated (parameter estimate = -0.06 and *t*-statistic = -3.75). In the second column, the interactions of IMIN and the indicator variables are included in the model. These results show that, in the presence of the interactions, IMIN itself is no longer significantly related to future returns. However, all three of the interactions with IMIN are statistically significant. The third and fourth columns control for beta, size, and book-to-market and other firm-specific characteristics. The magnitude and signs of IMIN and the interaction terms are relatively unchanged. Interestingly, the marginal contribution of the interaction between low investor attention and IMIN to future returns is small and not statistically significant in the expanded model with additional controls (Model 4). Overall, the results from this table show that information uncertainty and limits to arbitrage, but not limited attention, significantly contribute to the documented underreaction to IMIN. This differs from the extant findings in the related literature (see, for example, Atilgan *et al.*, 2018; Jiang and Zhu, 2017) that show limited attention as explanation for market underreaction.

6. Conclusion

Empirical research has largely focused on the *right* tail of the return distribution (e.g., 'stocks as lotteries). In contrast, we investigate the significance of extreme negative price changes (which the literature, e.g. Bali *et al*. (2011), suggests proxies for anti-lotteries) on the cross-section of stock returns. To better isolate firm-specific information shocks, we calculate idiosyncratic extreme minimum (IMIN) daily returns for each stock every month. We use IMIN to document the investors' reaction to extreme negative idiosyncratic returns. The evidence we report in this paper is inconsistent with the symmetric lottery preferences.

However, we do find evidence consistent with market underreaction to IMIN. Firms with extreme IMIN (most low) have low returns in subsequent months. Portfolio-level analyses and firm-level cross-sectional regressions indicate that high IMIN (large extreme negative daily return) is associated with negative contemporaneous monthly returns; moreover, IMIN forecasts return continuations for up to 24 months without subsequent reversals. This is surprising because most studies of momentum-like continuations find that they reverse after the short-term. We show that long/short portfolios earn significantly positive abnormal returns of 0.52% per month using value-weighted portfolios and 0.75% per month when using equal-weighted portfolios. These results are not driven by post-earnings announcement drift and are robust to numerous controls including size, book-to-market, momentum, turnover, lagged returns, idiosyncratic volatility, and skewness.

Finally, we explore three potential explanations for the apparent under reaction to IMIN: limited attention, structural uncertainty explanations, and limits to arbitrage. Surprisingly, we initially find that all three explanations significantly contribute to the documented underreaction when looked at separately. However, when we examine all three explanations simultaneously, we find that information uncertainty and limits to arbitrage, but not limited attention, significantly contribute to the documented underreaction to IMIN. Overall, the results in this study suggest that either lottery preferences are asymmetric or IMIN (and by extension, any measure of extreme past returns) does not proxy for hazard stocks. In addition, contrary to other studies investigating hazard stocks, we show that limited attention has little to do with the return continuation following extreme negative returns. Rather, information uncertainty and limits to arbitrage are the main contributors to the drift associated with IMIN.

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Table 1: Summary Statistics and Correlation Table

The table provides time-series averages of cross-sectional summary statistics (Panel A) and correlation tables (Panel B). RET is monthly stock return. EXRET is monthly stock returns in excess of the risk free rate. IMIN is idiosyncratic minimum return computed as the minimum idiosyncratic daily return within a month from Carhart (1997) four factor model. For ease of interpretation, we multiply IMIN by -1. BETA is a firm's market beta. SIZE is the log of the firm's market capitalization. BEME is the firm's book-to-market ratio. MOM is momentum calculated as the compound return of the previous six months, skipping the immediate previous one month. RET(-1) is the previous month return for reversal. TURN is share turnover. IVOL is idiosyncratic volatility computed as the standard deviation of the idiosyncratic daily return within a month from Carhart (1997) four factor model. ISKEW is idiosyncratic skewness computed as the skewness of the idiosyncratic daily return within a month from Carhart (1997) four factor model. MIN is the minimum daily return within a month. For ease of interpretation, we multiplied MIN by -1 (high IMIN indicates more negative idiosyncratic return). MAX is the maximum daily return within a month. The data is from 1969:07 to 2014:12.

	RET	EXRET	IMIN	BETA	SIZE	BEME	MOM	RET(-1)	TURN	IVOL	ISKEW	MIN	MAX
Panel A: Summary Statistics													
MEAN	0.011	0.007	0.038	0.863	11.999	0.870	0.110	0.017	0.891	0.020	0.182	0.046	0.056
STD	0.107	0.107	0.023	0.578	1.687	1.045	0.344	0.115	1.201	0.011	0.750	0.027	0.037
Panel B: Correlation Matrix													
RET	1	1.000	-0.035	-0.019	0.001	0.016	0.027	-0.027	-0.011	-0.039	-0.003	-0.027	-0.044
EXRET	1.000	1	-0.035	-0.019	0.001	0.016	0.027	-0.027	-0.011	-0.039	-0.003	-0.027	-0.044
IMIN	-0.035	-0.035	1	0.172	-0.308	-0.020	0.027	0.014	0.283	0.880	-0.205	0.783	0.596
BETA	-0.019	-0.019	0.172	1	0.291	-0.158	0.003	-0.020	0.391	0.204	0.022	0.243	0.220
SIZE	0.001	0.001	-0.308	0.291	1	-0.183	0.015	0.013	0.069	-0.338	-0.034	-0.243	-0.235
BEME	0.016	0.016	-0.020	-0.158	-0.183	1	0.048	0.021	-0.076	-0.021	0.008	-0.038	-0.020
MOM	0.027	0.027	0.027	0.003	0.015	0.048	1	0.014	0.140	0.030	0.004	0.036	0.026
RET(-1)	-0.027	-0.027	0.014	-0.020	0.013	0.021	0.014	1	0.115	0.146	0.254	-0.193	0.317
TURN	-0.011	-0.011	0.283	0.391	0.069	-0.076	0.140	0.115	1	0.318	0.045	0.271	0.295
IVOL	-0.039	-0.039	0.880	0.204	-0.338	-0.021	0.030	0.146	0.318	1	0.152	0.706	0.784
ISKEW	-0.003	-0.003	-0.205	0.022	-0.034	0.008	0.004	0.254	0.045	0.152	1	-0.187	0.353
MIN	-0.027	-0.027	0.783	0.243	-0.243	-0.038	0.036	-0.193	0.271	0.706	-0.187	1	0.487
MAX	-0.044	-0.044	0.596	0.220	-0.235	-0.020	0.026	0.317	0.295	0.784	0.353	0.487	1

Table 2: Single Sort – Average Returns and Carhart (1997) 4 Alphas

The table reports equal and value weighted portfolio returns and Carhart (1997) four factor alphas sorted by IMIN and IMAX. IMIN (IMAX) is idiosyncratic minimum (maximum) return computed as the minimum (maximum) idiosyncratic daily return within a month from Carhart (1997) four factor model. The sorting is done using lagged values. The column 'H-L' reports investment strategies that that goes long in the high IMIN (IMAX) stocks and short the low IMIN (IMAX) stocks. For ease of interpretation, we multiplied MIN by -1 (high IMIN indicates more negative idiosyncratic return). Newey-West corrected t-statistics are reported parenthesis. *, **, *** represent significance levels at the 10%, 5%, and 1%. The data is from 1969:07 to 2014:12.

	Low	2	3	4	High	H – L
Panel A: Equal Weighted IMIN Portfolio Returns and Alphas						
Average Return	1.23	1.31	1.32	1.16	0.60	-0.63***
	(6.67)	(6.00)	(5.39)	(4.24)	(1.97)	(-3.37)
Carhart4 Alpha	0.23	0.21	0.17	-0.01	-0.52	-0.75***
	(3.82)	(4.19)	(3.92)	(-0.14)	(-7.34)	(-7.28)
Panel B: Value Weighted IMIN Portfolio Returns and Alphas						
Average Return	0.98	1.06	0.98	0.91	0.59	-0.39*
	(5.93)	(5.53)	(4.29)	(3.54)	(1.92)	(-1.89)
Carhart4 Alpha	0.10	0.10	-0.02	-0.10	-0.42	-0.52***
	(2.24)	(2.66)	(-0.32)	(-1.35)	(-3.98)	(-3.78)
Panel C: Equal Weighted IMAX Portfolio Returns and Alphas						
Average Return	1.19	1.36	1.32	1.19	0.56	-0.63***
	(6.41)	(6.31)	(5.39)	(4.37)	(1.81)	(-3.37)
Carhart4 Alpha	0.18	0.27	0.18	0.03	-0.59	-0.77***
	(2.93)	(5.48)	(3.89)	(0.68)	(-8.05)	(-7.35)
Panel D: Value Weighted IMAX Portfolio Returns and Alphas						
Average Return	0.97	1.05	0.97	1.11	0.67	-0.29
	(5.81)	(5.55)	(4.27)	(4.12)	(2.22)	(-1.41)
Carhart4 Alpha	0.09	0.08	0.02	0.08	-0.39	-0.47***
	(2.04)	(2.09)	(0.44)	(1.06)	(-3.72)	(-3.63)

Table 3 – Double Sort - Carhart (1997) Alphas after Controlling for Characteristics

The table reports equal weighted Carhart (1997) four factor alphas after controlling for stock characteristics, following Table VII of Ang *et al*. (2006). We first sort stocks into quintiles based on the characteristics, and then, within each quintile portfolio, we sort stocks into quintiles based on IMIN. The five IMIN portfolios are then averaged over each of the five characteristic portfolios. Thus, the portfolio returns represent IMIN quintile portfolios after controlling the characteristic. IMIN is idiosyncratic minimum return computed as the minimum idiosyncratic daily return within a month from Carhart (1997) four factor model. For ease of interpretation, we multiplied MIN by -1 (high IMIN indicates more negative idiosyncratic return). The other variables are defined in Table 1. Newey-West corrected t-statistics are reported parenthesis. *, **, *** represent significance levels at the 10%, 5%, and 1%. The data is from 1969:07 to 2014:12.

	Low IMIN	2	3	4	High IMIN	H - L
BETA	0.21	0.21	0.19	0.01	-0.44	-0.65***
	(3.82)	(4.78)	(4.55)	(0.31)	(-7.75)	(-8.60)
SIZE	0.26	0.21	0.16	-0.05	-0.50	-0.76***
	(3.91)	(3.84)	(3.40)	(-1.14)	(-7.43)	(-6.88)
BEME	0.22	0.20	0.19	0.04	-0.40	-0.62***
	(3.99)	(4.52)	(4.34)	(1.02)	(-6.14)	(-7.03)
MOM	0.25	0.20	0.15	-0.01	-0.45	-0.70***
	(4.61)	(4.95)	(3.46)	(-0.19)	(-6.79)	(-8.25)
TURNOVER	0.23	0.19	0.14	-0.04	-0.47	-0.70***
	(4.63)	(4.50)	(3.41)	(-1.02)	(-8.23)	(-10.14)
RET(-1)	0.21	0.21	0.14	0.03	-0.51	-0.72***
	(4.11)	(5.12)	(3.57)	(0.76)	(-8.06)	(-9.09)
IVOL	0.11	0.03	0.02	0.01	-0.09	-0.20***
	(2.68)	(0.79)	(0.52)	(0.25)	(-2.03)	(-5.61)
IMAX	0.18	0.08	0.05	-0.04	-0.19	-0.37***
	(3.84)	(1.91)	(1.27)	(-0.85)	(-4.22)	(-7.46)
MAX	0.07	-0.00	-0.05	-0.08	-0.21	-0.28***
	(1.64)	(-0.08)	(-1.23)	(-1.90)	(-3.82)	(-4.90)
ISKEW	0.22	0.23	0.19	0.02	-0.58	-0.79***
	(3.58)	(4.72)	(4.23)	(0.51)	(-7.88)	(-7.51)
MIN	0.21	0.14	0.01	-0.12	-0.52	-0.73***
	(5.08)	(3.60)	(0.29)	(-2.48)	(-9.58)	(-12.58)

Table 4: Fama and MacBeth (1973) Regression

The table reports Fama and MacBeth (1973) OLS regression results. IMIN is idiosyncratic minimum return computed as the minimum idiosyncratic daily return within a month from Carhart (1997) four factor model. For ease of interpretation, we multiplied MIN by -1 (high IMIN indicates more negative idiosyncratic return). The other variables are defined in Table 1. Newey-West corrected t-statistics are reported parenthesis. *, **, *** represent significance levels at the 10%, 5%, and 1%. The data is from 1969:07 to 2014:12.

	1	2	3
Intercept	0.011***	0.018***	0.020***
	(6.184)	(3.416)	(4.135)
IMIN	**-0.132***	**-0.146***	**-0.036***
	(-5.006)	**(-10.926)**	**(-1.857)**
BETA		0.001	0.000
		(0.548)	(0.234)
SIZE		-0.001*	-0.001**
		(-1.819)	(-2.378)
BEME		0.001**	0.001**
		(2.286)	(2.142)
MOM			0.007***
			(4.535)
RET(-1)			-0.034***
			(-9.944)
TURNOVER			0.002***
			(3.688)
IVOL			-0.167***
			(-3.164)
ISKEW			0.001***
			(4.07)
MAX			-0.051***
			(-7.527)
Adj R2	0.015	0.053	0.071

Table 5: Equal Weighted Univariate Portfolio Returns and Alphas using "n" lags of IMIN

Panels A and B of this table reports equal weighted portfolio returns and Carhart (1997) four factor alphas, respectively, sorted by different lags of IMIN. The column 'H-L' reports investment strategies that that goes long in the high IMIN stocks and short the low IMIN stocks. IMIN is idiosyncratic minimum return computed as the minimum idiosyncratic daily return within a month from Carhart (1997) four factor model. For ease of interpretation, we multiplied MIN by -1 (high IMIN indicates more negative idiosyncratic return). Newey-West corrected t-statistics are reported parenthesis. *, **, *** represent significance levels at the 10%, 5%, and 1%. The data is from 1969:07 to 2014:12.

Lags	Low IMIN	2	3	4	High IMIN	H - L
Panel A: Average Return						
1	1.23	1.31	1.32	1.16	0.60	-0.63***
	(6.67)	(6.00)	(5.39)	(4.24)	(1.97)	(-3.37)
2	1.24	1.29	1.26	1.14	0.68	-0.56***
	(6.77)	(6.09)	(5.20)	(4.14)	(2.20)	(-2.95)
3	1.20	1.27	1.23	1.18	0.73	-0.46**
	(6.46)	(5.99)	(5.03)	(4.32)	(2.39)	(-2.48)
6	1.22	1.22	1.20	1.13	0.88	-0.34*
	(6.68)	(5.67)	(5.02)	(4.17)	(2.90)	(-1.87)
9	1.20	1.23	1.20	1.15	0.92	-0.29*
	(6.45)	(5.70)	(5.07)	(4.29)	(3.08)	(-1.66)
12	1.19	1.19	1.22	1.11	1.06	-0.13
	(6.28)	(5.58)	(5.12)	(4.21)	(3.54)	(-0.73)
15	1.19	1.22	1.20	1.17	1.04	-0.15
	(6.34)	(5.71)	(5.04)	(4.45)	(3.50)	(-0.89)
18	1.18	1.21	1.20	1.17	1.09	-0.09
	(6.21)	(5.68)	(5.11)	(4.48)	(3.69)	(-0.54)
21	1.17	1.19	1.21	1.19	1.10	-0.07
	(6.25)	(5.58)	(5.21)	(4.55)	(3.74)	(-0.43)
24	1.18	1.16	1.21	1.19	1.16	-0.02
	(6.31)	(5.45)	(5.14)	(4.61)	(3.96)	(-0.13)
Panel B: Carhart 4 Alpha						
1	0.23	0.21	0.17	-0.01	-0.52	-0.75***
	(3.82)	(4.19)	(3.92)	(-0.14)	(-7.34)	(-7.28)
2	0.23	0.20	0.12	-0.01	-0.46	-0.70***
	(3.97)	(4.15)	(2.61)	(-0.17)	(-7.53)	(-7.47)
3	0.19	0.18	0.09	0.03	-0.41	-0.59***
	(3.03)	(3.41)	(2.12)	(0.68)	(-6.25)	(-5.86)
6	0.23	0.13	0.07	-0.02	-0.28	-0.51***
	(3.97)	(2.57)	(1.56)	(-0.36)	(-4.41)	(-5.40)
9	0.21	0.15	0.08	0.00	-0.26	-0.46***
	(3.84)	(3.01)	(1.72)	(0.00)	(-4.15)	(-5.33)
12	0.18	0.11	0.09	-0.04	-0.12	-0.30***
	(3.34)	(2.40)	(1.96)	(-0.93)	(-1.80)	(-3.37)
15	0.18	0.14	0.07	0.02	-0.15	-0.33***

	(3.19)	(3.05)	(1.62)	(0.36)	(-2.53)	(-3.89)
18	0.16	0.13	0.07	0.03	-0.11	-0.27***
	(2.91)	(2.71)	(1.46)	(0.56)	(-1.73)	(-3.10)
21	0.16	0.10	0.10	0.03	-0.11	-0.26***
	(2.95)	(2.06)	(2.27)	(0.73)	(-1.67)	(-3.21)
24	0.17	0.08	0.08	0.02	-0.04	-0.21**
	(3.36)	(1.73)	(1.65)	(0.41)	(-0.56)	(-2.49)

Panel C – Fama and MacBeth (1973) Regression using "n" lags of IMIN

The table reports Fama and MacBeth (1973) OLS regression results using different lags of IMIN. IMIN is idiosyncratic minimum return computed as the minimum idiosyncratic daily return within a month from Carhart (1997) four factor model. For ease of interpretation, we multiplied MIN by -1 (high IMIN indicates more negative idiosyncratic return). Newey-West corrected t-statistics are reported parenthesis. *, **, *** represent significance levels at the 10%, 5%, and 1%. The data is from 1969:07 to 2014:12.

	1	2	3	4	5	6	7	8	9	10	11
Intercept	0.015***	0.012***	0.011***	0.010***	0.009***	0.009***	0.009***	0.009***	0.009***	0.008***	0.008***
	(7.377)	(6.332)	(6.106)	(5.703)	(5.249)	(4.908)	(4.584)	(4.67)	(4.518)	(4.432)	(4.269)
IMIN	-0.142**										
	(-2.271)										
lag_IMIN		-0.114***									
		(-4.613)									
lag2IMIN			-0.088***								
			(-3.274)								
lag3IMIN				-0.075***							
				(-2.793)							
lag6IMIN					-0.047*						
					(-1.747)						
lag9IMIN						-0.039					
						(-1.524)					
lag12IMIN							-0.023				
							(-0.902)				
lag15IMIN								-0.026			
								(-1.031)			
lag18IMIN									-0.016		
									(-0.649)		
lag21IMIN										-0.011	
										(-0.413)	
lag24IMIN											-0.003
											(-0.14)

Adj R2	0.038	0.013	0.013	0.013	0.012	0.011	0.011	0.011	0.01	0.01	0.01

Table 6 – Dependent Bivariate Sort, first by Investor Attention then by IMIN

The table reports equal weighted Carhart (1997) four factor portfolio alphas from a dependent bivariate sort, first by attention proxies (institutional ownership ratio, number of analyst following or firm size) and then by IMIN. The column 'H-L' reports investment strategies that that goes long in the high IMIN stocks and short the low IMIN stocks. IMIN is idiosyncratic minimum return computed as the minimum idiosyncratic daily return within a month from Carhart (1997) four factor model. For ease of interpretation, we multiplied MIN by -1 (high IMIN indicates more negative idiosyncratic return). Newey-West corrected t-statistics are reported parenthesis. *, **, *** represent significance levels at the 10%, 5%, and 1%. The data is from 1980:03 to 2014:12 (1969:07 to 2014:12 for Market Capitalization).

	Low IMIN	2	3	4	High IMIN	H - L
Pane A: Double Sort by **Institutional Ownership Ratio (IOR)**, and then by IMIN						
Low IOR	0.41	0.20	-0.05	-0.30	-1.08	-1.49***
	(3.65)	(1.64)	(-0.41)	(-2.27)	(-7.15)	(-9.49)
2	0.26	0.20	0.12	-0.20	-0.62	-0.88***
	(2.78)	(2.31)	(1.64)	(-2.32)	(-5.36)	(-5.35)
3	0.32	0.25	0.18	0.11	-0.27	-0.59***
	(3.81)	(3.27)	(2.44)	(1.49)	(-2.64)	(-3.87)
4	0.29	0.23	0.30	0.15	-0.08	-0.37***
	(3.33)	(2.69)	(3.68)	(1.99)	(-0.93)	(-2.81)
High IOR	0.22	0.19	0.23	0.34	0.10	-0.12
	(2.42)	(1.93)	(2.72)	(3.59)	(0.94)	(-0.88)
Pane B: Double Sort by **Number of Analysts Following** and then by IMIN						
Low Follow	0.35	0.29	0.00	-0.18	-0.76	-1.10***
	(2.93)	(2.48)	(0.02)	(-1.45)	(-5.40)	(-6.99)
2	0.39	0.13	0.22	-0.10	-0.65	-1.04***
	(3.88)	(1.15)	(2.31)	(-1.06)	(-5.44)	(-6.87)
3	0.27	0.19	0.11	0.09	-0.45	-0.72***
	(2.93)	(2.30)	(1.51)	(1.33)	(-3.59)	(-4.12)
4	0.20	0.32	0.31	0.13	-0.12	-0.32*
	(1.95)	(3.67)	(3.86)	(1.91)	(-1.19)	(-1.95)
High Follow	0.23	0.25	0.13	0.25	-0.06	-0.29**
	(2.61)	(2.80)	(1.27)	(2.75)	(-0.59)	(-1.99)
Pane C: Double Sort by **Market Capitalization** and then by IMIN						
Small	0.46	0.27	0.13	-0.18	-0.84	-1.30***
	(4.15)	(2.41)	(1.17)	(-1.65)	(-7.71)	(-11.05)
2	0.35	0.20	0.13	-0.13	-0.78	-1.13***
	(4.30)	(2.81)	(1.86)	(-1.75)	(-7.71)	(-8.50)
3	0.20	0.23	0.17	-0.04	-0.52	-0.73***
	(2.89)	(3.48)	(2.73)	(-0.70)	(-5.37)	(-5.15)
4	0.19	0.19	0.23	0.06	-0.29	-0.48***
	(2.69)	(2.90)	(3.67)	(1.04)	(-3.18)	(-3.45)
Big	0.08	0.18	0.14	0.05	-0.09	-0.17
	(1.24)	(3.20)	(2.73)	(0.97)	(-0.92)	(-1.22)

Table 7 – Fama and MacBeth (1973) Regression with Interaction between IMIN and Attention Proxies

The table reports Fama and MacBeth (1973) OLS regression results using the interaction between IMIN and different attention (ATTN) proxies (Institutional Ownership Ratio, Number of Analyst Following a Firm, and the Size of the Firm). IMIN is idiosyncratic minimum return computed as the minimum idiosyncratic daily return within a month from Carhart (1997) four factor model. For ease of interpretation, we multiplied MIN by -1 (high IMIN indicates more negative idiosyncratic return). The other variables are defined in Table 1. Newey-West corrected t-statistics are reported parenthesis. *, **, *** represent significance levels at the 10%, 5%, and 1%. The data is from 1980:03 to 2014:12 (1969:07 to 2014:12 for Market Capitalization).

Attention (ATTN) Proxy	Panel A: Institutional Ownership			Panel B: Number of Analyst Following			Panel C: Firm Size		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Intercept	0.013***	0.022***	0.023***	0.014***	0.017***	0.020***	0.024***	0.022***	0.023***
	(5.685)	(3.912)	(4.122)	(5.554)	(3.064)	(3.704)	(4.074)	(3.626)	(3.756)
IMIN	-0.216***	-0.210***	-0.140***	-0.161***	-0.152***	-0.073***	-0.379***	-0.384***	-0.248***
	(-8.067)	(-10.481)	(-5.705)	(-7.389)	(-9.582)	(-3.243)	(-4.424)	(-5.631)	(-3.268)
ATTN	-0.003	0.001	0.003	-0.000*	-0.000	-0.000	-0.001**	-0.001**	-0.001*
	(-1.302)	(0.725)	(1.324)	(-1.78)	(-0.962)	(-0.196)	(-2.367)	(-2.013)	(-1.938)
IMIN*_ATTN_	**0.230*** **	**0.221*** **	**0.168*** **	**0.004* **	**0.004** **	**0.003**	**0.019** **	**0.020*** **	**0.015** **
	(5.58)	**(5.542)**	**(4.128)**	**(1.778)**	**(2.258)**	**(1.404)**	**(2.188)**	**(3.177)**	**(2.253)**
BETA		-0.000	-0.000		0.000	0.000		0.000	-0.000
		(-0.119)	(-0.153)		(0.224)	(0.15)		(0.129)	(-0.004)
SIZE		-0.001**	-0.001**		-0.000	-0.001			
		(-2.331)	(-2.503)		(-1.118)	(-1.643)			
BEME		0.000	0.000		0.001	0.000		0.001	0.000
		(0.866)	(0.621)		(1.096)	(0.774)		(1.116)	(0.838)
MOM			0.006***			0.006***			0.006***
			(3.569)			(3.544)			(3.253)
RET(-1)			-0.026***			-0.026***			-0.026***
			(-7.054)			(-6.943)			(-7.043)
TURNOVER			0.001			0.001***			0.001***
			(1.446)			(2.712)			(2.726)

IVOL			-0.043			-0.094			-0.086
			(-0.725)			(-1.597)			(-1.455)
ISKEW			0.001***			0.001***			0.001***
			(2.76)			(3.123)			(3.212)
MAX			-0.045***			-0.046***			-0.047***
			(-5.944)			(-5.965)			(-6.115)
Adj R2	0.020	0.051	0.067	0.019	0.049	0.065	0.022	0.048	0.064

Table 8: Dependent Bivariate Sort, first by Information Uncertainty then by IMIN

The table reports equal weighted Carhart (1997) four factor portfolio alphas from a dependent bivariate sort, first by an Information Uncertainty (IU) proxy and then by IMIN. IU is constructed using earnings accruals following Francis *et al*. (2005, 2007). The column 'H-L' reports investment strategies that that goes long in the high IMIN stocks and short the low IMIN stocks. IMIN is idiosyncratic minimum return computed as the minimum idiosyncratic daily return within a month from Carhart (1997) four factor model. For ease of interpretation, we multiplied MIN by -1 (high IMIN indicates more negative idiosyncratic return). Newey-West corrected t-statistics are reported parenthesis. *, **, *** represent significance levels at the 10%, 5%, and 1%. The data is from 1969:07 to 2014:12.

	Low IMIN	2	3	4	High IMIN	H - L
Low IU	0.18	0.20	0.25	0.26	0.06	-0.12
	(2.32)	(2.90)	(3.38)	(3.95)	(0.70)	(-1.14)
2	0.20	0.27	0.33	0.33	0.08	-0.12
	(2.67)	(3.88)	(3.88)	(4.18)	(0.88)	(-1.08)
3	0.31	0.32	0.25	0.29	-0.18	-0.49***
	(3.70)	(4.00)	(2.79)	(3.64)	(-1.88)	(-3.82)
4	0.26	0.19	0.22	0.05	-0.33	-0.59***
	(3.00)	(2.35)	(2.42)	(0.53)	(-3.55)	(-4.32)
High IU	0.23	0.16	0.13	-0.19	-0.80	-1.03***
	(2.88)	(1.57)	(1.29)	(-1.95)	(-6.63)	(-6.57)

Table 9: Fama and MacBeth (1973) Regression with Interaction Information Uncertainty Proxy and IMIN

The table reports Fama and MacBeth (1973) OLS regression results using the interaction between IMIN and an Information Uncertainty (IU) proxy. IU is constructed using earnings accruals following Francis *et al*. (2005, 2007). IMIN is idiosyncratic minimum return computed as the minimum idiosyncratic daily return within a month from Carhart (1997) four factor model. For ease of interpretation, we multiplied MIN by -1 (high IMIN indicates more negative idiosyncratic return). The other variables are defined in Table 1. Newey-West corrected t-statistics are reported parenthesis. *, **, *** represent significance levels at the 10%, 5%, and 1%. The data is from 1969:07 to 2014:12.

	MODEL (1)	MODEL (2)	MODEL (3)
Intercept	0.016*	0.021**	0.023**
	(1.738)	(2.058)	(2.304)
IMIN	-0.426	-0.437	-0.339
	(-0.944)	(-0.969)	(-0.75)
IU	0.013*	0.010	0.010
	(1.669)	(1.421)	(1.47)
IMIN*IU	**-0.509*****	**-0.461*****	**-0.445*****
	(-4.004)	**(-3.982)**	**(-3.852)**
BETA		0.001	0.000
		(0.458)	(0.093)
SIZE		-0.000	-0.001*
		(-1.39)	(-1.859)
BEME		0.000	0.000
		(0.985)	(0.994)
MOM			0.006***
			(3.76)
RET(-1)			-0.033***
			(-8.885)
TURNOVER			0.002***
			(2.739)
IVOL			-0.127**
			(-2.39)
ISKEW			0.001***
			(4.261)
MAX			-0.052***
			(-5.644)
Adj R2	0.013	0.050	0.067

Table 10: Bivariate Sort, first by Limits to Arbitrage and then by IMIN

The table reports equal weighted Carhart (1997) four factor portfolio alphas from a dependent bivariate sort, first by Limits to Arbitrage proxies (Bid Ask Spread, Relative Short Interest or Idiosyncratic Volatility orthogonalized to IMIN) and then by IMIN. The column 'H-L' reports investment strategies that that goes long in the high IMIN stocks and short the low IMIN stocks. IMIN is idiosyncratic minimum return computed as the minimum idiosyncratic daily return within a month from Carhart (1997) four factor model. For ease of interpretation, we multiplied MIN by -1 (high IMIN indicates more negative idiosyncratic return). Newey-West corrected t-statistics are reported parenthesis. *, **, *** represent significance levels at the 10%, 5%, and 1%. The data is from 1963:12 to 2014:12 (1973:01 to 2014:12 for Relative Short Interest).

	Low IMIN	2	3	4	High IMIN	H - L
Panel A: Double Sort by Bid Ask and then by IMIN						
Low Bid Ask	0.27	0.23	0.29	0.30	0.29	0.02
	(3.42)	(3.05)	(3.75)	(3.56)	(3.34)	(0.31)
2	0.24	0.25	0.26	0.28	0.22	-0.02
	(3.76)	(4.06)	(3.62)	(3.86)	(2.50)	(-0.21)
3	0.20	0.22	0.25	0.12	0.02	-0.18**
	(3.30)	(3.58)	(3.72)	(1.84)	(0.25)	(-2.08)
4	0.11	0.11	0.05	-0.13	-0.48	-0.60***
	(1.88)	(1.70)	(0.76)	(-2.03)	(-6.20)	(-6.13)
High Bid Ask	0.12	-0.21	-0.24	-0.58	-1.21	-1.33***
	(1.43)	(-2.44)	(-2.28)	(-5.02)	(-10.44)	(-11.93)
Panel A: Double Sort by Relative Short Interest and then by IMIN						
Low RSI	0.36	0.41	0.46	0.27	-0.01	-0.37***
	(3.74)	(3.99)	(3.95)	(2.16)	(-0.08)	(-2.79)
2	0.21	0.30	0.32	0.26	-0.23	-0.44***
	(2.38)	(3.27)	(2.99)	(2.29)	(-2.05)	(-3.46)
3	0.22	0.14	0.21	0.25	-0.12	-0.34**
	(2.40)	(1.59)	(2.12)	(2.23)	(-0.92)	(-2.57)
4	0.02	0.23	0.12	-0.13	-0.25	-0.27**
	(0.21)	(2.18)	(1.19)	(-1.18)	(-1.84)	(-2.00)
High RSI	0.02	-0.02	-0.09	-0.19	-1.06	-1.08***
	(0.19)	(-0.14)	(-0.75)	(-1.56)	(-6.94)	(-6.37)
Panel A: Double Sort by IVOL unrelated to IMIN and then by IMIN						
Low IVOL	0.11	0.13	0.26	0.25	-0.42	-0.53***
	(1.46)	(1.98)	(4.37)	(3.94)	(-5.72)	(-4.72)
2	0.25	0.22	0.27	0.27	-0.07	-0.32***
	(3.51)	(3.27)	(4.30)	(4.02)	(-1.03)	(-3.40)
3	0.27	0.24	0.27	0.21	-0.09	-0.36***
	(4.01)	(3.79)	(3.97)	(3.57)	(-1.35)	(-3.61)
4	0.28	0.22	0.24	0.05	-0.44	-0.72***
	(4.45)	(3.46)	(3.78)	(0.97)	(-5.42)	(-6.41)
High IVOL	0.18	-0.02	-0.24	-0.53	-1.37	-1.55***
	(3.45)	(-0.28)	(-3.24)	(-5.55)	(-9.88)	(-9.89)

Table 11: Fama and MacBeth (1973) Regression with Interaction between IMIN and Limits to Arbitrage Proxies

The table reports Fama and MacBeth (1973) OLS regression results using the interaction between IMIN and different Limits to Arbitrage proxies Bid Ask Spread, Relative Short Interest or Idiosyncratic Volatility orthogonalized to IMIN). IMIN is idiosyncratic minimum return computed as the minimum idiosyncratic daily return within a month from Carhart (1997) four factor model. IMIN is idiosyncratic minimum return computed as the minimum idiosyncratic daily return within a month from Carhart (1997) four factor model. For ease of interpretation, we multiplied MIN by -1 (high IMIN indicates more negative idiosyncratic return). The other variables are defined in Table 1. Newey-West corrected t-statistics are reported parenthesis. *, **, *** represent significance levels at the 10%, 5%, and 1%. The data is from 1963:12 to 2014:12 (1973:01 to 2014:12 for Relative Short Interest).

Limits to Arbitrage Proxies	Panel A: Bid Ask Spread			Panel B: Relative Short Interest			Panel C: IVOL unrelated to IMIN		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Intercept	0.009***	0.015***	0.017***	0.011***	0.022***	0.025***	0.011***	0.021***	0.019***
	(5.096)	(2.99)	(3.525)	-5.274	-3.734	-4.619	-6.101	-4.143	-3.87
IMIN	-0.080	-0.075***	0.052*	-0.072***	-0.123***	0.014	-0.111***	-0.137***	-0.081***
	(-1.467)	(-3.403)	(1.871)	(-3.042)	(-7.457)	-0.533	(-3.722)	(-8.345)	(-5.353)
Limit2Arb	0.005	0.008	0.021***	-0.022	-0.046**	-0.058***	-0.11	-0.258***	-0.01
	(0.281)	(1.14)	(2.868)	(-0.992)	(-2.186)	(-2.726)	(-1.182)	(-4.675)	(-0.155)
IMIN*Limit2Arb	**0.482**	**-0.125**	**-0.183**	**-0.064*** **	**-0.057*** **	**-0.065*** **	**-0.071*** **	**-0.060*** **	**-0.054*** **
	(0.486)	**(-0.378)**	**(-0.555)**	**(-4.383)**	**(-4.306)**	**(-4.669)**	**(-6.032)**	**(-6.319)**	**(-5.712)**
BETA		0.001	-0.000		0.002	0.002		0.001	0
		(0.433)	(-0.093)		-1.549	-1.564		-1.059	-0.147
SIZE		-0.001*	-0.001**		-0.001***	-0.001***		-0.001***	-0.001**
		(-1.649)	(-2.22)		(-2.603)	(-3.401)		(-2.732)	(-2.313)
BEME		0.001**	0.001**		0.001***	0.001**		0.001**	0.001**
		(2.223)	(2.121)		-2.623	-2.377		-2.035	-2.034
MOM			0.007***			0.005***			0.007***
			(4.677)			-2.609			-4.545
RET(-1)			-0.032***			-0.028***			-0.034***
			(-9.93)			(-7.284)			(-9.97)
TURNOVER			0.002***			0.002**			0.002***
			(3.954)			-2.501			-3.719

IVOL			-0.217***			-0.240***			
			(-4.187)			(-3.371)			
ISKEW			0.001***			0.002***			0.001***
			(5.234)			-5.235			-3.208
MAX			-0.053***			-0.049***			-0.049***
			(-7.906)			(-5.728)			(-7.252)
Adj R2	0.026	0.057	0.073	0.017	0.053	0.074	0.021	0.055	0.071

Table 12: Fama and MacBeth (1973) Regression Results with Interaction between IMIN, Information Uncertainty, Limits to Arbitrage, and Attention Proxies

The table reports Fama and MacBeth (1973) OLS regression results using the interaction between IMIN and an indicator of low attention (ATTN_low), high information uncertainty (IU_high), and high limits to arbitrage (LIMIT2ARB_high). First, we follow Stambaugh et al. (2015) and create an aggregate rank for limited investor attention (from size, institutional ownership, and number of analyst), for information uncertainty (from earnings accruals quality measure following Francis *et al*., 2005, 2007), and for limits to arbitrage (from bid-ask spread, idiosyncratic volatility, and short interest ratio) as a sum of the ranks of each proxy. Then, we create an indicator for ATTN_low if the aggregate attention ranking is in the lowest quintile. Similarly, we create indicators for IU_high and separately for LIMIT2ARB_high if the overall information uncertainty and limits to arbitrage rankings are in the highest quintile. IMIN is idiosyncratic minimum return computed as the minimum idiosyncratic daily return within a month from Carhart (1997) four factor model. IMIN is idiosyncratic minimum return computed as the minimum idiosyncratic daily return within a month from Carhart (1997) four factor model. For ease of interpretation, we multiplied MIN by -1 (high IMIN indicates more negative idiosyncratic return). The other variables are defined in Table 1. Newey-West corrected t-statistics are reported parenthesis. *, **, *** represent significance levels at the 10%, 5%, and 1%. The data is from 1980:03 to 2014:12.

	MODEL (1)	MODEL (2)	MODEL (3)	MODEL (4)
Intercept	0.015***	0.013***	0.014***	0.013***
	(6.058)	(5.428)	(5.247)	(5.137)
IMIN	-0.060***	-0.009	-0.017	-0.009
	(-3.753)	(-0.446)	(-0.900)	(-0.296)
IMIN*_ATTN_low_		**-0.036****	**-0.032***	**-0.020**
		(-2.103)	**(-1.900)**	**(-1.188)**
IMIN*_IU_high_		**-0.048*****	**-0.043*****	**-0.050*****
		(-2.976)	**(-2.615)**	**(-2.911)**
IMIN*_LIMIT2ARB_high_		**-0.051*****	**-0.042*****	**-0.043*****
		(-3.394)	**(-2.951)**	**(-2.957)**
ATTNR_low	-0.000	-0.000	-0.000	-0.000*
	(-0.917)	(-1.552)	(-1.642)	(-1.667)
IU_high	-0.000	0.000	-0.000	-0.000
	(-1.577)	(0.414)	(-0.119)	(-0.173)
LIMIT2ARB_high	-0.000*	-0.000	-0.000***	-0.000
	(-1.697)	(-1.173)	(-3.592)	(-1.482)
BETA			0.002	0.001
			(0.96)	(0.658)
SIZE			-0.002***	-0.002***
			(-3.812)	(-3.634)
BEME			0.001	0.000
			(1.211)	(0.987)
MOM				0.004**
				(2.046)

RET(-1)				-0.024***
				(-5.49)
TURNOVER				0.001*
				(1.717)
IVOL				0.015
				(0.175)
ISKEW				0.001*
				(1.724)
MAX				-0.036***
				(-3.201)
Adj R2	0.032	0.036	0.059	0.077