Hazard Stocks and Expected Returns

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Abstract

Hazard stocks are the opposite of lottery stocks. We proxy hazard stocks with the minimum daily idiosyncratic return over the past month, “IMIN,” and examine the relation between hazard stocks and expected returns. The literature on lottery stocks implies that investors should discount hazard stocks. Anomalously, we find a negative relation between IMIN and future returns. Hedge portfolios that long high IMIN stocks and short low IMIN stocks generate monthly alphas of -0.52% to -0.76%. The results are robust after controlling for numerous firm characteristics and corporate events. The hazard stock anomaly is primarily driven by limits to arbitrage and, to a lesser degree, by firm-level information uncertainty. Via the Reg SHO pilot program, we provide causal evidence that the apparent asymmetric preferences across lottery and hazard stocks are due to arbitrage asymmetry (Stambaugh et al., 2015). This demonstrates that asymmetric arbitrage may yield what appear to be asymmetric preferences.

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

JEL classification: G10, G11, G12

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1. Introduction

Recent studies document empirical evidence of investors' preference for lottery stocks (e.g. Kumar, 2009). 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 term hazard stocks, and examine the relation between hazard stocks and expected returns. Contrary to lottery stocks which are prone to experience extreme positive returns, hazard stocks are prone to experience extreme negative returns. These parallel definitions of hazard stocks and lottery stocks suggest that the findings in the extant literature regarding lottery stocks could be generalized to hazard stocks. That is, if investors are willing to pay a premium for lottery stocks then they should discount hazard stocks. This underpricing would then translate into higher future returns. Anomalously, however, we find that hazard stocks earn abnormally lower average future returns, which is inconsistent with the notion that hazard stocks are contemporaneously heavily discounted. This seems to imply that investors do not have symmetric preferences across lottery and hazard stocks. We show that this hazard stock anomaly is strongly associated with limits to arbitrage and, to a lesser degree, firm-level information uncertainty. Importantly, we find that arbitrage asymmetry (Stambaugh et al., 2015) is a significant contributor to this effect. Specifically, we provide causal evidence that relaxing limits to arbitrage (to wit, short-sale constraints) eliminates the apparent overpricing of hazard stocks. In this setting we find that hazard stocks do earn a premium in future returns, revealing that, in the absence of short-sale constraints, investors appear to price lottery and hazard stocks consistently (i.e. symmetrically).

[1] The evidence presented in Bali et al. (2011) is consistent with the existence of investors who prefer lottery-like payoffs.

Analogous to Bali et al. (2011), we calculate a proxy for hazard stocks as the minimum daily idiosyncratic return with respect to the Fama and French (1993) and Carhart (1997) four-factor model for each stock every month, labeled IMIN. We multiply IMIN by negative one so that higher values represent stocks with greater hazard characteristics. 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 component than positive returns due to the increased correlations that arise in down markets.[2] These increased correlations can mask investors' response to the idiosyncratic portion of an extreme return.

Our first main result is that the market underreacts to hazard stocks, appearing to overprice them contemporaneously. Specifically, firms with high IMIN (lowest idiosyncratic returns) have low returns in subsequent months. Portfolios long in high IMIN stocks and short low IMIN stocks earn significantly abnormal returns of -0.52% per month using value-weighted portfolios and -0.76% per month when using equal-weighted portfolios. We find similar results using Fama and MacBeth (1973) regressions. Moreover, this overpricing is persistent, as IMIN forecasts negative abnormal returns for at least up to six months without subsequent reversals. Importantly, these findings remain unchanged when we control for earnings surprises, suggesting the results are not related to post-earnings announcement drift. We also control for undesirable corporate events such as dividend omissions (Michaely et al., 1995; Lie, 2005), dividend cuts (Michaely et al., 1995; Liu et al., 2008; Ham et al. 2020), analyst downgrades (Womack, 1996), and downward earnings

[2] Szado (2009), Chan et al. (2011), Lee et al. (2011), and Yang et al. (2012) find that returns, even across asset classes, are more correlated during market downturns. Ang and Chen (2002) and Ang et al. (2006a) demonstrate stocks have higher CAPM betas when the market has negative returns, especially extreme downside price movements. Nonetheless, although we focus on the idiosyncratic component of MIN, the minimum daily return, our results are qualitatively similar when analyzing raw MIN. Thus, our overall results and conclusions are not dependent on model choice.

forecast revisions (Diether et al., 2002). Thus, IMIN is not merely an artifact of negative firm-specific news. Finally, hazard stock anomaly findings are also robust to numerous controls including size, book-to-market, momentum, turnover, lagged returns, idiosyncratic volatility, MIN, maximum daily returns or MAX, and idiosyncratic MAX or IMAX.[3]

A corollary to our first main result is that we have uncovered a striking difference between investors' preferences for lottery stocks and hazard stocks. Investors pay a premium for lottery stocks but don't appear to discount hazard stocks. Instead, the market seemingly underreacts to IMIN. The literature offers several potential explanations for underreaction including limited investor attention, information uncertainty, and limits to arbitrage. Under the limited investor 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 information 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 generate an apparent underreaction is limits to arbitrage that prevent investors from arbitraging away the overpricing. If arbitrageurs are impeded from trading misvalued stocks, then they cannot quickly exploit mispricing and, thus, prices do not converge to

[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.

fundamental values as rapidly as the market efficiency hypothesis suggests (e.g. Pontiff, 1996; Shleifer and Vishny, 1997; Pontiff, 2006). In each of these cases, information is incorporated into prices more slowly than in a perfectly efficient market, generating the underreaction.

To better understand the hazard stock anomaly, we examine the limited attention, rational learning (resolving information 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 analyst following (e.g. Bali et al., 2014; Chichernea et al., 2015) and abnormally low Google search volume index (Da et al. 2011). We use an earnings and accruals quality measure (Dechow and Dichev, 2002; Francis et al., 2005, 2007) to proxy for information uncertainty. Lastly, we use bid-ask spread (Bhardwaj and Brooks, 1992; Lam and Wei, 2011), market capitalization (Lakonishok et al., 1994), institutional ownership (Asquith et al., 2005; Nagel, 2005), and idiosyncratic volatility (Ali et al., 2003) to proxy for limits to arbitrage. We initially consider each of the three major explanations for underreaction separately and find evidence supporting all three.

Next, we attempt to disentangle the limited 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 are statistically significant and have the expected sign (i.e., they amplify the IMIN effect). We then investigate the robustness of these results by examining the structural changes exogenously introduced by promulgation of the 2000 Regulation Fair Disclosure (Reg FD) Act, the 2002 Sarbans-Oxley Act (SOX), and the 2001 SEC-mandated stock exchange decimalization. These particular rules increased market liquidity and improved the overall information environment (Eleswarapu et al., 2004; Arping and Sautner, 2013; Chordia et al., 2014; Lee et al., 2014; Gao and Zhang, 2019). Since all three rules occurred at approximately the same time, for parsimony we split the sample into pre- and post-2001 periods for our analysis. We find that after 2001, the effect of information uncertainty is attenuated substantially but the effect of limits to arbitrage remains economically large and statistically significant. Thus, we conclude that the IMIN effect is driven primarily by limits to arbitrage and, to a lesser extent, by information uncertainty.

Our main findings are counterintuitive to the predictions of the literature on lottery preferences. This literature proposes that investors overprice lottery stocks whereas we find that investors also overprice hazard stocks. These results strongly suggest an asymmetry in the preferences used to price lottery stocks versus hazard stocks. Investors should not simultaneously favor (i.e., overprice) lottery stocks and hazard stocks. A solution to this conundrum is suggested in Stambaugh et. al. (2015). As demonstrated by Stambaugh et al. (2015), arbitrage is asymmetric in that "many investors who would buy a stock they see as underpriced are reluctant or unable to short a stock they see as overpriced" (pp.1904). Consequently, underpricing will less frequently persist than overpricing. We investigate this intuition in the context of the hazard stock anomaly and find that the negative IMIN effect is large in the most overpriced stocks, but it is not present in the most underpriced stocks. We refine this analysis by taking advantage of a semi-natural experiment provided by the SEC's Regulation SHO pilot program which temporarily reduced short-sale constraints and thereby relaxed limits to arbitrage. We find that the negative relation between IMIN and future returns is reversed among the pilot stocks in the program. Thus, we provide causal evidence that limits to arbitrage generate the negative IMIN effect and, when limits to arbitrage are sufficiently relaxed, the IMIN effect is actually positive as predicted by lottery preferences. Hence, the apparent asymmetric preferences across lottery and hazard stocks is a manifestation of arbitrage asymmetry.

We contribute to the literature in several ways. First, we introduce IMIN as a measure of hazard characteristics. Second, we are the first to document the hazard stock anomaly. This anomaly is counterintuitive to the concept of lottery preferences. Third, we find limits to arbitrage is a prominent driver of this anomaly. Lastly, we provide causal evidence showing asymmetric arbitrage keeps hazard stocks in an overpriced state, concealing the lottery preferences that exist when arbitrage constraints are sufficiently relaxed.

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 first major empirical results on the relation between IMIN and future returns. Section 5 investigates various explanations for the results reported in Section 4, including the limited investor attention, structural uncertainty (rational learning), and limits to arbitrage hypotheses. Section 6 documents the strong asymmetric relationship between the IMIN effect and limits to arbitrage. In this section we employ the Reg SHO pilot to demonstrate that the hazard stock anomaly is reversed in the absence of short-sales constraints. Section 7 describes further analyses performed for robustness purposes. Section 8 concludes.

2. Related Literature

2.1. Lottery Stocks

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. This result is consistent with the existence of investors who prefer lottery-like payoffs.

The difference between the MAX measure and others is that it focuses on only extreme positive returns to identify lottery stocks. If lottery preferences are symmetric (i.e., 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) explore the minimum raw daily return in a month, MIN. However, unlike MAX, Bali et al. (2011) find any return predictability associated with MIN is not robust to subsample analyses and appears to be limited to small, illiquid stocks. Additionally, they find MIN has no return predictability 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 of one, if any, between extreme negative price changes and future returns.

Jiang and Zhu (2017) identify positive and negative stock price jumps as large discontinuous price changes relative to a martingale process. Atilgan et al. (2020) use a 12-month Value-at-Risk (VaR) measure as a proxy for left-tail risk. There are important differences, however, in the measures of extreme price changes in this paper (IMIN), Jiang and Zhu (2017), and Atilgan et al. (2020). First, and perhaps most importantly, since IMIN is an analogous measure to the Bali et al. (2011) MAX measure, we can compare the return predictability of lottery stocks with hazard stocks. The second major difference across the measures of extreme returns is their exposure to systematic risk. Bali et al. (2011) and Atilgan et al. (2020) 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 Bali et al. (2011), Jiang and Zhu (2017), and Atilgan et al. (2020) measures. However, our idiosyncratic measures isolate firm-specific shocks, 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.[4]

2.2. Limited Investor Attention

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 semi-strong form of market efficiency. Bolstering these theories, numerous empirical studies link underreaction to information and limited investor attention.[5] 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 investor 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. (2020) also identify underreaction to recent losses, albeit indirectly since they do not overtly estimate price changes. Rather, they compute the Value-at-Risk (VaR) measure from the empirical distribution of daily losses over the last year. They find a negative relation between the magnitude of the VaR measure and future returns, which they call 'left-tail momentum'. They also note that this higher risk/lower return combination is anomalous in that it

[4] 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.

[5] Studies that demonstrate that limited investor attention and underreaction 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).

appears to violate the basic principles of the CAPM. Furthermore, they show that for stocks that have lower measures of investor attention, this anomaly is more severe.

2.3. Information Uncertainty

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 underreaction 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 the evolution of investors' updated beliefs about these parameters. Supporting this theory, Francis et al. (2007) build upon Dechow and Dichev (2002) and Francis et al. (2005) to find that the well-known post-earnings-announcement-drift is related to uncertainty induced by low quality earnings and accruals.[6] 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 and the new information. Naturally, this will manifest as a partial adjustment towards the new information and appear to be an underreaction 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.

2.4. Limits to Arbitrage

Limits to arbitrage is yet another mechanism that may generate underreaction in financial markets. Arbitrageurs will only engage in trading on mispricing if their proceeds from doing so

[6] 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 3.1 below for a fuller explanation.

exceed the associated transaction and holding costs. Therefore, these costs are considered limits to arbitrage. If the limits to arbitrage are substantial, then mispricing will not be rapidly corrected, and the price will exhibit a drift rather than a sharp return to fundamental value. The literature establishes common barriers to arbitrageurs. For example, firm size (market capitalization) is inversely related to arbitrage costs in a variety of dimensions (e.g. Lakonishok et al, 1994; Ali et al., 2003). The bid-ask spread represents a transaction cost that inhibits arbitrage activity (Bhardwaj and Brooks, 1992; Lam and Wei, 2011). Institutional ownership is associated with greater liquidity and lower short-sale constraints (Asquith et al., 2005; Nagel, 2005). A stock's idiosyncratic volatility adds substantial risk to arbitrageurs' portfolios because they are typically not well diversified (Wurgler and Zhuravskaya, 2002; Pontiff, 2006). Thus, 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; Au et al., 2009, Stambaugh et al., 2015; Cao and Han, 2016).

There is a voluminous literature documenting anomalies that can be explained by limits to arbitrage. For instance, limits to arbitrage have been empirically linked to anomalies associated with book-to-market ratio (Ali et al., 2003), post-earnings announcement drift (Mendenhall, 2004), discretionary accruals (Mashruwala et al., 2006), asset growth (Lam and Wei, 2011), cash holdings (Li and Luo, 2016), gross- and cash based-operating profitability (DeLisle et al. 2020), and many others. Additionally, Chordia et al. (2014) show that returns to many anomalies are reduced by half after the decimalization of stock exchanges, which dramatically reduced limits to arbitrage such as bid-ask spreads. Brav et al. (2010) make the interesting discovery that limits to arbitrage affect the overpriced leg of the value, momentum, and post-earnings announcement drift anomalies, but not the underpriced leg. Stambaugh et al. (2015) explore this further with a composite mispricing measure and find arbitrage risk (i.e. idiosyncratic volatility) has a greater impact on the future returns of overpriced stocks than those of underpriced stocks. Their results are consistent with what they call “arbitrage asymmetry.” In other words, arbitraging underpricing away is easier to accomplish than arbitraging overpricing away as a large investor base can buy an underpriced stock but have trouble shorting an overpriced stock. Subsequent studies document similar evidence of asymmetric arbitrage in other anomalies such as short-term return reversals, size, book-to-market, and lottery stocks (Cao and Han, 2016; Zhong and Gray, 2016; Bergsma and Tayal, 2019). Thus, short-sale constraints appear to be large arbitrage costs that impede arbitrageurs with pessimistic views about a stocks outlook from shorting the stock (D'Avolio 2002; Asquith et al., 2005). With asymmetric arbitrage in mind, Chu et al. (2020) investigate the impact of relaxing short-sale constraints on Stambaugh et al.’s (2015) eleven anomalies. They take advantage of the Regulation SHO pilot program, which removed short-sale constraints from approximately 1000 stocks for a period of two years and provide causal evidence that relaxation of short-sale constraints considerably reduced the anomaly portfolio returns. They also show that this reduction is attributable only to the short leg of the anomaly portfolios.

3. Data, Variable Construction, and Descriptive Statistics

3.1. Data and Variable Construction

We obtain stock return and related data from CRSP, accounting information from COMPUSTAT, analyst and related data from IBES and institutional ownership data 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 1964 to December 2014.

IMIN and Related Variables: We compute daily idiosyncratic returns by regressing daily excess returns on the Fama and French (1993) and Carhart (1997) 4-factors (MKT, SMB, HML, and UMD) within a month. Our main variable of interest, the monthly measure of idiosyncratic minimum return (namely IMIN), is the minimum of the residuals from this regression within a month. For ease of interpretation, we multiply IMIN by -1. Thus, a higher IMIN reflects a more negative idiosyncratic minimum return and, thus, hazard stocks. Similarly, IMAX is computed as 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. MIN and MAX are, respectively, the minimum and maximum raw returns within a month. We require stocks to have at least 15 trading days within a month to be included in our sample.

We compute monthly beta, 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 observations to be included in the sample. SIZE is the market capitalization of the firm, computed as the price per share multiplied by the number of shares outstanding and reported in thousands. MOM is momentum and computed by compounding returns over previous six months, skipping previous one month. RET(-1) is reversal, and defined as a return during the immediate prior month 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). *SUE* is an analyst forecast-related measure of standardized unexpected earnings computed as the difference between the actual earnings per share (EPS) and analyst consensus forecast as of the month before earnings announcement, scaled by the stock price at the end of the quarter prior to the earnings announcement. This definition follows Livnat and Mendenhall (2006), as they find this measure is related to a larger post-earnings announcement drift than time-series measures.

Extant studies of negative corporate events report that bad news is particularly prone to underreaction (e.g. Womack, 1996; Hong et al., 2000; Chan, 2003; Taffler et al., 2004), suggesting that investors could interpret the identification of a hazard stock as bad news, and thus underreact to such a realization. Thus, in order to rule out IMIN is just an artifact of undesirable firm-level events, we control for such negative news. *NEG_NEWS* is a parsimonious binary variable (NEG_NEWS) that equals one if the firm had a dividend omission (Michaely et al., 1995; Lie, 2005), dividend cut (Michaely et al., 1995; Liu et al., 2008; Ham et al. 2020), analyst downgrade (Womack, 1996), or downward earnings forecast revision (Diether et al., 2002) and zero otherwise.

Investor Attention Proxies: Our investor attention measures follow the prior literature and include *Google SVI* and *ANALYSTS* (e.g., Hirshleifer and Teoh, 2003; Peng, 2005, Hirshleifer et al., 2013; Da, Engelberg, and Gao, 2011; Bali et al., 2014; Chichernea et al., 2015). *ANALYSTS* is the number of analysts following a particular stock reported by IBES. Naturally, larger firms, firms primarily held by institutions, and firms with large analyst following indicate greater investor attention. GSVI is the abnormal Google search volume index, derived following Da, Engelberg, and Gao (2011). Specifically, we compute abnormal Google-SVI as the log of SVI during the month minus the log of median SVI during the previous four months. Google Trends data is available only from 2004 and IBES provides data from early 1980s.

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 and accrual quality for firm j (EAQ_j) as follows:

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

where ε are the residuals from the following regression:

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

$TCA_{j,t}$ 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 $t+1$; $\Delta REV_{j,t}$ is change in firm j's revenue from year $t-1$ to year t, and $PPE_{j,t}$ is the gross value of firm j's property, plant and equipment in 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 institutional ownership proxies for short-sale constraints. *IOR* is the institutional ownership ratio computed using Thomson Reuters' 13f filings as the ratio of the number of shares held by institutions to the total number of shares outstanding. Idiosyncratic volatility, *IVOL*, is defined above. *SIZE* is also defined above.

3.2. Descriptive Statistics

Table 1 presents the time series averages of cross-sectional mean and median and correlation coefficients for our main variables of interest. Panel A shows that a typical firm in our sample has a monthly return of 1.1% and idiosyncratic minimum return, IMIN, of 3.8% (recall that we multiply IMIN by -1 for ease of interpretation). 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, MAX, and IMAX at 88%, 78%, 60%, and 69%, respectively. To alleviate a potential concern that we might be re-documenting results associated with IVOL, MIN, MAX, and IMAX in the analysis below, we control for these variables via bivariate sort procedure and multivariate regressions. The main results we report are also qualitatively similar when we rank orthogonalize IMIN with these variables (unreported).

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

In this section, we document that hazard stocks earn negative future returns. We first conduct univariate and bivariate portfolio-level analyses. We then utilize Fama-MacBeth (1973) regressions to conduct firm-level analyses. We conclude this section by showing that the negative portfolio returns earned by hazard stocks persist for up to at least six months.

4.1. Portfolio-Level Analysis

4.1.1. Univariate Analysis

Table 2 presents equal- and value-weighted average monthly returns and Fama and French (1993) and Carhart (1997) four-factor alphas for 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.

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 -0.76% per month (*t*-statistic = -7.19), relative to the Fama and French (1993) - 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 = -1.88) suggesting that the return difference attributed to IMIN is, in part, driven by small stocks. However, the value-weighted Fama and French (1993)-Carhart (1997) four-factor alpha is still economically large and statistically significant, -0.52% per month with *t*-statistic = -3.81, confirming that the value-weighting scheme does not eliminate the abnormal returns due to IMIN.

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. An 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 Fama and French (1993)-Carhart (1997) four-factor of -0.78% per month (*t*-statistic = -7.28) confirming that the return difference on the two portfolios is not due to commonly 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. However, the value-weighting scheme does not eliminate the abnormal returns due to IMAX, as there is an economically large and statistically significant hedge portfolio alpha of -0.48% per month (*t*-statistic = -3.67) 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 underreaction and, therefore, we focus on IMIN throughout the rest of the paper.

Taken altogether, the results are consistent with the market underreacting to hazard stocks. In other words, hazard stocks are contemporaneously overpriced. Since investors pay a premium for lottery stocks, we expected to find that investors who prefer extreme right-tail returns to shy away from hazard stocks and, consequently, require a premium to invest in them. One explanation is that investors do not have symmetric preferences for extreme returns that imply paying a premium for lottery stocks while discounting hazard stocks. We return to this puzzling asymmetry in Section 6.

We also directly control for earnings surprises in the Fama-MacBeth (1973) regressions (as discussed in Section 4.2 below) by including standardized unexpected earnings (SUE) and find qualitatively and quantitatively similar results, suggesting that post-earnings announcement drift (PEAD) is not driving our main findings. As a robustness check (unreported), we also remove firm-months in which firms release an earnings announcement and find similar results.

4.1.2. Bivariate Analysis

To confirm that the IMIN effect documented in Table 2 is not subsumed by firm characteristics known to be associated with the cross-section of stock returns, we perform a sequential bivariate sort similar to the one in Ang et al. (2006, Table 7). We first sort stocks in our sample into quintiles based on firm characteristics, and then, within each quintile, we sort firms into quintiles by IMIN. In Table 3 we report, for each of the IMIN-characteristic portfolios, the average alpha of 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 12 characteristics we examined – market beta, firm size, book-to-market, momentum, reversal, turnover, idiosyncratic volatility, idiosyncratic skewness, MAX, IMAX, MIN, and SUE. The Fama and French (1993) - Carhart (1997) four-factor alphas range from -0.20% per month (*t*-statistic = -5.60) for IVOL-sorted portfolios to -0.80% per month (*t*-statistic = -7.37) 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 stock returns. Next, we examine this further using a multivariate regression framework.

4.2. Firm-Level Analysis

We further examine the robustness of 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, with a point estimate of -0.13 and *t*-statistic of -4.99. In column (2), we control for variables commonly used to explain the cross-section of stock returns – beta, size, and book-to-market – and continue to find qualitatively similar results, with a point estimate of -0.15 and *t*-statistic of -11.35. In column (3), we control for additional firm characteristics that have been found to explain the cross-section of stock returns such as momentum, reversal, turnover, idiosyncratic volatility, idiosyncratic skewness, maximum daily return. The magnitude of the IMIN coefficient is smaller (-0.042) but remains statistically significant (*t*-statistic = -2.19). In column (4), we re-run model (3) by replacing MAX with IMAX and the result remains qualitatively similar. In the last columns, (5) through (8), we include earnings surprises (SUE) and negative firm news (NEG_NEWS) as additional control variables and the relation between IMIN and returns remains unchanged, illustrating that IMIN is not simply an artifact of earnings surprise or bad corporate news.

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). In addition, IMIN effect is not subsumed by the post-earnings announcement drift (PEAD) associated with SUE nor negative corporate news. Overall, 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, these results suggest that investors underreact to (i.e., contemporaneously overprice) hazard stocks.

4.3. 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 Fama and French (1993)-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 -28 basis points (*t*-statistic = -1.65) at nine lags. At 12 lags and beyond, the economic magnitude of this strategy is small and not statistically significant. However, the results in Panel B show that the Fama and French (1993)-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 regressions. 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, we find 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 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 to Hazard Stocks

The results presented thus far indicate that investors underreact to IMIN and do not discount high IMIN (hazard) stocks in a manner that is consistent with lottery stock premiums, and thus appearing to overprice hazard stocks. 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 information uncertainty models. In the case of information 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, i.e. limits to arbitrage. In this case, their ability to arbitrage away mispricing is limited. This is likely to be more severe for overpricing (e.g. D'Avolio, 2002; Asquith et. al., 2005; Stambaugh et. al., 2015).

Therefore, we investigate these three mechanisms for the underreaction – investor attention, information uncertainty and limits to arbitrage – using various proxies we outlined in Section 3.1. We first determine whether these mechanisms have individual explanatory power for the underreaction to IMIN. Then, we conclude this section by considering all three explanations simultaneously.

5.1. Analysis of Each Potential Mechanism

We follow prior literature and use Google abnormal search volume index (GSVI) (Da et al., 2011) and analyst coverage (Hirshleifer and Teoh, 2003; Peng, 2005; Hirshleifer et al., 2013; Chichernea et al., 2015) as a proxy for investor attention. Our proxy for information uncertainty (IU) is based on earnings accrual quality following Dechow and Dichev (2002) and Francis et al. (2005, 2007). We proxy for limits to arbitrage using bid-ask spread, idiosyncratic volatility

(IVOL), firm size, and institutional ownership ratio (IOR) (e.g., Ali et al., 2003; Lam and Wei, 2011). We provide detail information about the construction of these proxy variables in Section 3.

In Table 6, we report the effect of these proxies on the relationship between IMIN and returns using Fama and MacBeth (1973) regressions. Each column in Table 6 represents a cross-sectional regression employing a different proxy for the underreaction mechanism. Each regression controls for IMIN, the proxy, an interaction term (IMIN*Proxy), and numerous firm characteristics. We find that across the various specifications IMIN and future returns are either significantly negatively correlated or not reliably different from zero. The key coefficient of interest is the interaction term. In every specification it is highly significant and has the expected sign (the *t*-statistics range in magnitude from 2.30 to 4.99). Note that larger values of GSVI and Number of Analysts indicate greater investor attention, so the positive interaction term indicates that there is less underreaction when the firm is widely followed. Likewise, larger values of Firm Size and IOR indicate greater limits to arbitrage, so the positive interaction term indicates that there is less underreaction with less significant limits to arbitrage. Conversely, larger values of the Bid-Ask Spread and IVOL indicate greater limits to arbitrage, so the negative interaction term is expected. Finally, larger values of IU indicate greater uncertainty, so the negative interaction term indicates that there is more underreaction when information uncertainty is higher.

Taken together, the results presented in the columns of Table 6 indicate that the influence of IMIN on returns is amplified by greater limited investor attention, information uncertainty, and limits to arbitrage. Furthermore, none of the interaction effect is being driven by other firm characteristics such as firm size, earnings surprises, negative firm-level corporate news, or MAX *inter alia*. The full analysis of these individual mechanisms presented in the Appendix shows that these results are quite robust to various specifications of the regression model.

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

Thus far we have shown that greater limited investor attention, information uncertainty, and limits to arbitrage appear to magnify the market's underreaction to hazard stocks. 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 number of analysts and Google SVI), for information uncertainty (from an earnings quality measure), and for limits to arbitrage (from bid-ask spread, idiosyncratic volatility, size, and institutional ownership) as a sum of the ranks of each proxy. Then, we create an indicator variable 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 reverse individual ranking for firm size and institutional ownership in constructing the aggregate limits-to-arbitrage ranking in order to maintain the same interpretation.

We again employ Fama and MacBeth (1973) regressions in an attempt to discern the relative importance of each explanation for investors underreaction to hazard stocks. The results are presented in Table 7. 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 = -0.076 and *t*-statistic = -4.93). The remaining columns control for the interaction terms, beta, size, book-to-market, and other firm-specific characteristics including MAX, IMAX, SUE, and negative corporate news. The table shows that the relation between future returns and the interaction term between IMIN and *IU_high* is negative and statistically highly significant. Similarly, the relation between future returns and the interaction term between IMIN and *LIMIT2ARB_high* is also negative and statistically significant. However, the marginal contribution of the interaction between low investor attention and IMIN to future returns is small and not statistically significant.

All in all, the results from this table show that information uncertainty and limits to arbitrage, but not limited investor attention, significantly contribute to the documented underreaction to IMIN. The results also show that the IMIN effect is not simply an artifact of earnings surprises nor bad corporate news about the firm. This differs from recent papers (see, for example, Jiang and Zhu, 2017; Atilgan et al., 2020) that conclude limited attention is an important contributor to market underreaction.

5.3. Decimalization, Reg FD, and SOX

In this subsection, we consider time trends in limited attention, limits to arbitrage, and information uncertainty. In particular, trading and information costs have been falling over time. This suggests that influences of limits to arbitrage and information uncertainty should be declining and, consequently, their effect on IMIN should also be declining. Thus, as an additional check on our conclusions we examine the introduction in the early 2000s of decimalization in the equity markets, the promulgation of the 2000 Regulation Fair Disclosure (Reg FD), and the passage of the 2002 Sarbanes-Oxley Act (SOX). If our conclusions are robust, then we should see the IMIN effect declining after these changes. Moreover, we should find that the influence of limits to arbitrage and information uncertainty have decreased.

Chordia et al. (2014) study several market anomalies and document that return predictability decreased and, in some cases, disappeared in recent years. The authors argue that the attenuation of return predictability is due to increased liquidity and arbitrage activity caused in part by the SEC's requirement that all exchanges decimalize by April 2001. We follow their analysis and split our sample into pre- and post-decimalization periods as this represents a dramatic change in market liquidity and arbitrage costs associated with decreased bid-ask spreads.[7] Furthermore, the break between the pre- and post-decimalization periods also corresponds with the introduction of Regulation Fair Disclosure (Reg FD) and the passage of the Sarbanes-Oxley Act (SOX).[8] Eleswarapu et al. (2004) find that trading costs measures like effective spreads and price impact decline in the wake of the adoption of Reg FD. In addition, studies such as Arping and Sautner (2013) and Gao and Zhang (2019) show that SOX enhanced firm transparency and internal controls. Reg FD and SOX are both intended to improve the timely dissemination of more accurate information to the markets. To the extent that the regulations are successful in that goal (e.g. Lee et al., 2014), we expect these improvements to render information uncertainty less important and, thus, lessen the impact of IU on investors' underreaction to IMIN.

We present the results of this analysis in Table 8. Before 2001, the correlation between IMIN and future returns is strong, even in the presence of interaction terms. Importantly, this subsample period analysis confirms the earlier full sample period result that this relation is stronger when information uncertainty and limits to arbitrage are high, but that investor attention does not seem to affect the results. After decimalization, there is still an IMIN effect but, as we observed in the full sample results displayed in Table 7, limits to arbitrage are the dominant explanation, with information uncertainty playing a lesser role. The impact of information uncertainty on the documented investor underreaction to IMIN (i.e. the interaction term IMIN**IU_high*) has declined

[7] We thank an anonymous referee for providing this suggestion.
[8] Reg FD was adopted in October 2000; decimalization was mandated to be complete by April 2001; and SOX was passed in July 2002. For parsimony we use the decimalization date as our cutoff date in the analysis that follows.

and is only marginally significant in the post-2001 period. Moreover, although the impact of limits to arbitrage on the documented investor underreaction to IMIN (i.e. IMIN**LIMITS2ARB_high*) remains highly significant, the magnitude is sharply attenuated. In sum, we find that the underreaction to hazard stocks has clearly declined in more recent years, but it persists as a significant anomaly. Furthermore, this underreaction continues to be greater when limits to arbitrage are high.

6. Asymmetric Lottery Preferences or Asymmetric Arbitrage?

Our main findings are counterintuitive to the extant literature on lottery stocks. Specifically, the literature on lottery stocks finds that investors overreact to extreme positive returns, but we show that investors underreact to extreme negative returns. These results suggest an asymmetry in the preference for lottery stocks without a concomitant dislike of hazard stocks. Given our finding that the underreaction to hazard stocks is largely driven by limits to arbitrage, a compelling explanation for what appears to be asymmetric preferences may be found in Stambaugh et. al. (2015). They show that limits to arbitrage affect overpriced and underpriced stocks differently. Arbitrageurs are able to eliminate underpricing more effectively than overpricing. This results in what the authors refer to as “arbitrage asymmetry.” This arbitrage asymmetry allows for negative abnormal returns among contemporaneously overpriced stocks but does not create similar returns for contemporaneously underpriced stocks.

Lottery preferences imply that high MAX stocks are desired and, thus, appear to be contemporaneously overpriced while hazard stocks (i.e. high IMIN) are disliked and should thus be contemporaneously underpriced. However, limits to arbitrage may prevent investors from pushing hazard stock prices down far enough for them to appear to be underpriced (or even priced consistently with standard mean-variance preferences). In other words, when a stock realizes a high IMIN return and identified as a hazard stock, it is not contemporaneously discounted sufficiently due to limits to arbitrage. Thus, both high MAX and high IMIN stocks are contemporaneously overpriced. Therefore, investors may have symmetric, lottery-like preferences regarding returns in both tails of the return distribution but, due to arbitrage asymmetry, it may not appear so. Asymmetric limits to arbitrage do not work against the overpricing of lottery stocks but do work against the underpricing of hazard stocks.

6.1. Arbitrage Asymmetry and Hazard Stock Returns

In the spirit of Stambaugh et. al. (2015), we explore the extent to which mispricing plays a role in the IMIN effect. We first sort all stocks in our sample into quintiles based on IMIN and also on the mispricing score measure developed and provided by Stambaugh et al. (2015).[9] The highest values of the mispricing score are associated with the stocks that are most overpriced, as measured by a composite rank of 11 well-documented anomalies. If asymmetric arbitrage is driving the IMIN effect, then there will be an IMIN effect in overpriced stocks but not in underpriced stocks. Table 9 reports average monthly returns from an independent sort. We also report high-minus-low raw and Carhart (1997) four-factor alphas from the zero-cost investment strategy that is long high IMIN stocks and short low IMIN stocks. Significantly, we observe an arbitrage asymmetry where the magnitude of High-Low IMIN portfolio return is monotonically increasing (in absolute terms) as we go from the most underpriced to the most overpriced stocks. Moreover, arbitrageurs eliminate IMIN effects in the case of underpriced stocks but not in the case of most overpriced stocks. Finally, the IMIN effect is the strongest and statistically significant amongst the most overpriced stocks. Consistent with Stambaugh et al.'s (2015) asymmetric

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[9] We thank Professor Robert Stambaugh for making the mispricing score data available for download from his website http://finance.wharton.upenn.edu/~stambaug/

arbitrage conjecture, we conclude that the IMIN effect occurs, at least in part, because limits to arbitrage prevent high IMIN stocks from rapidly leaving an overpriced state and, subsequently, these stocks have large negative abnormal returns.

6.2. Regulation SHO

In the previous subsection, we argue that limits to arbitrage contemporaneously leaves high IMIN stocks in an overpriced state, resulting in negative future abnormal returns. We show in Table 9 that the negative IMIN effect is predominant among the most-overpriced stocks and vanishes for the most underpriced stocks. A key element of the asymmetric arbitrage hypothesis is the binding nature of short-sale constraints. If short-sale constraints do not truly limit selling, then lottery preferences imply that hazard stocks would be contemporaneously underpriced (i.e., the magnitude of the IMIN would be even larger), followed by positive future abnormal returns.

The Rule 202T pilot program of Regulation SHO (Reg SHO) provides a setting to examine relaxed short-sale constraints. This program removed short-sale price tests on approximately one-third of the stocks in the Russell 3000 index, relaxing the prohibitive uptick rule and making it much easier to short the selected pilot stocks. Following the main analysis in Chu et al. (2020), we use this program as semi-natural experiment capable of establishing a causal link between limits to arbitrage and the negative IMIN effect.[10] We obtain the list of pilot stocks from the SEC website.[11] The analysis is limited to stocks included in the June 2004 Russell 3000 index that were listed on the NYSE or Amex (share codes 1 and 2).[12] As a result, 1,016 nonpilot stocks and 503 pilot stocks are included in our final sub-sample over 1984:01 – 2007:06 time period for Eq. (4)

[10] We thank the anonymous referee for this suggestion.
[11] https://www.sec.gov/spotlight/shopilot.htm
[12] NASDAQ stocks are excluded because a significant proportion of trading volume in NASDAQ-listed stocks was executed via ArcEx and INET at this time. Neither of these venues enforced the short-sale constraint (bid-price rule). See Diether et al. (2009) for details. Therefore, we would not expect to see any effect on NASDAQ stocks in the pilot group and they are excluded from the analysis.

and 1984:01 – 2014:12 for Eq. (5). Observations in May and June of 2005 and July and August of 2008 are deleted from the sample period. We separately sort pilot and non-pilot stocks into deciles based on lagged IMIN and form high-minus-low return portfolios.

Following equations (1) and (2) in Chu et al. (2020), we employ the following two difference-in-difference specifications:

$$r_{it} = \gamma_t + \beta Pilot_i \times During_t + \beta_1 Pilot_i + \varepsilon_{it} , \tag{4}$$

$$r_{it} = \gamma_t + \beta Pilot_i \times During_t + \beta_1 Pilot_i + \beta_2 Pilot_i \times Post_t + \varepsilon_{it}. \tag{5}$$

The dependent variable, r_{it}, is the weighted monthly return of high-minus-low IMIN portfolio *i* in month *t*. We use gross return, defined as one plus last month return, as a weight in forming each portfolio. $Pilot_i$ is an indicator equal to 1 if portfolio *i* is formed on pilot firms, and zero otherwise. $During_t$ is an indicator equal to 1 if month *t* is between July 2005 and June 2007. $Post_t$ is indicator equal 1 if month t is after August 2007 and zero otherwise. γ_t denotes time fixed effects. Note, the β estimate is identical in Eq.(4) and (5).

In the first specification of Eq. (4), a difference-in-difference (DiD) coefficient, β, represents two differences between pilot versus non-pilot stocks: one is during the *pre-pilot* period and the other one is during the *pilot* period. Since we multiplied IMIN by (-1), larger IMIN indicates a more negative idiosyncratic return. Thus, if the DiD coefficient, β, is positive then Regulation SHO increases IMIN returns for *pilot* stocks relative to *nonpilot* stocks during the pilot period.[13] In the second specification of Eq. (5), a DiD coefficient, β_2, is expected to be close to

[13] This moves the net return differential during the pilot period closer to zero. In contrast, the expected sign for β in Eq.(1) in Chu et al. (2020) is hypothesized to be negative. This is because the expected sign for anomalous returns in their long-leg is higher than in their short-leg, so that the long-minus-short portfolios earn positive returns. Thus, a negative β in Chu et. al (2020) likewise moves the net return differential closer to zero during the pilot period.

zero and statistically insignificant since the difference between pilot and nonpilot stocks should disappear after the Reg SHO trial expires.

We report the regression coefficients in Table 10. The β estimate in Eq. (4) is positive and statistically significant across all Panels (point estimate is 0.973 with a *t*-statistic of 2.090 in Panel A). That is, the Reg SHO program increased the IMIN long-short portfolio returns by 97 basis points per month. Given the average gross-return-weighted IMIN long-short portfolio return in this sample is -64 basis points per month, the result from the Reg SHO program translates to positive 0.33% (0.97%-0.64%=0.33%) monthly return for IMIN long-short portfolios.[14] Similarly, the IMIN effect becomes positive in the case of equal- and value-weighted IMIN long-short portfolio returns and equals to 0.47% (1.060%-0.59%=0.47%) and 0.59% (1.081%-0.49%=0.59%), respectively. Thus, we conclude that when short-sale constraints are relaxed, we no longer observe the negative IMIN effect (i.e., an apparent underreaction to hazard stocks). In fact, consistent with lottery preferences, the IMIN effect is *positive* among the pilot stocks during the program. Furthermore, we also find that β_2 in Eq. (5) is positive but statistically no different from zero (0.354 with *t*-statistics 0.852 in model (2)), indicating that the portfolio return difference between pilot and nonpilot firms disappears when the pilot program ceases. Lastly, the results are qualitatively similar when we construct equal- or value-weighted IMIN portfolios rather than gross-return-weighted portfolios.

Taken together, the observed increase in returns for the IMIN long-short portfolio comprised of stocks in the pilot program indicates that the IMIN anomaly is attenuated when the

[14] To make a comparison, we calculated average gross-return-weighted return for high-minus-low IMIN decile over 1984:01 – 2007:06. The sample includes NYSE and AMEX stocks (share codes 1 and 2) over 1984:01 – 2007:06, and excluding May and June 2005. The average gross-return-weighted, equal- and value- weighted returns for long-short IMIN portfolios are -0.64%, -0.59%, and -49% per month, respectively.

short-sale constraint is relaxed. The fact that the net return is positive reveals investors' preferences regarding hazard stocks is symmetric to that of lottery stocks: ceteris paribus, investors demand a premium to hold hazard stocks and pay a premium to hold lottery stocks. Moreover, once the Reg SHO pilot has been completed, the insignificant β_2 coefficient indicates that the subsequent re-imposition of short-sale constraints on pilot stocks has returned pilot stocks to the status quo ex ante; that is, subject to an IMIN effect. Thus, we conclude that short-sale constraints measurably impede arbitrage, resulting in the observed underreaction to IMIN and negative future returns. In the absence of short-sale constraints, however, the relation between hazard stocks and future returns is positive, which is consistent with the predictions of the lottery preference literature.

7. Robustness Checks

We run a battery of robustness checks corresponding to the main results. First, we use an alternative measure of standardized unexpected earnings derived following Bernard and Thomas (1989) and find that it has no effect on our overall analyses. Second, we replicate the Fama-MacBeth (1973) regression analyses using individual categories of NEG_NEWS. Third, we replicate the portfolio results using value-weighted portfolio returns. Fourth, we replicate results similar to those in Table 2 using CAPM and Fama and French (1993) three-factor portfolio returns. Fifth, we removed earnings announcement dates, and replicated our main analysis. Sixth, we replicate results similar to those in Table 9 using value-weighted results and providing CAPM and Fama and French (1993) three-factor alphas for High-Low IMIN portfolio. Seventh, we provide portfolio results to complement analysis in Table 10. Eighth, we replicate the bivariate portfolio level analysis using dependent and independent sorts. Finally, we replicate Tables 2 and 4 using MIN instead of IMIN and find similar results. Unreported results are available upon request.

8. Conclusion

Empirical research has largely focused on the *right* tail of the return distribution (e.g., 'stocks as lotteries'). In contrast, we focus on the *left* tail and investigate the significance of extreme negative price changes ('hazard stocks') 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. Our first main result is that the market underreacts to IMIN, appearing to contemporaneously overprice hazard stocks. Specifically, we show that portfolios long high IMIN stocks and short low IMIN stocks earn significantly abnormal returns of -0.52% per month using value-weighted portfolios and -0.76% per month when using equal-weighted portfolios. Moreover, this underreaction is persistent, forecasting negative abnormal returns for at least up to 6 months without subsequent reversals. We also use Fama and MacBeth (1973) regression analyses to control for a battery of firm characteristics and corporate events.

We investigate this hazard stock anomaly by examining three potential sources of underreaction: limited investor attention, rational learning (information uncertainty), and limits to arbitrage. The key takeaway here is that the IMIN effect is amplified by low earnings quality, low investor attention, and higher limits to arbitrage. However, when we consider the three explanations together, we find little support for the investor attention explanation. Furthermore, we split the sample into pre- and post-2001 periods for our analysis and document that after 2001 the effect of information uncertainty is attenuated substantially but the effect of limits to arbitrage remains economically large and statistically significant. Thus, we conclude that the IMIN effect is driven primarily by limits to arbitrage and, to a lesser degree by information uncertainty.

Our results are puzzling because investors with lottery preferences should not simultaneously pay a premium for both lottery stocks and hazard stocks. We resolve this apparent contradiction by appealing to the notion of 'asymmetric arbitrage' as outlined in Stambaugh et. al. (2015). They argue that arbitrageurs are generally able to eliminate underpricing more efficiently than overpricing. This arbitrage asymmetry allows for negative abnormal returns among contemporaneously overpriced stocks but does not create similar returns for contemporaneously underpriced stocks. As a result, underpricing will be observed more often than overpricing. Using the Stambaugh et. al (2015) mispricing score measure, we show that the negative IMIN effect is large for the most overpriced stocks but is indistinguishable from zero for the most underpriced stocks. We exploit a semi-natural experiment, the SEC's Regulation SHO pilot program, to provide causal evidence that limits to arbitrage generate the negative IMIN effect. Reg SHO reduced short-sale constraints on a subset of exchange-traded stocks over 2005-2007. We find that during the period the pilot program was in effect, the negative relation between IMIN and future returns is reversed among the pilot stocks in the program. This evidence is consistent with short-sale constraints driving the negative IMIN effect and that when they are temporarily lifted, the IMIN effect is actually positive as predicted by the lottery preferences literature. We conclude that it is arbitrage asymmetry which generates what appears to be asymmetric preferences across lottery and hazard stocks.

Appendix A

In the main text we proposed three potential mechanisms that drive the observed underreaction to IMIN: 1) limited investor attention; 2) information uncertainty; and, 3) limits to arbitrage. In this section, we examine each of these potential mechanisms in detail.

A.1. Limited Investor Attention

We begin by investigating whether investor attention helps explain investors underreaction to hazard stocks via a double sort procedure and a Fama and MacBeth (1973) regressions. We follow the prior literature and use Google abnormal search volume index, GSVI (e.g. Da et al. (2011)) and analyst coverage (e.g., Hirshleifer and Teoh (2003), Peng (2005), and Hirshleifer et al. (2013), Chichernea et al. (2015)) as proxy for investor attention. To establish the incremental power of analyst coverage over other firm characteristics in explaining IMIN effect, we follow Hong et al. (2000) and orthogonalize this variable with respect to natural logarithm of firm size and Nasdaq indicator variable. We then perform an independent bivariate sort. Specifically, each month, we independently sort all stocks in our sample into quintiles based on residual analyst coverage (or abnormal Google-SVI) and IMIN. The sorting is done using lagged values. Following Hong et al. (2000), we measure residual coverage six months before starting pre-formation ranking period. We report the results in Table A1.

Panel A of Table A1 shows that the underreaction to hazard stocks is most pronounced for portfolios characterized as low attention. Specifically, stocks in the lowest attention quintile (i.e., lowest residual analyst coverage quintile) have a statistically significant and economically large high-minus-low IMIN alpha of -1.35%. However, this alpha monotonically decreases in magnitude as attention increases. The highest attention quintile (i.e. high residual analyst coverage quintile) earns an alpha of only -0.62%. Panel B shows similar results when using GSVI as an alternate measure of attention. Stocks in the lowest attention quintile earn a statistically significant and economically large high-minus-low IMIN alpha of -1.11% whereas stocks in the highest attention quintile earn only –0.39% and is not statistically significant. Taken together, these results provide evidence that the underreaction 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 A2. Panel A reports results from using analyst coverage as attention measure and Panel B reports results from using GSVI as attention measure. In the first column of each panel, we perform a regression that controls for IMIN, the attention proxy, and an interaction term. We find that IMIN and future returns are negatively correlated and the coefficient on the interaction term is positive. Note that larger values of the attention proxy indicate greater attention, so the positive interaction term indicates that there is less underreaction, which is consistent with the portfolio sort results we reported in Table A1 above. In the second column of each panel of Table A2, we control for beta, size, and book-to-market. The interaction of IMIN with investor attention loads in a qualitatively similar way. In the third column of each panel, we control for several additional firm characteristics – momentum, reversal, turnover, idiosyncratic volatility, idiosyncratic skewness, maximum daily return. Finally, in the last five models of each panel of Table A2, we control for IMAX, earnings surprises, and negative firm-level news. The results are again qualitatively similar. That is, we continue to find a negative relation between IMIN and returns but this relation is attenuated by the positive relation between the interaction term and returns. In Panel B, we observe a positive relation between IMIN and the interaction term but the coefficients on IMIN are no longer significant.

Taken together, the results from Tables A1 and A2 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 including earnings surprises, negative firm-level corporate news, and IMAX.

A.2. Information Uncertainty

Next, we repeat the previous analysis for information uncertainty (IU). As we discussed in Section 3, we estimate IU following Dechow and Dichev (2002) and Francis et al. (2005, 2007). We report results from using independent double sort in Table A3 and Fama-MacBeth regression analysis in Table A4.

Table A3 shows that there is no IMIN effect in the lowest two information uncertainty quintiles and the IMIN effect is driven by the highest three information uncertainty quintiles. Importantly, the IMIN effect monotonically increases as we move from the lowest to the highest information uncertainty (IU) quintiles. We further examine this result using Fama and MacBeth (1973) regressions and present the results in Table A4. In the first column, we first perform a regression that controls for IMIN, IU, 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 information uncertainty is higher. In the second column, we control for beta, size, and book-to-market and find similar results. In subsequent columns, we control for additional firm characteristics. Importantly, in columns 3 and 4, we control for MAX and IMAX, and in columns 5 to 8, we control for negative firm-level news and SUE. We continue to find similar results.

Taken together, the results from Tables A3 and A4 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, including IMAX, negative firm-level news, and earnings surprises.

A.3. Limits to Arbitrage

Finally, we analyze the limits to arbitrage mechanism in the same fashion that we analyzed investor attention and information uncertainty above. Again, as detailed in Section 3, proxies for limits to arbitrage are bid-ask spread, idiosyncratic volatility (IVOL), firm size, and institutional ownership ratio (IOR). We follow Nagel (2005) and orthogonalize institutional ownership ratio with respect to firm size and squared firm size. Furthermore, we orthogonalize idiosyncratic volatility to IMIN and residual institutional ownership ratio to avoid confounding effect of these variables.

Table A5 reports results from independent bivariate sorts. Panels A, B, and C, and D show that the underreaction to hazard stocks is most pronounced for stocks characterized as having high Bid-Ask spread, high idiosyncratic volatility, low market capitalization, and low institutional ownership. This evidence supports the hypothesis that the underreaction to hazard stocks is, at least in part, due to limits to arbitrage. We find qualitatively similar results when we use dependent double sorts (available upon request).

Next, we use Fama and MacBeth (1973) regressions to further examine the effect of limits to arbitrage on the underreaction to hazard stocks and report results in Table A6. Each of the four Panels A, B, C, and D report results for each of the four limits to arbitrage proxies we use: Bid-Ask spread, idiosyncratic volatility, market capitalization and institutional ownership. In the first column of each Panel, we first perform a regression that controls for IMIN, one of the limits to arbitrage proxy, and an interaction term between IMIN and this proxy. Panels A and B show that the interaction terms between IMIN and bid-ask spread, and between IMIN and idiosyncratic volatility are both negative and highly statistically significant. Similarly, Panels C and D show that the interaction terms between IMIN and firm size, and between IMIN and institutional ownership are positive and highly statistically significant. Recall, larger values of the bid-ask spread and IVOL (firm size or IOR) indicate greater (smaller) limits to arbitrage, so the negative (positive) interaction term indicates that there is more (less) underreaction with higher (lower) limits to arbitrage.

Taken together, the results from Tables A5 and A6 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. We also demonstrate that IMIN is not simply an artifact of earnings surprise or bad corporate news about the firm.

Table A1. Independent Bivariate Sort by Investor Attention and IMIN

The table reports equal weighted Fama and French (1993)-Carhart (1997) four factor portfolio alphas from an independent bivariate sort by attention proxy (residual analyst coverage or abnormal Google search volume index) and IMIN. Analyst coverage (log(1+Number of Analysts)) is orthogonalized with respect to Log(Size) and Nasdaq indicator variable as in Hong, Lim, and Stein (2000). Abnormal Google-SVI is derived following Da, Engelberg, and Gao (2011). The sorting is done using lagged values. Following Hong, Lim, and Stein (2000), we measure residual coverage six months before starting pre-formation ranking period. The column 'H-L' reports investment strategy that is long high IMIN stocks and short low IMIN stocks. IMIN is idiosyncratic minimum return computed as the minimum idiosyncratic daily return within a month from Fama and French (1993)-Carhart (1997) four factor model. For ease of interpretation, we multiplied IMIN by -1 (high IMIN indicates more negative idiosyncratic return). Newey-West (1987) corrected t-statistics with 6 lags are reported in parentheses. *, **, *** represent statistical significance at the 10%, 5%, and 1% levels, respectively. The data is from 1984:01 to 2014:12 in Panel A and 2004:01 to 2014:12 in Panel B.

	Low IMIN	2	3	4	High IMIN	H - L
Pane A: Double Sort by **Residual Analyst Coverage** and IMIN						
Low Coverage	0.65	0.50	-0.12	-0.13	-0.75	-1.35***
	(3.43)	(2.11)	(-0.59)	(-0.58)	(-3.00)	(-4.07)
2	0.46	0.33	0.15	-0.42	-0.71	-1.20***
	(2.04)	(1.64)	(0.69)	(-1.99)	(-2.87)	(-3.72)
3	0.33	0.17	-0.19	0.17	-0.69	-1.08***
	(2.18)	(0.79)	(-0.85)	(0.61)	(-2.86)	(-3.39)
4	0.29	-0.17	0.27	0.28	-0.76	-0.95***
	(1.61)	(-0.74)	(1.20)	(1.30)	(-2.47)	(-3.01)
High Coverage	0.12	-0.16	0.13	0.01	-0.44	-0.62**
	(0.72)	(-0.73)	(0.65)	(0.06)	(-1.68)	(-2.09)
Pane B: Double Sort by **Google-SV**I and IMIN						
Low G-SVI	0.17	-0.01	-0.25	-0.47	-0.94	-1.11***
	(1.54)	(-0.12)	(-3.08)	(-5.68)	(-5.20)	(-6.48)
2	0.11	0.19	-0.15	-0.07	-0.39	-0.49
	(0.75)	(2.51)	(-1.58)	(-0.68)	(-1.55)	(-1.35)
3	0.20	0.17	0.10	-0.11	-0.39	-0.55***
	(3.01)	(1.57)	(0.89)	(-0.78)	(-2.79)	(-3.39)
4	0.51	0.39	0.37	0.18	-0.43	-0.85***
	(8.77)	(3.38)	(4.47)	(1.22)	(-2.89)	(-4.60)
High G-SVI	0.65	0.39	0.57	0.58	0.26	-0.39
	(3.50)	(4.54)	(4.73)	(3.94)	(1.85)	(-1.58)

Table A2. Fama and MacBeth (1973) Regressions with Interaction between IMIN and Attention Proxies

The table reports Fama and MacBeth (1973) regression results using the interaction between IMIN and different attention (ATTN) proxies (number of analysts following in Panel A or abnormal Google SVI in Panel B). IMIN is idiosyncratic minimum return computed as the minimum idiosyncratic daily return within a month from Fama and French (1993)-Carhart (1997) four factor model. For ease of interpretation, we multiplied IMIN by -1 (high IMIN indicates more negative idiosyncratic return). NEG_NEWS equals 1 if any of the following events occur in the previous month: dividend cut, dividend omission, analysts downgrades, or downward earnings forecast revision, and 0 otherwise. The other variables are defined in Tables 1. All variables are lagged by one month. Newey-West (1987) corrected t-statistics with 6 lags are reported in parentheses. *, **, *** represent statistical significance at the 10%, 5%, and 1% levels, respectively. The data is from 1984:01 to 2014:12 in Panel A and 2004:01 to 2014:12 in Panel B.

Panel A. *ATTN* = Number of Analyst Following

	1	2	3	4	5	6	7	8
Intercept	0.013***	0.018***	0.023***	0.023***	0.023***	0.024***	0.023***	0.023***
	(5.062)	(2.864)	(4.016)	(4.097)	(3.966)	(4.148)	(4.098)	(4.182)
IMIN	-0.141***	-0.142***	-0.089***	-0.083***	-0.087***	-0.091***	-0.089***	-0.083***
	(-5.641)	(-6.878)	(-3.159)	(-2.954)	(-3.095)	(-3.236)	(-3.171)	(-2.963)
ATTN	-0.000**	-0.000	-0.000	-0.000	0.000	-0.000	0.000	0.000
	(-2.517)	(-1.247)	(-0.153)	(-0.105)	(0.713)	(-0.027)	(0.831)	(0.872)
IMIN**ATTN*	0.005***	0.004***	0.003**	0.003*	0.003**	0.003**	0.003**	0.003**
	(2.642)	(2.877)	(2.026)	(1.931)	(2.341)	(1.985)	(2.301)	(2.201)
BETA		0.002	0.001	0.001	0.001	0.001	0.001	0.001
		(0.763)	(0.543)	(0.405)	(0.555)	(0.539)	(0.551)	(0.413)
SIZE		-0.001	-0.001**	-0.001**	-0.001*	-0.001**	-0.001**	-0.001**
		(-1.144)	(-2.085)	(-2.125)	(-1.933)	(-2.234)	(-2.083)	(-2.124)
BEME		-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
		(-1.098)	(-1.298)	(-1.261)	(-1.325)	(-1.269)	(-1.295)	(-1.259)
MOM			0.007***	0.007***	0.006***	0.006***	0.006***	0.006***
			(3.135)	(3.194)	(3.013)	(2.915)	(2.792)	(2.848)
RET(-1)			-0.029***	-0.031***	-0.030***	-0.029***	-0.030***	-0.032***
			(-6.465)	(-6.838)	(-6.678)	(-6.503)	(-6.715)	(-7.088)
TURNOVER			0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
			(3.03)	(3.112)	(3.333)	(2.993)	(3.296)	(3.381)
IVOL			-0.102	-0.229**	-0.101	-0.092	-0.091	-0.225**
			(-1.35)	(-2.138)	(-1.347)	(-1.216)	(-1.214)	(-2.1)
ISKEW			0.001**	0.000	0.001**	0.001**	0.001**	0.000
			(2.476)	(0.929)	(2.401)	(2.372)	(2.298)	(0.663)
MAX			-0.030***		-0.031***	-0.030***	-0.031***	
			(-2.982)		(-3.039)	(-2.976)	(-3.033)	
IMAX				0.016				0.018
				(0.588)				(0.665)
NEG_NEWS					-0.002*		-0.002*	-0.002*
					(-1.815)		(-1.764)	(-1.812)
SUE						0.158***	0.158***	0.157***
						(4.155)	(4.14)	(4.098)
Adj R2	0.022	0.055	0.076	0.076	0.077	0.077	0.078	0.078

Panel B: *ATTN* = Abnormal Google Search Volume Index or GSVI.

	1	2	3	4	5	6	7	8
Intercept	0.010**	0.005	0.007	0.009	0.005	0.007	0.005	0.006
	(2.432)	(0.811)	(1.289)	(1.494)	(0.853)	(1.316)	(0.876)	(1.083)
IMIN	-0.090***	-0.085***	0.029	0.036	0.033	0.028	0.032	0.039
	(-3.038)	(-3.558)	(0.726)	(0.923)	(0.81)	(0.7)	(0.786)	(1.002)
ATTN	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
	(3.714)	(3.503)	(3.211)	(3.009)	(3.203)	(3.245)	(3.237)	(3.035)
IMIN**ATTN*	0.036*	0.041**	0.045**	0.048**	0.045**	0.045**	0.045**	0.048**
	(1.914)	(2.172)	(2.359)	(2.534)	(2.366)	(2.355)	(2.362)	(2.534)
BETA		0.001	0.001	0.001	0.001	0.001	0.001	0.001
		(0.488)	(0.52)	(0.365)	(0.501)	(0.513)	(0.493)	(0.341)
SIZE		0.000	0.000	0.000	0.000	0.000	0.000	0.000
		(0.791)	(0.46)	(0.309)	(1.176)	(0.441)	(1.162)	(1.006)
BEME		-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
		(-1.134)	(-1.056)	(-1.044)	(-1.07)	(-1.068)	(-1.083)	(-1.068)
MOM			-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
			(-0.22)	(-0.188)	(-0.288)	(-0.243)	(-0.31)	(-0.28)
RET(-1)			-0.011*	-0.012**	-0.011*	-0.011*	-0.011*	-0.013**
			(-1.778)	(-2.108)	(-1.938)	(-1.795)	(-1.958)	(-2.304)
TURNOVER			-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
			(-0.533)	(-0.423)	(-0.123)	(-0.552)	(-0.14)	(-0.026)
IVOL			-0.213	-0.530***	-0.208	-0.208	-0.204	-0.528***
			(-1.612)	(-2.682)	(-1.578)	(-1.575)	(-1.542)	(-2.69)
ISKEW			0.001***	0.000	0.001***	0.001***	0.001***	0.000
			(3.362)	(0.327)	(3.178)	(3.359)	(3.18)	(0.068)
MAX			-0.028**		-0.029**	-0.029**	-0.029**	
			(-2.143)		(-2.189)	(-2.2)	(-2.246)	
IMAX				0.097**				0.098**
				(2.299)				(2.329)
NEG_NEWS					-0.004***		-0.004***	-0.004***
					(-8.539)		(-8.576)	(-8.512)
SUE						0.038	0.036	0.037
						(0.937)	(0.929)	(0.926)
Adj R2	0.007	0.035	0.054	0.054	0.055	0.055	0.055	0.055

Table A3. Independent Bivariate Sort by Information Uncertainty and IMIN

The table reports equal weighted Fama and French (1993)-Carhart (1997) four factor portfolio alphas from an independent bivariate sort by an Information Uncertainty (IU) proxy and IMIN. IU is constructed using earnings accruals following Dechow and Dichev (2002) and Francis *et al*. (2005, 2007). The sorting is done using lagged values. The column 'H-L' reports investment strategy that is long high IMIN stocks and short low IMIN stocks. IMIN is idiosyncratic minimum return computed as the minimum idiosyncratic daily return within a month from Fama and French (1993)-Carhart (1997) four factor model. For ease of interpretation, we multiplied IMIN by -1 (high IMIN indicates more negative idiosyncratic return). Newey-West (1987) corrected t-statistics with 6 lags are reported in parentheses. *, **, *** represent statistical significance at the 10%, 5%, and 1% levels, respectively. The data is from 1964:01 to 2014:12.

	Low IMIN	2	3	4	High IMIN	H - L
Low IU	0.18	0.27	0.24	0.16	0.01	-0.15
	(2.38)	(4.04)	(3.27)	(2.22)	(0.14)	(-1.31)
2	0.17	0.27	0.35	0.31	0.06	-0.12
	(2.29)	(3.52)	(4.40)	(3.34)	(0.60)	(-0.96)
3	0.31	0.33	0.30	0.25	-0.15	-0.47***
	(3.76)	(4.13)	(3.44)	(2.98)	(-1.59)	(-3.65)
4	0.26	0.21	0.29	0.07	-0.37	-0.63***
	(3.04)	(2.41)	(3.52)	(0.68)	(-4.32)	(-4.96)
High IU	0.20	0.21	0.13	-0.05	-0.57	-0.77***
	(2.37)	(2.37)	(1.22)	(-0.54)	(-5.00)	(-5.11)

Table A4. Fama and MacBeth (1973) Regressions with Interaction Information Uncertainty Proxy and IMIN

The table reports Fama and MacBeth (1973) regression results using the interaction between IMIN and an Information Uncertainty (IU) proxy. IU is constructed using earnings and accruals quality measure following Dechow and Dichev (2002) and Francis *et al*. (2005, 2007). IMIN is idiosyncratic minimum return computed as the minimum idiosyncratic daily return within a month from Fama and French (1993)-Carhart (1997) four factor model. For ease of interpretation, we multiplied IMIN by -1 (high IMIN indicates more negative idiosyncratic return). NEG_NEWS equals 1 if any of the following events occur in the previous month: dividend cut, dividend omission, analysts downgrades, or downward earnings forecast revision, and 0 otherwise. The other variables are defined in Tables 1. All variables are lagged by one month. Newey-West (1987) corrected t-statistics with 6 lags are reported in parentheses. *, **, *** represent statistical significance at the 10%, 5%, and 1% levels, respectively. The data is from 1964:01 to 2014:12 in the first four models and from 1984:01 to 2014:12 in the remaining models.

	1	2	3	4	5	6	7	8
Intercept	0.010***	0.017***	0.020***	0.020***	0.017***	0.020***	0.017***	0.018***
	(4.609)	(2.713)	(3.392)	(3.463)	(2.917)	(3.438)	(2.963)	(3.035)
IMIN	-0.026	-0.040**	0.007	0.011	0.011	0.005	0.009	0.013
	(-0.897)	(-2.254)	(0.261)	(0.388)	(0.386)	(0.182)	(0.307)	(0.449)
IU	0.012**	0.011**	0.013**	0.013**	0.014**	0.013**	0.013**	0.013**
	(2.171)	(2.077)	(2.363)	(2.331)	(2.457)	(2.337)	(2.431)	(2.395)
IMIN*IU*	-0.570***	-0.595***	-0.629***	-0.622***	-0.634***	-0.627***	-0.632***	-0.624***
	(-4.032)	(-4.246)	(-4.472)	(-4.521)	(-4.498)	(-4.494)	(-4.519)	(-4.567)
BETA		0.002	0.001	0.001	0.001	0.001	0.001	0.001
		(0.903)	(0.547)	(0.443)	(0.556)	(0.569)	(0.577)	(0.467)
SIZE		-0.001	-0.001*	-0.001*	-0.000	-0.001*	-0.000	-0.000
		(-1.347)	(-1.87)	(-1.893)	(-1.225)	(-1.922)	(-1.277)	(-1.301)
BEME		-0.001**	-0.001**	-0.001**	-0.001**	-0.001**	-0.001**	-0.001**
		(-2.138)	(-2.083)	(-2.06)	(-2.04)	(-2.065)	(-2.023)	(-2.001)
MOM			0.005**	0.005**	0.005**	0.005**	0.005**	0.005**
			(2.414)	(2.455)	(2.239)	(2.293)	(2.116)	(2.162)
RET(-1)			-0.027***	-0.029***	-0.028***	-0.027***	-0.028***	-0.030***
			(-6.02)	(-6.498)	(-6.275)	(-6.029)	(-6.285)	(-6.769)
TURNOVER			0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
			(2.858)	(2.889)	(3.168)	(2.864)	(3.17)	(3.194)
IVOL			-0.082	-0.233**	-0.077	-0.072	-0.068	-0.223*
			(-1.05)	(-2.042)	(-0.991)	(-0.926)	(-0.867)	(-1.965)
ISKEW			0.001**	0.000	0.001**	0.001**	0.001**	0.000
			(2.182)	(0.324)	(2.084)	(2.081)	(1.987)	(0.138)
MAX			-0.031***		-0.032***	-0.031***	-0.032***	
			(-2.622)		(-2.716)	(-2.682)	(-2.776)	
IMAX				0.026				0.027
				(0.875)				(0.882)
NEG_NEWS					-0.001		-0.001	-0.001
					(-0.412)		(-0.426)	(-0.452)
SUE						0.069*	0.070**	0.069**
						(1.965)	(2.022)	(1.988)
Adj R2	0.015	0.052	0.073	0.072	0.073	0.073	0.074	0.073

Table A5. Independent Sort by Limits to Arbitrage and IMIN

The table reports equal weighted Fama and French (1993)-Carhart (1997) four factor portfolio alphas from an independent bivariate sort by Limits to Arbitrage proxy (Bid Ask Spread, Idiosyncratic Volatility orthogonalized to IMIN, Firm Size, or Residual Institutional Ownership) and IMIN. Residual Institutional Ownership is orthogonalized with respect to firm size and squared firm size as in Nagel (2005). The sorting is done using lagged values. The column 'H-L' reports investment strategy that is long high IMIN stocks and short low IMIN stocks. IMIN is idiosyncratic minimum return computed as the minimum idiosyncratic daily return within a month from Fama and French (1993)-Carhart (1997) four factor model. For ease of interpretation, we multiplied IMIN by -1 (high IMIN indicates more negative idiosyncratic return). Newey-West (1987) corrected *t*-statistics with 6 lags are reported in parentheses. *, **, *** represent statistical significance at the 10%, 5%, and 1% levels, respectively. The data is from 1964:01 to 2014:12 in Panels A, B, and C, and from 1984:01 to 2014:12 in Panel D.

	Low IMIN	2	3	4	High IMIN	H - L
Panel A: Double Sort by **Bid Ask** and IMIN						
Low Bid Ask	0.26	0.32	0.32	0.31	-0.02	-0.25
	(3.50)	(3.86)	(3.64)	(2.68)	(-0.09)	(-1.14)
2	0.24	0.25	0.25	0.28	0.18	-0.06
	(3.86)	(4.05)	(3.54)	(3.09)	(1.57)	(-0.61)
3	0.20	0.20	0.24	0.08	-0.04	-0.23**
	(2.97)	(3.32)	(3.97)	(1.24)	(-0.41)	(-2.36)
4	0.12	0.10	0.13	-0.04	-0.42	-0.54***
	(1.39)	(1.54)	(2.06)	(-0.62)	(-5.78)	(-4.94)
High Bid Ask	0.23	0.01	-0.12	-0.22	-0.78	-1.01***
	(1.29)	(0.05)	(-1.39)	(-2.60)	(-7.74)	(-5.07)
Panel B: Double Sort by **IVOL** orthogonalized to IMIN and IMIN						
Low IVOL	0.14	0.08	0.19	0.28	-0.15	-0.30***
	(1.63)	(1.07)	(2.90)	(4.67)	(-2.65)	(-2.81)
2	0.23	0.29	0.23	0.14	-0.21	-0.43***
	(3.51)	(4.61)	(3.34)	(2.06)	(-2.14)	(-3.41)
3	0.28	0.24	0.25	0.07	-0.25	-0.52***
	(4.49)	(3.88)	(4.26)	(1.07)	(-2.33)	(-3.92)
4	0.30	0.24	0.21	-0.02	-0.61	-0.91***
	(4.75)	(4.12)	(3.66)	(-0.33)	(-6.19)	(-6.99)
High IVOL	0.20	0.17	0.04	-0.30	-1.07	-1.27***
	(1.74)	(2.61)	(0.68)	(-4.11)	(-9.14)	(-7.07)
Panel C: Double Sort by **Market Capitalization** and IMIN						
Small	0.50	0.43	0.34	0.07	-0.56	-1.06***
	(4.30)	(3.88)	(3.05)	(0.70)	(-5.62)	(-9.59)
2	0.36	0.25	0.26	-0.02	-0.60	-0.96***
	(4.13)	(3.08)	(3.94)	(-0.34)	(-6.47)	(-7.59)
3	0.21	0.22	0.18	-0.01	-0.54	-0.75***
	(2.70)	(3.08)	(3.01)	(-0.20)	(-5.60)	(-5.21)
4	0.17	0.24	0.15	-0.02	-0.47	-0.64***

	(2.39)	(3.52)	(2.28)	(-0.26)	(-4.62)	(-4.37)
Big	0.13	0.13	0.04	-0.00	-0.33	-0.46***
	(2.04)	(2.26)	(0.66)	(-0.06)	(-2.31)	(-2.59)
Panel D: Double Sort by **Residual Institutional Ownership** (**IOR)** and IMIN						
Low IOR	0.29	0.13	0.07	-0.19	-0.81	-1.12***
	(3.58)	(1.46)	(0.81)	(-1.65)	(-5.47)	(-6.31)
2	0.33	0.34	0.22	0.05	-0.48	-0.82***
	(4.17)	(4.23)	(3.19)	(0.68)	(-4.23)	(-5.12)
3	0.41	0.24	0.30	0.19	-0.39	-0.78***
	(4.60)	(3.01)	(4.11)	(2.12)	(-3.65)	(-4.80)
4	0.25	0.26	0.28	0.16	-0.17	-0.41***
	(2.61)	(2.94)	(3.68)	(2.12)	(-1.82)	(-2.99)
High IOR	0.27	0.17	0.18	0.05	-0.19	-0.46***
	(2.60)	(1.74)	(2.02)	(0.61)	(-2.06)	(-3.50)

Table A6. Fama and MacBeth (1973) Regressions with Interaction between IMIN and Limits to Arbitrage Proxies

The table reports Fama and MacBeth (1973) regression results using the interaction between IMIN and different Limits to Arbitrage proxy (Bid Ask Spread, Idiosyncratic Volatility, Firm Size, or Institutional Ownership Ratio). IMIN is idiosyncratic minimum return computed as the minimum idiosyncratic daily return within a month from Fama and French (1993)-Carhart (1997) four factor model. For ease of interpretation, we multiplied IMIN by -1 (high IMIN indicates more negative idiosyncratic return). NEG_NEWS equals 1 if any of the following events occur in the previous month: dividend cut, dividend omission, analysts downgrades, or downward earnings forecast revision, and 0 otherwise. The other variables are defined in Tables 1. All variables are lagged by one month. Newey-West (1987) corrected t-statistics with 6 lags are reported in parentheses. *, **, *** represent statistical significance at the 10%, 5%, and 1% levels, respectively. In each Panel, Models 1 through 4 use data from 1964:01 to 2014:12 and Models 5 through 8 use data from 1984:01 to 2014:12.

Panel A. *Limit2Arb* = Bid Ask Spread

	1	2	3	4	5	6	7	8
Intercept	0.009***	0.014***	0.016***	0.016***	0.014**	0.017***	0.014***	0.015***
	(5.223)	(2.889)	(3.345)	(3.393)	(2.577)	(3.179)	(2.674)	(2.806)
IMIN	-0.039	-0.062***	0.060**	0.061**	-0.012	-0.020	-0.016	-0.016
	(-1.083)	(-3.425)	(2.529)	(2.52)	(-0.429)	(-0.704)	(-0.555)	(-0.553)
Limit2Arb	0.014**	0.010**	0.024***	0.022***	0.016***	0.015***	0.016***	0.015***
	(1.99)	(2.179)	(5.726)	(5.37)	(3.12)	(3.079)	(3.131)	(2.937)
IMIN**Limit2Arb*	-0.465***	-0.412***	-0.481***	-0.463***	-0.208***	-0.203***	-0.203***	-0.186**
	(-4.284)	(-5.502)	(-6.423)	(-6.133)	(-2.688)	(-2.638)	(-2.634)	(-2.462)
BETA		0.001	-0.000	-0.000	0.001	0.001	0.001	0.000
		(0.585)	(-0.005)	(-0.214)	(0.344)	(0.345)	(0.34)	(0.195)
SIZE		-0.001	-0.001**	-0.001**	-0.000	-0.001	-0.000	-0.000
		(-1.571)	(-2.077)	(-2.071)	(-0.666)	(-1.502)	(-0.772)	(-0.833)
BEME		0.001**	0.001**	0.001**	-0.001	-0.001	-0.001	-0.001
		(2.19)	(2.121)	(2.162)	(-1.412)	(-1.414)	(-1.386)	(-1.38)
MOM			0.007***	0.007***	0.006***	0.006***	0.006***	0.006***
			(4.587)	(4.629)	(2.853)	(2.808)	(2.629)	(2.683)
RET(-1)			-0.034***	-0.036***	-0.028***	-0.027***	-0.028***	-0.030***
			(-10.351)	(-11.267)	(-6.688)	(-6.482)	(-6.738)	(-7.228)
TURNOVER			0.002***	0.002***	0.001***	0.001***	0.001***	0.001***
			(3.972)	(3.895)	(3.594)	(3.182)	(3.559)	(3.67)
IVOL			-0.209***	-0.304***	-0.147**	-0.136**	-0.137**	-0.298***
			(-4.04)	(-4.417)	(-2.169)	(-2.001)	(-2.019)	(-3.037)
ISKEW			0.001***	0.001***	0.001***	0.001***	0.001***	0.000
			(5.167)	(3.394)	(3.053)	(3.026)	(2.943)	(0.684)
MAX			-0.051***		-0.034***	-0.034***	-0.034***	
			(-7.663)		(-3.432)	(-3.359)	(-3.42)	
IMAX				-0.015				0.027
				(-0.862)				(1.038)
NEG_NEWS					-0.002*		-0.002*	-0.002*
					(-1.726)		(-1.688)	(-1.748)
SUE						0.161***	0.161***	0.160***
						(4.282)	(4.268)	(4.222)
Adj R2	0.024	0.057	0.073	0.072	0.070	0.070	0.071	0.071

Panel B. *Limit2Arb* = IVOL

	1	2	3	4	5	6	7	8
Intercept	0.007***	0.016***	0.013***	0.013***	0.011**	0.014**	0.011**	0.012**
	(4.355)	(3.368)	(2.795)	(2.855)	(1.968)	(2.573)	(2.066)	(2.157)
IMIN	0.167***	0.146***	0.117***	0.115***	0.048*	0.038	0.044	0.048*
	(5.813)	(6.824)	(4.629)	(4.533)	(1.72)	(1.385)	(1.575)	(1.711)
Limit2Arb	-0.109	-0.209***	0.016	-0.103	-0.007	-0.001	0.002	-0.149
	(-1.101)	(-3.663)	(0.258)	(-1.277)	(-0.087)	(-0.016)	(0.02)	(-1.269)
IMIN**Limit2Arb*	-5.649***	-4.822***	-4.957***	-4.784***	-2.723***	-2.646***	-2.690***	-2.653***
	(-5.571)	(-6.866)	(-7.079)	(-6.918)	(-5.068)	(-4.916)	(-4.986)	(-4.821)
BETA		0.001	-0.000	-0.000	0.000	0.000	0.000	0.000
		(0.902)	(-0.076)	(-0.289)	(0.29)	(0.283)	(0.287)	(0.137)
SIZE		-0.001**	-0.001*	-0.001*	-0.000	-0.000	-0.000	-0.000
		(-2.264)	(-1.788)	(-1.799)	(-0.326)	(-1.17)	(-0.433)	(-0.484)
BEME		0.001**	0.001**	0.001**	-0.001	-0.001	-0.001	-0.001
		(2.19)	(2.192)	(2.244)	(-1.286)	(-1.295)	(-1.264)	(-1.241)
MOM			0.007***	0.007***	0.006***	0.006***	0.006***	0.006***
			(4.638)	(4.674)	(2.823)	(2.78)	(2.605)	(2.662)
RET(-1)			-0.035***	-0.037***	-0.030***	-0.029***	-0.030***	-0.032***
			(-10.209)	(-11.12)	(-6.734)	(-6.532)	(-6.772)	(-7.182)
TURNOVER			0.002***	0.002***	0.001***	0.001***	0.001***	0.001***
			(3.952)	(3.864)	(3.703)	(3.298)	(3.68)	(3.779)
ISKEW			0.001***	0.001***	0.001***	0.001***	0.001***	0.000
			(5.893)	(3.791)	(3.697)	(3.652)	(3.579)	(1.532)
MAX			-0.052***		-0.034***	-0.033***	-0.034***	
			(-7.715)		(-3.343)	(-3.268)	(-3.336)	
IMAX				-0.010				0.021
				(-0.613)				(0.774)
NEG_NEWS					-0.002		-0.002	-0.002
					(-1.539)		(-1.491)	(-1.54)
SUE						0.159***	0.159***	0.158***
						(4.185)	(4.174)	(4.132)
Adj R2	0.022	0.056	0.072	0.071	0.069	0.069	0.070	0.070

Panel C. *Limit2Arb* = Firm Size

	1	2	3	4	5	6	7	8
Intercept	0.031***	0.029***	0.028***	0.028***	0.024***	0.027***	0.024***	0.024***
	(5.557)	(5.057)	(5.135)	(5.131)	(4.125)	(4.59)	(4.181)	(4.184)
IMIN	-0.505***	-0.495***	-0.305***	-0.303***	-0.302***	-0.296***	-0.297***	-0.282***
	(-8.041)	(-9.395)	(-5.402)	(-5.341)	(-3.634)	(-3.58)	(-3.57)	(-3.321)
Limit2Arb	-0.002***	-0.002***	-0.001***	-0.001***	-0.001**	-0.001***	-0.001**	-0.001**
	(-4.421)	(-3.931)	(-3.74)	(-3.733)	(-2.164)	(-2.814)	(-2.216)	(-2.195)
IMIN**Limit2Arb*	0.031***	0.030***	0.022***	0.022***	0.018***	0.017***	0.018***	0.017***
	(4.856)	(6.374)	(4.622)	(4.655)	(2.849)	(2.706)	(2.742)	(2.592)
BETA		0.001	0.000	-0.000	0.001	0.001	0.001	0.001
		(0.402)	(0.119)	(-0.102)	(0.434)	(0.429)	(0.431)	(0.283)
SIZE		0.001**	0.001**	0.001**	-0.001	-0.001	-0.001	-0.001
		(2.209)	(2.042)	(2.106)	(-1.402)	(-1.409)	(-1.381)	(-1.36)
MOM			0.007***	0.007***	0.006***	0.006***	0.005**	0.006***
			(4.539)	(4.579)	(2.75)	(2.711)	(2.538)	(2.594)
RET(-1)			-0.035***	-0.038***	-0.030***	-0.029***	-0.030***	-0.032***
			(-10.295)	(-11.141)	(-6.761)	(-6.553)	(-6.795)	(-7.177)
TURNOVER			0.002***	0.002***	0.001***	0.001***	0.001***	0.001***
			(3.504)	(3.399)	(3.328)	(2.935)	(3.314)	(3.405)
IVOL			-0.151***	-0.228***	-0.100	-0.092	-0.090	-0.211*
			(-2.848)	(-3.161)	(-1.315)	(-1.208)	(-1.183)	(-1.945)
ISKEW			0.001***	0.001***	0.001**	0.001**	0.001**	0.000
			(4.159)	(3.228)	(2.473)	(2.452)	(2.363)	(0.975)
MAX			-0.048***		-0.032***	-0.031***	-0.031***	
			(-7.091)		(-3.134)	(-3.072)	(-3.129)	
IMAX				-0.021				0.013
				(-1.256)				(0.48)
NEG_NEWS					-0.002		-0.002	-0.002
					(-1.51)		(-1.458)	(-1.517)
SUE						0.158***	0.158***	0.157***
						(4.175)	(4.168)	(4.122)
Adj R2	0.028	0.054	0.072	0.071	0.069	0.069	0.070	0.070

Panel D. *Limit2Arb* = Institutional Ownership Ratio (IOR)

	1	2	3	4	5	6	7	8
Intercept	0.012***	0.022***	0.023***	0.023***	0.020***	0.023***	0.021***	0.021***
	(5.132)	(3.609)	(4.071)	(4.13)	(3.615)	(4.153)	(3.697)	(3.76)
IMIN	-0.224***	-0.228***	-0.169***	-0.164***	-0.166***	-0.170***	-0.167***	-0.163***
	(-6.175)	(-7.892)	(-5.396)	(-5.266)	(-5.323)	(-5.429)	(-5.357)	(-5.222)
Limit2Arb	-0.002	-0.001	0.000	0.000	0.001	0.000	0.001	0.001
	(-1.091)	(-0.367)	(0.215)	(0.212)	(0.269)	(0.217)	(0.269)	(0.265)
IMIN*Limit2Arb*	0.254***	0.241***	0.172***	0.173***	0.173***	0.170***	0.170***	0.171***
	(5.549)	(5.334)	(3.717)	(3.684)	(3.719)	(3.659)	(3.662)	(3.629)
BETA		0.001	0.001	0.000	0.001	0.001	0.001	0.000
		(0.535)	(0.391)	(0.249)	(0.389)	(0.388)	(0.385)	(0.244)
SIZE		-0.001*	-0.001**	-0.001**	-0.001	-0.001**	-0.001*	-0.001*
		(-1.923)	(-2.303)	(-2.332)	(-1.623)	(-2.391)	(-1.712)	(-1.743)
BEME		-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
		(-1.422)	(-1.551)	(-1.524)	(-1.524)	(-1.526)	(-1.499)	(-1.473)
MOM			0.007***	0.007***	0.006***	0.006***	0.006***	0.006***
			(3.089)	(3.136)	(2.914)	(2.874)	(2.699)	(2.745)
RET(-1)			-0.029***	-0.031***	-0.030***	-0.029***	-0.030***	-0.032***
			(-6.67)	(-7.028)	(-6.923)	(-6.706)	(-6.958)	(-7.316)
TURNOVER			0.001*	0.001**	0.001**	0.001*	0.001**	0.001**
			(1.91)	(1.968)	(2.275)	(1.901)	(2.264)	(2.324)
IVOL			-0.060	-0.168	-0.057	-0.051	-0.048	-0.160
			(-0.801)	(-1.564)	(-0.759)	(-0.674)	(-0.633)	(-1.497)
ISKEW			0.001**	0.000	0.001**	0.001**	0.001*	0.000
			(2.162)	(0.874)	(2.051)	(2.065)	(1.955)	(0.584)
MAX			-0.029***		-0.030***	-0.029***	-0.030***	
			(-3.013)		(-3.076)	(-3.012)	(-3.074)	
IMAX				0.009				0.011
				(0.356)				(0.419)
NEG_NEWS					-0.002		-0.002	-0.002
					(-1.614)		(-1.563)	(-1.607)
SUE						0.157***	0.158***	0.156***
						(4.209)	(4.201)	(4.147)
Adj R2	0.020	0.053	0.072	0.071	0.072	0.072	0.073	0.073

References

Ali, A., Hwang, L.-S., Trombley, M.A., 2003. Arbitrage risk and the book-to-market anomaly. Journal of Financial Economics 69, 355-373.

Ang, A., Chen, J., 2002. Asymmetric correlations of equity portfolios. Journal of Financial Economics 63, 443-494.

Ang, A., Chen, J., Xing, Y., 2006a. Downside Risk. Review of Financial Studies 19, 1191-1239.

Ang, A., Hodrick, R., Xing, Y., Zhang, X., 2006b. The cross section of volatility and expected returns. Journal Of Finance 51, 259-299.

Arping, S., Sautner, Z., 2013. Did SOX Section 404 Make Firms Less Opaque? Evidence from Cross-Listed Firms. Contemporary Accounting Research 30, 1133-1165.

Asquith, P., Pathak, P.A., Ritter, J.R., 2005. Short interest, institutional ownership, and stock returns. Journal of Financial Economics 78, 243-276.

Atilgan, Y., Bali, T.G., Demirtas, K.O., Gunaydin, A.D., 2020. Left-tail momentum: Underreaction to bad news, costly arbitrage and equity returns. Journal of Financial Economics 135, 725-753.

Au, A.S., Doukas, J.A., Onayev, Z., 2009. Daily short interest, idiosyncratic risk, and stock returns. Journal of Financial Markets 12, 290-316.

Bali, T.G., Cakici, N., Whitelaw, R.F., 2011. Maxing out: Stocks as lotteries and the cross-section of expected returns. Journal of Financial Economics 99, 427-446.

Bali, T.G., Peng, L., Shen, Y., Tang, Y., 2014. Liquidity Shocks and Stock Market Reactions. Review of Financial Studies 27, 1434-1485.

Bergsma, K., Tayal, J., 2019. Short Interest and Lottery Stocks. Financial Management 48, 187-227.

Bernard, V.L., Thomas, J.K., 1989. Post-Earnings-Announcement Drift: Delayed Price Response or Risk Premium? Journal of Accounting Research 27, 1-36.

Bhardwaj, R.K., Brooks, L.D., 1992. The January Anomaly: Effects of Low Share Price, Transaction Costs, and Bid-Ask Bias. Journal Of Finance 47, 553-575.

Brav, A., Heaton, J.B., 2002. Competing Theories of Financial Anomalies. Review of Financial Studies 15, 575-606.

Brav, A., Heaton, J.B., Li, S., 2010. The Limits of the Limits of Arbitrage. Review of Finance 14, 157-187.

Cao, J., Han, B., 2016. Idiosyncratic risk, costly arbitrage, and the cross-section of stock returns. Journal of Banking & Finance 73, 1-15.

Carhart, M.M., 1997. On Persistence in Mutual Fund Performance. Journal Of Finance 52, 57-82.

Chan, K.F., Treepongkaruna, S., Brooks, R., Gray, S., 2011. Asset market linkages: Evidence from financial, commodity and real estate assets. Journal of Banking & Finance 35, 1415-1426.

Chan, W.S., 2003. Stock price reaction to news and no-news: drift and reversal after headlines. Journal of Financial Economics 70, 223-260.

Chichernea, D.C., Ferguson, M.F., Kassa, H., 2015. Idiosyncratic Risk, Investor Base, and Returns. Financial Management 44, 267-293.

Chordia, T., Subrahmanyam, A., Tong, Q., 2014. Have capital market anomalies attenuated in the recent era of high liquidity and trading activity? Journal of Accounting and Economics 58, 41-58.

Chu, Y., Hirshleifer, D., Ma, L., 2020. The Causal Effect of Limits to Arbitrage on Asset Pricing Anomalies. Journal Of Finance 75, 2631-2672.

D'Avolio, G., 2002. The market for borrowing stock. Journal of Financial Economics 66, 271-306.

Da, Z., Engelberg, J., Gao, P., 2011. In Search of Attention. Journal Of Finance 66, 1461-1499.

Daniel, K., Titman, S., 1997. Evidence on the characteristics of cross-sectional variation in stock returns. Journal Of Finance 52, 1-33.

De Bondt, W.F.M., Thaler, R., 1985. Does the Stock Market Overreact? Journal Of Finance 40, 793-805.

Dechow, P.M., Dichev, I.D., 2002. The Quality of Accruals and Earnings: The Role of Accrual Estimation Errors. The Accounting Review 77, 35-59.

DeLisle, R.J., Yüksel, H.Z., Zaynutdinova, G.R., 2020. What's In A Name? A Cautionary Tale Of Profitability Anomalies And Limits To Arbitrage. Journal of Financial Research 43, 305-344.

DellaVigna, S., Pollet, J.M., 2009. Investor Inattention and Friday Earnings Announcements. Journal Of Finance 64, 709-749.

Diether, K.B., Lee, K.-H., Werner, I.M., 2009. It's SHO Time! Short-Sale Price Tests and Market Quality. Journal Of Finance 64, 37-73.

Diether, K.B., Malloy, C.J., Scherbina, A., 2002. Differences of Opinion and the Cross Section of Stock Returns. Journal Of Finance 57, 2113-2141.

Eleswarapu, V.R., Thompson, R., Venkataraman, K., 2004. The Impact of Regulation Fair Disclosure: Trading Costs and Information Asymmetry. The Journal of Financial and Quantitative Analysis 39, 209-225.

Fama, E.F., French, K.R., 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33, 3-56.

Fama, E.F., MacBeth, J., 1973. Risk, return, and equilibrium: empirical tests. Journal of Political Economy 71, 607-636.

Francis, J., LaFond, R., Olsson, P., Schipper, K., 2005. The market pricing of accruals quality. Journal of Accounting and Economics 39, 295-327.

Francis, J., Lafond, R., Olsson, P., Schipper, K., 2007. Information Uncertainty and Post-Earnings-Announcement-Drift. Journal of Business Finance & Accounting 34, 403-433.

Gao, F., Zhang, I.X., 2019. The Impact of the Sarbanes-Oxley Act on the Dual-Class Voting Premium. The Journal of Law and Economics 62, 181-214.

Ham, C.G., Kaplan, Z.R., Leary, M.T., 2020. Do dividends convey information about future earnings? Journal of Financial Economics 136, 547-570.

Hirshleifer, D., Hsu, P.-H., Li, D., 2013. Innovative efficiency and stock returns. Journal of Financial Economics 107, 632-654.

Hirshleifer, D., Lim, S.S., Teoh, S.H., 2009. Driven to Distraction: Extraneous Events and Underreaction to Earnings News. Journal Of Finance 64, 2289-2325.

Hirshleifer, D., Lim, S.S., Teoh, S.H., 2011. Limited Investor Attention and Stock Market Misreactions to Accounting Information. The Review of Asset Pricing Studies 1, 35-73.

Hirshleifer, D., Teoh, S.H., 2003. Limited attention, information disclosure, and financial reporting. Journal of Accounting and Economics 36, 337-386.

Hong, H., Lim, T., Stein, J.C., 2000. Bad News Travels Slowly: Size, Analyst Coverage, and the Profitability of Momentum Strategies. Journal Of Finance 55, 265-295.

Hong, H., Stein, J.C., 1999. A Unified Theory of Underreaction, Momentum Trading, and Overreaction in Asset Markets. Journal Of Finance 54, 2143-2184.

Jiang, G.J., Zhu, K.X., 2017. Information Shocks and Short-Term Market Underreaction. Journal of Financial Economics 124, 43-64.

Kumar, A., 2009. Who Gambles in the Stock Market? Journal Of Finance 64, 1889-1933.

Lakonishok, J., Shleifer, A., Vishny, R.W., 1994. Contrarian investment, extrapolation, and risk. Journal Of Finance 49, 1541-1578.

Lam, F.Y.E.C., Wei, K.C.J., 2011. Limits-to-arbitrage, investment frictions, and the asset growth anomaly. Journal of Financial Economics 102, 127-149.

Lee, E., Strong, N., Zhu, Z., 2014. Did Regulation Fair Disclosure, SOX, and Other Analyst Regulations Reduce Security Mispricing? Journal of Accounting Research 52, 733-774.

Lee, S.-C., Lin, C.-T., Yang, C.-K., 2011. The asymmetric behavior and procyclical impact of asset correlations. Journal of Banking & Finance 35, 2559-2568.

Lewellen, J., Shanken, J., 2002. Learning, Asset-Pricing Tests, and Market Efficiency. Journal Of Finance 57, 1113-1145.

Li, X., Luo, D., 2016. Investor Sentiment, Limited Arbitrage, and the Cash Holding Effect*. Review of Finance 21, 2141-2168.

Lie, E., 2005. Operating performance following dividend decreases and omissions. Journal of Corporate Finance 12, 27-53.

Liu, Y., Szewczyk, S.H., Zantout, Z., 2008. Underreaction to Dividend Reductions and Omissions? Journal Of Finance 63, 987-1020.

Livnat, J., Mendenhall, R.R., 2006. Comparing the Post–Earnings Announcement Drift for Surprises Calculated from Analyst and Time Series Forecasts. Journal of Accounting Research 44, 177-205.

Mashruwala, C., Rajgopal, S., Shevlin, T., 2006. Why is the accrual anomaly not arbitraged away? The role of idiosyncratic risk and transaction costs. Journal of Accounting and Economics 42, 3-33.

Mendenhall, Richard R., 2004. Arbitrage Risk and Post-Earnings-Announcement Drift. The Journal of Business 77, 875-894.

Michaely, R., Thaler, R.H., Womack, K.L., 1995. Price Reactions to Dividend Initiations and Omissions: Overreaction or Drift? Journal Of Finance 50, 573-608.

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

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

Ottaviani, M., Sørensen, P.N., 2015. Price Reaction to Information with Heterogeneous Beliefs and Wealth Effects: Underreaction, Momentum, and Reversal. American Economic Review 105, 1-34.

Peng, L., 2005. Learning with Information Capacity Constraints. Journal of Financial and Quantitative Analysis 40, 307-329.

Peng, L., Xiong, W., 2006. Investor attention, overconfidence and category learning. Journal of Financial Economics 80, 563-602.

Pontiff, J., 1996. Costly Arbitrage: Evidence from Closed-End Funds. Quarterly Journal of Economics 111, 1135-1151.

Pontiff, J., 2006. Costly arbitrage and the myth of idiosyncratic risk. Journal of Accounting and Economics 42, 35-52.

Savor, P.G., 2012. Stock returns after major price shocks: The impact of information. Journal of Financial Economics 106, 635-659.

Shleifer, A., Vishny, R.W., 1997. The Limits of Arbitrage. Journal Of Finance 52, 35-55.

Stambaugh, R.F., Yu, J., Yuan, Y.U., 2015. Arbitrage Asymmetry and the Idiosyncratic Volatility Puzzle. Journal Of Finance 70, 1903-1948.

Szado, E., 2009. VIX Futures and options: A Case Study of Portfolio Diversification During the 2008 Financial Crisis. Journal of Alternative Investments 12, 66-85.

Taffler, R.J., Lu, J., Kausar, A., 2004. In denial? Stock market underreaction to going-concern audit report disclosures. Journal of Accounting and Economics 38, 263-296.

Womack, K.L., 1996. Do Brokerage Analysts' Recommendations Have Investment Value? Journal Of Finance 51, 137-167.

Wurgler, J., Zhuravskaya, E., 2002. Does Arbitrage Flatten Demand Curves for Stocks? Journal of Business 75, 583-608.

Yang, J., Zhou, Y., Leung, W.K., 2012. Asymmetric Correlation and Volatility Dynamics among Stock, Bond, and Securitized Real Estate Markets. Journal of Real Estate Finance and Economics 45, 491-521.

Zhong, A., Gray, P., 2016. The MAX effect: An exploration of risk and mispricing explanations. Journal of Banking & Finance 65, 76-90.

Table 1. Summary Statistics and Correlation Table

The table provides time-series averages of cross-sectional summary statistics (Panel A) and correlation coefficients of firms' main characteristics (Panel B). RET is monthly stock return. EXRET is monthly stock returns in excess of the risk-free rate. IMIN (IMAX) is idiosyncratic minimum (maximum) return computed as the minimum (maximum) idiosyncratic daily return within a month from Fama and French (1993)-Carhart (1997) four factor model. For ease of interpretation, we multiply IMIN by -1 (high IMIN indicates more negative idiosyncratic return). BETA is a firm's market beta. SIZE is the log of the firm's market capitalization reported in thousands. 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. TURN is share turnover. IVOL (ISKEW) is idiosyncratic volatility (skewness) computed as the standard deviation (skewness) of the idiosyncratic daily return within a month from Fama and French (1993)-Carhart (1997) four factor model. MIN (MAX) is the minimum (maximum) raw daily return within a month. SUE is IBES-based measure of standardized unexpected earnings derived following Livnat and Mendenhall (2006). The data is from 1964:01 to 2014:12. For SUE, it is from 1984:01 to 2012:12.

	RET	EXRET	IMIN	BETA	SIZE	BEME	MOM	RET(-1)	TURN	IVOL	ISKEW	MIN	MAX	IMAX	SUE
Panel A: Summary Statistics															
MEAN	0.011	0.007	0.038	0.863	11.997	0.869	0.110	0.017	0.893	0.020	0.182	0.046	0.056	0.043	-0.001
STD	0.107	0.107	0.023	0.578	1.686	1.045	0.345	0.115	1.203	0.011	0.751	0.027	0.037	0.029	0.007
Panel B: Correlation Matrix															
RET	1	1.000	-0.035	-0.017	0.001	0.016	0.027	-0.028	-0.010	-0.039	-0.003	-0.027	-0.044	-0.035	0.016
EXRET	1.000	1	-0.035	-0.017	0.001	0.016	0.027	-0.028	-0.010	-0.039	-0.003	-0.027	-0.044	-0.035	0.016
IMIN	-0.035	-0.035	1	0.171	-0.307	-0.020	0.027	0.014	0.283	0.880	-0.205	0.783	0.596	0.694	-0.049
BETA	-0.017	-0.017	0.171	1	0.294	-0.160	0.004	-0.019	0.390	0.203	0.024	0.242	0.220	0.162	0.026
SIZE	0.001	0.001	-0.307	0.294	1	-0.184	0.015	0.013	0.070	-0.337	-0.034	-0.242	-0.234	-0.297	0.080
BEME	0.016	0.016	-0.020	-0.160	-0.184	1	0.048	0.021	-0.076	-0.020	0.008	-0.038	-0.020	-0.012	-0.015
MOM	0.027	0.027	0.027	0.004	0.015	0.048	1	0.014	0.140	0.030	0.004	0.036	0.026	0.024	0.157
RET(-1)	-0.028	-0.028	0.014	-0.019	0.013	0.021	0.014	1	0.115	0.146	0.255	-0.193	0.318	0.218	0.008
TURN	-0.010	-0.010	0.283	0.390	0.070	-0.076	0.140	0.115	1	0.319	0.044	0.271	0.295	0.278	0.024
IVOL	-0.039	-0.039	0.880	0.203	-0.337	-0.020	0.030	0.146	0.319	1	0.152	0.706	0.784	0.908	-0.060
ISKEW	-0.003	-0.003	-0.205	0.024	-0.034	0.008	0.004	0.255	0.044	0.152	1	-0.187	0.353	0.448	-0.009
MIN	-0.027	-0.027	0.783	0.242	-0.242	-0.038	0.036	-0.193	0.271	0.706	-0.187	1	0.487	0.531	-0.038
MAX	-0.044	-0.044	0.596	0.220	-0.234	-0.020	0.026	0.318	0.295	0.784	0.353	0.487	1	0.825	-0.046
IMAX	-0.035	-0.035	0.694	0.162	-0.297	-0.012	0.024	0.218	0.278	0.908	0.448	0.531	0.825	1	-0.056
SUE	0.016	0.016	-0.049	0.026	0.080	-0.015	0.157	0.008	0.024	-0.060	-0.009	-0.038	-0.046	-0.056	1

Table 2. Single Sort – Average Returns and Four-Factor Alphas

The table reports equal and value weighted portfolio returns and Fama and French (1993) - Carhart (1997) four factor alphas sorted by IMIN or IMAX. IMIN (IMAX) is idiosyncratic minimum (maximum) return computed as the minimum (maximum) idiosyncratic daily return within a month from Fama and French (1993) and Carhart (1997) four factor model. The sorting is done using lagged values. The column 'H-L' reports investment strategy that is long high IMIN (IMAX) stocks and short low IMIN (IMAX) stocks. For ease of interpretation, we multiplied IMIN by -1 (high IMIN indicates more negative idiosyncratic return). Newey-West (1987) corrected *t*-statistics with 6 lags are reported in parentheses. *, **, *** represent statistical significance at the 10%, 5%, and 1% levels, respectively. The data is from 1964:01 to 2014:12.

	Low IMIN Lesser Hazard	2	3	4	High IMIN Greater Hazard	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***
	(6.66)	(5.98)	(5.38)	(4.23)	(1.98)	(-3.37)
Carhart4 Alpha	0.24	0.22	0.18	-0.00	-0.53	-0.76***
	(3.91)	(4.29)	(4.10)	(-0.00)	(-7.26)	(-7.19)
Panel B: Value Weighted IMIN Portfolio Returns and Alphas						
Average Return	0.98	1.05	0.98	0.92	0.58	-0.39*
	(5.90)	(5.49)	(4.24)	(3.55)	(1.91)	(-1.88)
Carhart4 Alpha	0.10	0.10	-0.02	-0.09	-0.43	-0.52***
	(2.23)	(2.59)	(-0.35)	(-1.33)	(-4.03)	(-3.81)
Panel C: Equal Weighted IMAX Portfolio Returns and Alphas						
Average Return	1.19	1.36	1.33	1.19	0.56	-0.63***
	(6.40)	(6.29)	(5.38)	(4.37)	(1.80)	(-3.37)
Carhart4 Alpha	0.19	0.28	0.19	0.04	-0.59	-0.78***
	(3.03)	(5.51)	(4.03)	(0.85)	(-7.99)	(-7.28)
Panel D: Value Weighted IMAX Portfolio Returns and Alphas						
Average Return	0.96	1.05	0.97	1.10	0.67	-0.29
	(5.79)	(5.51)	(4.24)	(4.10)	(2.21)	(-1.41)
Carhart4 Alpha	0.09	0.08	0.03	0.08	-0.39	-0.48***
	(2.04)	(2.04)	(0.46)	(1.02)	(-3.79)	(-3.67)

Table 3. Double Sort - Four-Factor Alphas after Controlling for Firms' Characteristics

The table reports equal weighted Fama and French (1993)-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 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 for the characteristic. IMIN is idiosyncratic minimum return computed as the minimum idiosyncratic daily return within a month from Fama and French (1993)-Carhart (1997) four factor model. For ease of interpretation, we multiply IMIN by -1 (high IMIN indicates more negative idiosyncratic return). The other variables are defined in Table 1. Newey-West (1987) corrected t-statistics with 6 lags are reported in parentheses. *, **, *** represent statistical significance at the 10%, 5%, and 1% levels, respectively. The data is from 1964:01 to 2014:12.

	Low IMIN Lesser Hazard	2	3	4	High IMIN Greater Hazard	H - L
BETA	0.22	0.21	0.20	0.02	-0.43	-0.65***
	(3.90)	(4.90)	(4.77)	(0.48)	(-7.79)	(-8.70)
SIZE	0.27	0.22	0.17	-0.04	-0.51	-0.77***
	(3.99)	(3.95)	(3.64)	(-1.06)	(-7.34)	(-6.82)
BEME	0.23	0.21	0.20	0.05	-0.40	-0.63***
	(4.13)	(4.46)	(4.59)	(1.13)	(-6.21)	(-7.13)
MOM	0.26	0.21	0.15	-0.00	-0.45	-0.71***
	(4.76)	(5.11)	(3.63)	(-0.06)	(-6.71)	(-8.21)
RET(-1)	0.22	0.22	0.15	0.04	-0.51	-0.73***
	(4.31)	(5.24)	(3.69)	(0.84)	(-7.93)	(-9.02)
TURNOVER	0.24	0.20	0.14	-0.03	-0.47	-0.71***
	(4.76)	(4.60)	(3.55)	(-0.80)	(-8.16)	(-9.97)
IVOL	0.12	0.04	0.02	0.01	-0.08	-0.20***
	(2.90)	(1.01)	(0.68)	(0.34)	(-1.84)	(-5.60)
ISKEW	0.23	0.24	0.20	0.02	-0.58	-0.80***
	(3.65)	(4.81)	(4.48)	(0.57)	(-7.77)	(-7.37)
MAX	0.07	0.01	-0.04	-0.08	-0.20	-0.28***
	(1.71)	(0.21)	(-1.05)	(-1.84)	(-3.66)	(-4.77)
IMAX	0.18	0.09	0.05	-0.03	-0.18	-0.37***
	(3.89)	(2.18)	(1.45)	(-0.69)	(-4.10)	(-7.36)
MIN	0.22	0.15	0.01	-0.11	-0.52	-0.74***
	(5.29)	(3.74)	(0.35)	(-2.25)	(-9.53)	(-12.81)
SUE	0.27	0.20	0.22	0.13	-0.27	-0.54***
	(3.52)	(2.97)	(3.70)	(2.21)	(-3.37)	(-4.20)

Table 4. Fama and MacBeth (1973) Regressions

The table reports Fama and MacBeth (1973) regression results. IMIN (IMAX) is idiosyncratic minimum return computed as the minimum (maximum) idiosyncratic daily return within a month from Fama and French (1993)-Carhart (1997) four factor model. For ease of interpretation, we multiplied IMIN by -1 (high IMIN indicates more negative idiosyncratic return). NEG_NEWS equals 1 if any of the following events occur in the previous month: dividend cut, dividend omission, analysts downgrades, or downward earnings forecast revision, and 0 otherwise. The other variables are defined in Table 1. All variables are lagged by one month. Newey-West (1987) corrected t-statistics with 6 lags are reported in parentheses. *, **, *** represent statistical significance at the 10%, 5%, and 1% levels, respectively. The data is from 1964:01 to 2014:12 in the first four models and from 1984:01 to 2014:12 in the remaining models.

	1	2	3	4	5	6	7	8
Intercept	0.011***	0.018***	0.020***	0.020***	0.017***	0.020***	0.017***	0.017***
	(6.153)	(3.405)	(4.102)	(4.105)	(3.035)	(3.602)	(3.126)	(3.211)
IMIN	-0.128***	-0.150***	-0.042**	-0.039**	-0.060**	-0.067**	-0.063**	-0.057**
	(-4.992)	(-11.348)	(-2.188)	(-1.993)	(-2.314)	(-2.554)	(-2.407)	(-2.227)
BETA		0.001	0.000	0.000	0.001	0.001	0.001	0.001
		(0.684)	(0.358)	(0.140)	(0.580)	(0.571)	(0.576)	(0.427)
SIZE		-0.001*	-0.001**	-0.001**	-0.000	-0.001*	-0.000	-0.000
		(-1.802)	(-2.336)	(-2.323)	(-0.870)	(-1.679)	(-0.971)	(-1.013)
BEME		0.001**	0.001**	0.001**	-0.001	-0.001	-0.001	-0.001
		(2.151)	(2.012)	(2.074)	(-1.475)	(-1.477)	(-1.450)	(-1.428)
MOM			0.007***	0.007***	0.006***	0.006***	0.006**	0.006***
			(4.552)	(4.590)	(2.799)	(2.755)	(2.582)	(2.634)
RET(-1)			-0.035***	-0.037***	-0.030***	-0.029***	-0.030***	-0.032***
			(-10.231)	(-11.096)	(-6.703)	(-6.505)	(-6.742)	(-7.151)
TURNOVER			0.002***	0.002***	0.001***	0.001***	0.001***	0.001***
			(3.759)	(3.658)	(3.589)	(3.183)	(3.566)	(3.646)
IVOL			-0.165***	-0.256***	-0.112	-0.104	-0.102	-0.244**
			(-3.121)	(-3.574)	(-1.499)	(-1.381)	(-1.360)	(-2.301)
ISKEW			0.001***	0.001***	0.001**	0.001**	0.001**	0.000
			(3.984)	(2.759)	(2.367)	(2.357)	(2.264)	(0.521)
MAX			-0.049***		-0.032***	-0.031***	-0.032***	
			(-7.223)		(-3.203)	(-3.137)	(-3.198)	
IMAX				-0.015				0.021
				(-0.909)				(0.802)
NEG_NEWS					-0.002		-0.002	-0.002
					(-1.476)		(-1.424)	(-1.473)
SUE						0.159***	0.159***	0.158***
						(4.201)	(4.193)	(4.145)
Adj R2	0.014	0.053	0.070	0.070	0.074	0.074	0.075	0.074

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 Fama and French (1993)-Carhart (1997) four factor alphas, respectively, sorted by different lags of IMIN. The column 'H-L' indicates investment strategy that is long high IMIN stocks and short low IMIN stocks. Panel C reports Fama and MacBeth (1973) regression results using different lags of IMIN. IMIN is idiosyncratic minimum return computed as the minimum idiosyncratic daily return within a month from Fama and French (1993)-Carhart (1997) four factor model. For ease of interpretation, we multiplied IMIN by -1 (high IMIN indicates more negative idiosyncratic return). Newey-West (1987) corrected t-statistics with 6 lags are reported in parentheses. *, **, *** represent statistical significance at the 10%, 5%, and 1% levels, respectively. The data is from 1964:01 to 2014:12.

Panel A: Average Return						
Lags	Low IMIN	2	3	4	High IMIN	H - L
1	1.23	1.31	1.32	1.16	0.60	-0.63***
	(6.66)	(5.98)	(5.38)	(4.23)	(1.98)	(-3.37)
2	1.24	1.29	1.26	1.15	0.68	-0.56***
	(6.77)	(6.06)	(5.18)	(4.15)	(2.20)	(-2.95)
3	1.20	1.27	1.23	1.18	0.74	-0.46**
	(6.45)	(5.97)	(5.02)	(4.31)	(2.39)	(-2.47)
6	1.22	1.22	1.20	1.14	0.89	-0.34*
	(6.65)	(5.65)	(5.01)	(4.17)	(2.90)	(-1.86)
9	1.20	1.23	1.20	1.15	0.92	-0.28*
	(6.42)	(5.68)	(5.05)	(4.28)	(3.07)	(-1.65)
12	1.19	1.19	1.22	1.11	1.06	-0.13
	(6.26)	(5.56)	(5.12)	(4.20)	(3.53)	(-0.73)
15	1.19	1.22	1.20	1.17	1.04	-0.15
	(6.32)	(5.69)	(5.04)	(4.44)	(3.49)	(-0.88)
18	(-0.52)	(-0.52)	(-0.52)	(-0.52)	(-0.52)	(-0.52)
	(-0.52)	(-0.52)	(-0.52)	(-0.52)	(-0.52)	(-0.52)
21	1.17	1.18	1.22	1.19	1.10	-0.07
	(6.22)	(5.55)	(5.21)	(4.54)	(3.74)	(-0.41)
24	1.19	1.16	1.21	1.19	1.17	-0.02
	(6.30)	(5.42)	(5.14)	(4.60)	(3.96)	(-0.12)
Panel B: Carhart 4 Alpha						
1	0.24	0.22	0.18	-0.00	-0.53	-0.76***
	(3.91)	(4.29)	(4.10)	(-0.00)	(-7.26)	(-7.19)
2	0.24	0.21	0.12	0.00	-0.46	-0.70***
	(4.06)	(4.28)	(2.66)	(0.05)	(-7.38)	(-7.38)
3	0.19	0.19	0.10	0.04	-0.41	-0.60***
	(3.11)	(3.55)	(2.30)	(0.78)	(-6.11)	(-5.75)
6	0.23	0.14	0.07	-0.01	-0.28	-0.51***
	(4.01)	(2.70)	(1.73)	(-0.21)	(-4.29)	(-5.28)
9	0.21	0.16	0.08	0.01	-0.25	-0.47***
	(3.85)	(3.14)	(1.86)	(0.12)	(-4.07)	(-5.20)

12	0.19	0.12	0.09	-0.03	-0.12	-0.31***
	(3.35)	(2.49)	(2.11)	(-0.81)	(-1.74)	(-3.32)
15	0.18	0.15	0.08	0.02	-0.15	-0.33***
	(3.20)	(3.09)	(1.77)	(0.50)	(-2.46)	(-3.79)
18	0.16	0.14	0.07	0.03	-0.10	-0.26***
	(2.88)	(2.81)	(1.62)	(0.70)	(-1.63)	(-2.98)
21	0.16	0.10	0.11	0.04	-0.10	-0.26***
	(2.96)	(2.07)	(2.53)	(0.82)	(-1.55)	(-3.12)
24	0.18	0.08	0.08	0.03	-0.03	-0.21**
	(3.42)	(1.73)	(1.82)	(0.55)	(-0.47)	(-2.45)

Panel C: Fama and MacBeth (1973) Regressions using "n" lags of IMIN

	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***
	(7.373)	(6.326)	(6.091)	(5.699)	(5.237)	(4.890)	(4.573)	(4.650)	(4.493)	(4.412)	(4.252)
IMIN	-0.143**										
	(-2.270)										
lag_IMIN		-0.115***									
		(-4.659)									
lag2IMIN			-0.088***								
			(-3.278)								
lag3IMIN				-0.075***							
				(-2.799)							
lag6IMIN					-0.047*						
					(-1.747)						
lag9IMIN						-0.038					
						(-1.501)					
lag12IMIN							-0.023				
							(-0.894)				
lag15IMIN								-0.026			
								(-1.009)			
lag18IMIN									-0.015		
									(-0.612)		
lag21IMIN										-0.010	
										(-0.391)	
lag24IMIN											-0.003
											(-0.120)
Adj R2	0.038	0.013	0.013	0.013	0.012	0.011	0.011	0.010	0.010	0.010	0.010

Table 6. Fama and MacBeth (1973) Regressions with Interaction between IMIN and Various Proxies for Underreaction Mechanism

The table reports Fama and MacBeth (1973) regression results using the interaction between IMIN and different proxies (GSVI, Number of Analysts, IU, Bid Ask Spread, Idiosyncratic Volatility, Firm Size, or Institutional Ownership Ratio). IMIN is idiosyncratic minimum return computed as the minimum idiosyncratic daily return within a month from Fama and French (1993)-Carhart (1997) four factor model. For ease of interpretation, we multiplied IMIN by -1 (high IMIN indicates more negative idiosyncratic return). NEG_NEWS equals 1 if any of the following events occur in the previous month: dividend cut, dividend omission, analysts downgrades, or downward earnings forecast revision, and 0 otherwise. The other variables are defined in Tables 1. All variables are lagged by one month. Newey-West (1987) corrected t-statistics with 6 lags are reported in parentheses. *, **, *** represent statistical significance at the 10%, 5%, and 1% levels, respectively. The data is from 1984:01 to 2014:12.

Mechanism	Investor Attention		Information Uncertainty	Limits to Arbitrage			
Proxy	GSVI	# Analysts	IU	Bid-Ask	IVOL	Size	IOR
Intercept	0.005	0.023***	0.017***	0.014***	0.011**	0.024***	0.021***
	(0.876)	(4.098)	(2.963)	(2.674)	(2.066)	(4.181)	(3.697)
IMIN	0.032	-0.089***	0.009	-0.016	0.044	-0.297***	-0.167***
	(0.786)	(-3.171)	(0.307)	(-0.555)	(1.575)	(-3.570)	(-5.357)
Proxy	0.002***	0.000	0.013**	0.016***	0.002	-0.001**	0.001
	(3.237)	(0.831)	(2.431)	(3.131)	(0.020)	(-2.216)	(0.269)
IMIN*Proxy	0.045**	0.003**	-0.632***	-0.203***	-2.690***	0.018***	0.170***
	(2.362)	(2.301)	(-4.519)	(-2.634)	(-4.986)	(2.742)	(3.662)
BETA	0.001	0.001	0.001	0.001	0.000	0.001	0.001
	(0.493)	(0.551)	(0.577)	(0.340)	(0.287)	(0.431)	(0.385)
SIZE	0.000	-0.001**	-0.000	-0.000	-0.000		-0.001*
	(1.162)	(-2.083)	(-1.277)	(-0.772)	(-0.433)		(-1.712)
BEME	-0.001	-0.001	-0.001**	-0.001	-0.001	-0.001	-0.001
	(-1.083)	(-1.295)	(-2.023)	(-1.386)	(-1.264)	(-1.381)	(-1.499)
MOM	-0.001	0.006***	0.005**	0.006***	0.006***	0.005**	0.006***
	(-0.310)	(2.792)	(2.116)	(2.629)	(2.605)	(2.538)	(2.699)
RET(-1)	-0.011*	-0.030***	-0.028***	-0.028***	-0.030***	-0.030***	-0.030***
	(-1.958)	(-6.715)	(-6.285)	(-6.738)	(-6.772)	(-6.795)	(-6.958)
TURNOVER	-0.000	0.001***	0.001***	0.001***	0.001***	0.001***	0.001**
	(-0.140)	(3.296)	(3.170)	(3.559)	(3.680)	(3.314)	(2.264)
IVOL	-0.204	-0.091	-0.068	-0.137**		-0.090	-0.048
	(-1.542)	(-1.214)	(-0.867)	(-2.019)		(-1.183)	(-0.633)
ISKEW	0.001***	0.001**	0.001**	0.001***	0.001***	0.001**	0.001*
	(3.180)	(2.298)	(1.987)	(2.943)	(3.579)	(2.363)	(1.955)
MAX	-0.029**	-0.031***	-0.032***	-0.034***	-0.034***	-0.031***	-0.030***
	(-2.246)	(-3.033)	(-2.776)	(-3.42)	(-3.336)	(-3.129)	(-3.074)
NEG_NEWS	-0.004***	-0.002*	-0.001	-0.002*	-0.002	-0.002	-0.002
	(-8.576)	(-1.764)	(-0.426)	(-1.688)	(-1.491)	(-1.458)	(-1.563)
SUE	0.036	0.158***	0.070**	0.161***	0.159***	0.158***	0.158***
	(0.929)	(4.140)	(2.022)	(4.268)	(4.174)	(4.168)	(4.201)
Adj R2	0.055	0.078	0.074	0.071	0.070	0.070	0.073

Table 7. Information Uncertainty, Limited Investor Attention, or Limits to Arbitrage? Fama and MacBeth (1973) Regressions Results

The table reports Fama and MacBeth (1973) 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, following the spirit of Stambaugh et al. (2015) we create an aggregate rank for limited investor attention (number of analysts and Google SVI), for information uncertainty (from earnings accruals quality measure following Dechow and Dichev (2002) and Francis et al. (2005, 2007), and for limits to arbitrage (bid-ask spread, idiosyncratic volatility, firm size, or institutional ownership 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 for bid-ask spread, IVOL, and in the lowest quintile for firm size and institutional ownership ratio. IMIN is idiosyncratic minimum return computed as the minimum idiosyncratic daily return within a month from Fama and French (1993)-Carhart (1997) four factor model. For ease of interpretation, we multiplied IMIN by -1 (high IMIN indicates more negative idiosyncratic return). NEG_NEWS equals 1 if any of the following events occur in the previous month: dividend cut, dividend omission, analysts downgrades, or downward earnings forecast revision, and 0 otherwise. The other variables are defined in Tables 1. Newey-West (1987) corrected t-statistics with 6 lags are reported in parentheses. *, **, *** represent statistical significance levels at the 10%, 5%, and 1% levels, respectively. The data is from 1984:01 to 2014:12.

	1	2	3	4	5
Intercept	0.010***	0.003	0.003	0.003	0.003
	(3.802)	(1.119)	(1.203)	(1.120)	(1.206)
IMIN	-0.076***	-0.026	-0.025	-0.024	-0.023
	(-4.933)	(-0.933)	(-0.909)	(-0.865)	(-0.828)
IMIN**ATTN_low*		0.024	0.023	0.028	0.026
		(0.881)	(0.833)	(1.024)	(0.976)
IMIN**IU_high*		-0.043***	-0.042***	-0.043***	-0.042***
		(-2.945)	(-2.902)	(-2.907)	(-2.862)
IMIN**LIMIT2ARB_high*		-0.060***	-0.058***	-0.060***	-0.059***
		(-4.017)	(-3.871)	(-4.041)	(-3.895)
ATTNR_low	0.000	0.000***	0.000***	0.000***	0.000***
	(0.557)	(2.709)	(2.635)	(3.477)	(3.383)
IU_high	-0.000**	-0.000	-0.000	-0.000	-0.000
	(-2.301)	(-1.270)	(-1.229)	(-1.247)	(-1.207)
LIMIT2ARB_high	-0.000	0.000	0.000	0.000*	0.000
	(-0.135)	(1.642)	(0.469)	(1.656)	(0.444)
BETA		0.001	0.001	0.001	0.001
		(0.517)	(0.442)	(0.542)	(0.462)
SIZE		-0.001***	-0.001***	-0.001***	-0.001***
		(-2.839)	(-2.861)	(-2.667)	(-2.690)
BEME		-0.001*	-0.001*	-0.001*	-0.001*
		(-1.779)	(-1.737)	(-1.746)	(-1.706)
MOM		0.006***	0.006***	0.005**	0.005**
		(2.665)	(2.707)	(2.411)	(2.457)
RET(-1)		-0.028***	-0.030***	-0.029***	-0.031***
		(-5.983)	(-6.427)	(-6.236)	(-6.690)
TURNOVER		0.001**	0.001**	0.001**	0.001**
		(2.243)	(2.279)	(2.502)	(2.533)
IVOL		-0.045	-0.187	-0.032	-0.180
		(-0.515)	(-1.475)	(-0.373)	(-1.418)
ISKEW		0.001**	0.000	0.001**	0.000
		(2.450)	(0.434)	(2.253)	(0.252)
MAX		-0.027**		-0.029**	
		(-2.323)		(-2.484)	
IMAX			0.029		0.029
			(0.892)		(0.905)
NEG_NEWS				-0.001	-0.001
				(-0.788)	(-0.809)
SUE				0.063*	0.063*
				(1.879)	(1.859)
Adj R2	0.028	0.090	0.090	0.093	0.092

Table 8. Information Uncertainty, Limited Investor Attention, and Limits to Arbitrage in the Pre- and Post-2001

The table reports Fama and MacBeth (1973) 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*). Panel B and C report results for the periods of pre- and post-decimalization following the framework of Chordia, Subrahmanyam, and Tong (2014). IMIN is idiosyncratic minimum return computed as the minimum idiosyncratic daily return within a month from Fama and French (1993)-Carhart (1997) four factor model. ease of interpretation, we multiplied IMIN by -1 (high IMIN indicates more negative idiosyncratic return). NEG_NEWS equals 1 if any of the following events occur in the previous month: dividend cut, dividend omission, analysts downgrades, or downward earnings forecast revision, and 0 otherwise. The other variables are defined in Tables 1. Newey-West (1987) corrected t-statistics with 6 lags are reported in parentheses. *, **, *** represent statistical significance levels at the 10%, 5%, and 1% levels, respectively. The data is from 1984:01 to 2014:12.

	Panel A. Pre- 2001 (1984-2000)					Panel B. Post- 2001 (2001-2014)				
	1	2	3	4	5	1	2	3	4	5
Intercept	0.014***	0.007**	0.008**	0.007*	0.007*	0.006*	-0.003	-0.002	-0.002	-0.002
	(3.460)	(2.055)	(2.103)	(1.873)	(1.926)	(1.770)	(-0.811)	(-0.733)	(-0.575)	(-0.499)
IMIN	-0.086***	-0.074**	-0.071**	-0.074**	-0.070**	-0.064***	0.033	0.031	0.037	0.035
	(-3.811)	(-2.304)	(-2.236)	(-2.289)	(-2.230)	(-3.235)	(0.752)	(0.687)	(0.833)	(0.787)
IMIN**ATTN_low*		0.067	0.066	0.072	0.072		-0.029	-0.031	-0.027	-0.029
		(1.498)	(1.484)	(1.633)	(1.622)		(-1.407)	(-1.526)	(-1.280)	(-1.402)
IMIN**IU_high*		-0.048**	-0.047**	-0.047**	-0.047**		-0.037*	-0.036*	-0.036*	-0.036*
		(-2.362)	(-2.319)	(-2.333)	(-2.293)		(-1.772)	(-1.754)	(-1.746)	(-1.723)
IMIN**LIMIT2ARB_high*		-0.079***	-0.079***	-0.079***	-0.078***		-0.036**	-0.033**	-0.038***	-0.035**
		(-3.305)	(-3.257)	(-3.231)	(-3.182)		(-2.514)	(-2.283)	(-2.711)	(-2.476)
ATTN_low	0.000	0.000	0.000	0.000	0.000	0.000	0.000***	0.000***	0.000***	0.000***
	(0.095)	(0.754)	(0.714)	(1.318)	(1.259)	(0.805)	(5.405)	(5.464)	(6.052)	(6.111)
IU_high	-0.000**	-0.000	-0.000	-0.000	-0.000	-0.000	0.000	0.000	0.000	0.000
	(-2.421)	(-1.631)	(-1.600)	(-1.596)	(-1.563)	(-0.883)	(0.072)	(0.093)	(0.073)	(0.090)
LIMIT2ARB_high	-0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(-1.126)	(0.721)	(0.099)	(0.835)	(0.173)	(1.185)	(1.579)	(0.522)	(1.475)	(0.425)
BETA		0.002	0.002	0.002	0.002		-0.000	-0.001	-0.000	-0.001
		(0.820)	(0.749)	(0.836)	(0.761)		(-0.192)	(-0.213)	(-0.170)	(-0.196)
SIZE		-0.001	-0.001	-0.001	-0.001		-0.002***	-0.002***	-0.002***	-0.002***

		(-1.043)	(-1.056)	(-1.035)	(-1.049)		(-3.646)	(-3.670)	(-3.295)	(-3.321)
BEME		-0.001	-0.001	-0.001	-0.001		-0.001	-0.001	-0.001	-0.001
		(-1.565)	(-1.544)	(-1.518)	(-1.503)		(-0.898)	(-0.860)	(-0.903)	(-0.86)
MOM		0.010***	0.010***	0.009***	0.009***		0.000	0.000	-0.000	-0.000
		(3.948)	(3.966)	(3.600)	(3.625)		(0.039)	(0.072)	(-0.036)	(-0.005)
RET(-1)		-0.036***	-0.038***	-0.037***	-0.039***		-0.019***	-0.020***	-0.020***	-0.021***
		(-5.212)	(-5.659)	(-5.386)	(-5.827)		(-3.241)	(-3.478)	(-3.445)	(-3.705)
TURNOVER		0.002***	0.002***	0.002***	0.002***		-0.000	-0.000	0.000	0.000
		(2.829)	(2.798)	(2.945)	(2.907)		(-0.303)	(-0.206)	(0.030)	(0.128)
IVOL		-0.030	-0.093	-0.022	-0.090		-0.062	-0.303	-0.045	-0.291
		(-0.251)	(-0.613)	(-0.182)	(-0.594)		(-0.515)	(-1.444)	(-0.370)	(-1.379)
ISKEW		0.001*	0.000	0.001	0.000		0.001*	-0.000	0.001	-0.000
		(1.754)	(0.767)	(1.624)	(0.621)		(1.689)	(-0.231)	(1.541)	(-0.351)
MAX		-0.035**		-0.036**			-0.018		-0.020	
		(-2.122)		(-2.207)			(-1.097)		(-1.244)	
IMAX			-0.013		-0.011			0.079		0.079
			(-0.314)		(-0.280)			(1.592)		(1.577)
NEG_NEWS				0.002	0.002				-0.005***	-0.005***
				(1.017)	(1.012)				(-8.177)	(-8.196)
SUE				0.122***	0.121***				-0.008	-0.007
				(2.929)	(2.883)				(-0.162)	(-0.138)
Adj R2	0.031	0.094	0.094	0.096	0.096	0.025	0.085	0.085	0.088	0.088

Table 9. Arbitrage Asymmetry and Hazard Stock Returns

The table reports equal weighted portfolio returns from an independent bivariate sort by Mispricing Score and IMIN. Mispricing Score is by Stambaugh, et al. (2015). The sorting is done using lagged values. The column 'H-L' reports raw and Fama and French (1993)-Carhart (1997) four factor alphas from the investment strategy that is long high IMIN stocks and short low IMIN stocks. IMIN is idiosyncratic minimum return computed as the minimum idiosyncratic daily return within a month from Fama and French (1993)-Carhart (1997) four factor model. For ease of interpretation, we multiplied IMIN by -1 (high IMIN indicates more negative idiosyncratic return). Newey-West (1987) corrected *t*-statistics with 6 lags are reported in parentheses. *, **, *** represent statistical significance at the 10%, 5%, and 1% levels, respectively. The data is from 1965:07 to 2014:12.

						High-Low IMIN	
	Low IMIN: Lesser Hazard				High IMIN: Greater Hazard	Raw Return	4-FF Alpha
Most Underpriced	1.41	1.56	1.77	1.79	1.51	0.10	-0.15
	(7.73)	(7.42)	(7.61)	(6.98)	(5.23)	(0.60)	(-1.24)
2	1.33	1.45	1.52	1.49	1.16	-0.17	-0.38***
	(7.18)	(6.72)	(6.37)	(5.62)	(3.99)	(-1.05)	(-3.50)
3	1.22	1.32	1.37	1.37	1.00	-0.22	-0.45***
	(6.76)	(6.09)	(5.48)	(5.02)	(3.38)	(-1.22)	(-3.78)
4	1.09	1.17	1.15	1.10	0.75	-0.34*	-0.51***
	(5.70)	(5.00)	(4.52)	(3.83)	(2.36)	(-1.73)	(-4.19)
Most Overpriced	0.90	0.84	0.85	0.54	-0.07	-0.97***	-1.02***
	(4.26)	(3.28)	(2.95)	(1.71)	(-0.21)	(-4.44)	(-7.57)

Table 10. Hazard Stocks Anomaly and Regulation SHO

The table reports the results from difference-in-difference analysis in Eqs. (4) and (5):

$$r_{it} = \gamma_t + \beta Pilot_i \times During_t + \beta_1 Pilot_i + \varepsilon_{it} , \tag{4}$$

$$r_{it} = \gamma_t + \beta Pilot_i \times During_t + \beta_1 Pilot_i + \beta_2 Pilot_i \times Post_t + \varepsilon_{it}. \tag{5}$$

Results from Eq. (4) are reported in models (1), (3), and (5). Results from Eq. (5) are reported in models (2), (4), and (6). The dependent variable is gross-return-weighted, equal-weighted, and value-weighted returns on high-minus-low IMIN portfolios in Panels A, B, and C, respectively. $Pilot_i$ is an indicator equal to 1 if portfolio i is formed on pilot firms, and zero otherwise. $During_t$ is an indicator equal to 1 if month t is between July 2005 and June 2007. $Post_t$ is indicator equal 1 if month t is after August 2007 and zero otherwise. γ_t denotes time fixed effects (estimates are not reported in the table below). Expected sign as predicted in Chu et al. (2020) in Hypotheses 1 and 3. The sample consists of nonpilot and pilot stocks from the SEC's Reg SHO program and based on 2004 June Russell 3000 stocks excluding NASDAQ stocks. The sample period is from 1984:01 to 2007:06 in models (1), (3), and (5), and from 1984:01 to 2014:12 in models (2), (4), and (6). The following months are dropped from the sample: May and June 2005, and July and August 2007. Robust t-statistics are presented in parentheses. *, **, *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

		Dependent Variable: Returns on High-Low IMIN Portfolios					
	Expected Sign	Panel A: Gross-return-weighted		Panel B: Equal-weighted		Panel C: Value-weighted	
		Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)
Pilot_During(β)	Positive	0.973**	0.973**	1.060**	1.060**	1.081**	1.081**
		(2.090)	(2.089)	(2.320)	(2.319)	(2.436)	(2.435)
Pilot		0.061	0.061	-0.004	-0.004	-0.005	-0.005
		(0.292)	(0.292)	(-0.017)	(-0.017)	(-0.024)	(-0.024)
Pilot_Post(β_2)	Insignificant		0.354		0.399		0.348
			(0.852)		(1.013)		(0.891)
Constant		0.072	-0.034	0.118	-0.007	0.097	-0.017
		(0.524)	(-0.280)	(0.873)	(-0.062)	(0.734)	(-0.146)