Salient or Safe: Why do Predicted Stock Issuers Earn Low Returns?

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Abstract

Predicted stock issuers (PSIs) are firms with *expected* "high-investment and low-profit" (HILP) profiles that earn unusually low returns. We carefully document important features of PSI firms to provide new insights on the economic mechanism behind the HILP phenomenon. Our results show top-PSI firms are cash-strapped and dependent on external financing, and have lottery-like payoffs, high volatility, high Beta, and high shorting costs. Over the next two years, top-PSIs earn return-on-assets of -30% per year, report disappointing earnings, and experience strongly-negative analyst forecast revisions. They earn especially low returns in down markets and are nine times more likely to delist for performance reasons. We conclude that HILP firms earn low returns not because they safe, but because they are more salient to investors and are thus overpriced.

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1. Introduction

Studies in accounting and finance have reported many firm characteristics that predict cross-sectional stock returns. Two particularly noteworthy variables from recent literature are *profitability* and *investment*. Many studies show that "high-investment and low-profitability" (HILP, pronounced "help") firms earn low future returns, while firms with "low-investment and high-profitability" (LIHP) profiles earn high future returns.[1] Furthermore, these two attributes pair up well in time-series regressions, such that returns to their factor portfolios parsimoniously capture the monthly variation in returns for many other pricing anomalies. This last finding has given rise to asset pricing models that prominently feature *profitability* and *investment* as new risk factors (e.g., Hou, Xue, Zhang 2015a and 2015b; Fama and French 2015a, 2015b).[2]

While the predictive power of *profitability* and *investment* seems clear, the economic rationale for including them in asset pricing models is far less so. A large fundamental analysis literature in accounting, traceable back to Graham and Dodd (1934), advocates investing in profitable firms with high shareholder payouts and stable growth trajectories. If more profitable firms with high payouts (i.e., lower investment) are, ceteris paribus, "safer," why do they generate *higher* equilibrium returns? Conversely, if less profitable (or even loss-making) firms

[1] See Fairfield, Whisenant, and Yohn (2003), Titman, Wei, and Xie (2004), Hirshleifer, Hou, Teoh, and Zhang (2004), Richardson, Sloan, Soliman, and Tuna (2005), Cooper, Gulen, and Schill (2008), Xing (2008), Polk and Sapienza (2009), Hirshleifer and Jiang (2010), and Li and Sullivan (2015) for the investment effect, and Bernard and Thomas (1990), Haugen and Baker (1996), Piotroski (2000), Fama and French (2006), Novy-Marx (2013), Wang and Yu (2013), Lam et al. (2015), and Liu (2015) for the earnings, or profitability, effect.

[2] Hou et al. (2015a; HXZ) presents a *q*-factor model featuring the market factor, a size factor, an investment factor, and a profitability factor. They show these four factors largely summarize the cross-section of average stock returns, rendering about one-half of 80 market anomalies insignificant in the cross section. Fama and French (2015a) presents a five-factor model (FF-5), with four factors that are similar to those in Hou et al. (2015a), plus a value factor (based on the book-to-price ratio). Fama and French (2015b) show this five-factor model also digests many anomalies. Hou et al. (2015b) argues that the HXZ model is superior to the FF-5 model on conceptual as well as empirical grounds.

with higher investment are, as a group, "riskier," why do these firms earn *lower* equilibrium returns?

The answers to these questions have important ramifications for both the accounting and finance literature. With an exponential increase in the number of anomaly variables, the credibility of new "risk factors" cannot be based purely on their ability to explain return co-movements. Instead, researchers need to "closely scrutinize the theoretical plausibility and empirical evidence in favor or against their economic mechanism" (Kogan and Tian 2015, p.23). This is especially important in the case of *profitability* and *investment*, where the main empirical results seem to run counter to common intuition.[3]

In this study, we empirically evaluate the proposition that "high-investment-low-profitability" (HILP) firms earn lower returns not because they are "safer," but because they are more "salient" investments. A large literature in behavioral economics has examined the effect of signal saliency and statistical reliability on the proclivity of individuals to over- and under-weight individual signals. Following the lead of psychologists (e.g., Kahneman and Tversky 1974, Tversky and Kahneman 1992, and Griffin and Tversky 1992), economists have observed a broad tendency for investors to over-weight signals that are more salient or attention grabbing (e.g., Barber and Odean 2008, Hirshleifer et al. 2009, Da et al. 2011, Bordalo, Gennaioli, and Shleifer 2012, 2013a,b), and under-weight signals that are statistically reliable but less salient (e.g., DellaVigna and Pollet 2009, Gleason and Lee 2003, Giglio and Shue 2014, Cohen and Lou 2012, and Cohen et al. 2013). We posit that HILP stocks are salient (more "glamourous") firms

[3] These two new factors are unique in one other dimension. Unlike prior asset pricing factors, the sort variables for these two factors do not depend on stock prices or past returns. Both *profitability* and *investment* are pure accounting-based constructs. It seems sensible, therefore, to look for corroborating accounting-based evidence from firm characteristics and operating performance, in addition to return correlations, when trying to understand the economic driver behind these factors.

that are prone to overpricing, and that their lower future returns at least partially reflect a correction of this mispricing.

We investigate this hypothesis by developing a predictive model for future stock issuance. This research design is motivated by two important observations. First, there exists a direct link between firms' propensity to issue (repurchase) stock, and their expected profitability and investment profile. We show through a simple accounting identity that the combination of high *investment* and low *profitability* (HILP) will invariably give rise to a need for new capital (see Section 2.2 for details). Therefore, firms that are predicted stock issuers (PSIs) are precisely the *expected* HILP firms called for in asset pricing tests. It follows that, by carefully documenting the most important features of firms that make up the top-decile PSI portfolio, we will have the opportunity to gain considerable insight into the nature of the HILP anomaly, as well as the economic mechanism that drives this phenomenon.

Second, predicted stock issuers (PSIs) are also invariably salient. This is because they will engage the capital market by necessity and, in so doing, elevate their profile among investors. Empirically, we show top-decile PSI firms depend critically on future financing to fund their high expected investments in the face of negative internally-generated cash flows. Over the next several years, despite incurring large losses, top PSI firms still manage to substantially grow their assets, by issuing large amounts of new equity. Therefore, these firms should fit the profile of the attention-grabbing stocks described in the behavioral literature on saliency (in particular, Bordalo, Gennaioli, and Shleifer 2012 and 2013b).

Using financial data available from prior periods, we estimate a statistical model that identifies, ex ante, firms with a high propensity to issue stock in the future. Specifically, we compute a "predicted stock issuance" or "PSI" score for each firm based on five lagged firm characteristics: profitability, stock issuances, price momentum, book-to-market, and firm size. The resulting model projects these five firm characteristics onto the likelihood that it will issue stock in the next 12-months. We then sort firms into portfolios by their PSI-score and examine future PSI-based portfolio returns, operating performance, and risk characteristics. All financial data for PSI estimation are available prior to the portfolio formation date, so PSI scores are ex ante and contain no peek-ahead bias. In investing parlance, this is a "tradeable" strategy.

We show this simple model explains a significant portion (over 30%) of the cross-sectional variation in stock issuance over the next 12-months.[4] As expected, future issuance is negatively correlated with past profitability (*ROA*) and positively correlated with past stock issuance (*si*). In addition, firms with smaller market capitalization (*lnsize*), higher market-to-book ratios (*mb*), and more positive price momentum (*mom*) are more likely to issue stock. The estimated coefficients for these variables are quite stable over a 40-year sample period (1972 to 2011). The model is also effective in predicting stock issuances out-of-sample. On average, 66.2% of the firms in the top Predicted Stock Issuance (PSI) decile have positive stock issuance in the next 12-months, compared to just 13.4% of the firms in the bottom PSI decile.

More importantly, we show PSI is an excellent predictor of future investment and profitability. A key research design challenge in asset pricing is how to measure *expected* investment and earnings.[5] Our results show the PSI score finesses this problem. Over the next three years, bottom-PSI firms earn average ROAs of +4.5% to +6.1% per year, while top-PSI

[4] We define the amount of stock issuance, *si*, as the total equity issued minus dividends and repurchases, all divided by total assets. See Appendix 1 for details.
[5] Fama and French (2015a, p.2) formulate the Miller and Modigliani (1961) model in terms of expected earnings and investment, and state: "The research challenge posed by [the Miller and Modigliani (1961) model] has been to identify proxies for expected earnings and investments." In an earlier study, Fama and French (2006) attempt to predict future profitability and future asset growth, but find neither predicted variable is robustly related to future returns (see their Table 3). Interestingly, their in-sample R^2 for predicting investment is never above 0.20 (see their Table 2), while our average in-sample R^2 for predicting stock issuance is above 0.30.

firms log remarkably negative ROAs that average -29.4% to -31.4% per year. And while they are incurring these losses, these same top-PSI firms continue to grow total assets at +14.5% to +22.9% per year.[6] As expected, top-PSI firms achieve these high investment rates by issuing much more equity than bottom-PSI firms. In fact, we find that PSI deciles rank-order firms' future *investment* and *profitability* better than various blended measures of the same firms' current profitability and current investment.

Having established PSI as a good proxy for future HILP firms, we proceed to evaluate the "safer" versus the more "salient" explanation for the HILP puzzle. First, we document the risk and return profiles of the PSI-decile firms, and examine their return correlation with factors in the new asset pricing models. We recognize, however, that it is notoriously difficult to distinguish between these explanations on return evidence alone. Therefore, we further conduct an extensive set of ancillary (i.e. non-return-based) tests where the rational-pricing-based ("top-PSIs are safer") explanation makes sharply different predictions from the behavioral-based ("top-PSIs are more salient") explanation.

We find that top-decile PSI stocks are not "safer" by most conventional risk metrics, yet they earn low returns. Top-PSI firms are much smaller than bottom-PSI firms (average market capitalization of 245 million versus 2.945 billion); they have higher Beta (1.05 versus 0.86), more volatile daily returns (0.054 versus 0.026), and lower institutional ownership (20.7% versus 46.5%). At the same time, these top-PSI stocks earn significantly lower returns. In the next three post-formation years, annual returns to Top-PSI stocks average 9.1% to 10.4% lower than bottom-PSI stocks. In fact, over our 36-year sample period (1978-2013), returns to top-PSI stocks are statistically indistinguishable from ten-year Treasury yields. We observe these low

[6] We follow the recent asset pricing literature in defining *investment* in terms of annual percentage growth in total assets (e.g., Fama and French 2015a, and Hou et al. 2015a).

returns among future issuers (i.e. top-PSI firms that actually issue equity in year $t + 1$) as well as non-issuers (top-PSI firms that do not issue equity in year $t + 1$). Value-weighting rather than equal-weighting the portfolio makes little difference.[7]

We also examine monthly returns to PSI-based hedge portfolios after controlling for standard asset pricing factors. The alphas from both the value-weighted and equal-weighted versions of the PSI-hedge portfolio easily survive the CAPM and FF-3 control variables. As expected, PSI-based returns load heavily on *profitability* and *investment* in the new models. After controlling for the Fama-French (2015a; FF-5) factors, monthly excess return to the PSI-hedge portfolio drops by half (to 44 basis points per month), but remains significant. After controlling for the Hou et al. (2015a) factors, excess return to the PSI hedge portfolio drops to 37 basis points per month and is insignificant (t-stat of 1.69). Overall, these results show that monthly PSI returns closely track the returns on these two factors, and that most, if not all, of PSI's predictive power is attributable to its correlation with *profitability* and *investment*.

To recap the evidence so far, we show that: (a) top-PSI firms fit the high-investment-low-profit (HILP) profile, (b) they earn exceptionally low returns, (c) their monthly returns are largely explained by *profitability* and *investment* factors, and (d) they do not seem especially safe (i.e., they are smaller, have higher Beta, greater volatility, and lower institutional holdings). Although these findings are broadly consistent with a mispricing-based story, it is difficult to

[7] A significant literature (e.g., Masulis and Korwar, 1986; Spiess and Affleck-Graves, 1995; Loughran and Ritter, 1997; Eckbo, Masulis, and Norli, 2000; Brav, Geczy, and Gompers, 2000; Bessembinder and Zhang, 2013) documents a seasoned equity offering (SEO) puzzle, whereby SEO stocks earn abnormally low subsequent returns. Our analysis is related to, but distinct from, these studies. First, whereas these studies anchor on the SEO event itself, we develop an ex ante measure of issuer-like firms. Second, our results show that top-PSI firms earn low returns, whether or not they actually issue equity next year (i.e. whether or not they enter the SEO sample). This finding suggests the SEO effect is part of a broader phenomenon involving stocks that fit the PSI profile. Finally, we extend prior SEO studies by linking the two new asset pricing factors, *profitability* and *investment*, to the behavioral explanations suggested by prior literature.

reject a rational-pricing explanation on the basis of return-based evidence alone. We therefore turn to other ancillary (largely non-return-based) tests.

First, we document the future operating performance of extreme PSI-decile firms. If top-PSI firms are overpriced "glamour" stocks, we should see little or no improvement in their operating performance over time. Conversely, if they are "safer" firms with positive NPV projects, as suggested by *q*-theory, we should see appreciable performance improvement over time. Our results show top-PSI firms do not earn a profit in the post-formation years even before interest, taxes, and depreciation and amortization expenses. Bottom-PSI firms earn +16.1% and +14.9% in EBITDA (expressed as a percentage of total assets) over the next two years, while top-PSI firms earn -20.8% and -19.1%. Furthermore, top-PSI firms face serious cash-shortages, and most will need additional financing to continue functioning as going concerns, even if they do not increase their capital expenditures.[8] In addition, we find 7.7% of the top-decile PSI firms will delist for performance reasons in year t+1, compared to 0.8% of the bottom-decile PSI firms. In sum, top-PSI firms are cash-strapped, have extremely negative future earnings, and are almost ten times more likely to delist. These firms are not safe investments.

Second, we evaluate the performance of extreme-PSI stocks during down markets. A rational reason top-PSI firms earn low returns is that they perform particularly well in bad states of the world, thus offering investors a hedge when the marginal utility of consumption is high. In contrast, saliency theory (Bordalo, Gennaioli, Shleifer 2012, 2013b; BGS) predicts that stocks with lottery-like payoffs will exhibit pro-cyclical returns, and underperform in down markets.

[8] We follow DeAngelo et al. (2010) in computing pro forma cash holdings, assuming no new debt or equity financing. Although top-PSI firms begin with larger cash reserves, we find that 34.7% (51.9%) of these firms would run out of cash by the end of year t+1 (t+2) without new financing. Even if we assume no new capital expenditures, the pro forma cash balance for a typical top-PSI firm turns negative by the end of year t+2. The median cash deficit for such firms is -20% of total assets, indicating a dire need for future financing.

We define down markets several different ways, and in each case, we find that the top-PSI portfolio performs much worse than the bottom-PSI portfolio in bad states of the world. These firms are not useful hedges against bad states of the world. In fact, as predicted by BGS, their “saliency weights” appear to turn negative in bad states of the world, leading to especially poor performances.

Third, we examine the ability of PSI to forecast the direction of firms’ future cash flow shocks. An empirical link between a firm’s PSI score and its future cash flow shocks is important in separating out “safety-based” from “saliency-based” explanations. If a rationally-established discount rate is the primary reason for the low returns earned by top-PSI firms, PSI should not predict the direction of firms’ future cash flow shocks. Conversely, if PSI predicts future returns largely because it captures market mispricing, then firms with higher (lower) PSI should report, on average, more (less) disappointing future earnings. Relatedly, if analysts’ earnings expectations are too optimistic for top-PSI firms, we should also observe more negative subsequent analyst forecast revisions for these firms. Finally, if investors’ earnings expectations for top-PSI firms are also too high, we should see more negative short-window returns around future earnings news release dates for these firms.

Our findings strongly support all these predictions of BGS’s saliency theory. First, we find that over the next eight post-formation quarters, the average two-day announcement return for the top- (bottom-) decile PSI firm is -0.735% (+0.255%). In other words, focusing solely on the two-day earnings news release window, bottom-PSI firms outperform top-PSI firms by almost 1% per quarter for each of the next eight quarters. We find similar results for analyst forecast errors (*FE*) and future analyst estimate revisions (*REV*). As predicted, top-PSI firms have much more negative forecast revisions (*REV*) and forecast errors (*FE*) in the post-formation period. These results are robust to industry and year fixed effects, controls for momentum, size, and market-to-book ratios, as well as double-clustering of the errors. In each test, future earnings for top-PSI (i.e., expected-HILP) firms are more negative and more disappointing, suggesting their ex ante earnings expectations were too optimistic.

Finally, we test a long-standing prediction of both saliency theory and cumulative prospect theory. A key feature of these theories is that investors behave as if they overweight tail probabilities, leading to overvaluation of firms with a small likelihood of high returns, also known as "lottery-like" stocks (e.g. Barberis and Huang, 2008; Eraker and Ready, 2015; Gao and Lin, 2015). We examine the return distribution of top-PSI firms and show that it is indeed much more fat-tailed (i.e. lottery-like) when compared to the return distribution for bottom-PSI firms. We also show that "post-formation period" return distribution for top-PSI firms is shifted to the left of (and is stochastically dominated by) their "pre-formation period" returns. In other words, top-PSI firms perform much better in the two years prior to portfolio formation than they do in the two years after formation. If some investors use firms' pre-formation return distribution to select stocks, we would reasonably expect these firms to be overpriced relative to bottom-PSI firms.

Finally, to complete the mispricing story, we investigate top-PSI firms face higher shorting costs. Using the Beneish, Lee, and Nichols (2015) algorithm and detailed Markit Data Explorer (DXL) security lending market data, we document how often short sale constraints are binding for firms in each PSI decile. Our results show that while only 6% of the bottom-PSI firms are on "special" (i.e. are hard-to-borrow), a full 38% of the top-PSI firms are "special." Once again, our evidence is consistent with top-PSI firms being overpriced, but the rational arbitrageurs that seek to profit from the overpricing having to absorb elevated shorting costs.

In sum, we exploit a simple accounting identity that directly links HILP firms to firms that are expected to issue equity. We show, both analytically and empirically, that predicted stock issuers (PSIs) are precisely the *expected* HILP firms called for in asset pricing tests. By carefully studying the most important features of firms that make up the top-decile PSI portfolio, we show these *expected* HILP firms are unlikely to be "safer," as this term is commonly understood in the investment world. Instead, they exhibit many of the characteristics of the most "salient" stocks that the behavioral literature suggests are most prone to overvaluation.

Taken together, these results bring into question the standard rationale for including *profitability* and *investment* in asset pricing models. For a firm characteristic to be a risk proxy, it is important not only that its intertemporal payoffs co-vary with payoffs from other pricing anomalies; it is also important that the average payoff has the right sign. Although the monthly returns to top-PSI (i.e., *expected* HILP) firms are correlated with returns from other anomalies, *the sign of the "risk premium" is wrong*. By many measures, top-PSI (bottom-PSI) firms are riskier (safer), but earn lower (higher) returns. In the quest to better understand the economic drivers behind *profitability* and *investment*, our results point to mispricing-based explanations as a potentially more fruitful venue for future research than risk-based explanations.

Viewed more broadly, our results suggest future investigations into the state variables that impact "risk factors" might be better focused on frictions in the market for active arbitrage, rather than on macroeconomic fundamentals. A number of recent studies highlight the role of funding constraints faced by active investors (i.e., limitations in the availability of arbitrage capital) as an important driver of returns. A key finding is that payoffs to factor-based portfolios are correlated with funding or financing problems in the world of active investing. When active investors are facing funding constraints, many of these factors underperform.[9] Our results are broadly consistent with the findings from these studies. Specifically, our evidence suggests arbitrage constraints may help explain periods of high or low returns earned by the PSI-hedge portfolio.

Our study is related, and complementary, to a recent study by Stambaugh and Yuan (2017; here after SY), who develop two "mispricing factors" by aggregating information across 11 prominent anomalies.[10] While both studies entertain the possibility of mispricing factors, our work is distinct from SY in several important respects. First, SY's factors are an amalgamation of additional pricing anomalies, while we derive PSI by linking firms' predicted equity issuance to existing factors (*investment* and *profitability*). Second, the research focus in SY is on comparing the explanatory power of their factors to those of existing factors. In contrast, our focus is on evaluating the rational pricing vs. systemic mispricing explanations by taking a deeper dive into HILP firms. Third, we make a direct conceptual link between two existing "risk factors" and the behavioral literature on saliency. Finally, our results show that the risk premium on two existing factors have the wrong sign – i.e., the safer firms are, on average, earning *higher* returns. This finding has important implications for other anomaly-based pricing factors, include those developed by SY.

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[9] Theoretical models of this phenomenon include He and Krishnamurthy (2013), Cespa and Foucault (2014), and Brunnermeier and Pedersen (2009). The key idea is when arbitrage capital is scarce, active investors face deleveraging risk, which can cause their otherwise unrelated strategies (e.g., value, momentum, profitability, investment, event-arbitrage, and foreign exchange carry trades) to simultaneously underperform. Empirical studies have used different proxies to measure the tightness in funding constraints. For example, Hu, Pan, and Wang (2013) develop a market-wide measure for available arbitrage capital based on the observed "noise" in the pricing of U.S. Treasury bonds. They show this variable helps to explain hedge fund performance and the profitability of currency carry trades. Other measures of tightness in funding constraints include: the price impact of equity trades (Sadka, 2006; Pastor and Stambaugh, 2003); the amount of leverage on the books of securities broker-dealers (Adrian, Etula, and Muir, 2013); and the spread of overnight interbank loans (Nyborg and Ostberg, 2014). See Lee and So (2015, Chapter 5) for a summary of the arbitrage cost literature, including a discussion of funding constraints faced by active asset managers.

[10] The SY factors are the average rankings of firms within two anomaly clusters exhibiting the greatest return co-movement.

2. Hypothesis Development

2.1 Rational Pricing vs. Systemic Mispricing

Fama and French (2015a) and Hou, Xue, and Zhang (2015a) show that profitability and investment largely summarize the cross-section of stock returns. In motivating the inclusion of *investment* and *profitability* in their asset pricing models, both studies invoke a pricing tautology wherein stock prices are good proxies for the present-value of firms' expected payoff to shareholders (i.e. the "price equals value" assumption). Given this assumption, a *low price-implied discount rate* is needed to rationalize the relatively high price observed on "high-investment-low-profitability" (i.e., HILP) firms. Similarly, a *high price-implied discount rate* is necessary to rationalize the low price observed on "low-investment and high-profit" (LIHP) firms. Therefore, if market prices correctly reflect expected payoffs to shareholders, it follows that "high-investment and low-profitability" (HILP) firms must have lower expected returns, as a matter of tautology. This pricing tautology is central in the argument for the inclusion of *profitability* and *investment* as risk factors. Fama and French (2015a, p.1-2), for example, presents a variation of the residual income model and immediately appeals to the above tautology. Hou, Xue, and Zhang (2015a) follow a similar tack, but more closely align their work to production-based asset pricing theory.[11]

Even if we agree HILP firms have lower market-implied discount rates, we are no closer to understanding *why* investors are willing to grant them these rates. One explanation, suggested

[11] For example, Cochrane (1991, 1996), Lin and Zhang (2013), Berk, Green, and Naik (1999), Carlson, Fisher, and Giammarino (2004), and Zhang (2005). In these models, firms invest more when their marginal *q* (the net present value of future cash flows generated from an additional unit of assets) is high. Therefore, given expected profitability or cash flows, low discount rates imply high marginal *q* and high investment, and high discount rates imply low marginal *q* and low investment.

by rational pricing, is that these firms are "safer" investments, so investors settle for a lower return as compensation for holding them.   An alternative explanation, suggested by behavioral economics, is that HILP firms are more "salient" and overpriced, so their lower returns reflect a price adjustment to more sensible fundamentals.

It is important to note that the asset pricing tests themselves cannot distinguish between these two possibilities.[12] At the same time, the two contrasting explanations lead to sharply different predictions about the type of firm that should populate the extreme HILP portfolios. Under rational pricing theory, HILP firms are safer and have extremely positive NPV projects. Under the behavioral-based explanation, HILP firms are salient and overpriced, and their future performance will disappoint investors. In this study, provide new evidence on these two explanations using: (a) a predicted stock issuance (PSI) score as an improved proxy for *expected* HILP firms, and (b) a wide range of empirical tests, including many that are non-return-based.[13]

2.2 PSI as a proxy for future HILP firms

A central research challenge in testing these asset pricing models is to identify proxies for *expected* earnings and investment. While neither profitability nor investment is especially easy to predict, as Hou, Xue, and Zhang (2015b) noted, cross-sectional forecasts of profitability are

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[12] For example, Fama and French (2015a; p1) writes: "(t)he predictions drawn from [The dividend discount model or Miller and Modigliani (1961) model] … are the same whether the price is rational or irrational." Similarly, Hou et al. (2015a; p684) writes: "…we emphasize that the *q*-factor model is silent about the debate between rational asset pricing or mispricing."

[13] Another way to distinguish between the *q*-theory prediction and the mispricing explanation is to examine returns to the asset growth variable (a proxy for *investment*) in different cross-sectional subsamples, split by a given measure of either limits-to-arbitrage or investment frictions. If *q*-theory is the main driver of returns to the asset growth anomaly, proxies for investment friction should better explain cross-sectional differences; conversely if mispricing is the main driver of returns to the asset growth anomaly, limits-to-arbitrage proxies should exhibit greater explanatory power. Unfortunately test results to date have been quite mixed (see Lam and Wei, 2011; and Lyandres et al., 2008), in part because proxies for limits-to-arbitrage and proxies for investment friction are often highly correlated.

likely to be better than cross-sectional forecasts of investment. This is because investment is less persistent, in the cross-section, than profitability. While firms earning higher (lower) accounting rates-of-return tend to persist in the cross-section, high- (low-) investment firms in one period do not necessarily have high- (low-) investment in the future.

In this study, we posit (and show) that predicted stock issuance, PSI, provides a good empirical proxy for firms that are expected to have both high-investment and low-profits in the future (i.e., future HILP firms). Our approach is quite intuitive, as firms' financing policies are directly linked to their expected profitability and expected investment. Firms with high expected investment and low internally-generated funds (i.e. low profitability) are precisely the ones that will need additional external financing. Thus by developing a model to predict stock issuance, we are effectively constructing a model to predict expected earnings and investment.

This is easy to see through a simple accounting identity: Assets (A) equal Liabilities (L) plus Shareholders' Equity (SE), both at the beginning and the end of year t. Notationally,

$$A_t = L_t + SE_t \qquad (1)$$

$$A_{t-1} = L_{t-1} + SE_{t-1} \qquad (2)$$

Subtracting (2) from (1):

$$\Delta A_t = \Delta L_t + \Delta SE_t$$

Invoking the clean surplus relation, we can re-express the change in Shareholders Equity (ΔSE_t) as the sum of period t earnings ($EARN_t$) and net stock issuance ($NetIssue_t$), where $NetIssue_t$ is the total new equity issuances in year t, net of dividend payments and stock repurchases. We then get:

$$\Delta A_t = \Delta L_t + EARN_t + NetIssue_t \, ,$$

or,

$$\Delta A_t \quad - \quad EARN_t \quad = \quad \Delta L_t \quad + \quad NetIssue_t$$

Dividing both sides by beginning-of-period total assets (A_{t-1}), we have:

$$INV_t \quad - \quad ROA_t \quad = \quad \Delta L_t / A_{t-1} \quad + \quad SI_t \qquad (3)$$

Note that $INV_t = \Delta A_t / A_{t-1}$ is precisely the *Investment* variable in Fama and French (2015a) and Hou et al. (2015a), and that ROA_t closely tracks their *Profitability* variable.[14] In other words, the left-hand-side of equation (3) maps directly into the high-investment-low-profitability (HILP) firms featured in these asset pricing models. At the same time, note that the right-hand-side variable, $SI_t = NetIssue_t / A_{t-1}$, is the stock issuance variable in our study. Therefore, so long as the change in liabilities term ($\Delta L_t / A_{t-1}$) does not introduce too much noise, sorting firms by SI_t is essentially equivalent to sorting firms by HILP. We focus on equity (and do not include debt) issuance because of the relative importance of new equity capital to HILP firms, and because of its more direct link to the behavioral literature on saliency. Empirically, none of our main results are affected by the inclusion of net debt issuance.[15]

Equation (3) shows that by developing a *predictive* variable for SI (i.e. by deriving a predicted stock issuance, or PSI, score), we can effectively identify future HILP firms. In fact, if future financing is easier to predict than future investment, PSI can be a better proxy for firms'

[14] Both studies use earnings before extraordinary items (*EBIT*) in measuring *profitability*, but their measures vary slightly in construction. In Hou et al. (2015a), *profitability* is defined as the quarterly return-on-equity ($EBXI_q / SE_{q-1}$), while in Fama and French (2015a) it is an annual return-on-equity measure ($EBXI_t / SE_{t-1}$).

[15] Our decision to focus on net equity issuance is motivated by four conceptual considerations: (a) debt financing is not an option for many HILP firms, as they are unprofitable and have few collateralizable assets, (b) the literature on equity issuance is more developed and nominates a number of variables useful in estimating PSI, (c) saliency-based explanations are more applicable to equity investors, and (d) ceteris paribus, a more parsimonious model is preferable. Empirically, our tests show that: (a) the PSI variable (without inclusion of debt issuance) does an excellent job of predicting cross-sectional variation in *future* profitability and investment, and (b) the inclusion of net debt issuance has a negligible effect on our main results (untabulated but available upon request).

future investment and profitability than even their current level of investment and profits. We show later that this is indeed the case.

3. Data

Our sample contains all firms in 1972-2014 in the CRSP/Compustat database that are traded on the NYSE, AMEX, and NASDAQ exchanges. We require firms have positive book equity and non-missing values for assets, lagged assets, and revenues, and that the share price for the firms be greater than $0.50. Appendix 1 provides variable definitions. We start in 1972 when the availability of equity issuance data became widely available (Bradshaw, Richardson, and Sloan, 2006). We obtain analyst forecast data from I/B/E/S, institutional holdings from Thomson Reuters, and factor returns and breakpoints for FF-5 from the Kenneth French Data Library. We secured factor returns for the Hou et al. (2015a) model directly from the authors. To mitigate the impact of outliers, we winsorize all variables, except future returns, at 1 and 99 percentiles.

4. Predicting stock issuance

A large literature examines the market impact associated with seasoned equity offerings or SEOs (e.g., Masulis and Korwar, 1986; Spiess and Affleck-Graves, 1995; Eckbo, Masulis, and Norli, 2000). The main stylized fact from this literature is that issuing firms experience negative returns on the announcement date, and that these returns persist for many months. Our study is related to these SEO studies, but is distinct in several ways. First, while these studies examine firms that actually issue shares, we are interested in a broader set of firms that "fit the profile" of would-be issuers. As we show later, our main results hold whether or not these top-PSI firms actually issue shares in year t+1. This finding suggests the SEO effect may be part of a broader PSI phenomenon. Second, by carefully documenting the most important features of PSI firms, we establish a link (both conceptually and empirically) between HILPs and the price drift in the SEO literature. Specifically, we show many SEO firms are also HILP firms, and our results support a mispricing explanation for both phenomena.

In developing our predictive model for stock issuance, we are guided by prior studies that examine the timing of firms' stock issuance decision. First, prior work finds that profitability is relatively sticky in the cross-section and low-profit firms are more likely to issue stock (Hou et al., 2015b), therefore we include lagged profitability in the model. Second, Brav, Geczy, and Gompers (2000) and Billett, Flannery, and Garfinkel (2011) report seasoned equity issuers tend to issue repeatedly, so we also include a lagged *si* variable. Third, for both behavioral (Baker and Wurgler, 2002) and agency-based (Dittmar and Thakor, 2007) reasons, firms are expected to issue equity when their stock prices are relatively high, so we include the market-to-book ratio. Also, Alti and Sulaeman (2012) show that the short-term opportunity presented by the market (i.e. the receptivity of institutional investors as measured by recent changes in investor breadth) is an important determinant of the decision to issue shares. We include recent price momentum in the prediction model as a proxy for market receptivity. Finally, we also control for firm size. To keep the model parsimonious for interpretability, and to avoid overfitting, we estimate the following equation:

$$si_{i,t+1} = \beta_0 + \beta_1 roa_{i,t} + \beta_2 si_{i,t} + \beta_3 lnsize_{i,t} + \beta_4 mb_{i,t} + \beta_5 mom_{i,t} + \epsilon_{i,t} \qquad (4)$$

In Equation (4), *si* is net stock issuance, which is total equity issued less repurchases less dividends, scaled by end of year total assets; *roa* is return on assets, defined as income before extraordinary items scaled by end of year total assets; *lnsize* is the natural logarithm of market value at fiscal year-end; *mb* is market-to-book at fiscal year-end; and *mom* is the cumulative six-month return immediately after the fiscal year end $t - 1$.[16] We estimate Equation (4) using rolling five-year regressions starting in 1972, and report the results in Appendix 2.

As Appendix 2 shows, the estimated coefficients all have the expected signs. Lagged profitability is negatively associated with future stock issuance – on average a 1% increase in ROA is associated with a 0.20% drop in future issuance. Lagged stock issuance is positively associated with future stock issuance, with a 1% change in current-year *si* being associated with a 0.16% change in future *si*. As expected, future stock issuance is also negatively related to firm size, and positively related to market-to-book and momentum. The average R^2 value on these annual regressions is 31.3%, with fairly stable coefficients from year-to-year, suggesting that the model has significant explanatory power for future stock issuances.

We use these estimated coefficients to predict stock issuance for the following year. Specifically, to compute firm *i*'s PSI score, we use its accounting data from fiscal-year *t-1*, together with the estimated coefficients from the most recent PSI regression (i.e. the regression that combines data from years $t - 6$ to $t - 2$). For each calendar year in our sample (year *t*), we then sort firms into ten deciles based on their predicted stock issuance (PSI) score as of June 30 of that year. These procedures ensure the independent variables used in portfolio formation are all available prior to June 30.

[16] The portfolio formation date (June 30 of year t) is always at least six months after the fiscal year ended t-1. Therefore, all the variables, including price momentum, are available prior to portfolio formation.

5. Empirical results

5.1 Descriptive statistics and future returns

Table 1 presents descriptive statistics on our sample firms, sorted into deciles of predicted stock issuance. Average net financing in year $t – 1$ is 31.8% (-6.1%) for top decile PSI (bottom decile PSI) firms, and 82.0% (13.1%) of top-PSI (bottom-PSI) firms are net issuers in year $t – 1$. Consistent with the prediction model, at $t – 1$ top-PSI (bottom-PSI) firms are unprofitable (profitable) and small (large). At $t – 1$, average return-on-assets for top-PSI (bottom-PSI) firms is -0.332 (0.110), and average size is 245 million (2.945 billion). At $t – 1$, top-PSI (bottom-PSI) firms have relatively high (low) market-to-book of 7.560 (2.408), high (low) momentum of 0.233 (-0.062), and high (low) investment, *inv*, of 0.678 (0.131). Consistent with top-PSI (bottom-PSI) firms being smaller (larger), they also have lower (higher) institutional holdings, *instit_hldgs*, at 20.7 percent (46.5 percent) outstanding shares held by institutions as at fiscal year-end $t – 1$. Table 1 also reveals that top-PSI firms have significantly higher Beta, *beta*, than bottom-PSI firms (1.05 versus 0.86), greater volatility (*volatility*) in daily returns (0.054 versus 0.026), and higher short interest, *short_int* (0.035 versus 0.025). These descriptive statistics show that top-PSI stocks do not seem "safer" than bottom-PSI stocks by standard risk metrics.[17]

Table 2, Panel A presents future firm characteristics for PSI firms, and shows that over the next three years, average return on assets for top-PSI (bottom-PSI) firms are -31.4 percent (6.1 percent), -30.9 percent (5.0 percent), and -29.4 percent (4.5 percent) respectively. Future financing over the next three years is 16.3 percent (-4.7 percent), 14.1 percent (-4.3 percent), and

[17] The *short_int* variable in this table is the ratio of shares shorted divided by total shares outstanding. However, as Beneish, Lee, and Nichols (2015; BLN) notes, low *short_int* is not necessarily an indication of low short-sale demand; it could also reflect a low supply of lendable shares. This is especially likely in the case of top-PSI firms, which are smaller and have lower institutional ownership. We conduct a more detailed study of shorting costs later.

12.5 percent (-4.0 percent), and future investment is 22.9 percent (9.6 percent), 17.6 percent (8.6 percent), and 14.5 percent (8.0 percent). Given the persistence of these future fundamentals, the PSI prediction model is a strong predictor, ex-ante, of firms' future profitability and future investment. While top-PSI firms incur negatively ROAs, they continue to grow assets at high rates, and fund this growth by issuing substantially more equity than bottom-PSI firms.

Table 2, Panel B report results for stocks sorted on their current-year investment and profitability. In each year, we sort firms by investment (profitability) into 25 bins, and assign a score of 1 to 25 based on the bins, with higher (lower) investment (profitability) receiving a higher score. The table values in Panel B are mean future investment and profitability by decile ranking of the sum of firms' investment scores and profitability scores ("HILP score"). Among Top-HILP firms, future investment (profitability) for the next three years are 17.4 (-19.2) percent, 13.0 (-19.9) percent, and 11.3 (-18.3) percent, which are all significantly lower (higher) than that of Top-PSI firms. The spread between High- and Low-HILP firms for investment (profitability) for the next three years are 4.9 (26.3) percent, 1.3 (25.7) percent, and 0.6 (23.4) percent, which are much lower than the spreads between High- and Bottom-PSI firms. Figure 1 provides a graphic representation of the same result. This evidence suggests that PSI is better at capturing firms that will have persistent high-investment and low-profitability in the future, and can better distinguish these firms from those that have low-investment and high-profitability.

Table 2, Panel C presents sensitivity analyses where we vary the relative weight assigned to HI and LP when forming the HILP deciles. Specifically, a HI*x*LP*y* portfolio is one in which the weight placed on HI relative to LP is in the ratio of *x/y*. Table values in Panel C represent the spread differences between top and bottom deciles of PSI and HI*x*LP*y* firms. For example, in computing a firm's HI1LP2 ranking, we add its investment score to two times its profitability score. Similarly, in computing the HI5LP1 ranking, we multiply a firm's investment score by five and add it to its profitability score. Panel C reveals that while HI1LP2 firms have a wider spread in future profitability than the spread of HI1LP1 firms, their profitability spread is still narrower than the PSI spread. Furthermore, HI1LP2 no longer sorts firms well on investment, with investment spreads in the next three years ranging from -1.3 percent to 0.1 percent. When the investment score is weighed more heavily (e.g., HI3LP1 or HI5LP1), predictions of future investment improve slightly but predictions of profitability are extremely poor. Across all these perturbations, PSI rankings generally dominate HI*x*LP*y* rankings. Overall, these results suggest that PSI is better at capturing future differences in investment and profitability than HI*x*LP*y*.

Table 3 documents future returns on portfolios formed by decile of predicted equity issuance. Panel A presents equal-weighted returns, and reveals that a portfolio of top-PSI firms has average one-year buy-and-hold returns of 6.4 percent, which is 10.2 percent lower than the average return of 16.6 percent earned by a portfolio of bottom-PSI firms. After adjusting for the annualized yield on ten-year treasuries, top-PSI firms earn excess returns of 0.0 percent, while bottom-PSI firms earn 10.1 percent. The underperformance of the top-PSI firms persists in years t+2 and t+3. In fact, the excess return earned by top-PSI firms is not significantly different from zero for each of the next three years after portfolio formation.

Panel B show the results are similar with value-weighted returns. A portfolio of top-PSI firms has average one-year value-weighted buy-and-hold return of 4.6 percent, which is 10.8 percent lower than the 15.4 percent earned by a portfolio of bottom-PSI firms. Top-PSI firms earn value-weighted returns comparable to treasury yields in the first two post-formation years. However, in the third year, value-weighted returns to the top-PSI firms are not significantly different from those of bottom-PSI firms. Overall, the evidence in Panel B is consistent with top-PSI firms earning significantly lower returns than bottom-PSI firms over at least the next two years. In fact, over our 36-year sample period, top-PSI firms consistently earn returns that are essentially indistinguishable from treasury yields.

Table 4 presents future returns earned by PSI decile, where firms are further separated into those that actually issue shares over the next 12 months, and those that do not. This table shows that in year *t*, 66.2 percent of top-PSI firms issue equity (i.e. their *si* is positive), compared to 13.4 percent of bottom-PSI firms. Panel A presents raw buy-and-hold equal-weighted returns for all firms that are actual issuers in each of the next three years. Among actual issuers, top-PSI firms earn 6.5 percent over the first year, compared to 15.8 percent for bottom-PSI firms. In years t+2 and t+3, top-PSI firms earn 4.6 percent and 6.5 percent respectively, compared to 16.8 percent and 17.3 percent for bottom-PSI firms. Panel B reports future returns for firms that do not actually issue shares over the next 12 months. Among these firms, top-PSI firms also earn lower returns than bottom-PSI firms, although the results have lower statistical significance. In Panel C, we report returns for Issuers minus Non-Issuers (i.e. the difference in the returns reported in the first two panels), with bold fonts denoting observations that are significant at the 5 percent level. Across 30 subpopulations (10 deciles x 3 years), we find only three cases where there is a statistically significant difference between Issuer and Non-Issuer returns. In short, top-PSI firms underperform whether or not they actually issue equity in the future.

Table 5 presents results from regressing monthly portfolio returns on standard asset pricing factors. Panel A results are based on the CAPM model. On a value-weighted basis, the PSI hedge (long-short) portfolio has negative net market Beta of -0.81 (t-stat of -12.98), and earns positive monthly alpha of 144 basis points (t-stat of 5.05). The results are similar for equal-weighted portfolios, as the hedge portfolio exhibits negative market exposure and earns a positive monthly alpha of 120 basis points (t-stat of 4.67).

Panel B reports results based on the Fama-French three-factor model, which includes size and book-to-market factors. On both a value- and equal-weighted basis, the long-short portfolio has a negative loading on Beta (-0.48 and -0.21) and SMB (-0.80 and -0.77), and positive loading on HML (0.91 and 0.82). The long-short portfolio earns value-weighted alpha of 110 basis points (t-stat of 4.88) and equal-weighted alpha of 89 basis points (t-stat of 4.52). The large alphas from the CAPM and Fama-French three factor models suggest these models d not fully capture the excess returns in the long-short PSI portfolio.

Panel C presents results for the Fama-French five-factor model, which adds *profitability* and *investment* to the three-factor version. The hedge portfolio has negative market factor exposure (Beta of -0.34 and -0.12), negative exposure to SMB (-0.54 and -0.44), positive exposure to value (0.49 and 0.67), and positive exposure to profitability (1.09 and 1.18), for both value and equal-weighted portfolios. The value-weighted portfolio has positive exposure to investment (0.69), while the equal-weighted portfolio does not (0.05) at conventional significance levels (t-stat. of 4.87 and 0.43). The alphas are 0.47 percent (t-stat of 2.29) and 0.38 percent (t-stat of 2.28) for the value-weighted and equal-weighted long-short portfolios. These alphas are less than half of the alphas from the three-factor model, consistent with *profitability* and *investment* incrementally explaining around half of the three-factor model alpha. As expected, returns from PSI and returns from *profitability* and *investment* are highly correlated.

Panel D presents results on the Hou, Xue, and Zhang (2015a) *q*-factor model, which also contain *profitability* and *investment* factors. Similar to our findings for the Fama-French five factor model, the long-short PSI portfolio has positive exposure to *profitability* (1.20 and 0.82 for value- and equal-weighted, respectively) and *investment* (0.74 and 0.77, respectively). The alphas are 0.44 percent (t-stat of 1.81) and 0.37 percent (t-stat of 1.69) for the value- and equal-weighted long-short portfolios. Overall, as expected, these results show that the *profitability* and *investment* factors summarizing much of the excess returns of from the hedged PSI portfolio.

Thus far, we have shown that (a) top-PSI firms fit the low-profit-high-investment profile, (b) they earn exceptionally low returns, (c) their monthly returns are largely explained by profitability and investment, and (d) they are not safer by standard risk metrics. In the next section, we turn to ancillary tests to shed light on whether top-PSI firms are safer or more salient.

5.2 Are top-PSI firms safer or riskier?

We conduct four sets of tests. First, we examine several aspects of future fundamental performance. For this purpose, we focus cash flow profitability, cash burn rates, as well as future delisting statistics. If top-PSI firms are safer, they should exhibit improving future operating performance and declining cash burn rates over time, both of which would reduce their reliance on external financing for survival. Of course, they should also be less likely to delist for performance-related reasons.

Second, we analyze returns for top-PSI firms and bottom-PSI firms conditional on market performance or macroeconomic performance. If top-PSI firms are safer, their returns should hold up well during down markets and recessions, when the marginal utility of wealth is high. On the other hand, if these are salient firms as contemplated by BGS, their saliency weight will be context dependent. Specifically, up- (down-) side saliency will be prominent during up-

(down-) markets, leading to pro-cyclical returns. In other words, top-PSI firms should earn particularly low (high) returns during down (up) markets.

Third, we examine the ability of top-PSI and bottom-PSI to forecast the direction of firms' future cash flow expectation errors. If a rationally-established discount rate is the primary reason for the low returns earned by top-PSI firms, then PSI should not predict the direction of future cash flow expectation errors. On the other hand, if PSI captures sentiment-based mispricing, then it should predict future cash flow expectation errors. We use earnings announcement period returns, analyst forecast errors, and analyst forecast revisions, as proxies for expectation errors over firms' future cash flows.

Finally, we also examine return distribution and short-sale statistics for top-PSI and bottom-PSI firms. If we take seriously the behavioral based explanation, we should expect top-PSI firms to exhibit features commonly associated with more salient and glamourous stocks – specifically, strongly right-skewed return distributions. In addition, a noise trader based explanation would require some signs of constrained arbitrage in the highest PSI decile firms. Specially, we should see greater evidence of short-sale constraints being binding among these firms. The rational pricing story would not make such predictions.

Table 6 provides evidence on future cash burn rates and delisting statistics on portfolios that take long positions in bottom-PSI firms and short positions in top-PSI firms. Top-PSI (bottom-PSI) firms have high (low) cash holdings as a percentage of assets at 36.4 percent (16.6 percent). However, they also have lower (higher) EBITDA in $t - 1$ and in the next two years. EBITDA *in* $t - 1$ is -21.3 percent (20.1 percent) for top-PSI (bottom-PSI) firms, and EBITDA in the next two years at -20.8% (16.1%) and -19.1% (14.9%). Thus, top-PSI firms appear to hold more cash in anticipation of a higher cash burn rate in the future.

DeAngelo, DeAngelo, and Stulz (2010) show market-timing opportunities and corporate lifecycle stage only partially explain firms' decision to issue stock. Another key factor in the decision is the likelihood of running out of cash. Following their approach, we conduct a pro-forma analysis that measures what cash holdings would have been had the firms not engaged in any future external financing activities. Table 6 shows that in the one-year-ahead pro forma analysis, assuming no external financing, the average cash holdings of top-PSI firms would drop by 23.5 percent (i.e., it would become 12.9 percent at the end of the year). Conversely, the average cash holdings of bottom-PSI firms would rise 3.0 percent (to become 19.6 percent at the end of the year). Inferences are similar when we assume firms hold their capital expenditure policy constant, that is, if we assume no new capital expenditures from year $t-1$ to year $t+1$. Under this assumption, the average cash balance would be 12.5 percent for top-PSI firms and 19.4 percent for bottom-PSI firms. Without external financing, 34.7 percent of the top-PSI firms would run out of cash in year $t+1$, compared to 12.1 percent of the bottom-PSI firms.

The two-years-ahead results are even more striking. The average cash holdings for top-PSI firms, assuming no external financing for the next two years, would be -4.7 percent, compared to 22.9 percent for bottom-PSI firms. The results are again similar when we assume that firms hold their capital expenditure policy constant (-6.4 percent cash holdings for top-PSI firms and 22.4 percent cash holdings for bottom-PSI firms). We find that 51.9 percent of top-PSI firms would run a cash deficit in two years with no external financing, compared to 14.0 percent for bottom-PSI firms. Taken together, these results show top-PSI firms are seriously cash strapped and most would run out of cash unless they secure external financing.

Table 6 also shows that top-PSI firms experience an unusually high rate of delisting. About 11.4 percent of top-PSI firms experience delisting in the next year, and 7.7 percent of all top-PSI firms delist for performance related reasons.[18] In contrast, only 4.8 percent of bottom-PSI firms delist in the next year, and 0.8 percent of all bottom-PSI firms delist for performance related reasons. Overall, the evidence in Table 6 shows top-PSI firms are not safe investments.

Table 7 presents results on performance of portfolios of PSI firms relative to market performance during bad states of the world. The unconditional average monthly returns for top-PSI (bottom-PSI) firms are 30.4 (122.3) basis points. Conditional on market returns being negative, we find that the top-PSI and bottom-PSI firms generate negative average monthly returns of -7.57 percent and -2.65 percent, respectively. In down markets, the underperformance of the top-PSI firms is so severe that the average monthly return of the long-short portfolio is in fact positive, at 4.92 percent (t-stat of 9.24) on average. In other words, a good way to hedge market downturns would be to short top-PSI firms and long bottom-PSI firms. When the three-month market return is negative, the long-short portfolio generates cumulative three-month returns of 12.15 percent (t-stat. of 10.00), with most of the contribution coming from shorting top-PSI firms. We obtain results of similar magnitude for NBER recession months, although the smaller number of observations reduced the statistical power of the test. During these months, the hedged-portfolio returns 0.96 percent (t-stat. of 0.92). In three-month periods ending in a NBER recession, the hedged-portfolio returns 4.35 percent (t-stat. of 1.90). Overall, Table 7 results support the view that top-PSI firms underperform in down markets.

These findings are most consistent with the saliency theory model predictions in Bordalo, Gennaioli, and Shleifer (2012, 2013b; BGS). Similar to cumulative prospect theory (Tversky and Kahneman 1992; TK), in BGS agents also behave as if they overweigh the likelihood of small probability events. This behavior leads to a tendency to overpay for lottery-like stocks on

[18] We use CRSP delisting codes of 400 and 500-599 to capture firms that delist for performance reasons, based on Shumway (1997) and Beaver, McNichols, and Price (2007).

the upside and insurance-like on the downside. However, unlike TK, the BGS model features a context-dependent saliency weight that makes the saliency of a fat-tailed asset a function of prevailing market conditions. Specifically, when downside risk is more salient (e.g., during market downturns), BGS predicts worse performance for top-PSI firms, which is what we find.

Table 8 presents evidence on future cash flow news for top-PSI and bottom-PSI firms. First, we tabulate earnings announcement period returns, defined as the average cumulative two-day return in the [0, 1] event window around the next eight quarterly earnings releases. Panel A shows that bottom-PSI firms have average announcement period returns of +0.255 percent, compared to -0.735 percent for top-PSI firms, representing a significant difference in the long-short portfolio of 0.990 percent. In other words, 39% of the annual return differential between bottom-PSI and top-PSI firms is earned in 3.2% of the annual trading days – i.e., in the 8 days around quarterly earnings news releases.[19] This translates into an expected return to the PSI strategy that is 12 times larger on earnings news release dates. This concentration of returns around earnings announcement windows is consistent with the correction of ex ante expectation errors taking place when future earnings are released. Conversely, it is extremely difficult to reconcile this concentration of future returns with a risk-based explanation.

In Panel B, we tabulate one-year and two-year ahead analyst earnings forecast errors, defined as the actual earnings in each of the next two years, less the last consensus earnings forecast in May of the year of portfolio formation, all scaled by the fiscal year-end share price. Panel B reveals that analysts overestimate earnings per share of top-PSI firms by 0.094 and 0.145, compared to overestimating by 0.025 and 0.040 for bottom-PSI firms, over each of the

[19] This is calculated as the return differential, 99 basis points, times four quarters in a fiscal year, divided by the 10.2% annual return differential between high predicted stock issuance firms and low predicted stock issuance firms. The ratio of trading days during earnings announcements is 8 trading days, scaled by 250 trading days in the year, or 3.2%.

next two years. Consistent with more excessive analyst optimism in top-PSI firms, we find that analysts have a stronger tendency to revise downwards their forecasts for these firms.

In Panel C, we tabulate forecast revisions by analysts, defined as the latest consensus forecast prior to the earnings announcement date, less the last consensus forecast in May of the year of portfolio formation, all scaled by the fiscal year-end share price. We compute this measure for each of the next two years. Consistent with prior studies, we find that analysts tend to revise their forecasts downwards across all firms. However, Panel C shows that their revisions are much more negative for top-PSI firms. In one-year-ahead forecasts, the downward earnings per share forecast revisions for top-PSI (bottom-PSI) firms is -0.037 (-0.012). In two-year-ahead forecasts, the downward revision for top-PSI (bottom-PSI) firms is -0.094 (-0.028).

Panel D presents results of a pooled regression of all firms in the sample, and shows that the difference in expectation errors between bottom-PSI firms and top-PSI firms hold when we extend the analysis to a multivariate setting, controlling for momentum, size, market-to-book, as well as industry and year fixed-effects. In these pooled regressions, the strongest results are concentrated in the top-PSI firms. The coefficients on the long portfolio of bottom-PSI firms for one-year-ahead forecast errors, earnings announcement period returns, and forecast revisions, are 0.370 (t-stat. of 1.46), -0.128 (t-stat. of -1.41), and 0.242 (t-stat of 2.14). The coefficients on the short portfolio of top-PSI firms are -5.263 (t-stat. of -6.57), -0.930 (t-stat of -3.29), and -2.448 (t-stat of -6.47). Similarly, the two-year-ahead results for bottom-PSI firms are either insignificant or only marginally significant. In contrast, the coefficients for top-PSI firms in the two-year-ahead tests are all highly significant at -6.430 (t-stat. of -4.58), -1.029 (t-stat. of -4.14), and -4.937 (t-stat. of -5.18). Overall, these multivariate results broadly support the view that top-PSI firms are associated with the most over-optimistic earnings expectations.

We also compare the return distribution of extreme PSI firms. Several prior studies invoke a behavioral-based explanation for the lower returns associated with lottery-like stocks (e.g. Barberis and Huang, 2008; Eraker and Ready, 2015; Gao and Lin, 2015). Specifically, both Saliency Theory and Cumulative Prospect Theory predict that investors will overweight small probability outcomes, leading to overvaluation in stocks with lottery-like characteristics. Given our conjecture that top-PSI (i.e. expected HILP) firms are “glamour” stocks, we examine the extent to which their return distribution conforms to the profile for such firms.

Figures 2 and 3 present return distributions for top-PSI and bottom-PSI firms. In these figures, return distributions are tabulated from returns on individual stocks that enter the top-PSI or bottom-PSI portfolios, in one- and two-year periods before and after portfolio formation. Figure 2 compares the post-formation returns for top- and bottom- PSI firms for holding periods of one-year (Figure 2A) and two-years (Figure 2B). These figures show that top-PSI firms have both wider and more highly-skewed return distributions than bottom-PSI firms. The top-PSI firms have a higher probability of low returns, as well as a small probability of extremely high returns; by comparison, the bottom-PSI firms have returns that are closer to a normal distribution. Clearly top-PSI firms are much more “lottery-like” than the bottom-PSI firms. The wider return distribution of top-PSI firms suggests that they are harder to value, making them potentially more sensitive to investor sentiment effects (Baker and Wurgler; 2006, 2007). Their smaller size, higher volatility, and lower institutional holdings, also suggest would-be arbitrageurs face higher costs in trading top-PSI stocks.

Figure 3 examines the stability of the return distribution for top-PSI firms. Specifically, this figure compares the pre-formation and the post-formation return distribution for top-PSI firms. We posit, and find, that the pre-formation return distribution for these firms paints a much rosier picture than the post-formation return distribution. Figure 3A shows that the post-two-year distribution of returns for top-PSI firms is shifted to the left of the prior-two-year returns for the same firms. Figure 3B plots the empirical CDF function for these firms and show that the pre-formation distribution exhibits first-order stochastic dominance over the post-formation distribution. In fact, top-PSI firms earned a mean cumulative return of 38.5 percent in the two years prior to portfolio formation, compared to 5.4 percent for the same stocks in the two-year post-formation period. In contrast, the mean cumulative two-year pre-formation return for bottom-PSI stocks is 20.6 percent, compared to 32.0 percent for the same stocks in the two-year post-formation period. In both cases, these differences are statistically significant.

Finally, to complete the mispricing story, we investigate whether arbitrageurs seeking to profit from the overpricing of top-PSI firms would face higher shorting costs. Figure 4 reports shorting costs by PSI decile using 2004-2011 data from the Markit Data Explorers (DXL) dataset. To construct these graphs, stocks are sorted into ten deciles based on their PSI score at the end of June of each year. The graph depicts the mean Utilization rate and Specialness measure for each PSI decile in the month of portfolio formation. Utilization rate is the ratio of shares on loan to shares available for lending, and Specialness is the percentage of firms in each portfolio that are not easy-to-borrow (i.e., not "general collateral") stocks as defined in Beneish, Lee, and Nichols (2015; BLN).[20] Higher utilization rates and greater Specialness indicate higher shorting costs and more binding short-sale constraints.

Figure 4 shows that top-PSI stocks are indeed associated with higher shorting costs and more binding short-sale constraints. While only 5 or 6 percent of the bottom-PSI firms have elevated borrowing costs (i.e. are on "special"), a full 38.4% of the firms in the top-PSI decile

[20] BLN defines a stock as a "general collateral" if its Daily Cost of Borrowing Score (DBCS) from Markit DXL is either 1 or 2; a stock with a DBCS of 3 through 10 is deemed to be on "special."

have that distinction. At the same time, while average utilization rates are around 15 to 16 percent for most PSI deciles, they are 19.6% for firms in decile-9 and 28.4% for decile-10 firms. Once again, the evidence points to top-PSI firms being overpriced, with the arbitrageurs seeking to profit from this overpricing facing elevated shorting costs.

6. Summary

According to standard asset pricing theory, firms that are expected to have both high-investment and low-profitability (i.e., HILP firms) will earn low future returns. These low expected returns arise as a tautology if we assume the market value of a firm's publicly traded shares is a good approximation for the present value of expected payoff to its shareholders. However, valuation theory does not provide an explanation for the low market implied discount rates associated with HILP firms – we observe the "actual yields" assigned by the market are low, but we do not know *why* the market has assigned these rates.

In this study, we consider two competing explanations for HILP firms' low implied discount rates. The first explanation attributes these low rates to risk – that is, HILP firms deserve low discount rates because they are "safer" investments (perhaps because they have many positive NPV projects). The second explanation attributes these low rates to mispricing – that is, HILP firms earn low future returns because they are currently overpriced, and their prices eventually revert toward fundamentals. To distinguish between these two explanations, we exploit a simple accounting identity that directly links HILP firms to firms that are expected to issue equity. We show, both analytically and empirically, that predicted stock issuers (PSIs) are precisely the future HILP firms called for in tests of asset pricing models. It follows that, by carefully studying the most important features of firms that make up the top-decile PSI portfolio, we should be able to gain considerable insight into the nature of the HILP anomaly, as well as the economic mechanism that drives this phenomenon.

Our results show top-PSI firms earn unusually low returns – in fact, over a period of 36 years (1978-2013), these firms earned an average return no different from Treasury bonds. We find their abnormally low returns are correlated with, and largely explained by, payoffs to the *investment* and *profitability* factors in the new asset pricing models. We also show top PSI firms have risk attributes that are quite different from Treasuries – specifically, they are smaller firms, with low institutional ownership, high return volatility, and high Beta.

Contrary to rational pricing, top PSI firms do not experience improving fundamentals; nor do they exhibit any sign of having highly positive NPV projects. In fact, in the two years after portfolio formation, top-decile PSIs generate extremely negative ROAs that average -30% per year. They also report disappointing future earnings, experience negative short-window returns around the next eight quarterly earnings release dates, and have much more negative analyst forecast revisions than bottom PSI firms. Computing their pro forma cash flows, we find over 50% of the top-decile PSI firms will have negative cash balances by the end of year t+2 unless they receive additional funding, even without new investment. They also earn especially low returns during down markets, and are nine times more likely to delist for performance reasons than bottom PSIs.

Consistent with a behavioral-explanation based on BGS's saliency theory, or TK's cumulative prospect theory, we find that the distribution of the top-PSI firm returns is strikingly fat-tailed. Moreover, the post-formation return distribution for top-PSI firms shifts to the left relative to (i.e. is stochastically dominated by) their pre-formation return distribution. At the same time, top PSI firms are associated with greater short-sale demand, higher borrow costs, and are six times more likely to have binding short-sale constraints than bottom-PSI firms. These findings broadly support the view that top PSI firms (and HILP firms in general) earn low future returns because they are salient and therefore overpriced, not because they are safer.

Taken together, our results bring into question the standard rationale for including *profitability* and *investment* in asset pricing models. For a firm characteristic to be a risk proxy, it is important not only that its intertemporal payoffs co-vary with payoffs from other pricing anomalies; it is also important that these payoffs have the right sign. Although the monthly returns to top-PSI (i.e., expected HILP) firms are correlated with returns from other anomalies, the direction of the "risk premium" is wrong. In the quest to better understand the economic mechanism behind the *profitability* and *investment* factors, our results point to mispricing-based explanations as a potentially more fruitful venue for future research than risk-based explanations.

Note that we are not arguing investment strategies based on PSI, or some other variation of *profitability* and *investment*, are in any sense "riskless." Clearly payoffs to these strategies are stochastic and can be negative, potentially remaining so for long periods of time. However, our findings do suggest an apparent mismatch in the risk-to-return profile of such strategies. It seems odd that we are able to identify, ex ante, a full one-tenth of the publicly listed U.S. stocks that appear collectively risky as a basket, yet earn average returns no higher than Treasuries over a protracted period of time (i.e. 36 years). Perhaps part of the explanation lies in high short-sell costs. Given their lower institutional ownership no doubt shares of top-PSI firms are more difficult to borrow. This could help explain the sluggish price correction for these firms that seems to span many months.

Viewed more broadly, our results suggest future investigations into the state variables that impact "risk factors" (or the "stochastic discount factor") might be better focused on frictions in the market for active arbitrage, rather than on market-wide fundamentals. A number of recent studies have highlighted the role of funding constraints faced by active managers (i.e., intertemporal variations in the availability of arbitrage capital) as an important driver of hedge fund performance, as well as cross-sectional stock returns. Our results are broadly consistent with the findings from these studies.

If returns to *profitability* and *investment* portfolios reflect rewards to active trading against mispricing, it stands to reason that these returns will be negatively impacted when active managers face deleveraging risk or capital constraints. One testable hypothesis suggested by our result is that monthly returns to the PSI strategy (whereby one longs bottom-PSI firms, and shorts top-PSI firms) will be especially poor when arbitrage capital is scarce or significantly constrained. This prediction extends, of course, to returns from other investment strategies commonly employed by hedge funds. We believe this is a fruitful area for future research.

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Appendix 1: Variable definitions

Variable	Definition (Source)
si	Proceeds from sale of common and preferred stock, less cash payments for purchase of common and preferred stock, less cash payments for dividends, scaled by end of year total assets (Compustat)
roa	Income before extraordinary items divided by end of year total assets (Compustat)
size	Market value of equity at fiscal year-end (Compustat)
mb	Market to book ratio, fiscal year-end (Compustat)
mom	Return for the six-month period after fiscal year-end (Compustat)
instit_hldgs	Percentage of outstanding shares owned by institutions as at fiscal year-end (Thomson Reuters 13F)
EBITDA	Earnings before interest, taxes, depreciation and amortization, scaled by end of year total assets (Compustat)
inv	Ending assets less beginning assets, scaled by beginning assets (Compustat)
volatility	Standard deviation of daily stock returns in fiscal year (CRSP)
beta	Firm beta as at year-end (CRSP)
short_int	Open short interest at portfolio formation date as a percentage of common shares outstanding (Compustat)
ret_t	Holding period return for the next t months
vw_ret_t	Value weighted return for next t months
ew_ret_t	Equal weighted return for next t months

Appendix 2: Predicting Stock Issuances

This appendix presents the results of estimating:

$$si_{i,t+1} = \beta_0 + \beta_1 roa_{i,t} + \beta_2 si_{i,t} + \beta_3 lnsize_{i,t} + \beta_4 mb_{i,t} + \beta_5 mom_{i,t} + \epsilon_{i,t}$$

In this equation, $si_{i,t+1}$ is net stock issuance, defined as total equity issued in next fiscal year less repurchases less dividends scaled by total assets at the end of the next fiscal year, $roa_{i,t}$ is income before extraordinary items scaled by end of fiscal year total assets, $si_{i,t}$ is net stock issuance in the current fiscal year, $lnsize_{i,t}$ is the natural logarithm of market value of equity at fiscal year-end, $mb_{i,t}$ is market-to-book at fiscal year-end, $mom_{i,t}$ is six-month period return in the six months after fiscal year-end. Table values are the year-by-year results from estimating rolling five-year regressions. In each row, the start year is the first fiscal-year of the five-year period in which the rolling regression is being estimated. T-statistics on the average coefficients are Newey-West corrected for autocorrelation.

Estimation period	Intercept	roa	si	lnsize	mb	mom	R2	N
1972-1976	-0.004	-0.129	0.212	-0.001	0.002	0.006	0.162	12230
1973-1977	-0.003	-0.140	0.223	-0.001	0.002	0.005	0.185	13910
1974-1978	-0.003	-0.138	0.275	-0.001	0.003	0.005	0.203	14723
1975-1979	-0.003	-0.137	0.327	-0.001	0.005	0.006	0.231	14886
1976-1980	-0.004	-0.135	0.327	-0.001	0.006	0.010	0.262	15154
1977-1981	-0.006	-0.148	0.254	-0.001	0.008	0.023	0.269	15283
1978-1982	-0.007	-0.170	0.140	-0.001	0.009	0.027	0.261	15494
1979-1983	-0.010	-0.170	0.136	-0.001	0.010	0.036	0.278	15818
1980-1984	-0.008	-0.170	0.102	-0.001	0.010	0.043	0.274	16220
1981-1985	-0.008	-0.177	0.082	-0.002	0.011	0.044	0.276	16527
1982-1986	-0.006	-0.184	0.080	-0.002	0.011	0.042	0.284	16736
1983-1987	-0.005	-0.188	0.090	-0.003	0.010	0.042	0.301	16931
1984-1988	-0.003	-0.191	0.079	-0.004	0.009	0.034	0.297	17194
1985-1989	-0.004	-0.185	0.083	-0.003	0.008	0.031	0.297	17267
1986-1990	-0.005	-0.187	0.099	-0.003	0.007	0.031	0.304	17214
1987-1991	-0.007	-0.191	0.108	-0.002	0.007	0.033	0.312	17199
1988-1992	-0.006	-0.188	0.115	-0.002	0.008	0.036	0.318	17319
1989-1993	-0.003	-0.204	0.138	-0.003	0.008	0.042	0.341	17737
1990-1994	0.000	-0.228	0.130	-0.003	0.009	0.043	0.361	18572
1991-1995	0.002	-0.241	0.128	-0.003	0.009	0.045	0.364	19645
1992-1996	0.004	-0.260	0.124	-0.003	0.009	0.048	0.377	20813
1993-1997	0.007	-0.263	0.116	-0.004	0.009	0.051	0.362	21757
1994-1998	0.008	-0.253	0.114	-0.004	0.008	0.049	0.349	22111
1995-1999	0.009	-0.252	0.120	-0.005	0.007	0.047	0.344	21708
1996-2000	0.007	-0.268	0.119	-0.004	0.007	0.045	0.370	21071
1997-2001	0.004	-0.242	0.101	-0.004	0.006	0.039	0.341	20142
1998-2002	-0.001	-0.211	0.117	-0.003	0.006	0.036	0.328	18990
1999-2003	0.000	-0.202	0.135	-0.003	0.006	0.036	0.339	17832
2000-2004	0.001	-0.195	0.151	-0.003	0.006	0.036	0.342	16997
2001-2005	0.006	-0.180	0.160	-0.003	0.004	0.029	0.308	16732
2002-2006	0.012	-0.182	0.251	-0.004	0.004	0.029	0.348	15478
2003-2007	0.017	-0.234	0.246	-0.005	0.004	0.033	0.396	15626
2004-2008	0.017	-0.258	0.201	-0.005	0.003	0.034	0.375	16046
2005-2009	0.011	-0.239	0.202	-0.004	0.002	0.024	0.367	16282
2006-2010	0.007	-0.222	0.217	-0.003	0.002	0.019	0.364	15867
2007-2011	0.006	-0.231	0.233	-0.003	0.002	0.019	0.391	16616
Average	0.001	-0.200	0.159	-0.003	0.007	0.032	0.313	
t-statistic	0.26	-14.95	7.19	-6.72	7.28	7.60		

Table 1: Firm Characteristics by Predicted Stock Issuance (PSI) deciles

This table presents descriptive statistics for the sample firms. Table values represent the mean values of firm-year observations within each predicted stock issuance (PSI) decile. To construct this table, at the end of June of each year from 1978-2013, stocks are sorted to ten deciles based on their PSI score. Table values are descriptive statistics for year t-1. si is stock issuances less repurchases less dividends, scaled by end of fiscal-year assets, roa is current period income before extraordinary items scaled by end of fiscal-year assets, $size$ is the market value of equity at fiscal year-end in millions of dollars, mb is market-to-book at fiscal year-end, mom is six-month return after fiscal year-end, inv is investment, computed as change in total assets scaled by beginning of year total assets, $instit\_hldgs$ is percentage of shares held by institutions as at fiscal year-end, $beta$ is the year-end beta, and $volatility$ is the standard deviation of daily returns in the fiscal year. *, **, and *** indicate two-tailed t-test significance from zero, at the 10 percent, 5 percent, and 1 percent levels, respectively.

Panel A: Descriptive statistics by predicted stock issuance (PSI) decile

Decile	1	2	3	4	5	6	7	8	9	10	10-1	Sig.
Avg yr t-1 PSI	-0.061	-0.026	-0.015	-0.009	-0.002	0.006	0.021	0.049	0.113	0.318	0.379	***
Pct si >0 in yr t-1	0.131	0.174	0.229	0.283	0.339	0.394	0.468	0.567	0.675	0.820	0.689	***
roa	0.110	0.071	0.057	0.048	0.040	0.030	0.019	-0.005	-0.063	-0.332	-0.441	***
size	2945	2591	1905	1348	977	768	635	535	477	245	-2700	***
mb	2.408	1.975	1.837	1.794	1.805	1.920	2.128	2.532	3.648	7.560	5.152	***
mom	-0.062	-0.026	0.008	0.040	0.076	0.114	0.165	0.219	0.253	0.233	0.295	***
inv	0.131	0.134	0.136	0.146	0.156	0.169	0.205	0.277	0.428	0.678	0.547	***
instit_hldgs	0.465	0.456	0.439	0.413	0.381	0.342	0.311	0.290	0.276	0.207	-0.258	***
beta	0.860	0.864	0.871	0.896	0.930	0.932	0.954	1.023	1.118	1.054	0.195	***
volatility	0.026	0.026	0.027	0.029	0.031	0.034	0.037	0.042	0.047	0.054	0.028	***
short_int	0.025	0.021	0.022	0.024	0.023	0.022	0.020	0.022	0.027	0.035	0.010	***
N	13802	13824	13829	13819	13817	13831	13822	13826	13827	13807		

Table 2: Future Firm Characteristics by Predicted Stock Issuance (PSI) and High-Investment Low-Profitability (HILP) deciles

This table presents future firm characteristics for the sample firms. Table values represent the mean values of firm-year observations within each predicted stock issuance (PSI) decile or high-investment low-profitability (HILP) decile. To construct this table, at the end of June of each year from 1978-2013, stocks are sorted to ten deciles based on their PSI score. Panel A presents key firm characteristics for each PSI decile, and Panel B presents key firm characteristics for each HILP decile. We report mean roa, inv, and si for each of the next three years, where si is stock issuances less repurchases less dividends, scaled by end of fiscal-year assets, roa is current period income before extraordinary items scaled by end of fiscal-year assets, and inv is investment, computed as change in total assets scaled by beginning of year total assets. Variables with a suffix $\_n$ refer to the values of those variables n fiscal years ahead.

Panel C presents sensitivity analyses where we vary the relative weight assigned to HI and LP when forming the HILP deciles. Specifically, a HI*x*LP*y* portfolio is one in which the weight placed on HI relative to LP is in the ratio of *x/y*. Table values in Panel C represent the spread differences between top and bottom deciles of PSI and HI*x*LP*y* firms.

*, **, and *** indicate two-tailed t-test significance from zero, at the 10 percent, 5 percent, and 1 percent levels, respectively.

Panel A: Future firm characteristics by predicted stock issuance decile

Decile	roa_1	roa_2	roa_3	inv_1	inv_2	inv_3	si_1	si_2	si_3
1	0.061	0.050	0.045	0.096	0.086	0.080	-0.047	-0.043	-0.040
2	0.043	0.037	0.033	0.100	0.090	0.081	-0.026	-0.025	-0.024
3	0.034	0.029	0.027	0.104	0.088	0.085	-0.017	-0.017	-0.016
4	0.027	0.020	0.019	0.106	0.096	0.090	-0.010	-0.010	-0.011
5	0.021	0.016	0.012	0.114	0.100	0.093	-0.004	-0.005	-0.005
6	0.014	0.006	0.003	0.123	0.110	0.100	0.002	0.001	-0.001
7	0.005	-0.004	-0.005	0.139	0.121	0.105	0.009	0.006	0.004
8	-0.021	-0.029	-0.031	0.161	0.125	0.117	0.021	0.016	0.013
9	-0.072	-0.084	-0.084	0.192	0.145	0.120	0.044	0.040	0.035
10	-0.314	-0.309	-0.294	0.229	0.176	0.145	0.163	0.141	0.125
Spread	0.375	0.359	0.339	0.133	0.089	0.065	0.209	0.184	0.164
Sig.	***	***	***	***	***	***	***	***	***

Table 2 (continued)

Panel B: Future Firm characteristics by HILP score

Decile	roa_1	roa_2	roa_3	inv_1	inv_2	inv_3
1	0.070	0.058	0.051	0.125	0.117	0.107
2	0.059	0.050	0.045	0.122	0.117	0.103
3	0.051	0.041	0.037	0.137	0.115	0.103
4	0.032	0.023	0.017	0.133	0.109	0.098
5	-0.008	-0.014	-0.016	0.111	0.099	0.092
6	-0.108	-0.098	-0.089	0.102	0.101	0.100
7	-0.035	-0.039	-0.041	0.136	0.113	0.100
8	-0.016	-0.023	-0.026	0.154	0.118	0.104
9	-0.030	-0.037	-0.037	0.170	0.126	0.108
10	-0.192	-0.199	-0.183	0.174	0.130	0.113
Spread	0.263	0.257	0.234	0.049	0.013	0.006
Sig.	***	***	***	***	***	***
PSI Spread - HILP Spread	0.113	0.102	0.105	0.084	0.076	0.059
Sig.	***	***	***	***	***	***

Panel C: Spread for alternate defintions of HILP scores

	roa_1	roa_2	roa_3	inv_1	inv_2	inv_3
HI1LP2 Spread	0.307	0.294	0.267	0.001	-0.013	-0.010
PSI Spread - HI1LP2 Spread	0.068	0.065	0.071	0.132	0.102	0.075
Sig.	***	***	***	***	***	***
HI2LP1 Spread	0.218	0.217	0.200	0.096	0.043	0.023
PSI Spread - HI2LP1 Spread	0.157	0.142	0.139	0.037	0.046	0.042
Sig.	***	***	***	***	***	***
HI3LP1 Spread	0.147	0.157	0.146	0.136	0.064	0.039
PSI Spread - HI3LP1 Spread	0.228	0.202	0.192	-0.003	0.026	0.026
Sig.	***	***	***		***	***
HI5LP1 Spread	0.042	0.070	0.066	0.173	0.080	0.044
PSI Spread - HI5LP1 Spread	0.333	0.289	0.273	-0.040	0.009	0.022
Sig.	***	***	***	*	*	***

Table 3: Future returns by decile of predicted stock issuance

This table presents future returns on value-weighted and equal-weighted portfolios formed on predicted stock issuance (PSI) deciles. At the end of June of each year from 1978-2013, stocks are sorted to ten deciles based on their PSI score. The panels below present raw buy-and hold returns, buy-and-hold returns in excess of the average Ten-year treasury bond annualized yields (CRSP) over each of the next three years. Panel A presents equal-weighted returns and Panel B presents value weighted returns. *, **, and *** indicate difference from zero, significant at the 10 percent, 5 percent, and 1 percent levels, respectively, using a two-tailed t-test.

Panel A: Equal-weighted returns

Decile	1	2	3	4	5	6	7	8	9	10	10-1	Sig.
Raw buy-and-hold returns												
Year 1	0.166	0.167	0.177	0.169	0.176	0.174	0.164	0.169	0.144	0.064	-0.102	**
Year 2	0.166	0.173	0.174	0.174	0.168	0.164	0.174	0.157	0.151	0.062	-0.104	**
Year 3	0.163	0.152	0.162	0.173	0.165	0.158	0.159	0.159	0.140	0.072	-0.091	**
Buy-and-hold returns in excess of ten-year treasury bond annualized yields												
Year 1	0.101	0.103	0.113	0.104	0.112	0.110	0.100	0.104	0.080	0.000	-0.102	**
Year 2	0.102	0.109	0.109	0.110	0.104	0.099	0.109	0.093	0.087	-0.002	-0.104	**
Year 3	0.099	0.088	0.098	0.109	0.100	0.094	0.095	0.094	0.076	0.008	-0.091	**

Panel B: Value-weighted returns

Decile	1	2	3	4	5	6	7	8	9	10	10-1	Sig.
Raw buy-and-hold returns												
Year 1	0.154	0.124	0.126	0.130	0.144	0.160	0.132	0.140	0.099	0.046	-0.108	**
Year 2	0.152	0.142	0.128	0.161	0.134	0.154	0.140	0.140	0.103	0.071	-0.081	**
Year 3	0.134	0.143	0.113	0.151	0.145	0.125	0.138	0.132	0.128	0.135	0.001	
Buy-and-hold returns in excess of ten-year treasury bond annualized yields												
Year 1	0.089	0.059	0.062	0.066	0.080	0.095	0.068	0.075	0.035	-0.018	-0.108	**
Year 2	0.088	0.077	0.063	0.096	0.070	0.089	0.076	0.076	0.038	0.007	-0.081	**
Year 3	0.070	0.079	0.049	0.087	0.081	0.061	0.074	0.067	0.063	0.071	0.001	

Table 4: Future returns by decile of predicted stock issuance (Issuer versus Non-Issuer)

This table compares the future returns of Issuers versus Non-Issuers within each predicted stock issuance (PSI) decile. To construct this table, stocks are sorted into ten deciles at the end of June of each year from 1978-2013, based on their PSI score, computed using firm characteristics available up to to end of June. Within each PSI decile, firms are further divided into future issuers and future non-issuers based on the sign of their actual stock issuance in the next fiscal year (year t). The panels below present the percentage of actual future issuers within each PSI decile, as well as the average equal-weighted raw buy-and hold returns over each of the next three years. In Panels A and B, we also report the different between the top and bottom decile by PSI. *, **, and *** indicate difference from zero, significant at the 10 percent, 5 percent, and 1 percent levels, respectively, using a two-tailed t-test. In Panel C, bold fonts indicate the difference between Issuer and Non-issuer is significant at the 5 percent level.

Equal-weighted returns for future issuers and non-issuers

PSI Decile	1	2	3	4	5	6	7	8	9	10	10-1	Sig.
Actual yr t issuers	0.134	0.162	0.206	0.256	0.299	0.348	0.395	0.468	0.542	0.662	0.528	***
Panel A: Raw buy-and-hold returns for future issuers												
Year 1	0.158	0.153	0.162	0.145	0.171	0.180	0.168	0.163	0.139	0.065	-0.093	**
Year 2	0.168	0.168	0.162	0.173	0.169	0.146	0.169	0.134	0.139	0.046	-0.121	***
Year 3	0.173	0.153	0.160	0.157	0.156	0.147	0.149	0.144	0.131	0.065	-0.107	***
Panel B: Raw buy-and-hold returns for future non-issuers												
Year 1	0.167	0.168	0.179	0.174	0.175	0.173	0.168	0.177	0.155	0.074	-0.092	*
Year 2	0.163	0.173	0.175	0.174	0.166	0.172	0.178	0.181	0.171	0.098	-0.065	
Year 3	0.162	0.151	0.159	0.179	0.166	0.162	0.165	0.173	0.152	0.083	-0.079	**
Panel C: Difference (Issuers minus Non-issuers)												
Year 1	-0.008	-0.015	-0.017	**-0.029**	-0.004	0.008	0.000	-0.014	-0.016	-0.009		
Year 2	0.005	-0.006	-0.014	-0.001	0.003	-0.026	-0.009	**-0.047**	-0.031	**-0.051**		
Year 3	0.011	0.002	0.001	-0.022	-0.010	-0.015	-0.016	-0.030	-0.021	-0.018		

Table 5: Monthly Return Regressions for Long-Short Portfolios

This table presents time-series regressions of long-short portfolio returns on standard factor models. At the end of June of each year from 1978-2013, stocks are sorted to ten deciles based on their predicted stock issuance (PSI) score. A long position is taken in firms that are in the lowest decile of PSI, and a short position is taken in firms that are in the highest decile. Each regression estimates, using monthly return observations, the returns of the portfolio on standard factor models. We report results for both value-weighted portfolios and equal-weighted portfolios. Panel A depicts the CAPM model, and Panel B reflect results for the Fama-French three-factor (FF-3) model. Panel C reports results for the Fama and French (2015a) five factor model:

$$R_t = a + b\left(R_{m,t} - R_{f,t}\right) + sSMB_t + hHML_t + rRMW_t + cCMA_t + e_{it}$$

In this estimation, R_t is the monthly return on the portfolio, and all right hand side variables are based on the Fama and French (2015a) asset pricing model. Specifically, $R_{m,t} - R_{f,t}$ is the excess market return, SMB_t is the size factor, HML_t is the value factor, RMW_t is the FF-5 profitability factor, and CMA_t , or "conservative-minus-aggressive", is the FF-5 investment factor. Panel D presents results for the Hou, Xue, and Zhang (2015a) four-factor model:

$$R_t = a + b\left(R_{m,t} - R_{f,t}\right) + sSMB_t + hHML_t + iIA_t + rROE_t + e_{it}$$

where IA_t is the Hou et al. investment factor (defined as the change in total assets in year t-1 divided by beginning-of-year total assets), and ROE_t is the Hou et al. profitability factor (defined as earnings before extraordinary items in quarter t-1, divided by beginning-of-quarter total equity). Table values are coefficient estimates and t-statistics.

Panel A: Capital Asset Pricing Model (CAPM)

Value-Weighted Porfolios					Equal-Weighted Portfolios				
	a	b	t(a)	t(b)		a	b	t(a)	t(b)
L	0.0029	0.8169	3.19	40.92	L	0.0028	0.9234	2.61	39.49
S	-0.0115	1.6278	-4.51	29.17	S	-0.0092	1.4403	-3.11	22.31
L-S	0.0144	-0.8109	5.05	-12.98	L-S	0.0120	-0.5169	4.67	-9.22

Table 5 (Continued)

Panel B: Fama-French Three Factor Model (FF-3)

Value-Weighted Portfolios

	a	b	s	h	t(a)	t(b)	t(s)	t(h)
L	0.0022	0.8686	-0.0900	0.1690	2.53	42.26	-2.97	5.5
S	-0.0088	1.3494	0.7060	-0.7460	-4.22	27.9	9.89	-10.31
L-S	0.0110	-0.4808	-0.7960	0.9149	4.88	-9.16	-10.28	11.66

Equal-Weighted Portfolios

	a	b	s	h	t(a)	t(b)	t(s)	t(h)
L	0.0013	0.8675	0.6471	0.2228	2.36	65.76	33.24	11.29
S	-0.0076	1.0802	1.4159	-0.5948	-3.92	23.92	21.24	-8.8
L-S	0.0089	-0.2126	-0.7688	0.8176	4.52	-4.62	-11.32	11.87

Panel C: Fama-French Five Factor Model (FF-5)

Value-Weighted Portfolios

	a	b	s	h	r	c	t(a)	t(b)	t(s)	t(h)	t(r)	t(c)
L	0.0016	0.8896	-0.0882	0.0825	0.0524	0.1844	1.72	41.17	-2.72	1.96	1.22	2.92
S	-0.0031	1.2286	0.4491	-0.4107	-1.0348	-0.5062	-1.66	27.56	6.71	-4.74	-11.7	-3.89
L-S	0.0047	-0.3390	-0.5373	0.4932	1.0873	0.6906	2.29	-6.98	-7.37	5.22	11.28	4.87

Equal-Weighted Portfolios

	a	b	s	h	r	c	t(a)	t(b)	t(s)	t(h)	t(r)	t(c)
L	0.0007	0.8818	0.6736	0.1807	0.1107	0.0685	1.2	64.2	32.69	6.76	4.06	1.71
S	-0.0031	1.0060	1.1114	-0.4859	-1.0720	0.0198	-1.83	25.27	18.61	-6.28	-13.58	0.17
L-S	0.0038	-0.1242	-0.4378	0.6666	1.1827	0.0487	2.28	-3.17	-7.46	8.76	15.23	0.43

Table 5 (continued)

Panel D: Hou, Xue, Zhang (2015a) Q-factor Model

Value-Weighted Portfolios										
	a	b	s	i	r	t(a)	t(b)	t(s)	t(i)	t(r)
L	0.0026	0.8604	-0.1236	0.2449	-0.0966	2.80	40.26	-4.06	4.98	-2.74
S	-0.0018	1.2967	0.4532	-0.9561	-0.8352	-0.84	26.90	6.60	-8.61	-10.50
L-S	0.0044	-0.4363	-0.5768	1.2010	0.7386	1.81	-7.90	-7.33	9.44	8.10
Equal-Weighted Portfolios										
	a	b	s	i	r	t(a)	t(b)	t(s)	t(i)	t(r)
L	0.0019	0.8461	0.5763	0.1971	-0.1130	2.95	57.63	27.54	5.83	-4.66
S	-0.0018	1.0463	1.1549	-0.6191	-0.8837	-0.88	22.97	17.79	-5.90	-11.76
L-S	0.0037	-0.2002	-0.5786	0.8162	0.7707	1.69	-4.07	-8.26	7.21	9.50

Table 6: Cash Burn Rates and Delisting Statistics

This table presents cash burn and delisting statistics for extreme PSI-decile firms. To construct this table, stocks are sorted into ten deciles by their PSI scores at the end of June of each year from 1978-2013. Table values are for the lowest-PSI (Long) and highest-PSI (Short) decile firms. Cash Holdings is cash plus short-term investments. EBITDA is earnings before interest, taxes, depreciation and amortization. One-year and two-year ahead cash, assuming no financing is computed following DeAngelo et al. (2010), and reflects future cash holdings assuming no new debt or equity financing. The constant capex version further assumes the firm has no new capital expenditures. Median cash deficits are computed using pro forma cash holdings when a firm is "out of cash". A firm is deemed "out of cash" when its pro forma cash with no financing fall below zero. All accounting variables are scaled by total assets. Delisting rate is the proportion of firms that delist in the next year. Firms that delist for performance reasons are those with a CRSP delisting code of 400 or 500-599. Average delisting return is the average return in the month of delisting for firms that delist. *, **, and *** indicate two-tailed t-test significance at the 10 percent, 5 percent, and 1 percent levels, respectively.

	Low-PSI (Long)	High-PSI (Short)	L-S	Sig.
Current year Cash Holdings	0.166	0.364	-0.198	***
Profitability				
Current year EBITDA	0.201	-0.213	0.413	***
One-year ahead EBITDA	0.161	-0.208	0.369	***
Two-year ahead EBITDA	0.149	-0.191	0.340	***
One-year-ahead cash	0.158	0.327	-0.169	***
Pro Forma Cash				
One-year ahead-cash, assuming no financing	0.196	0.129	0.067	***
One-year ahead-cash, no financing, constant capex	0.194	0.125	0.069	***
One-year-ahead % firms out of cash, no financing	0.121	0.347	-0.226	***
Median cash deficit when cash < 0 , 1 year	-0.089	-0.220	0.132	***
Two-year ahead-cash, assuming no financing	0.229	-0.047	0.276	***
Two-year ahead-cash, no financing, constant capex	0.224	-0.064	0.288	***
Two-year-ahead % firms out of cash, no financing	0.140	0.519	-0.379	***
Median cash deficit when cash < 0, 2 years	-0.068	-0.202	0.134	***
Delistings over next year				
Proportion of firms delisted for any reason in Yr t	0.048	0.114	-0.065	***
Proportion of firms delisted for performance reasons	0.008	0.077	-0.069	***

Table 7: Portfolio Performance During Down Markets

This table presents performance statistics of each leg of the long-short portfolio during down markets. To construct this table, stocks are sorted into ten deciles based on their PSI score at the end of June of each year from 1978-2013. A long position (Long) is taken in firms that are in the lowest decile by PSI score, and a short (Short) position is taken in forms that are in the highest decile by PSI score. Table values reflect average monthly return of value-weighted portfolios, expressed in percentages. Average three-month returns are calculated every three months by compounding the monthly returns for each portfolio over the sample period. Monthly (and Average 3-month) returns are also reported conditional on the monthly (3-month) market return being negative. Finally, we report monthly returns to each portfolio during NBER recessions. For this purpose, a given 3-month observation is included in an NBER recession if the ending month falls within an NBER recession period. Market returns are based on monthly Fama-French market factor returns. N is the number of monthly observations in each reported category. T-statistics on the average coefficients are corrected using the Newey-West method for autocorrelation.

	L	S	L-S	t-stat	N
Average monthly return (percentage)	1.22	0.30	0.92	2.76	432
Monthly return when market return < 0	-2.65	-7.57	4.92	9.24	155
Monthly return during NBER recessions	0.22	-0.74	0.96	0.92	61
Average three-month return (percentage)	3.68	0.99	2.69	4.12	430
Average 3-month return when 3-month market return < 0	-3.34	-15.49	12.15	10.00	134
Average 3-month return during NBER recessions	-0.42	-4.77	4.35	1.90	61

Table 8: Earnings Announcement Returns, Forecast Errors, and Analyst Revisions

This table presents future earnings announcement returns, earning forecast errors, and analyst earning revisions for extreme-PSI firms in the two years following portfolio formation. To construct this table, firms are sorted into ten deciles based on their PSI score at the end of June of each year from 1978-2013. A long position is taken in firms that are in the lowest decile by PSI, and a short position is taken in forms in the highest decile by PSI. Panel A reports earnings announcement returns (EAret), defined as the average two-day return in the [0, 1] event window around the next eight-quarters after the portfolio formation date. Panel B reports analyst forecast errors (FE), defined as actual earnings in the next fiscal year (or two fiscal years ahead) minus the last consensus earnings forecast in May prior to portfolio formation, scaled by the fiscal year-end share price. Panel C reports analyst forecast revisions (REV), defined as the latest consensus forecast prior to the earnings announcement release date in each of the next two fiscal years, minus the consensus earnings forecast as in May prior to portfolio formation, scaled by fiscal year-end share price. Panel D presents a multivariate analysis of these variables controlling for different firm characteristics, pooling all firms in the sample. In this panel, “Long” (“Short”) is an indicator variable that is equal to 1 if the firm is in the lowest (highest) decile by PSI. Mom is the prior twelve month market adjusted stock return. Lnsize is the natural log of market value of equity of the firm at fiscal year-end. MB is the market to book ratio of the firm at fiscal year-end. In Panel D, the reported t-statistics on the coefficient estimates are two-way clustered by firm and by year. *, **, and *** indicate two-tailed statistical significance at the 10 percent, 5 percent, and 1 percent levels.

Panel A: Earnings announcement returns (EAret)	L	S	L-S	Sig.
Average two-day EA returns over next 8 quarters	0.255	-0.735	0.990	***

Panel B: Future forecast errors (FE)	L	S	L-S	Sig.
Average 1-yr ahead forecast error	-0.025	-0.094	0.070	***
Average 2-yr ahead forecast error	-0.040	-0.145	0.105	***

Panel C: Future estimate revisions (REV)	L	S	L-S	Sig.
Average 1-yr ahead forecast revision	-0.012	-0.037	0.025	***
Average 2-yr ahead forecast revision	-0.028	-0.094	0.067	***

Table 8 (continued)

Panel D: Multivariate analysis of forecast errors, revisions, and announcement returns

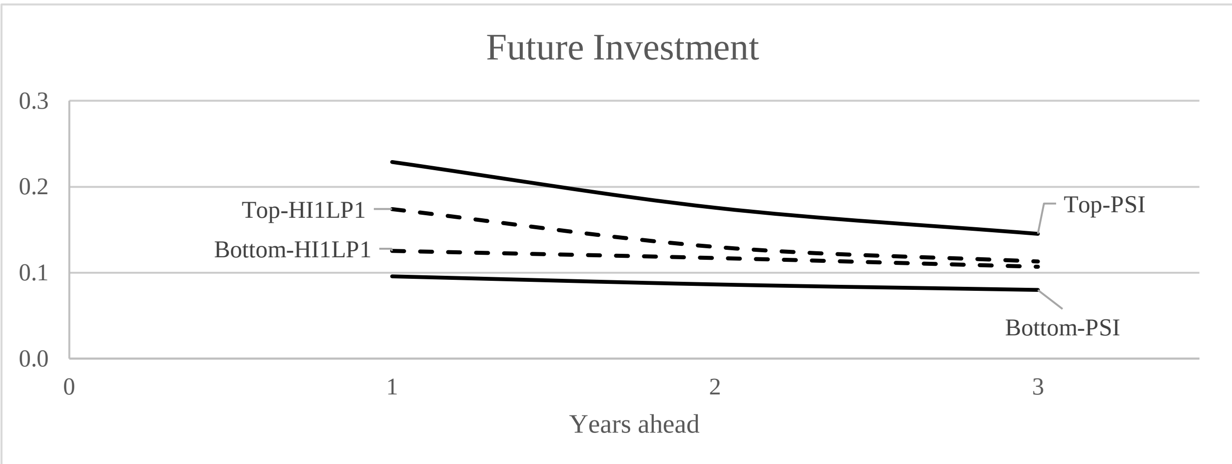
	One year ahead			**Two years ahead**		
	(1)	(2)	(3)	(4)	(5)	(6)
Variable	FE1	EAret1	REV1	FE2	EAret2	REV2
Long	0.370	-0.128	0.242**	-0.317	-0.0101	-0.330*
	(1.46)	(-1.41)	(2.14)	(-1.00)	(-0.13)	(-1.92)
Short	-5.263***	-0.930***	-2.448***	-6.430***	-1.029***	-4.937***
	(-6.57)	(-3.29)	(-6.47)	(-4.58)	(-4.14)	(-5.18)
Mom	6.627***	0.228***	2.743***	9.289***	0.140***	5.786***
	(7.73)	(3.63)	(6.52)	(8.12)	(2.99)	(7.89)
Lnsize	1.833***	0.000117	0.572***	2.549***	-0.0208	1.336***
	(12.88)	(0.01)	(11.38)	(13.12)	(-0.77)	(12.62)
MB	0.214***	-0.0109	0.0883***	0.173**	-0.0183	0.116**
	(3.19)	(-0.74)	(3.00)	(2.20)	(-1.50)	(2.16)
Observations	84,303	112,182	79,628	71,043	102,674	66,966
R-squared	0.076	0.005	0.067	0.083	0.005	0.083
Constant	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Clustering	F & Y	F & Y	F & Y	F & Y	F & Y	F & Y

Test of difference between coefficients in long and short portfolios

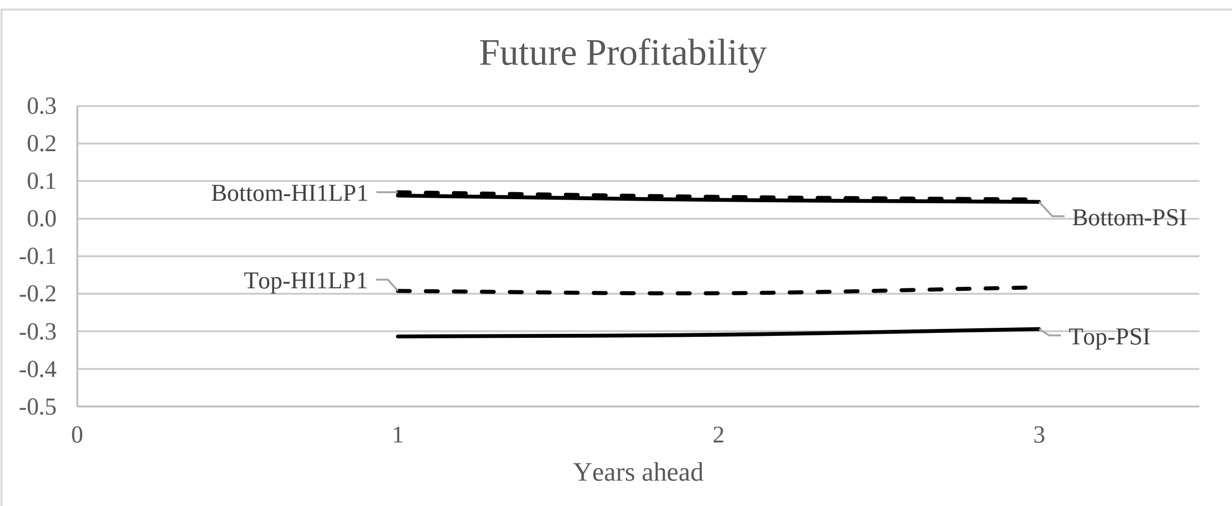
Long - Short	5.633	0.802	2.69	6.113	1.019	4.607
(F-stat)	(35.68)***	(7.99)***	(41.88)***	(17.90)***	(18.59)***	(22.82)***

Figure 1: Future Firm Characteristics of PSI firms and HILP firms

This figure presents future firm characteristics by extreme PSI and HILP deciles. In each graph, charted values depict the mean *roa* or *inv* of the firm-year observations in the next three years, for extreme decile firms based on predicted stock issuance (PSI) or high-income low-profitability (HI1LP1). Figure 1A presents future investment and Figure 1B presents future profitability. Variables with a suffix _n refer to the values of those variables n fiscal years ahead.



	inv_1	inv_2	inv_3
PSI spread	0.133	0.089	0.065
HI1LP1 spread	0.049	0.013	0.006
PSI – HI1LP1	0.084	0.076	0.059



	roa_1	roa_2	roa_3
PSI spread	0.375	0.359	0.339
HI1LP1 spread	0.263	0.257	0.234
PSI – HI1LP1	0.113	0.102	0.105

Figure 2: Distribution of Post-formation Returns (Top-PSI vs. Bottom-PSI)

This figure presents the distribution of post-formation returns for top-PSI and bottom-PSI firms. To construct these graphs, stocks are sorted into ten deciles based on the PSI score at the end of June of each year from 1978-2013. A long position is taken in firms that are in the lowest decile of predicted stock issuance, and a short position is taken in firms that are in the highest decile of predicted stock issuance. In each graph, the Long (Short) portfolio depicts the return distribution of the top-PSI (bottom-PSI) decile firms. Figure 2A is the return distribution for one-year post formation; Figure 2B is the distribution for two years post formation.

Figure 2A – Post One-year Return Distribution

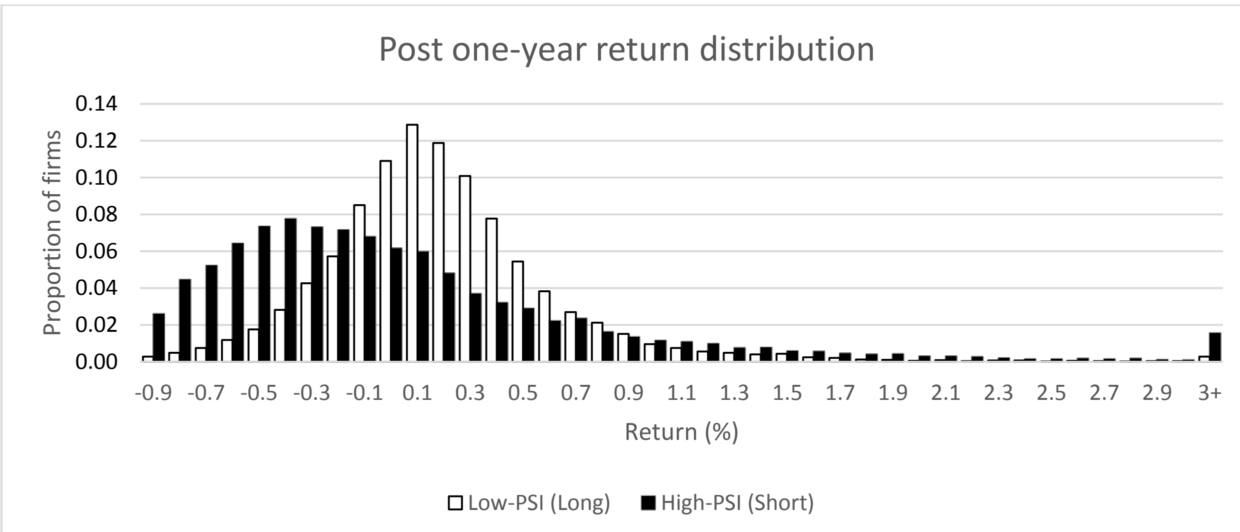


Figure 2B – Post Two-year Return Distribution

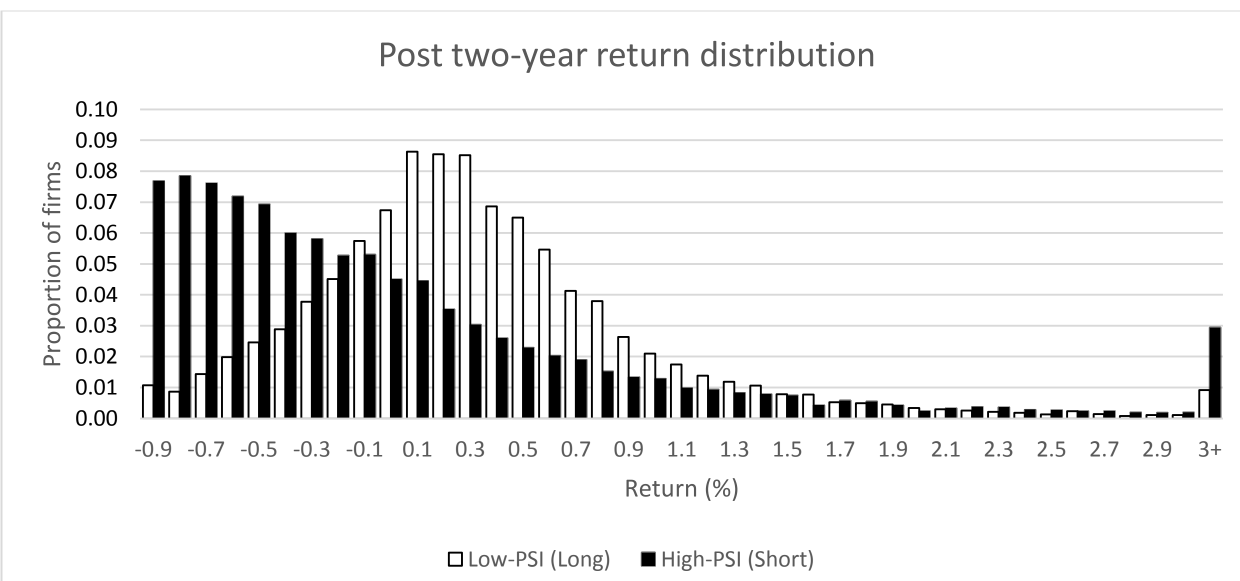


Figure 3: Return Distributions (Pre-Formation versus Post-Formation)

This figure compares the distribution of two-year returns before portfolio formation (Prior-two-year) with the distribution for the same firms after portfolio formation (Post-two-year). To construct these graphs, stocks are sorted into ten deciles based on their PSI score at the end of June of each year from 1978-2013. A long position is taken in firms that are in the lowest-decile of PSI, and a short position is taken in firms that are in the highest decile of PSI. Figure 3A reports the distributional frequencies for Top-PSI firms (the Short-leg of the hedge portfolio). Figure 3B reports the empirical cumulative distribution function for Top-PSI firms.

Figure 3A – Returns for Top-PSI firms: Prior-two-year versus Post-two-year

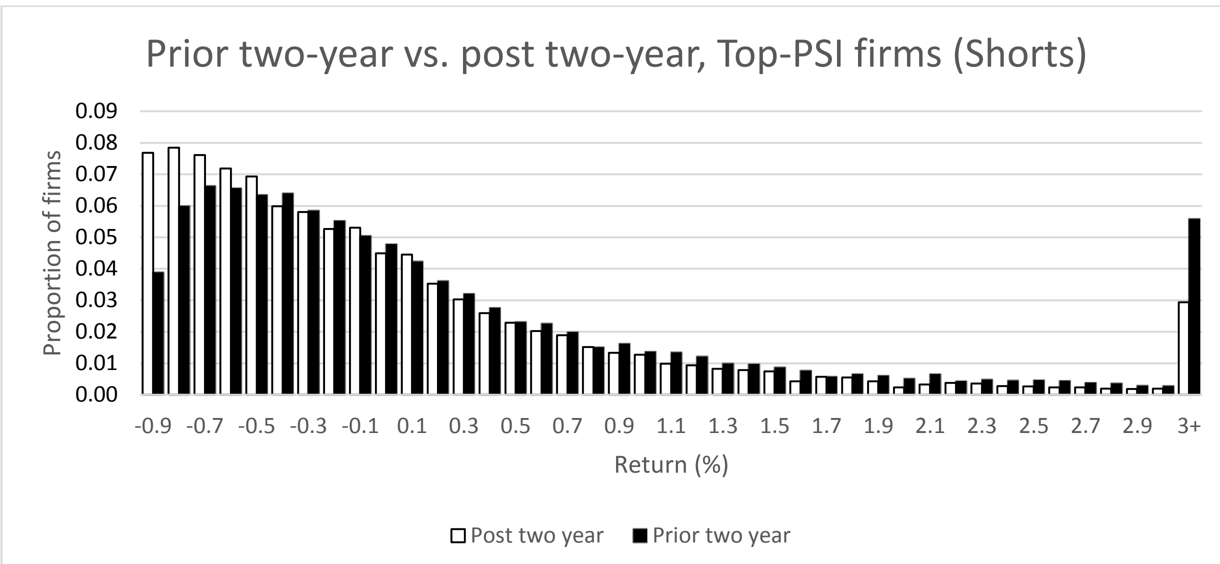


Figure 3B – Empirical CDFs for Top-PSI firms: Prior-two-year versus Post-two-year

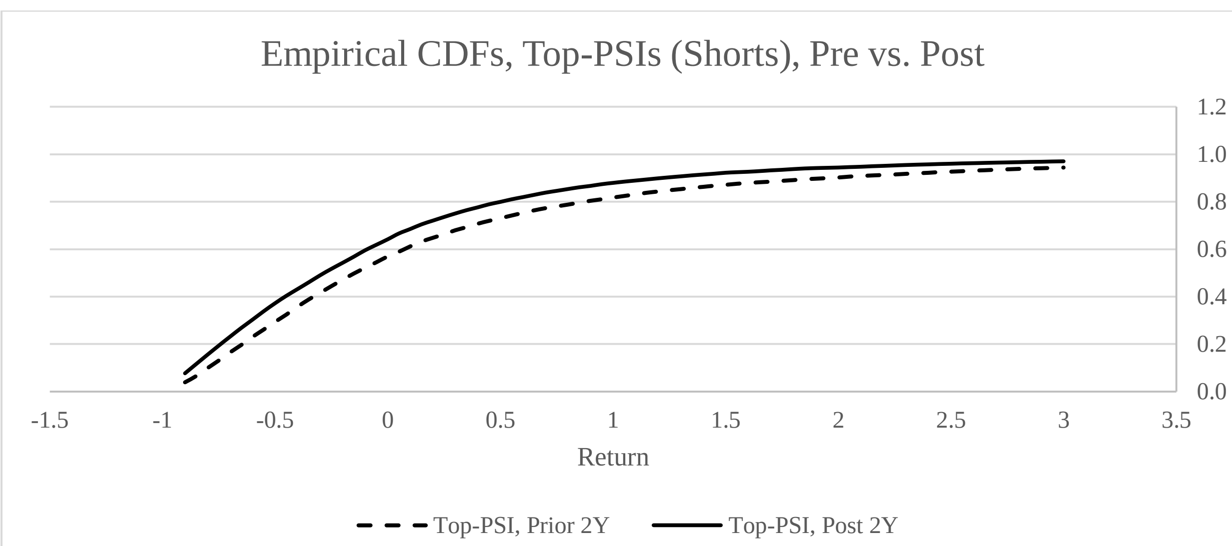


Figure 4: Shorting Costs by PSI decile

This figure presents shorting costs by PSI decile using 2004-2011 data from the Markit Data Explorers (DXL) dataset. To construct these graphs, stocks are sorted into ten deciles based on the PSI score at the end of June of each year. The graph depicts the mean Utilization rate and Specialness measure for each PSI decile in the month of portfolio formation. Utilization rate is the ratio of shares on loan to shares available for lending, and Specialness is the percentage of firms in each portfolio that are not easy-to-borrow (i.e., not "general collateral") stocks as defined in Beneish, Lee, and Nichols (2015). Higher utilization rates and greater Specialness indicate higher shorting costs and more binding short-sale constraints.

PSI Decile	1	2	3	4	5	6	7	8	9	10	10-1	Sig.
Specialness	6.3%	5.7%	5.4%	5.6%	8.1%	11.0%	13.5%	14.9%	18.9%	38.4%	32.1%	***
Utilization	16.3%	14.6%	15.0%	16.4%	17.6%	15.9%	14.8%	16.0%	19.6%	28.4%	12.1%	***