# Disentangling Anomalies: Risk versus Mispricing*

Justin Birru† Hannes Mohrschladt‡ Trevor Young§

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**Abstract**

Systematic mispricing primarily affects speculative stocks and tends to take the form of overpricing, predicting lower average returns. Because speculative stocks are typically deemed risky by rational models, failing to control for exposure to systematic mispricing can bias tests of risk-return tradeoffs. Controlling for the effects of systematic mispricing, we recover robust positive risk-return relations for a large number of cross-sectional risk proxies, including many low-risk and distress anomalies. We also recover robust positive illiquidity-return relations. We provide a unifying framework to explain a number of puzzles arising from the empirical failure of standard asset pricing models, and show that risk-return relations supporting rational models can be recovered from the data by accounting for the existence of time-varying common mispricing.

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†Fisher College of Business, The Ohio State University

‡Finance Center Münster, University of Münster

§A.B. Freeman School of Business, Tulane University

# 1 Introduction

Standard models of rational asset pricing predict that stocks with greater risk require higher returns. However, empirical evidence has proved elusive when examining straightforward measures of systematic risk or characteristics that should be priced (e.g., beta, illiquidity). In this paper, we argue that behavioral theories can predict that certain assets deemed riskier by standard models will exhibit predictably low expected returns. In particular, we point out a tug of war between behavioral and rational theories—behavioral forces predict low returns to speculative stocks (e.g., high beta, distressed, volatile, or illiquid stocks) while standard risk models predict the opposite. Sorts on risk or illiquidity variables therefore consist of two opposing forces that potentially offset one another, leading to muted return predictability, or even return predictability that contradicts cross-sectional predictions of standard models. Our main contribution is to provide a unifying explanation, and supportive empirical evidence, for a number of existing risk puzzles in the cross-section of stock returns. While a few risk-based factor models (e.g., Fama and French, 2015; Hou, Xue, and Zhang, 2015) can account for some of these puzzles, they do so by attributing the higher returns to risk, despite the fundamentals suggesting the firms are safer (e.g., lower beta, lower volatility, lower distress). Relying instead on three existing, distinct sets of mispricing factors, we find that after isolating the component of returns due to systematic mispricing the remaining return component that is hedged of mispricing exhibits cross-sectional return relations consistent with predictions from standard models of rational asset pricing. The evidence reconciles standard model predictions with a number of existing anomalies, including the low-risk, distress, and illiquidity puzzles.[1]

Our insight combines several key observations from the behavioral literature. First, a large literature provides evidence of the existence of mispricing, and a growing literature

[1]The low-risk and distress puzzles include anomalies related to beta and idiosyncratic volatility, and $O$-score and failure probability, respectively. By illiquidity puzzle, we are referring to the insignificant relation between illiquidity proxies and the cross-section of returns for value-weighted portfolios using NYSE breakpoints (see, e.g., Hou, Xue and Zhang, 2020).

takes seriously the argument that mispricing has a common sentiment-induced component across stocks.[2] Second, a growing literature suggests that mispricing tends to take the form of overpricing (e.g., due to short-sales constraints), suggesting that stocks most exposed to mispricing are likely to exhibit relatively low expected returns.[3] A third finding in the behavioral literature is that speculative stocks (those that are hard or highly subjective to value or hard to arbitrage) are likely to be most affected by market-wide sentiment-induced mispricing, suggesting that these stocks will have mispricing betas that are larger in absolute magnitude. This third literature argues that speculative stocks tend to be those that are high-beta, volatile, small, young, illiquid, prone to speculative demand, or potentially close to distress; a final observation is therefore that these proxies for speculativeness often overlap with proxies for risk. In short, behavioral theories predict that in the presence of limits to arbitrage, systematic noise trading can move prices away from fundamental value, typically in the direction of overpricing due to increased arbitrage frictions related to shorting. Predictable cross-sectional return patterns arise from the eventual correction of mispricing, with the strongest cross-sectional patterns existing for speculative stocks, as they have the greatest sensitivity to systematic mispricing (i.e., mispricing betas that are largest in magnitude). Combining the above observations suggests that speculative stocks should earn predictably low returns, on average.

If exposure to systematic mispricing was orthogonal to priced risk exposure, then systematic mispricing would not confound tests of standard asset pricing models. In contrast, if loadings on systematic mispricing are correlated with risk, then tests of standard models

[2]For empirical evidence consistent with a common sentiment-induced component of mispricing, see, for example, Baker and Wurgler (2006), Stambaugh, Yu and Yuan (2012), or Baker, Wurgler and Yuan (2012). For a more general discussion of factor models capturing common sources of mispricing, see Kozak, Nagel and Santosh (2018). Stambaugh and Yuan (2017) and Daniel, Hirshleifer and Sun (2020) identify mispricing factors capturing common elements of mispricing and motivate their analyses by appealing to existing evidence of a common sentiment-induced component of mispricing.

[3]De Long, Shleifer, Summers and Waldmann (1990) present a theory of noise trader risk in which systematic noise trader risk predicts higher returns for assets exposed to greater noise trading. However, empirical evidence finds that stocks with greater exposure to systematic noise trader sentiment exhibit lower returns (see, e.g., Glushkov, 2006; Young, 2019). The existing empirical evidence is consistent with Miller (1977), rather than De Long et al. (1990).

can be compromised. Existing behavioral literature argues that many prominent proxies for risk double as proxies for speculativeness and therefore correlate highly with exposure to systematic mispricing. Specifically, time-variation in mispricing reflecting waves of systematic sentiment should most affect stocks that are difficult to value and stocks that have greater limits to arbitrage (Baker and Wurgler, 2006). In practice, variables that proxy for difficulty to value are likely to be the same ones that proxy for limits to arbitrage (e.g., beta, volatility, size, age, illiquidity, distress), and a large empirical literature confirms that speculative stocks identified using these proxies covary more strongly with proxies for sentiment.[4] We focus on 12 speculative strategies (risk and illiquidity proxies) that have one clear speculative (risky or illiquid) leg and one clear non-speculative (non-risky or less illiquid) leg.[5] In sum, because increased sensitivity to mispricing results in low average returns for these speculative stocks, but standard (non-behavioral) models predict that these same assets should earn high average returns to compensate investors for bearing risk, failing to account for mispricing can render empirical tests of risk-based theories misleading.

Recently, three factor models interpreted as capturing time-variation in systematic mispricing have been introduced: the long- and short-horizon behavioral factors of Daniel et al. (2020), the performance and management mispricing factors of Stambaugh and Yuan (2017), and the quality-minus-junk factor of Asness, Frazzini and Pedersen (2019). The introduction of these mispricing factor models is central to our analysis as it allows us to take a different approach than the existing empirical literature.[6] Rather than regress returns on rationally motivated factors, we instead turn to mispricing factors. Analogous to deeming the portion of returns unexplained by rational factors as anomalous and potentially due to non-rational forces (i.e., alpha), we suggest that the portion of returns unexplained by mispricing factors primarily reflects non-behavioral forces. We ascribe the portion of returns unexplained by

[4] See, for example, Lee, Shleifer and Thaler (1991), Baker and Wurgler (2006), Kumar and Lee (2006), Kumar (2009), Baker et al. (2012), Hribar and McInnis (2012), Seybert and Yang (2012), Da, Engelberg and Gao (2015), Antoniou, Doukas and Subrahmanyam (2016), Birru (2018), and Birru and Young (2020).

[5] We reserve a detailed discussion of the rational and behavioral theories underlying the strategies for Section 2.

[6] Relying on existing and distinct factor models also reduces concerns of data mining.

mispricing factors as the risk component of returns. Of course, what we term the risk component can still include any effects not captured by the mispricing factors; however, any effects of systematic mispricing should be substantially weaker for this risk component than should be expected for returns that are not purged of systematic mispricing. We do not take a stance on which mispricing factor model might best capture systematic mispricing, but instead separately show our full set of results for each of the three models, offering three distinct tests of our main hypothesis. We find consistent results across all three models. Following Hou et al. (2020), we focus all of our analyses on value-weighted portfolios using NYSE breakpoints to mitigate the effects of microcaps.

First, we confirm empirically that the stocks most sensitive to mispricing are those that theory predicts to have greater noise trading or limits to arbitrage (e.g., high beta, high idiosyncratic volatility, and high illiquidity stocks). In particular, we show that portfolios sorted on our set of risk proxies that double as proxies for speculativeness exhibit sensitivity to mispricing factors that increases in speculativeness for all three of our mispricing factor models. Next, we use the loadings on the mispricing factors to decompose the portfolio returns into a mispricing component, reflecting the mispricing loadings, and a risk component, reflecting the residual returns that are orthogonal to the mispricing factors.

Figure 1 succinctly illustrates our main results by averaging across our 12 strategies and three mispricing factor models. Sorting riskier stocks into higher decile portfolios according to standard rational models, we do not find that riskier stocks average unconditionally higher returns, demonstrating the problem that others have also pointed out. However, after applying our decomposition, we find that the mispricing component exhibits monotonically decreasing returns across deciles, consistent with predictions of overpricing in the presence of short-sales impediments. In contrast, the residual component, which plausibly better reflects risk, exhibits monotonically increasing returns across deciles, consistent with predictions of standard rational models. Moreover, the long-short risk (mispricing) component averages statistically significant positive (negative) returns. Thus, in addition to recovering positive risk-return relations in the data, we are also able to recover monotonic risk-return relations, an important additional prediction of standard rational models. The results are consistent with negative returns to high mispricing-beta stocks obscuring the risk-return relation and with the hedging out of systematic mispricing generating a positive risk-return relation in the data. Moreover, our main results are robust to factor model specification, are not concentrated in microcaps, and are stable over time.

We test a number of additional predictions and find evidence consistent with our interpretation. If sensitivity to mispricing for the risky (i.e., speculative) leg drives the patterns we observe, we should fail to find similar patterns when examining anomalies that do not have one clear speculative leg and one clear non-speculative leg. Consistent with this prediction, we fail to find evidence of similar patterns when examining a set of prominent anomalies serving as placebos for which previous literature finds there does not exist clear speculative and non-speculative legs.

In addition, theories of time-varying sentiment-induced mispricing predict that the mispricing component should exhibit time-series comovement with non-return-based sentiment measures. Consistent with this prediction, we find that the mispricing component exhibits strong sensitivity to the Baker-Wurgler sentiment index in the predicted direction. Of the 36 (12 strategies times three mispricing factor models) long-short mispricing components, 34 exhibit statistically significant sensitivity to sentiment in the predicted direction at the 5% level. In contrast, the risk component is typically unrelated to sentiment, with only four of the 36 long-short risk components exhibiting significance at the 5% level, consistent with a negligible role for investor sentiment among classical finance theory. Finally, if the removal of systematic mispricing results in a remaining return that reflects risk, then we should expect the risk component to also capture risk. Predictions here are clearest for the risk proxy of beta. Consistent with theory we find that the tradable long-short beta portfolio that is hedged of mispricing exhibits a statistically significant positive CAPM beta.

Our research is related to a large literature documenting empirical return patterns that are seemingly inconsistent with predictions of standard rational models. The empirical failures of standard models of most relevance to us are those revolving around low-risk anomalies, distress anomalies, and illiquidity anomalies. For example, Black, Jensen and Scholes (1972) show that stocks with high (low) betas have negative (positive) CAPM alphas, contradicting predictions of standard models of rational asset pricing. Similarly, when examining variables proxying for closeness-to-distress, the literature fails to find a distress premium, or documents a premium that goes in the opposite direction (see, e.g., Ohlson, 1980; Campbell, Hilscher and Szilagyi, 2008). Finally, the literature also fails to find robust evidence that illiquidity proxies predict returns in a manner consistent with standard models of liquidity (Hou et al., 2020).

Our study is also related to work that empirically tests rational or behavioral explanations for the low risk or distress anomalies.[7] Asness, Frazzini, Israel, Mokowitz, and Pedersen (2018) show that the size effect is resurrected after controlling for the quality of a firm. Among behavioral explanations, Gao, Parsons and Shen (2018) provide cross-country evidence suggesting that the distress anomaly can potentially be explained by overconfidence. An, Wang, Wang and Yu (2020) show that a number of lottery-related anomalies, including both low-risk and distress anomalies, can be explained by reference-dependent preferences. Jin (2013) and Stambaugh, Yu and Yuan (2015) examine cross-sectional return predictions of idiosyncratic volatility by combining a number of anomalies, arguing that arbitrage frictions are more binding on the short side, and idiosyncratic volatility (ivol) represents risk that deters arbitrage. Combining 11 anomalies to represent mispricing, Stambaugh et al. (2015) find that the negative ivol-return relation for overpriced stocks outweighs the positive ivol-return relation for underpriced stocks, explaining the lower average returns for high idio-

[7]Among rational explanations, Schneider, Wagner and Zechner (2020) provide evidence that low-risk anomalies (beta and idiosyncratic volatility) are largely driven by a single component which reflects skewness. Jylhä (2018) provides empirical evidence supportive of a leverage constraint explanation (Black, 1972; Frazzini and Pedersen, 2014) for the beta anomaly. Chava and Purnanandam (2010) argue that distress anomalies reflect unexpectedly low sample-specific realized returns to distressed stocks. Eisdorfer, Goyal and Zhdanov (2018) provide cross-country evidence that risk related to takeover legislation and information transparency can potentially explain the distress anomaly.

syncratic volatility stocks. Liu, Stambaugh and Yuan (2018) apply this insight to explain the low beta anomaly, owing to the observation that there is a positive correlation between beta and idiosyncratic volatility. Similarly, we rely on the logic that mispricing should primarily take the form of overpricing. We combine this insight with the argument that there exists time-varying systematic mispricing, that stocks with the largest mispricing betas will be speculative stocks (those that are harder or more subjective to value and/or have greater limits to arbitrage), and that proxies for speculativeness tend to overlap with proxies for risk. Importantly, while previous research is able to explain the existence of some low-risk and distress anomalies, we provide a unifying theory for a number of low-risk, distress, and illiquidity puzzles. In addition, in contrast to existing research that seeks to explain anomaly puzzles as they exist in the data, we are able to both explain existing puzzles and also recover positive risk-return relations in the data that are consistent with predictions of standard models.

Our work is perhaps most closely related to the behavioral finance literature that examines cross-sectional implications of the effect of sentiment on proxies for speculativeness. Baker and Wurgler (2006) argue that characteristics such as age, volatility, size, and distance to distress can identify stocks most affected by sentiment. They provide empirical evidence that sentiment predicts the cross-section of returns in a manner consistent with this hypothesis, and a large literature finds consistent evidence and extends this set of characteristics. Building on this insight, Stambaugh et al. (2012) find that anomaly returns are higher following high sentiment periods, while Yu and Yuan (2011) and Shen, Yu and Zhao (2017) present evidence that sentiment-driven investors can undermine the traditional risk-return relation. Glushkov (2006) uses changes in non-traded sentiment proxies to calculate sentiment betas. Consistent with Baker and Wurgler (2006), he finds that characteristics such as size, volatility, and age proxy for sensitivity to sentiment, and further finds that high sentiment beta stocks underperform low sentiment beta stocks. In a similar vein, Young (2019) measures a stock's speculativeness as its return sensitivity to shifts in sentiment and documents that the relation between speculativeness and future returns is significantly negative. Relative to existing literature, we show that behavioral theory offers a unifying explanation for the empirical failure of rational asset pricing models in explaining a broad set of cross-sectional return relations with proxies for risk and illiquidity.

Our analysis provides a framework for thinking about rational factors that also reflect sorts on speculative variables.[8] We are able to recover return relations predicted by rational models in the data, but only after accounting for the sensitivity of these strategies to market-wide sentiment-induced mispricing. Our findings highlight the tug of war between behavioral and rational forces—behavioral forces predict low returns to speculative stocks (e.g., high beta, high volatility, high illiquidity) while standard rational explanations predict the opposite. This tug of war causes high-risk assets or illiquid assets (high beta, high volatility, high illiquidity) to have low or even negative returns relative to their low-risk or liquid counterparts. Considering mispricing when examining many prominent risk and illiquidity proxies delivers predictions in line with behavioral and rational theories of returns.

The paper proceeds as follows. Section 2 discusses the theoretical framework guiding our analysis. Section 3 discusses the empirical methodology. Section 4 presents our main empirical results. Section 5 tests additional predictions of our hypotheses and performs robustness checks. Section 6 concludes.

# 2 Predictions for the Cross-Section of Returns

In this section, we discuss the set of long-short strategies that we examine. We identify these strategies based on risk and illiquidity proxies for which there is one clear speculative leg and one clear non-speculative leg. In particular, the strategies' underlying proxy variables also reflect speculativeness such that the corresponding long-short returns have been shown to

[8]The existence of mispricing requires the presence of both noise traders and limits to arbitrage. The speculative variables we examine have been identified in the past literature as variables that are proxies for noise trading and/or limits to arbitrage. Therefore variables that proxy for limits to arbitrage (e.g., idiosyncratic volatility) or that proxy for noise trading (e.g., age, nominal price) should exhibit the predicted effects, but do not deliver clear predictions regarding expected relative effects.

exhibit relatively high sensitivity to sentiment. We restrict our sample of strategies to only those for which there exist clear return predictions based on traditional risk- and illiquidity-related arguments. For all of the strategies we examine, the speculative (non-speculative) leg is also the leg that these traditional arguments suggest to have greater (lower) risk or illiquidity. Our set of 12 strategies includes market beta, size, nominal stock price, firm age, idiosyncratic volatility, dispersion of opinion, cash flow volatility, failure probability, downside beta, Amihud (2002) illiquidity, and high-low spread. The Appendix provides detailed variable definitions. Next, we discuss standard asset pricing predictions for the variables we study. In Section 2.2, we discuss behavioral justifications for the variables that we focus on.

## 2.1 Predictions of Rational Models

For each of the 12 strategies, we shortly discuss why the underlying variables should predict the cross-section of returns based on the most standard asset pricing arguments, but we also note that additional rational arguments for many variables exist. Starting with the most well-known asset pricing model, the CAPM predicts higher expected returns for stocks with higher market betas to compensate for systematic market risk exposure (Sharpe, 1964; Lintner, 1965; Mossin, 1966). Moreover, theories of time-varying risk premiums predict that market values decrease in risk premiums (Ball, 1978; Berk, 1995). Size and price are two straightforward measures of market value that should directly reflect these time-varying risk premiums.[9] Hence, small and low-priced stocks should have higher expected returns than large and high-priced stocks.

Standard theories predict higher expected returns for bearing risk related to uncertainty about future earnings. Additionally, extensions of the CAPM in which investors hold un-diversified portfolios predict that investors will demand compensation for idiosyncratic risk (Levy, 1978; Merton, 1987; and Malkiel and Xu, 2002). High dispersion of analysts' fore-

[9]See Blume and Husic (1973) and Bar-Yosef and Brown (1979) for arguments that lower (higher) share price will be associated with higher (lower) systematic risk.

casts indicates less predictable future earnings and also reflects the type of idiosyncratic risk referred to by Merton (1987).[10] Standard theories therefore predict that stocks with high dispersion of opinion or high idiosyncratic volatility should earn higher returns than stocks with low dispersion of opinion or stocks with low idiosyncratic volatility. Similarly, assets with greater information uncertainty should experience higher average returns. Thus, stocks with higher cash flow volatility (Zhang, 2006) should have relatively large expected returns.

Theories of distress predict higher expected returns for firms facing larger distress risk. Moreover, if stocks of financially distressed companies tend to move together, then distress risk might not be diversifiable such that it requires a risk premium (see Chan and Chen, 1991; Fama and French, 1992, 1996; and Campbell et al., 2008 for thorough discussion on why distress risk should be priced). We therefore expect high $O$-score stocks and high failure probability stocks to earn higher returns (Ohlson, 1980 and Campbell et al., 2008). Altman (1968) suggests that young firms are likely to exhibit higher bankruptcy risk, and Altman, Iwanicz-Drozdowska, Laitinen and Suvas (2017) confirm that failure risk is higher for young firms. In general, assets that tend to move down in a declining market to a greater extent than they move up in an increasing market will have low returns precisely when wealth is low and will therefore require higher expected returns. Hence, a strategy based on downside beta should also earn a risk premium (Ang, Chen and Xing, 2006a). Rational theories therefore suggest that high failure probability, high $O$-score, young, and high downside beta firms should earn higher average returns.

Finally, less liquid assets should earn higher expected returns. We include two variables that directly proxy for liquidity, Amihud (2002) illiquidity and high-low bid-ask spread (Corwin and Schultz, 2012). Stocks with high illiquidity or large high-low spreads should earn higher average returns than stocks with lower illiquidity or lower high-low spreads.

We note that other rational theories not discussed here also provide similar predictions as the risk and illiquidity explanations above and that interconnections between the strategies

[10] Abel (1989) and Banerjee (2011) also predict that assets for which there is increased disagreement bear increased risk that should be compensated with higher expected returns.

exist. For example, return volatility, firm size, and nominal stock price enter directly in the failure probability model of Campbell et al. (2008), with smaller stocks, lower price stocks, and stocks with more volatile returns receiving higher failure probability scores. Further, theories of real growth options predict that growth options are risky such that firms with more growth options are expected to have higher returns (e.g., Berk, Green and Naik, 1999; Carlson, Fisher and Giammarino, 2004; Gârleanu, Panageas and Yu, 2012). Strategies formed on sorts of size and age should earn risk premiums for bearing this risk, predicting that small and young stocks to earn higher average returns than large and old stocks, respectively. Also, many of our strategies may fit under more than one of the rational theories discussed above. An additional straightforward rationale for many of the strategies that we focus on is that they reflect trading frictions. Firms facing more trading frictions should have higher expected returns. Indeed, Hou et al. (2020) classify seven of the 12 strategies we study as reflecting trading frictions.[11]

Table 1 presents risk predictions for the set of strategies that we study. Throughout our analysis, we denote long and short legs according to the predictions of the aforementioned traditional arguments, that is, high-risk or high-illiquidity stocks enter the long leg of each strategy. For each strategy, the table specifies long leg and short leg as well as risk and mispricing predictions for long-short leg returns. These predictions provide the basis for our empirical analyses.

## 2.2 Predictions of Behavioral Models

There are three components to our argument that speculative stocks should exhibit lower average returns. Each component reflects a prominent concept in the literature typically discussed in isolation. Our investigation combines these three components.

First, a commonly accepted view is that mispricing at least partly reflects time-varying

[11]In particular, Hou et al. (2020) classify market beta (Dimson, 1979; Frazzini and Pedersen, 2014), size (Banz, 1981), price (Miller and Scholes, 1982), idiosyncratic volatility (Ang, Hodrick, Xing and Zhang, 2006b), downside beta (Ang et al., 2006a), illiquidity (Amihud, 2002), and high-low bid-ask spread (Corwin and Schultz, 2012) as frictions.

market-wide sentiment.[12] Second, mispricing is more likely to take the form of overpricing than underpricing.[13] One potential explanation for this is that limits to short selling particularly hinder the ability of arbitrageurs to combat overpricing (Miller, 1977). Increased arbitrage impediments to shorting relative to going long imply that speculative stocks tend to be overvalued rather than undervalued. Third, a large literature argues that sentiment should most affect speculative stocks. We focus our discussion in this section on the third component, as this argument dictates the appropriate cross-sectional risk proxies that should be considered. There are two primary arguments for why sentiment should most affect speculative stocks.

The first argument is that sentiment is likely to most strongly affect stocks with subjective valuations as the relatively subjective nature of valuations for these stocks makes it easier for noise traders to defend valuations from much too high or too low as suits their irrational optimism or pessimism. In contrast, sentiment is unlikely to have a strong effect on investor perceptions of value for safe bond-like stocks that have a more concrete valuation, for example, because they are in a stable, well-understood industry, or because they are large, mature, dividend-paying firms with a stable earnings history. Baker and Wurgler (2006) argue that sentiment is most likely to show up in the valuations of speculative stocks that are likely to be small, young, volatile, and potentially close to distress, among other attributes. Second, even if it were the case that sentiment instead induces equally biased beliefs across all stocks, mispricing should show up most strongly for the subset of stocks for which arbitrage is most limited. As Baker and Wurgler (2006, 2007) point out, stocks that are most difficult to arbitrage are likely to share similar attributes to those that are the most difficult or subjective to value, namely difficult-to-arbitrage stocks are likely to be small, young, volatile, and potentially close to distress. Empirical evidence showing that

[12] Recent literature discussing this concept includes Daniel, Hirshleifer and Subrahmanyam (2001), Barberis and Shleifer (2003), Baker and Wurgler (2006), Hirshleifer and Jiang (2010), Baker et al. (2012), Stambaugh et al. (2012), Stambaugh and Yuan (2017), and Daniel et al. (2020).

[13] See corresponding empirical evidence in Nagel (2005), Jin (2013), Stambaugh et al. (2012), Stambaugh et al. (2015), and Drechsler and Drechsler (2016).

sentiment most strongly affects returns of these groups of stocks can be found in a lengthy list of papers, including Baker and Wurgler (2006).[14]

We start with the set of categories suggested by Baker and Wurgler (2006). In particular, we focus on risk proxies that fall within the categories of size, age, volatility, or distance-to-distress.[15] This yields six risk proxies associated with volatility (idiosyncratic volatility), size (size), age (age), and distress ($O$-score, failure probability, and downside beta).

To this list we add beta, price, cash flow volatility, dispersion of opinion, high-low spread, and Amihud illiquidity. High-low spread and illiquidity are direct measures of trading frictions, suggesting increased sensitivity to sentiment due to limits to arbitrage. Beta and price are also associated with trading frictions (Hou et al., 2020).[16] In addition, evidence suggests that shorting costs increase in dispersion of opinion (e.g., D'Avolio, 2002), suggesting that dispersion of opinion proxies for limits to arbitrage that specifically prevent correction of overpricing.

Moreover, stocks with high beta, low price, high cash flow volatility, and high dispersion of opinion are particularly prone to speculative trading and tend to be difficult to value. For example, existing literature argues that speculative demand is greatest for high beta stocks (Barber and Odean, 2000, 2001). Empirically, Stambaugh et al. (2012), Da et al. (2015), and Antoniou et al. (2016) show that high beta stocks exhibit significantly increased sensitivity to sentiment relative to low beta stocks. Existing literature also suggests that low price stocks are likely to be affected by speculative demand (Black, 1986; Kumar and Lee, 2006; Kumar,

[14] A non-exhaustive list of papers examining variables discussed here and providing empirical evidence that they are strongly related to sentiment includes Lee et al. (1991), Baker and Wurgler (2006), Glushkov (2006), Kumar and Lee (2006), Lemmon and Portniaguina (2006), Baker et al. (2012), Mian and Sankaraguruswamy (2012), Hribar and McInnis (2012), Seybert and Yang (2012), and Da et al. (2015).

[15] Baker and Wurgler (2006) also argue and provide evidence that non-dividend paying stocks and stocks of unprofitable companies are more sensitive to sentiment. We exclude these categories as they are not related to cross-sectional predictions from traditional asset pricing models. Baker and Wurgler (2006) also examine book-to-market, but fail to find evidence that book-to-market is linearly related to sentiment, instead finding that both extreme deciles are sensitive to sentiment, arguing that this reflects that low book-to-market is associated with extreme growth and high book-to-market values is associated with distress.

[16] Further, Baker, Bradley and Wurgler (2011) discuss limits to arbitrage arising from benchmarking mandates of institutional investors. As they point out, limits to arbitrage driven by benchmarking mandates are particularly likely to discourage arbitrage activity in low-risk anomalies (Baker et al. (2011) specifically focus on beta and volatility).

2009; Brandt, Brav, Graham and Kumar, 2010; Birru and Wang, 2016) and Kumar and Lee (2006) provide evidence that low-priced stocks are more sensitive to sentiment. Finally, cash flow volatility and dispersion of opinion are direct proxies for difficulty to value (Zhang, 2006).

More broadly, Birru (2018) classifies 63 cross-sectional strategies as speculative strategies or non-speculative strategies (19 as speculative and 44 as non-speculative). Our classification of speculative anomalies is consistent with the classification and lengthy discussion provided in that paper, as the 12 strategies we examine are a subset of the 19 strategies classified as speculative strategies in Birru (2018), with the exception of downside beta which is not one of the 63 variables examined in that paper.[17] We focus on fewer anomalies than Birru (2018) because we are only interested in speculative strategies that also have clear predictions from rational models. Overall, existing theory strongly argues that sentiment-induced mispricing should primarily affect speculative stocks and existing empirical literature provides evidence that stocks that are small, young, volatile, distressed, high-beta, high-trading-friction, or otherwise hard-to-value exhibit increased sensitivity to sentiment. We note that many of these speculative characteristics also line up with proxies for illiquidity and low-risk and distress anomalies. Further consistent with these strategies possessing a speculative long leg and non-speculative short leg, in unreported analyses we find that the correlations across the 12 strategies are on average large and positive.

In sum, previous literature makes the case that there is a common sentiment-related component to mispricing, that mispricing tends to result in overpricing, and that speculative stocks are most sensitive to sentiment-related mispricing. Next we examine the empirical implications of combining these three predictions of behavioral theory with predictions of standard asset pricing models. To do so, we focus on 12 variables identified as risk proxies according to rational models that also double as proxies for speculativeness according to

[17] Downside beta has precedent as a speculative anomaly. Da et al. (2015) use it as one of three speculative variables (along with beta and volatility) and document that downside beta is sensitive to their daily sentiment measure.

behavioral models.

### 2.3 Combining Rational and Behavioral Predictions

Coupled together, rational and mispricing-based theories predict two forces pushing in opposing directions, suggesting unclear unconditional effects. Table 2 highlights this intuition by reporting the unconditional returns to the strategies that we study. As is the case for all of our portfolio analyses, strategy returns reflect value-weighted differences in long-short decile $(10-1)$ portfolio returns using NYSE breakpoints. Consistent with previous literature, the strategies do not exhibit significant returns in the direction predicted by standard asset pricing models (see Hou et al., 2020). Specifically, we find that the risky or illiquid leg is often statistically indistinguishable from, or even underperforms, the less risky leg. For example, the strategy that goes long high-beta stocks and short low-beta stocks yields a mean return of $-0.07\%$ per month ($t$-statistic $= -0.24$). Moreover, none of the other 11 strategies exhibit significant positive risk-return relations. Collectively, the evidence in Table 2 provides empirical support for our premise that unconditional sorts on various risk and illiquidity proxies exhibit muted or even contradictory return predictability compared to the predictions of standard models.

## 3 Systematic Mispricing: Methodology and Predictions

In this section, we discuss the mispricing factor models that we use and discuss predictions for covariances of strategy portfolio returns with mispricing factors. We then empirically examine the sensitivity of strategy portfolio returns to mispricing factors.

### 3.1 Measuring Systematic Mispricing

Theoretical models, some dating back decades, predict that both risk and mispricing factors can explain returns, but only recently has the literature tackled the empirical challenge of jointly incorporating both risk and mispricing factors in a factor model. We focus on three recent prominent papers that propose factors to capture time-variation in mispricing and corresponding return premiums. First, we use the mispricing factors from Daniel et al. (2020), who propose both a short- and long-horizon behavioral factor. Second, we use the mispricing factors from Stambaugh and Yuan (2017) that aim at capturing time-variation in common elements of mispricing. Finally, we use the quality-minus-junk factor from Asness et al. (2019) because they provide evidence that the factor is related to analysts' expectational errors, and interpret quality-minus-junk as capturing time-variation in aggregate mispricing to at least some degree.

Daniel et al. (2020) propose two factors, FIN and PEAD, that they argue capture commonality in mispricing. They argue that FIN captures mispricing of a persistent nature, while PEAD captures mispricing of a transient nature.[18] Stambaugh and Yuan (2017) introduce two behavioral factors (PERF and MGMT) created by combining information in two different clusters of anomalies. The two factors can loosely be interpreted as short-term (PERF) and long-term (MGMT) mispricing factors that capture common covariance in mispricing by combining correlated anomalies. Stambaugh and Yuan (2017) motivate their analysis by arguing that common covariance in anomalies reflects a common mispricing source, such as market-wide sentiment.[19] Asness et al. (2019) propose a quality-minus-junk factor. While they do not focus on the theoretic justification for the new factor, they test a mispricing interpretation of their factor and provide evidence they argue is consistent with the interpretation that quality-minus-junk captures systematic mispricing.

We source the factor returns from the authors' websites. Consistent with the common goal of the mispricing models, Appendix Table A1 shows that for each model, the factors are positively correlated with factors from the other two models. Our sample period is July 1972

[18]Daniel et al. (2020) argue that their two behavioral factors can capture commonality in mispricing due to psychological biases and that the explanatory power of behavioral factors can be at least partly attributed to "fluctuating sentiment that induces commonality in mispricing and return."

[19]Stambaugh and Yuan (2017) specifically argue that their mispricing factors are "motivated by evidence that anomalies in part reflect mispricing and possess common sentiment effects."

to December 2016, which is determined by the combined data availability of the factors. Our empirical analyses include all NYSE, Amex, and Nasdaq common ordinary US stocks with monthly return data from the Center for Research in Security Prices (CRSP). We account for delistings following Shumway (1997). Our empirical tests are based on portfolio analyses that use value-weighted returns and NYSE breakpoints, ensuring that disproportionate weight is not given to microcaps (Fama and French, 2008; Hou et al., 2020). All of our portfolios are rebalanced at a monthly frequency. We follow the guidance of rational asset pricing models and present long-short strategy returns with the long leg composed of stocks requiring higher returns according to standard models.[20]

## 3.2 Mispricing Predictions

The three mispricing models we use are composed of factors that purport to capture the correction of mispricing. The factors are composed of strategies that exhibit abnormal returns with the short leg of the factors reflecting the overvalued leg with lower average returns. Because mispricing tends to take the form of overpricing rather than underpricing, the returns to the mispricing factors are disproportionately driven by their short legs. For example, Stambaugh et al. (2012) show that the short leg of the 11 anomalies they study is on average much more sensitive to sentiment than the long leg. As such, the short leg of the mispricing factors should be the leg sensitive to sentiment.

Because our 12 strategies are formed such that the long legs of our strategies are composed of high risk or illiquid stocks (that are also speculative), we expect that the long legs of our strategies should be exposed to the same sentiment-induced mispricing reflected in the short legs of the factors. The predicted positive correlation between the long leg of our strategies and the short leg of the mispricing factors suggests that the long-short portfolios of the strategies should load negatively on the mispricing factors. Negative loadings reflect the

[20]For example, high beta (low beta) stocks are in the long (short) leg of the beta strategy; high idiosyncratic volatility stocks are in the long leg of the idiosyncratic volatility strategy, and illiquid stocks are in the long leg of the illiquidity strategy. See Table 1 for detailed identities of the long and short legs for all of the strategies.

prediction that when mispricing is corrected, the largest effects are exhibited by speculative stocks, and, on average, the correction of the mispricing is in the form of low expected returns due to the prevalence of overpricing. As a result, we predict that the mispricing component should exhibit particularly low returns for speculative (i.e., risky and illiquid) stocks.

### 3.3 Mispricing Sensitivity

To help motivate our analyses, we first present evidence that our set of strategies indeed exhibits sensitivity to the mispricing factors in the manner predicted. If the long legs of the strategies we examine double as proxies for speculativeness, we would expect them to be most affected by sentiment-induced overvaluation such that the long legs should exhibit mispricing factor loadings that are largest in magnitude. In addition, mispricing theories predict that overvaluation is more prevalent than undervaluation because of arbitrage frictions that are more binding on the short side opportunities (e.g., Miller, 1977). Consequently, as the stocks in the long leg are comparably hard to value and have greater limits to arbitrage, the stocks in the long leg are more likely to be overvalued than undervalued.

We empirically examine this combined argument in Table 3. For each of the 12 strategies under consideration, we report the long-leg, short-leg, and long-short portfolio returns' factor loadings with respect to the monthly mispricing factors FIN, PEAD, MGMT, PERF, and QMJ. For 59 out of the 60 strategy-factor-combinations, the high-risk long leg loads more negatively on the mispricing factor than the low-risk short leg, and the difference in sensitivity is significant in the vast majority of cases. The evidence is consistent with the long leg of our strategies possessing more negative mispricing betas than the short leg, consistent with speculative (i.e., risky and illiquid) stocks exhibiting greater sensitivity to systematic mispricing resulting in systematic overvaluation.

Examining empirical evidence across mispricing factors reveals that PEAD exhibits the weakest relation to the long-short portfolio returns.[21] This observation is potentially in line

[21]Even though the effect magnitude is lowest for PEAD, the average long-short portfolio return across

with the argument in Daniel et al. (2020) that the short-term PEAD factor is unlikely to be stable over time, motivating them to use daily returns over a one-month horizon to estimate firm-level loadings. We follow this methodology for both PEAD and PERF when examining sensitivity to mispricing using loadings estimated at the stock-level.

While Table 3 confirms the link between each of the 12 strategies and mispricing at the portfolio level, Table 4 provides additional evidence at the stock level. For each stock, we regress monthly returns over the preceding 24 months (minimum 12 months) on the behavioral factors FIN and PEAD, or the mispricing factors MGMT and PERF, or QMJ. Since PEAD and PERF tend to pick up short-term rather than long-term mispricing, their regression estimates are based on daily returns of the previous month (minimum of 15 days).[22] Table 4 presents value-weighted averages of the corresponding stock-level regression coefficients. We find that speculative (i.e., high-risk or illiquid) stocks again tend to carry more negative mispricing factor loadings (in 54 out of the 60 strategy-factor-combinations). Overall, this evidence indicates that the most risky or illiquid stocks are also the stocks that are most exposed to systematic mispricing.

# 4 Main Results: Risk versus Mispricing

In this section, we decompose strategy returns into a mispricing component and a risk component. The mispricing component is composed of returns reflecting loadings on mispricing factors, while the risk component reflects the remaining return that is hedged of the effects of systematic mispricing.

all 12 strategies is still significantly related to PEAD (untabulated factor loading of $-0.42$ and $t$-statistic of $-3.06$).

[22]Results are robust if we instead use monthly returns for PEAD and PERF. Appendix Table A2 supports the daily procedure by examining the persistence of factor loadings. It shows to what extent stock-level factor loadings predict subsequent portfolio factor loadings. The analyses provide support for a 24-month estimation horizon for FIN, MGMT, and QMJ and a one-month estimation horizon for PEAD and PERF. Moreover, the use of daily returns is consistent with Daniel et al. (2020).

## 4.1 Decomposing Returns into Risk and Mispricing Components

To the extent that returns of our set of 12 strategies partly reflect systematic mispricing, failing to account for mispricing is likely to confound empirical tests of return predictions of rational asset pricing models. Indeed, the evidence from the previous section shows that riskier or more illiquid stocks tend to load relatively more significantly on mispricing factors. In this section, we attempt to isolate and remove the component of returns related to mispricing factors. We examine whether the mispricing component and the remaining risk component exhibit returns consistent with theoretical models.

To evaluate our predictions, for each strategy and factor model, we regress the long-short strategy returns on the mispricing factor(s), according to the following specification:

$$R_{i,t} = \alpha_{i,j} + \boldsymbol{\beta}_{i,j}\boldsymbol{X}_{j,t} + \epsilon_{i,t}, \tag{1}$$

where $R_{i,t}$ is the long-short return to strategy $i$ in month $t$ and $\boldsymbol{\beta}_{i,j}$ and $\boldsymbol{X}_{j,t}$ are vectors of loadings and mispricing factors, respectively, corresponding to factor model $j$. We define the mispricing component as the sum of the product(s) of the estimated loading(s) and factor(s), i.e., $\hat{\boldsymbol{\beta}}_{i,j}\boldsymbol{X}_{j,t}$, and the risk component as the estimated intercept, i.e., $\hat{\alpha}_{i,j}$. This decomposition generates an explained component of returns, representing mispricing, and an unexplained component of returns, representing risk. Because our portfolio strategies are long the most risky or illiquid stocks and short the least risky or least illiquid stocks, we should expect long-short strategy returns that are positive for the risk component and negative for the mispricing component.

Table 5 presents the decomposition results. Across the strategies and factor models, the long-short risk component is always positive and predominantly significant. Conversely, the long-short mispricing component is always significantly negative. For example, focusing on beta and the Daniel et al. (2020) mispricing factors, the long-short risk component averages 0.99% per month ($t$-statistic = 3.90). In sharp contrast, the long-short mispricing component averages $-1.06\%$ per month ($t$-statistic = $-5.87$). These two opposing forces, of roughly equal magnitude, explain the unconditional average return of $-0.07\%$ per month ($t$-statistic = $-0.24$) reported in Table 2.[23] Examining the decomposition results for the other strategies and factor models, we find that the risk and mispricing components evince economic magnitudes of similar direction and size, highlighting the countervailing forces that determine speculative returns.

Table 6 examines whether our decomposition results are robust to using factor loadings determined at the stock level, as opposed to the portfolio level. As in Section 3, we continue to estimate factor loadings using an estimation window of 24 months for FIN, MGMT, and QMJ and using an estimation window of one month for PEAD and PERF, and use the estimated loadings to generate the mispricing and risk components at the stock level. The results are similar to those in Table 5. We continue to find long-short portfolio returns that are significantly positive for the risk component and significantly negative for the mispricing component for all 12 strategies. Overall, the evidence is consistent with the interpretation that risk and mispricing components are a pervasive feature of speculative variables. Consequently, accounting for mispricing when examining prominent risk proxies delivers predictions in line with both behavioral and rational theories of returns.

## 4.2 Average Strategy Returns Across Deciles

We next investigate whether our return-decomposition methodology is consistent with both risk- and mispricing-based predictions concerning monotonicity. Standard models predict that returns should be monotonic in risk. We evaluate this prediction by examining relative returns across strategy deciles. Figure 1 summarizes this analysis by averaging across the strategies and factor models. Excess returns of strategy deciles are not monotonic but instead exhibit a slight inverse U-shaped pattern as one moves from the short leg reflecting low risk

[23] Appendix Table A3 shows that these findings are qualitatively the same if we apply alternative market beta estimation procedures as proposed by Fama and French (1992), Frazzini and Pedersen (2014), Hong and Sraer (2016), Liu et al. (2018), or Hou et al. (2020). In unreported analyses we also confirm that the long-short risk component of the beta strategy retains a positive and statistically significant CAPM beta.

portfolios to the risky portfolios in the long leg. However, consistent with both rational and behavioral models, when moving from low risk to high risk portfolios the risk and mispricing components are monotonically increasing and decreasing, respectively.

Table 7 tabulates this evidence and additionally provides statistical significance. The first column shows the non-monotonic pattern in unconditional excess returns. The second column shows that the risk component averaged across the strategies and factor models is monotonically increasing, and that the difference in portfolio returns is similar when comparing any adjacent deciles. Consequently, the average difference in risk components between deciles 5 and 1 is very similar to the average difference in risk components between deciles 10 and 6 (0.27% and 0.28%, respectively). The remaining risk columns show that the monotonically increasing return pattern also holds for each mispricing factor model in isolation.

In contrast, arbitrage frictions that disproportionately affect shorting predict that the effects of mispricing are monotonic, but not necessarily linear, as they should be particularly pronounced for the most speculative decile for which impediments to shorting are likely disproportionately constraining. Table 7 shows that returns to the mispricing component are indeed monotonic, and consistent with theory, the most speculative decile exhibits returns that are relatively extreme. The return differential for decile 10 relative to decile 9 is the largest of any adjacent deciles. Moreover, comparing the mispricing components of deciles 5 and 1 yields a return spread of only $-0.22\%$, while the corresponding difference between deciles 10 and 6 is $-0.52\%$. The resulting difference in differences is highly significant ($-0.31\%$ and $t$-statistic $= -4.84$) and is consistent with mispricing effects disproportionately stemming from the overvalued leg.

Figure 1 shows decile analyses aggregated across all strategies. We next show decile portfolios for strategies individually. Figures 2 and 3 provide more granular analysis by plotting the risk and mispricing components, respectively, of each decile portfolio and strategy, averaged over the mispricing factor models. The plots of the risk (mispricing) component have predominantly positive (negative) slopes, consistent with the monotonicity findings in Figure 1. Overall, our results suggest that risk-return monotonicity predictions are borne out in the data, but only after accounting for the effects of systematic mispricing.

# 5 Corroborating Evidence and Robustness Checks

## 5.1 Placebo Tests

Our motivation is that long-short strategies with one speculative leg and one non-speculative leg are inherently sensitive to sentiment. Therefore, these strategies should exhibit a significantly negative mispricing component if speculative stocks make up the long legs of the strategies. Likewise, to the extent that the speculative legs also double as a proxies for priced risk, the strategies should also exhibit a significantly positive risk component. To further strengthen this argument, we conduct placebo tests using three alternative strategies that do not have clear speculative and non-speculative legs. We consider strategies based on asset growth, accruals, and book-to-market.

We examine these strategies because conceptually they do not have one clear speculative and one clear non-speculative leg, and previous research typically fails to find evidence that these anomalies are sensitive to sentiment. Baker and Wurgler (2006) argue that both legs of the book-to-market anomaly are speculative as high book-to-market firms are associated with distress, and low book-to-market firms are associated with high growth. Consistent with this, previous research fails to identify strong variation in long-short returns for book-to-market when conditioning on sentiment (see, e.g., Baker and Wurgler, 2006; Stambaugh et al., 2012). We are also unaware of existing arguments for accruals or asset growth exhibiting particularly high speculativeness in one leg relative to the other. Consistent with this, Keloharju, Linnainmaa and Nyberg (2016) find no evidence of differences in asset growth anomaly returns between high- and low-sentiment periods. Stambaugh et al. (2012) document significant differences in high and low sentiment times for both the asset growth anomaly and the accruals anomaly; however, the differences they document are about half of those of more speculative anomalies they examine (e.g., $O$-score). As a result, we might expect accruals and asset-growth to exhibit a somewhat more monotonic relation with mispricing factors than book-to-market. Nevertheless, none of the three anomalies should exhibit exposure to mispricing factors similar to what we document for our main strategies that have one clear speculative leg and one clear non-speculative leg.

We follow the literature by sorting stocks with the highest (lowest) returns into the long (short) leg of each strategy. As in Figures 2 and 3, Figures 4 and 5 plot the risk and mispricing components, respectively, of each placebo strategy, averaged over the mispricing factor models. Unlike the findings in the previous section based on speculative strategies, the non-speculative strategies do not exhibit return patterns consistent with our hypotheses. In particular, the slope of the mispricing component in Figure 5 exhibits no clear monotonic pattern for the non-speculative strategies, which contrasts with the monotonically decreasing pattern we observe for the speculative strategies. More specifically, the results suggest that it is not always the case that the leg deemed "risky" based on its higher returns is more sensitive to mispricing factors. These results are consistent with the existing literature failing to find strong evidence that these placebo anomalies are sensitive to sentiment, suggesting they are unlikely to be particularly exposed to systematic mispricing.[24] Examining the risk component of each placebo strategy, the long leg exhibits higher returns than the short leg. However, this observation is not driven by accounting for the effects of systematic mispricing, as is the case for our speculative strategies. Rather, by construction, it reflects our sort of stocks with the highest (lowest) returns into the long (short) leg of each strategy. The placebo tests underscore that our hypotheses pertain only to those strategies that have clear speculative and non-speculative legs.

[24]This does not rule out mispricing as an underlying explanation for the anomalies, but suggests that a mispricing explanation should not depend on variation in common sentiment.

## 5.2 Sentiment Sensitivity

Our hypotheses predict that the mispricing component of returns disproportionately reflects sentiment-induced mispricing, while the risk component disproportionately reflects risk or illiquidity. To further test this interpretation of our results, we examine the sensitivity of the long-short risk and mispricing components to investor sentiment. We follow Baker and Wurgler (2006) and regress long-short returns from month $t$ on the Baker and Wurgler (2006) sentiment index measured at month $t-1$. Behavioral theories predict low (high) subsequent returns to speculative assets when sentiment is high (low), owing to the future correction of mispricing. As the long leg of the risk strategies is also the speculative leg, we expect the long-short strategy returns to be negatively related to lagged sentiment levels. We separately regress the risk and mispricing components on the lagged Baker-Wurgler sentiment index:

$$R_{i,t}^{RISK} = \alpha_i^{RISK} + \beta_i^{RISK} S_{t-1} + \epsilon_{i,t}^{RISK}; \tag{2}$$

$$R_{i,t}^{MP} = \alpha_i^{MP} + \beta_i^{MP} S_{t-1} + \epsilon_{i,t}^{MP}, \tag{3}$$

where $R_{i,t}^{RISK}$ and $R_{i,t}^{MP}$ refer to the risk and mispricing component, respectively, of the long-short return $R_{i,t}$ to strategy $i$ in month $t$. We run regressions separately for each decile of each strategy and test whether sentiment has predictive power for these two components. If the mispricing factors are effective in isolating the component of returns that reflects sentiment-induced mispricing, then we should not expect $\beta_i^{RISK}$ to show a predictive relation between sentiment and the risk component of future strategy returns. Conversely, we expect sentiment to have strong predictive ability for the mispricing component of future strategy returns, that is, we expect negative $\beta_i^{MP}$ estimates.

Table 8 reports the sensitivity of the risk and mispricing components of each strategy to lagged sentiment. Across the strategies, sentiment tends to exhibit little to no predictive power for the risk component, consistent with standard rational explanations that sentiment has no role in the return-generating process. In fact, sentiment is only a statistically significant predictor of the risk component (at the 5% level) for four of the 36 specifications. In contrast, sentiment negatively and significantly (at the 5% level) predicts the mispricing component for 34 of the 36 specifications, in line with mispricing-based predictions that sentiment helps identify variation in mispricing and that our set of speculative proxies at least partly reflect mispricing.[25] In short, the analysis in this subsection helps corroborate the validity of our methodology and lends support to both risk and mispricing-based explanations for predictable variation in returns.

### 5.3 Subperiods

We next investigate the stability of our findings across different time periods. Figure 6 summarizes the dynamics of our return-decomposition methodology over time. Averaging across the strategies and factor models, we plot the 10-year moving average of the long-short strategy returns as well as both the risk and mispricing components. Over our sample period, the risk and mispricing components are always positive and negative, respectively, and accordingly the overall strategy returns tend to converge toward zero, consistent with our earlier findings.

Table 9 provides a different perspective on subperiods by separately examining the decomposition results in three subperiods of equal number of months. To be clear, our hypotheses suggest that over a sufficiently long sample period, the long leg of our strategies should have relatively low returns for the mispricing component. However, when sentiment is low, we expect speculative stocks to have relatively high returns in the near future for the mispricing component. Therefore, our tests in this section are primarily tests of whether the main results we present are disproportionately driven by a specific sample period, or are instead a feature of any sufficiently long sample period. We again find that the risk and mispricing components are largely stable in each subperiod. Overall, the subperiod evidence demonstrates that our findings are not confined to any one particular period.

[25]The two instances for which there is not significance at the 5% level have coefficients in the predicted direction and $t$-statistics of $-1.92$ and $-1.16$.

### 5.4 Mispricing Orthogonal to Market Risk

Finally, we account for the possibility that our mispricing factors unintentionally capture some aspect of systematic market risk.[26] Specifically, we orthogonalize each of the mispricing factors to the market factor since Daniel et al. (2020), Stambaugh and Yuan (2017), and Asness et al. (2019) provide evidence that the proposed mispricing factors are negatively correlated with market returns. We use the resulting mispricing factors, adjusted for exposure to market risk, to decompose strategy returns into risk and mispricing components. This analysis provides an important check on our assumption that the mispricing factors indeed capture mispricing.

As in Figure 1, we plot the long-short overall returns as well as their risk and mispricing components, averaged across the strategies and factor models, using the decomposition based on the orthogonalized mispricing factors. Once again, Figure 7 shows that the pattern and magnitude of effects are consistent with our main results. Moreover, Appendix Tables A4 and A5 confirm that these results hold for the strategies in aggregate and individually, respectively.

## 6 Conclusion

A host of existing evidence suggests that systematic mispricing induces return predictability, and that the strongest effects should be exhibited by stocks with speculative characteristics, as these stocks will have large exposure to mispricing factors. Owing to arbitrage frictions that are more binding for short-selling, speculative stocks should tend to be overvalued and therefore exhibit low future returns, on average. Building on these insights, we test a straightforward hypothesis; rational models predicting higher expected returns for risky or illiquid stocks may fail to find strong support in the data for rational risk and illiquidity proxies that also proxy for speculativeness. Using mispricing factors from three distinct

[26] Of course, market returns, or any other proxy for systematic risk, may also reflect mispricing to some extent.

models, we provide evidence consistent with this hypothesis. After isolating and removing the mispricing component from strategy returns, risky stocks and illiquid stocks generate statistically and economically significantly larger returns than their less risky or less illiquid counterparts, consistent with predictions from standard models.

As researchers have identified many empirical "puzzles" that pervade cross-sectional stock-return data and prove difficult to explain with rational asset pricing models, attention has also turned to introducing more complex models of rational risk preferences that can generate cross-sectional return predictions resembling existing anomalies. We instead take seriously predictions of standard rational models and examine whether insights of behavioral finance can prove helpful in reconciling rational models with the apparent absence of support in the data. We rely on behavioral insights related to systematic mispricing, prevalence of overpricing, and increased sensitivity to systematic mispricing for speculative stocks – coupled with the observation that speculative stocks tend to overlap with rational proxies for risk and illiquidity. Our approach, grounded in behavioral theory and supported by empirical evidence, suggests that traditional predictions of rational asset pricing models do have empirical validity in the data and can be recovered by accounting for the existence of systematic mispricing and its implications for the cross-section of returns.

Our argument can be generalized to accommodate any common component in mispricing that primarily affects speculative stocks, if one takes for granted the first two components of our argument (existence of a common component to mispricing and that mispricing disproportionately manifests as overpricing rather than underpricing).[27] We focus on behavioral theories related to common sentiment-induced mispricing as this is the theory for which predictions are clearest, for which empirical support is long-standing and well-established, and for which there are three distinct sets of pre-existing empirical mispricing factors central to our analysis (thereby reducing concerns of data mining). In particular, sentiment offers

[27]For example, recent evidence suggests that demand shocks of institutional investors can induce a common component in mispricing, potentially due to institutional frictions unrelated to sentiment (see, e.g., DeVault, Sias and Starks, 2019).

a well-established theory, predicting speculative assets covary with a common component of mispricing in a manner that can explain existing empirical risk and illiquidity puzzles.

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# Appendix: Variable Definitions

BETA: The market beta is updated monthly and calculated based on daily stock returns from months $t-12$ to $t-1$ with a minimum of 200 daily returns required.

SIZE: Firm size is the market value of equity and updated annually at the end of June. It is calculated as share price times number of shares outstanding.

PRC: The price is updated monthly and equals the nominal share price at the end of month $t-1$.

AGE: Following Jiang, Lee and Zhang (2005), firm age is measured as the number of months between the firm's first appearance in CRSP and month $t-1$. It is updated on a monthly basis.

IVOL: The calculation of idiosyncratic return volatility follows Ang et al. (2006b). IVOL is updated monthly and is estimated as the volatility of daily return residuals with respect to the Fama and French (1993) three-factor model in month $t-1$. We require a minimum of 15 daily observations.

DISP: Following Hou et al. (2020), the dispersion in analyst forecasts is updated monthly and equals the ratio of the standard deviation of earnings forecasts to the absolute value of the consensus mean forecast in month $t-1$. The corresponding I/B/E/S sample starts in January 1976 such that portfolio returns are used from February 1976 onwards.

VCF: Cash flow volatility is the volatility of cash flow from operations over the preceding five years with a minimum of three years required as defined in Zhang (2006). It is updated at the end of each June based on annual accounting data from the preceding five calendar years.

OSCR: The $O$-score estimation follows Hou et al. (2020). $O$-scores are updated at the end of each June based on annual accounting data from the preceding calendar year.

FP: The estimation of failure probability (Campbell et al., 2008) follows Hou et al. (2020). It is updated on a monthly basis using accounting data with a lag of at least four months between fiscal quarter end and portfolio formation.

DB: Downside beta (Ang et al., 2006a) is estimated based on daily stock returns from months $t-12$ to $t-1$ with a minimum of 50 daily observations required. The beta estimation only considers those days that have a market return below the average market return over months $t-12$ to $t-1$ (Hou et al., 2020).

ILLIQ: The Amihud (2002) illiquidity measure is updated monthly and equals the ratio of absolute daily stock returns to daily dollar trading volume averaged over months $t-6$ to $t-1$ with a minimum of 50 daily observations required (Hou et al., 2020). The dollar trading volume equals share price times number of shares traded. The trading volume of Nasdaq stocks is adjusted following Gao and Ritter (2010).

HLS: High-low spread estimates for month $t-1$ follow Corwin and Schultz (2012). They are sourced from Shane A. Corwin's homepage and are updated monthly.

AG: Asset growth is the relative annual change in a firm's balance sheet total assets following Cooper, Gulen and Schill (2008). AG is updated at the end of each June based on annual accounting data from the preceding two calendar years.

ACC: The calculation of accruals follows Sloan (1996). Accruals are scaled by the firm's average amount of balance sheet total assets at the end of the preceding two fiscal year ends. ACC is updated at the end of each June based on annual accounting data from the preceding two calendar years.

BM: The calculation of the book-to-market ratio follows Fama and French (1993). BM is updated at the end of each June based on annual book equity data from the preceding calendar year and the firm's market capitalization at the end of the preceding calendar year.

Figure 1. Risk and Mispricing Components of Decile Portfolios
This figure shows monthly average value-weighted decile portfolio returns decomposed into risk and mispricing components. We allocate stocks to decile portfolios based on each of the 12 strategies at the end of each month using NYSE breakpoints. For each decile portfolio, we generate the risk and mispricing components by regressing the portfolio returns on FIN and PEAD (DHS-model of Daniel et al., 2020), MGMT and PERF (SY-model of Stambaugh and Yuan, 2017), or QMJ (AFP-model of Asness et al., 2019). The intercept plus the residual corresponds to the risk component, and the remainder of the fitted value corresponds to the mispricing component. We average the risk and mispricing components across the 12 strategies and three factor models. The sample period is July 1972 to December 2016. For DISP, the sample period starts in February 1976.

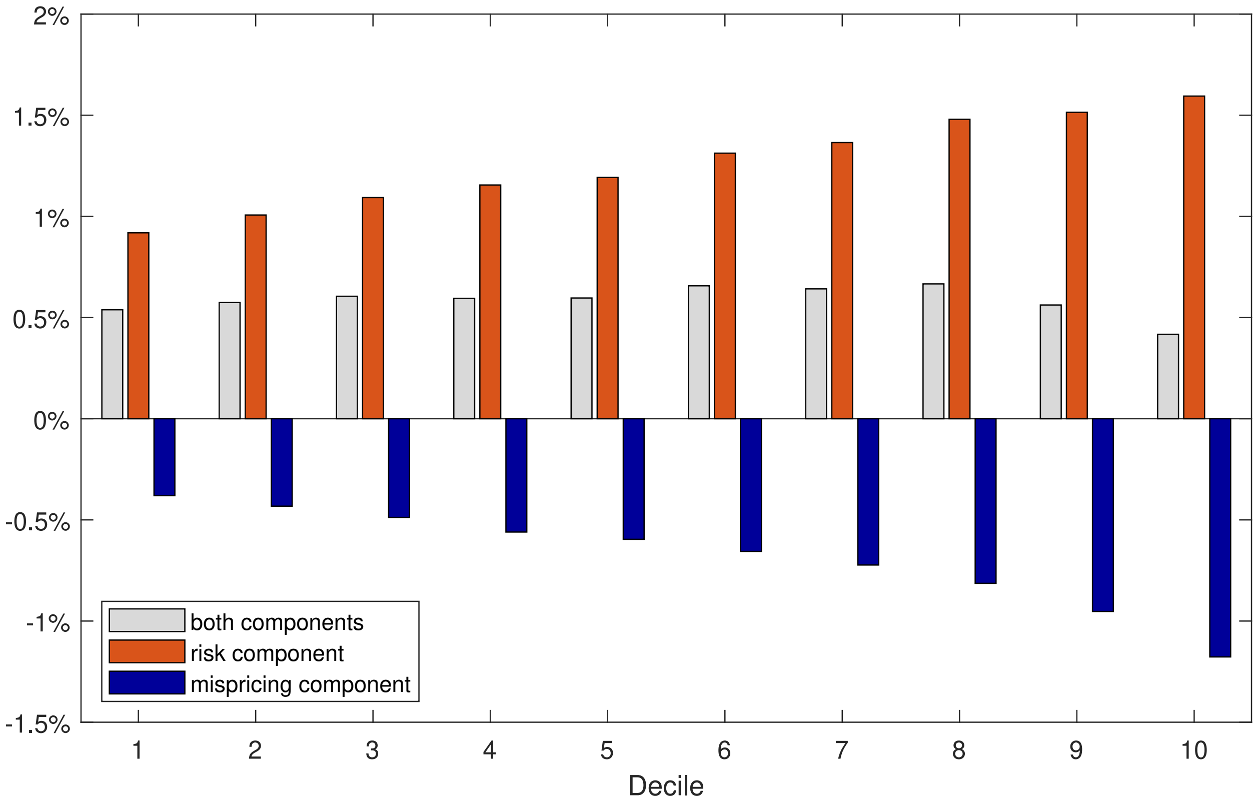

Figure 2. Risk Component of Decile Portfolios

This figure shows the monthly average risk component of value-weighted decile portfolios. We allocate stocks to decile portfolios based on each of the 12 strategies at the end of each month using NYSE breakpoints. For each decile portfolio, we generate the risk and mispricing components by regressing the portfolio returns on FIN and PEAD (DHS-model of Daniel et al., 2020), MGMT and PERF (SY-model of Stambaugh and Yuan, 2017), or QMJ (AFP-model of Asness et al., 2019). The risk component is given by the intercept plus the residual. For each strategy, we average the risk components across the three factor models. The sample period is July 1972 to December 2016. For DISP, the sample period starts in February 1976.

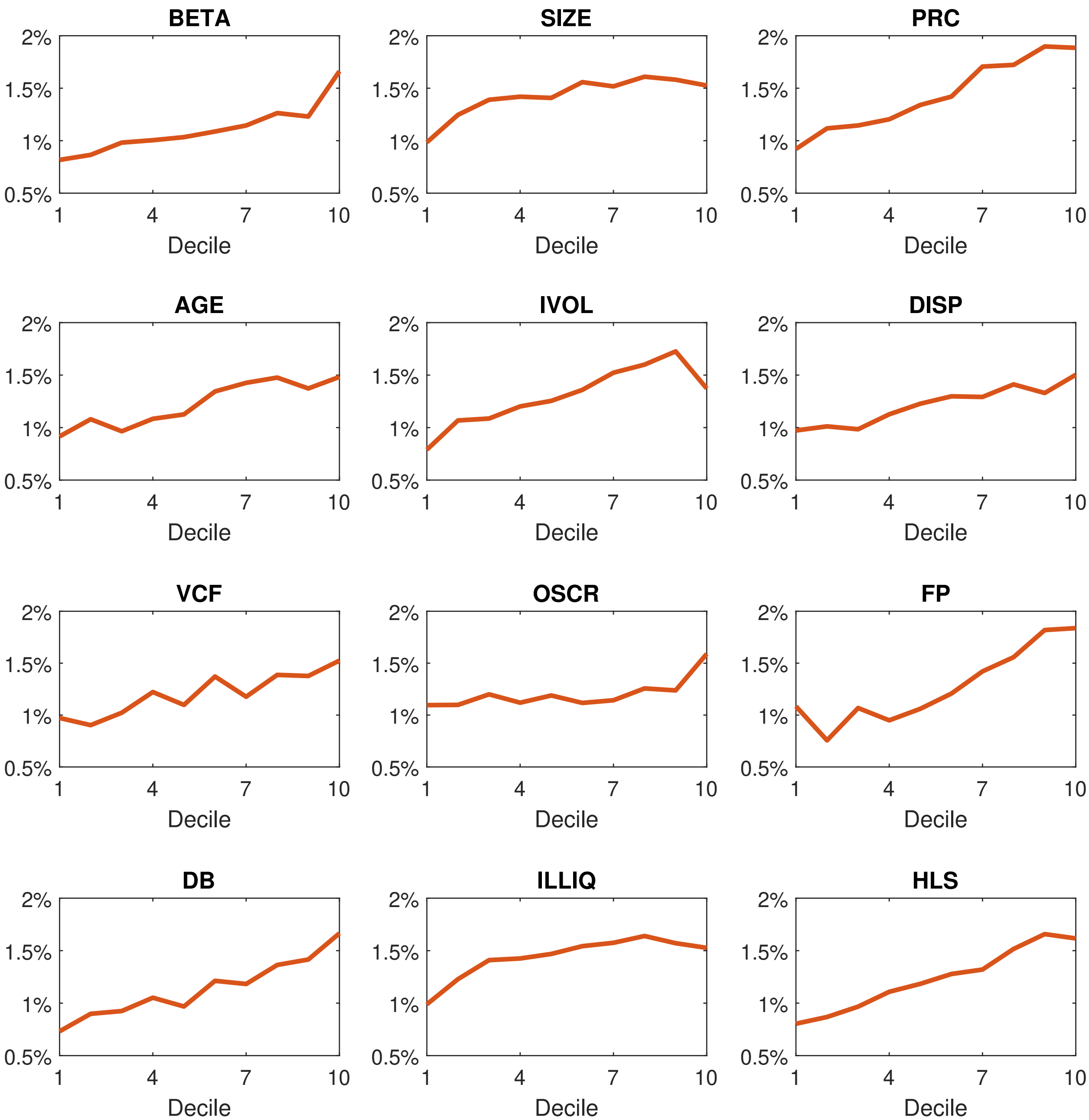

Figure 3. Mispricing Component of Decile Portfolios

This figure shows the monthly average mispricing component of value-weighted decile portfolios. We allocate stocks to decile portfolios based on each of the 12 strategies at the end of each month using NYSE breakpoints. For each decile portfolio, we generate the risk and mispricing components by regressing the portfolio returns on FIN and PEAD (DHS-model of Daniel et al., 2020), MGMT and PERF (SY-model of Stambaugh and Yuan, 2017), or QMJ (AFP-model of Asness et al., 2019). The mispricing component is given by the fitted value minus the intercept. For each strategy, we average the mispricing components across the three factor models. The sample period is July 1972 to December 2016. For DISP, the sample period starts in February 1976.

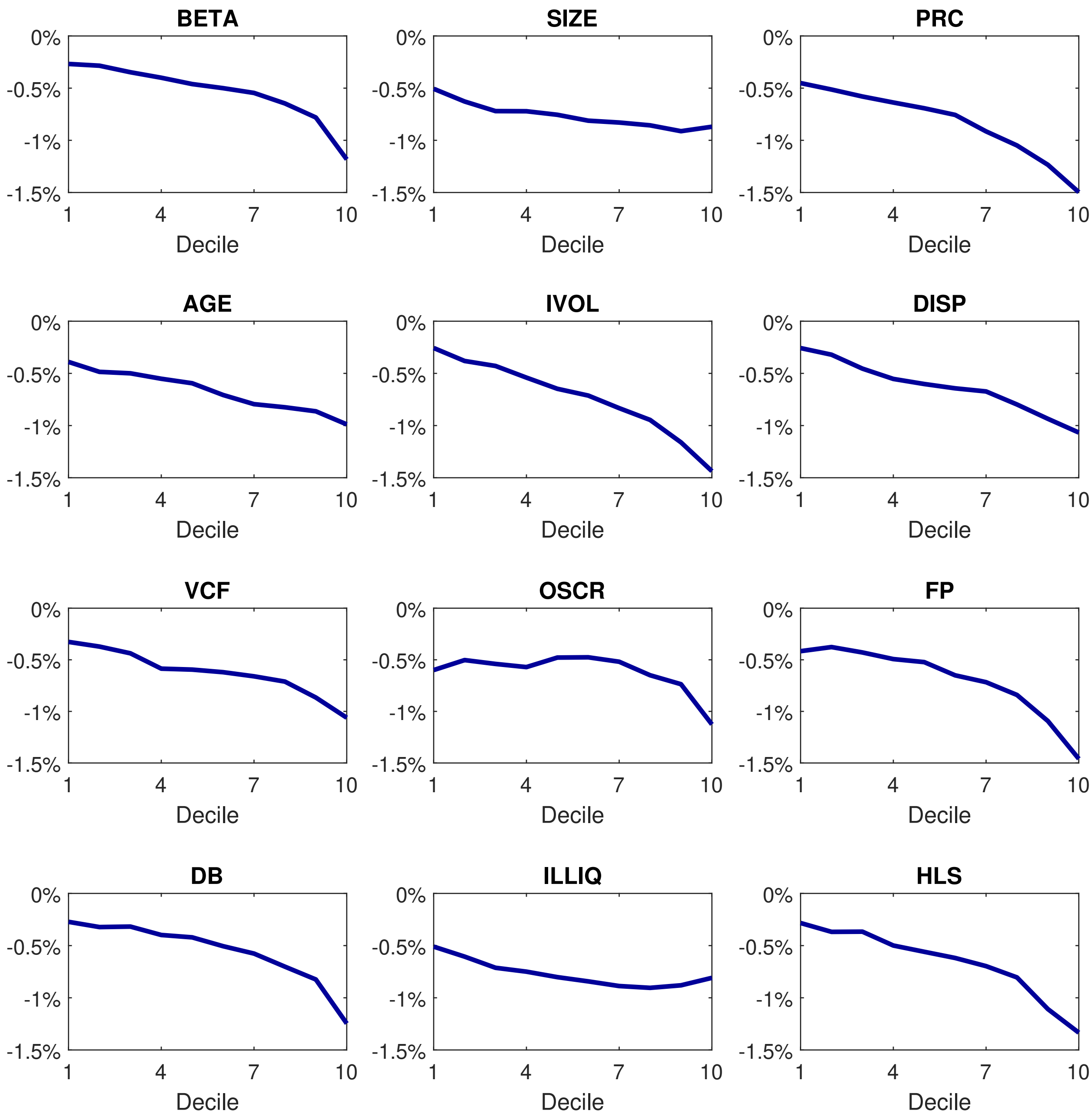

Figure 4. Risk Component of Decile Portfolios — Placebo Tests
This figure shows the monthly average risk component of value-weighted decile portfolios. We allocate stocks to portfolios based on asset growth (high-AG stocks in decile 1; Cooper et al., 2008), accruals (high-ACC stocks in decile 1; Sloan, 1996), or book-to-market ratio (high-BM stocks in decile 10; Fama and French, 1992) at the end of each month using NYSE breakpoints. For each decile portfolio, we generate the risk and mispricing components by regressing the portfolio returns on FIN and PEAD (DHS-model of Daniel et al., 2020), MGMT and PERF (SY-model of Stambaugh and Yuan, 2017), or QMJ (AFP-model of Asness et al., 2019). The risk component is given by the intercept plus the residual. For each placebo strategy, we average the risk components across the three factor models. The sample period is July 1972 to December 2016.

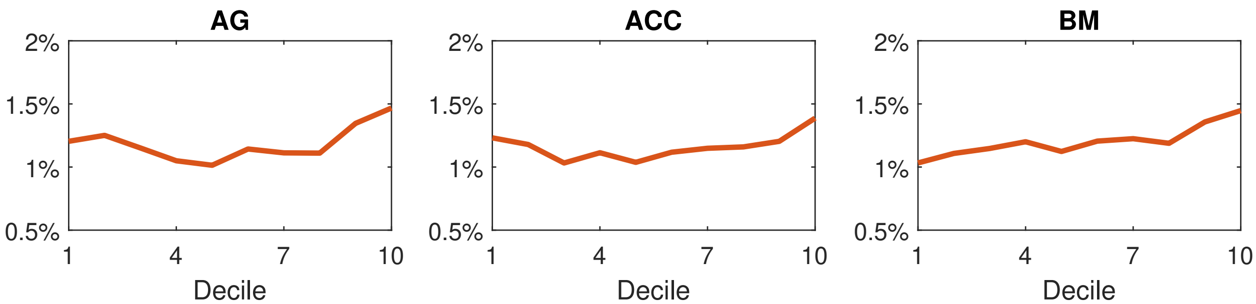


Figure 5. Mispricing Component of Decile Portfolios — Placebo Tests
This figure shows the monthly average mispricing component of value-weighted decile portfolios. We allocate stocks to portfolios based on asset growth (high-AG stocks in decile 1; Cooper et al., 2008), accruals (high-ACC stocks in decile 1; Sloan, 1996), or book-to-market ratio (high-BM stocks in decile 10; Fama and French, 1992) at the end of each month using NYSE breakpoints. For each decile portfolio, we generate the risk and mispricing components by regressing the portfolio returns on FIN and PEAD (DHS-model of Daniel et al., 2020), MGMT and PERF (SY-model of Stambaugh and Yuan, 2017), or QMJ (AFP-model of Asness et al., 2019). The mispricing component is given by the fitted value minus the intercept. For each placebo strategy, we average the mispricing components across the three factor models. The sample period is July 1972 to December 2016.

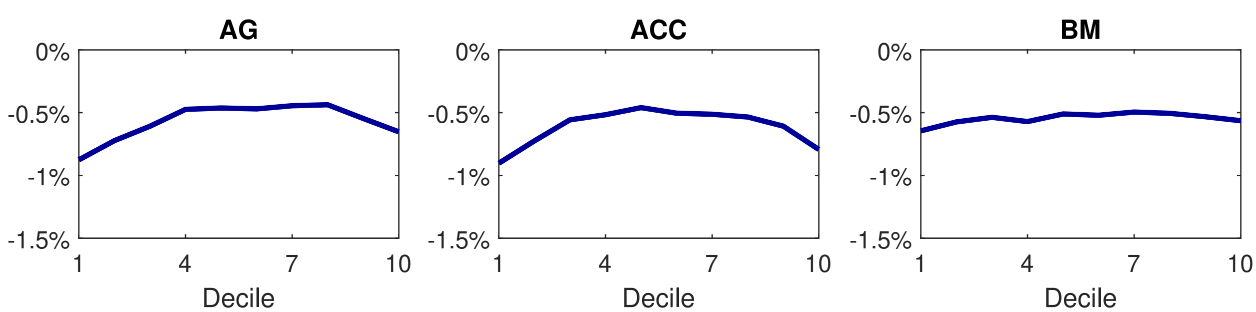

Figure 6. Long-Short Portfolio Returns Over Time
This figure shows value-weighted long-short portfolio returns decomposed into risk and mispricing components. We allocate stocks to decile portfolios based on each of the 12 strategies at the end of each month using NYSE breakpoints. The long-short returns are the difference between extreme decile portfolio returns in the following month. We generate the risk and mispricing components by regressing the long-short returns on FIN and PEAD (DHS-model of Daniel et al., 2020), MGMT and PERF (SY-model of Stambaugh and Yuan, 2017), or QMJ (AFP-model of Asness et al., 2019). The intercept plus the residual corresponds to the risk component, and the remainder of the fitted value corresponds to the mispricing component. We average the risk and mispricing components across the 12 strategies and three factor models. This figure depicts the 10-year moving averages of the risk and mispricing components. The sample period is July 1972 to December 2016. For DISP, the sample period starts in February 1976.

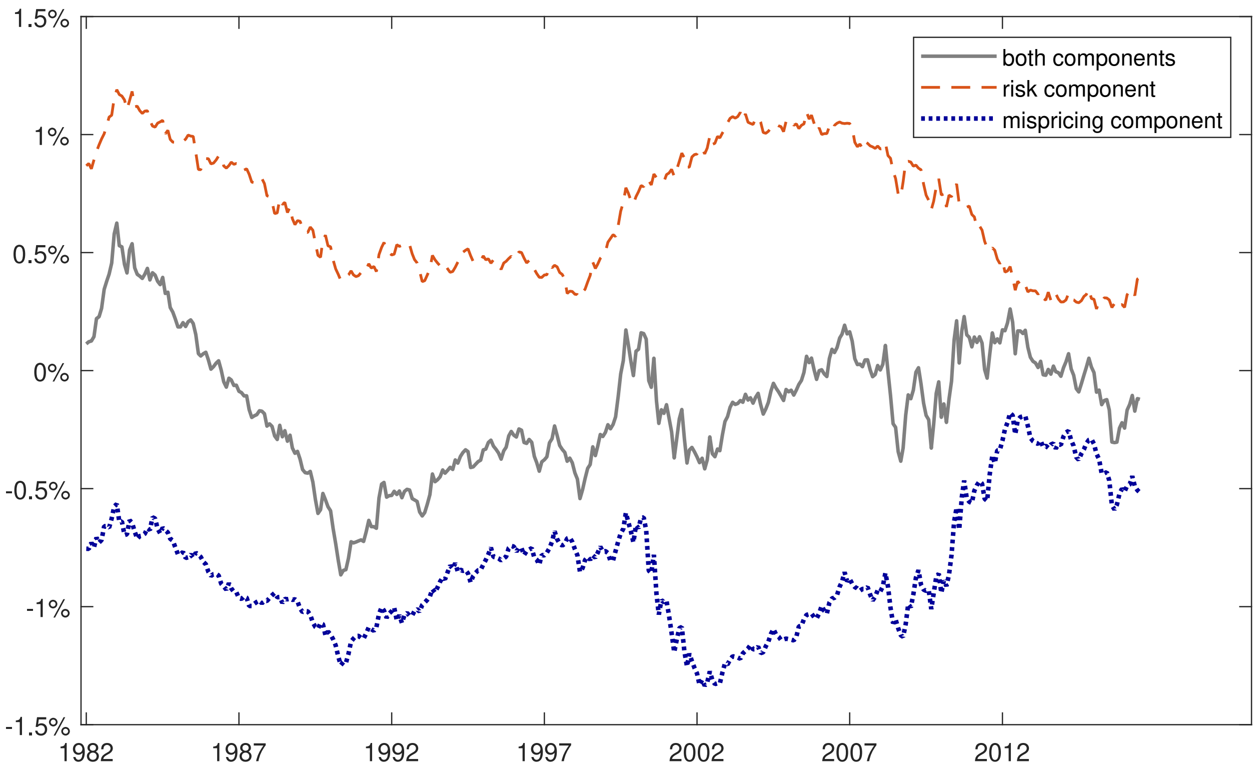

Figure 7. Market-Risk-Adjusted Risk and Mispricing Components of Decile Portfolios
This figure shows monthly average value-weighted decile portfolio returns decomposed into risk and mispricing components. We allocate stocks to decile portfolios based on each of the 12 strategies at the end of each month using NYSE breakpoints. For each decile portfolio, we generate the risk and mispricing components by regressing the portfolio returns on FIN and PEAD (DHS-model of Daniel et al., 2020), MGMT and PERF (SY-model of Stambaugh and Yuan, 2017), or QMJ (AFP-model of Asness et al., 2019). The intercept plus the residual corresponds to the risk component, and the remainder of the fitted value corresponds to the mispricing component. We average the risk and mispricing components across the 12 strategies and three factor models. For this analysis, we orthogonalize the mispricing factors with respect to the market factor by regressing each mispricing factor on the market excess return. The intercept plus the residual constitutes the orthogonalized mispricing factor. The sample period is July 1972 to December 2016. For DISP, the sample period starts in February 1976.

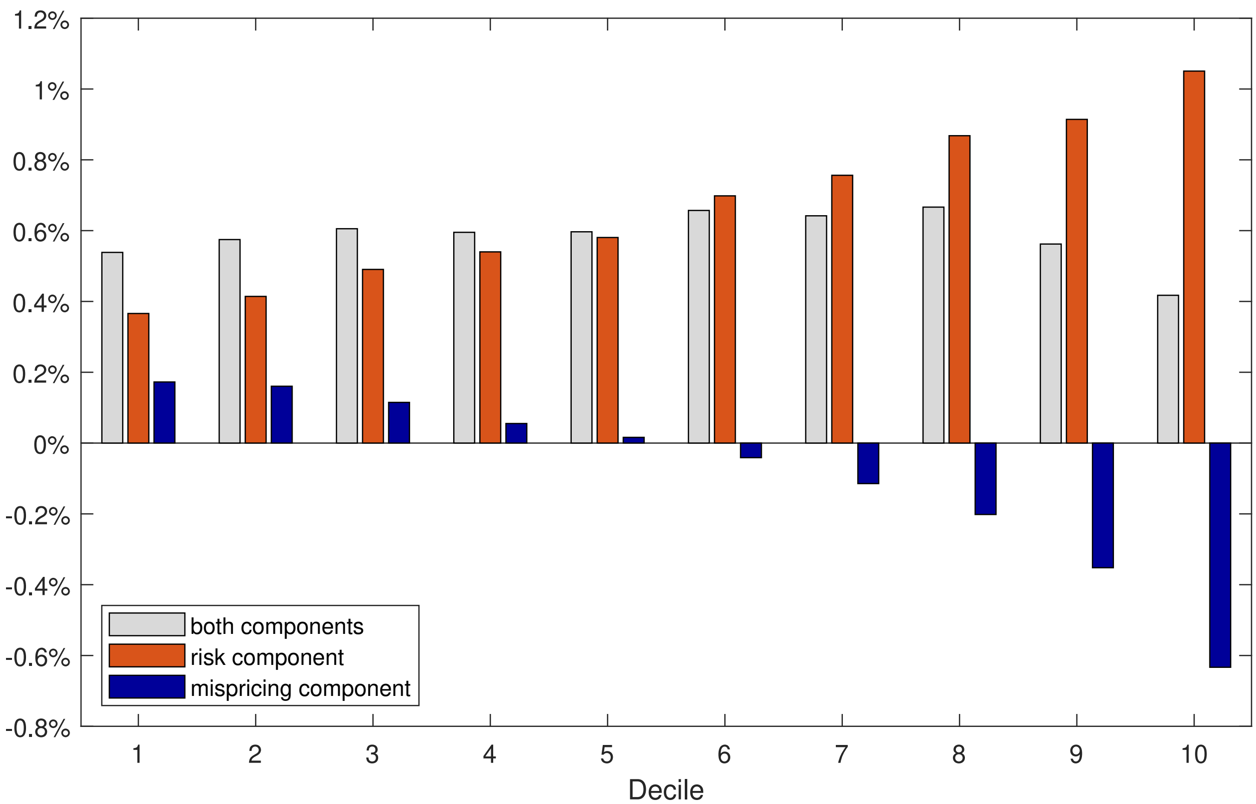

Table 1. Strategies and Return Predictions

This table describes the 12 strategies we focus on and the risk and mispricing predictions for the strategies. For each strategy, the table reports the long leg, short leg, and the leg that is both risky (or illiquid) and also speculative. The last two columns separately report return predictions for long-short portfolio returns based on theories of risk and mispricing.

| Strategy | Description of Strategy Legs | | | Long − Short Predictions | |
|---|---|---|---|---|---|
| | Long Leg | Short leg | Risky and Speculative Leg | Risk | Mispricing |
| Beta | High beta | Low beta | Long leg | Positive | Negative |
| Size | Small | Large | Long leg | Positive | Negative |
| Price | Low-price | High-price | Long leg | Positive | Negative |
| Age | Young | Old | Long leg | Positive | Negative |
| Ivol | High ivol | Low ivol | Long leg | Positive | Negative |
| Dispersion | High disp | Low disp | Long leg | Positive | Negative |
| CF Volatility | High vol | Low vol | Long leg | Positive | Negative |
| $O$-Score | Near distress | Safe | Long leg | Positive | Negative |
| Failure Probability | Near distress | Safe | Long leg | Positive | Negative |
| Downside Beta | High beta | Low beta | Long leg | Positive | Negative |
| Illiquidity | Illiquid | Liquid | Long leg | Positive | Negative |
| High-Low Spread | High spread | Low spread | Long leg | Positive | Negative |

Table 2. Strategy Returns

This table reports excess returns of value-weighted decile portfolios based on each of the 12 strategies. We allocate stocks to decile portfolios at the end of each month using NYSE breakpoints. The sample period is July 1972 to December 2016. For DISP, the sample period starts in February 1976. The $t$-statistics in parentheses refer to the difference portfolio and are based on standard errors following Newey and West (1987) using six lags.

| Decile | BETA | SIZE | PRC | AGE | IVOL | DISP | VCF | OSCR | FP | DB | ILLIQ | HLS |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| low | 0.55 | 0.48 | 0.47 | 0.53 | 0.53 | 0.71 | 0.65 | 0.50 | 0.67 | 0.46 | 0.48 | 0.52 |
| 2 | 0.58 | 0.62 | 0.60 | 0.59 | 0.69 | 0.69 | 0.53 | 0.60 | 0.38 | 0.58 | 0.62 | 0.50 |
| 3 | 0.63 | 0.67 | 0.56 | 0.47 | 0.66 | 0.53 | 0.59 | 0.66 | 0.64 | 0.61 | 0.70 | 0.60 |
| 4 | 0.60 | 0.70 | 0.57 | 0.53 | 0.66 | 0.57 | 0.64 | 0.55 | 0.46 | 0.65 | 0.68 | 0.61 |
| 5 | 0.57 | 0.65 | 0.65 | 0.53 | 0.61 | 0.63 | 0.50 | 0.71 | 0.54 | 0.55 | 0.67 | 0.62 |
| 6 | 0.59 | 0.75 | 0.66 | 0.64 | 0.65 | 0.65 | 0.75 | 0.64 | 0.56 | 0.71 | 0.70 | 0.66 |
| 7 | 0.60 | 0.69 | 0.79 | 0.63 | 0.69 | 0.62 | 0.52 | 0.62 | 0.70 | 0.61 | 0.69 | 0.62 |
| 8 | 0.62 | 0.75 | 0.67 | 0.65 | 0.65 | 0.61 | 0.68 | 0.61 | 0.72 | 0.66 | 0.73 | 0.71 |
| 9 | 0.45 | 0.67 | 0.66 | 0.51 | 0.56 | 0.39 | 0.51 | 0.50 | 0.73 | 0.59 | 0.69 | 0.55 |
| high | 0.48 | 0.66 | 0.39 | 0.49 | -0.06 | 0.44 | 0.46 | 0.46 | 0.38 | 0.42 | 0.72 | 0.28 |
| 10-1 | -0.07 | 0.18 | -0.08 | -0.03 | -0.60 | -0.28 | -0.18 | -0.03 | -0.29 | -0.04 | 0.24 | -0.24 |
| $t$-stat | (-0.24) | (0.81) | (-0.25) | (-0.16) | (-1.86) | (-1.01) | (-0.82) | (-0.16) | (-0.98) | (-0.14) | (1.23) | (-0.76) |

Table 3. Mispricing Sensitivity of Long-Short Portfolio Returns

This table reports mispricing factor loadings for long and short decile portfolios. We allocate stocks to decile portfolios based on each of the 12 strategies at the end of each month using NYSE breakpoints. The factor loadings correspond to the slope coefficients from time-series regressions of the monthly value-weighted portfolio returns on PEAD and FIN (DHS-model of Daniel et al., 2020), MGMT and PERF (SY-model of Stambaugh and Yuan, 2017), or QMJ (AFP-model of Asness et al., 2019). The sample period is July 1972 to December 2016. For DISP, the sample period starts in February 1976. The $t$-statistics in parentheses refer to the difference portfolio and are based on standard errors following Newey and West (1987) using six lags.

| | BETA | SIZE | PRC | AGE | IVOL | DISP | VCF | OSCR | FP | DB | ILLIQ | HLS |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $\beta_{FIN}$ | | | | | | | | | | | | |
| Short | -0.21 | -0.50 | -0.56 | -0.32 | -0.21 | -0.27 | -0.29 | -0.71 | -0.68 | -0.20 | -0.52 | -0.26 |
| Long | -1.21 | -0.91 | -1.31 | -1.16 | -1.48 | -1.01 | -1.23 | -1.22 | -1.12 | -1.32 | -0.74 | -1.35 |
| L-S | -0.99 | -0.41 | -0.75 | -0.84 | -1.27 | -0.75 | -0.95 | -0.51 | -0.44 | -1.12 | -0.21 | -1.10 |
| $t$-stat | (-7.63) | (-2.91) | (-7.77) | (-9.05) | (-13.79) | (-9.91) | (-18.50) | (-8.57) | (-2.45) | (-11.03) | (-2.56) | (-9.73) |
| $\beta_{PEAD}$ | | | | | | | | | | | | |
| Short | -0.13 | -0.29 | -0.04 | -0.32 | -0.21 | -0.16 | -0.21 | -0.23 | 0.44 | -0.20 | -0.26 | -0.16 |
| Long | -0.58 | -0.31 | -1.08 | -0.14 | -0.64 | -0.62 | -0.25 | -0.25 | -1.43 | -0.48 | -0.46 | -0.62 |
| L-S | -0.44 | -0.01 | -1.04 | 0.18 | -0.43 | -0.46 | -0.04 | -0.02 | -1.87 | -0.28 | -0.19 | -0.46 |
| $t$-stat | (-1.84) | (-0.06) | (-4.23) | (1.67) | (-1.79) | (-2.08) | (-0.41) | (-0.19) | (-8.46) | (-1.30) | (-1.11) | (-1.82) |
| $\beta_{MGMT}$ | | | | | | | | | | | | |
| Short | -0.32 | -0.72 | -0.83 | -0.51 | -0.32 | -0.44 | -0.45 | -1.02 | -1.02 | -0.29 | -0.75 | -0.45 |
| Long | -1.55 | -1.07 | -1.53 | -1.51 | -1.82 | -1.17 | -1.63 | -1.50 | -1.47 | -1.79 | -0.90 | -1.55 |
| L-S | -1.24 | -0.35 | -0.70 | -1.00 | -1.51 | -0.72 | -1.18 | -0.48 | -0.46 | -1.50 | -0.16 | -1.10 |
| $t$-stat | (-11.62) | (-2.25) | (-6.08) | (-7.53) | (-11.47) | (-5.14) | (-14.44) | (-4.23) | (-4.38) | (-14.71) | (-1.39) | (-7.30) |
| $\beta_{PERF}$ | | | | | | | | | | | | |
| Short | -0.16 | -0.26 | -0.08 | -0.21 | -0.15 | -0.10 | -0.17 | -0.16 | 0.09 | -0.18 | -0.24 | -0.11 |
| Long | -0.68 | -0.46 | -1.07 | -0.44 | -0.82 | -0.78 | -0.42 | -0.61 | -1.16 | -0.61 | -0.52 | -0.88 |
| L-S | -0.52 | -0.21 | -0.99 | -0.23 | -0.67 | -0.68 | -0.25 | -0.45 | -1.25 | -0.43 | -0.28 | -0.77 |
| $t$-stat | (-4.05) | (-2.53) | (-9.98) | (-3.63) | (-5.52) | (-6.81) | (-4.08) | (-6.11) | (-16.99) | (-3.71) | (-4.00) | (-6.48) |
| $\beta_{QMJ}$ | | | | | | | | | | | | |
| Short | -0.60 | -0.77 | -0.72 | -0.62 | -0.43 | -0.37 | -0.55 | -0.80 | -0.92 | -0.57 | -0.78 | -0.46 |
| Long | -1.96 | -1.76 | -2.76 | -1.73 | -2.56 | -2.13 | -1.78 | -2.21 | -2.27 | -2.09 | -1.60 | -2.43 |
| L-S | -1.36 | -0.99 | -2.04 | -1.11 | -2.13 | -1.76 | -1.23 | -1.41 | -1.35 | -1.52 | -0.82 | -1.97 |
| $t$-stat | (-7.15) | (-5.55) | (-13.08) | (-5.56) | (-13.98) | (-20.97) | (-11.25) | (-15.52) | (-4.83) | (-8.72) | (-6.50) | (-11.91) |

Table 4. Mispricing Sensitivity of Long-Short Portfolios: Stock Level
This table reports mispricing factor loadings at the stock level for long and short decile portfolios. We allocate stocks to decile portfolios based on each of the 12 strategies at the end of each month using NYSE breakpoints. For each stock and month, the factor loadings correspond to the slope coefficients from time-series regressions of the stock excess returns on FIN and PEAD (DHS-model of Daniel et al., 2020), MGMT and PERF (SY-model of Stambaugh and Yuan, 2017), or QMJ (AFP-model of Asness et al., 2019). The FIN, MGMT, and QMJ factor loadings are based on monthly excess returns in the preceding 24 months (minimum 12 months). The PEAD and PERF factor loadings are based on daily excess returns in the preceding month (minimum 15 days). The sample period is July 1974 to December 2016. For DISP, the sample period starts in February 1976. The $t$-statistics in parentheses refer to the difference portfolio and are based on standard errors following Newey and West (1987) using six lags.

| | BETA | SIZE | PRC | AGE | IVOL | DISP | VCF | OSCR | FP | DB | ILLIQ | HLS |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $\beta_{FIN}$ | | | | | | | | | | | | |
| Short | -0.23 | -0.58 | -0.61 | -0.44 | -0.37 | -0.49 | -0.40 | -0.79 | -0.86 | -0.27 | -0.60 | -0.47 |
| Long | -1.47 | -0.92 | -1.20 | -1.13 | -1.37 | -1.00 | -1.32 | -1.30 | -1.07 | -1.50 | -0.77 | -1.21 |
| L-S | -1.24 | -0.34 | -0.59 | -0.69 | -0.99 | -0.51 | -0.93 | -0.50 | -0.21 | -1.23 | -0.17 | -0.74 |
| $t$-stat | (-14.50) | (-6.11) | (-7.48) | (-14.30) | (-14.99) | (-8.40) | (-16.64) | (-9.68) | (-3.25) | (-15.62) | (-3.42) | (-9.67) |
| $\beta_{PEAD}$ | | | | | | | | | | | | |
| Short | 0.02 | 0.18 | 0.27 | 0.15 | 0.14 | 0.22 | 0.16 | 0.20 | 0.55 | 0.03 | 0.19 | 0.16 |
| Long | 0.17 | 0.06 | -0.14 | 0.19 | -0.09 | -0.02 | 0.18 | 0.12 | -0.34 | 0.22 | 0.05 | 0.01 |
| L-S | 0.15 | -0.12 | -0.41 | 0.04 | -0.23 | -0.24 | 0.03 | -0.08 | -0.89 | 0.19 | -0.14 | -0.15 |
| $t$-stat | (1.32) | (-2.61) | (-7.03) | (1.20) | (-3.26) | (-3.95) | (0.60) | (-1.70) | (-12.58) | (1.96) | (-2.85) | (-2.13) |
| $\beta_{MGMT}$ | | | | | | | | | | | | |
| Short | -0.34 | -0.68 | -0.78 | -0.53 | -0.43 | -0.58 | -0.46 | -0.93 | -1.05 | -0.39 | -0.70 | -0.60 |
| Long | -1.64 | -1.08 | -1.34 | -1.39 | -1.67 | -1.24 | -1.60 | -1.61 | -1.37 | -1.78 | -0.93 | -1.41 |
| L-S | -1.30 | -0.40 | -0.56 | -0.86 | -1.24 | -0.66 | -1.14 | -0.67 | -0.32 | -1.39 | -0.23 | -0.81 |
| $t$-stat | (-15.54) | (-6.14) | (-6.63) | (-12.59) | (-14.32) | (-10.50) | (-17.41) | (-10.14) | (-4.09) | (-16.05) | (-3.57) | (-8.81) |
| $\beta_{PERF}$ | | | | | | | | | | | | |
| Short | -0.08 | 0.24 | 0.33 | 0.26 | 0.14 | 0.27 | 0.19 | 0.47 | 0.44 | -0.07 | 0.27 | 0.13 |
| Long | 0.15 | -0.17 | -0.39 | -0.06 | -0.19 | -0.29 | 0.13 | -0.19 | -0.41 | 0.08 | -0.18 | -0.26 |
| L-S | 0.23 | -0.41 | -0.72 | -0.32 | -0.33 | -0.57 | -0.06 | -0.66 | -0.85 | 0.14 | -0.45 | -0.39 |
| $t$-stat | (1.59) | (-7.75) | (-15.61) | (-8.96) | (-5.85) | (-10.08) | (-1.47) | (-17.70) | (-18.26) | (1.22) | (-8.44) | (-6.10) |
| $\beta_{QMJ}$ | | | | | | | | | | | | |
| Short | -0.67 | -0.69 | -0.66 | -0.68 | -0.51 | -0.40 | -0.57 | -0.64 | -1.05 | -0.71 | -0.71 | -0.65 |
| Long | -1.97 | -1.87 | -2.58 | -1.55 | -2.27 | -2.04 | -1.73 | -2.32 | -1.91 | -2.09 | -1.70 | -2.08 |
| L-S | -1.31 | -1.18 | -1.92 | -0.87 | -1.76 | -1.64 | -1.16 | -1.68 | -0.86 | -1.38 | -1.00 | -1.43 |
| $t$-stat | (-8.72) | (-17.29) | (-23.83) | (-12.66) | (-21.77) | (-26.41) | (-18.77) | (-26.35) | (-8.39) | (-10.19) | (-14.39) | (-16.58) |

Table 5. Risk and Mispricing Components of Long-Short Portfolios
This table reports the risk and mispricing components of value-weighted long-short portfolio returns. We allocate stocks to decile portfolios based on each of the 12 strategies at the end of each month using NYSE breakpoints. The long-short returns are the difference between extreme decile portfolio returns in the following month. We generate the risk and mispricing components by regressing the long-short returns on FIN and PEAD (DHS-model of Daniel et al., 2020), MGMT and PERF (SY-model of Stambaugh and Yuan, 2017), or QMJ (AFP-model of Asness et al., 2019). The intercept plus the residual corresponds to the risk component, and the remainder of the fitted value corresponds to the mispricing component. The sample period is July 1972 to December 2016. For DISP, the sample period starts in February 1976. The $t$-statistics in parentheses are based on standard errors following Newey and West (1987) using six lags.

| | BETA | SIZE | PRC | AGE | IVOL | DISP | VCF | OSCR | FP | DB | ILLIQ | HLS |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $\text{RISK}_{\text{DHS}}$ | 0.99 | 0.51 | 1.16 | 0.52 | 0.68 | 0.52 | 0.60 | 0.38 | 1.22 | 1.02 | 0.53 | 0.92 |
| | (3.90) | (2.45) | (2.95) | (4.00) | (2.34) | (1.93) | (3.66) | (1.99) | (4.15) | (4.14) | (2.43) | (3.10) |
| $\text{RISK}_{\text{SY}}$ | 1.07 | 0.54 | 0.99 | 0.77 | 0.81 | 0.59 | 0.75 | 0.56 | 0.79 | 1.21 | 0.52 | 0.97 |
| | (4.71) | (2.51) | (3.30) | (5.54) | (3.39) | (2.71) | (4.57) | (3.10) | (4.08) | (5.69) | (2.74) | (3.73) |
| $\text{RISK}_{\text{AFP}}$ | 0.48 | 0.58 | 0.74 | 0.41 | 0.26 | 0.48 | 0.31 | 0.53 | 0.25 | 0.57 | 0.57 | 0.55 |
| | (1.90) | (2.84) | (2.76) | (2.61) | (1.15) | (2.67) | (1.68) | (4.06) | (0.88) | (2.43) | (3.23) | (2.38) |
| $\text{MP}_{\text{DHS}}$ | -1.06 | -0.33 | -1.24 | -0.55 | -1.27 | -0.80 | -0.78 | -0.42 | -1.51 | -1.06 | -0.29 | -1.16 |
| | (-5.87) | (-4.52) | (-7.94) | (-3.61) | (-5.55) | (-5.70) | (-4.57) | (-4.58) | (-8.97) | (-5.25) | (-7.07) | (-5.81) |
| $\text{MP}_{\text{SY}}$ | -1.14 | -0.36 | -1.08 | -0.80 | -1.41 | -0.87 | -0.93 | -0.60 | -1.08 | -1.25 | -0.28 | -1.20 |
| | (-5.92) | (-5.91) | (-5.28) | (-5.70) | (-5.92) | (-5.21) | (-5.66) | (-5.68) | (-4.60) | (-5.79) | (-5.01) | (-5.86) |
| $\text{MP}_{\text{AFP}}$ | -0.55 | -0.40 | -0.82 | -0.44 | -0.86 | -0.76 | -0.49 | -0.57 | -0.54 | -0.61 | -0.33 | -0.79 |
| | (-3.40) | (-3.40) | (-3.40) | (-3.40) | (-3.40) | (-3.47) | (-3.40) | (-3.40) | (-3.40) | (-3.40) | (-3.40) | (-3.40) |

Table 6. Risk and Mispricing Components of Long-Short Portfolios: Stock Level

This table reports risk and mispricing components of value-weighted long-short portfolio returns based on stock level mispricing factor loadings. We allocate stocks to decile portfolios based on each of the 12 strategies at the end of each month using NYSE breakpoints. For each stock and month, the factor loadings correspond to the slope coefficients from time-series regressions of the stock excess returns on FIN and PEAD (DHS-model of Daniel et al., 2020), MGMT and PERF (SY-model of Stambaugh and Yuan, 2017), or QMJ (AFP-model of Asness et al., 2019). The FIN, MGMT, and QMJ factor loadings are based on monthly excess returns in the preceding 24 months (minimum 12 months). The PEAD and PERF factor loadings are based on daily excess returns in the preceding month (minimum 15 days). The risk and mispricing components are based on the stock-level factor loadings. The sample period is July 1974 to December 2016. For DISP, the sample period starts in February 1976. The $t$-statistics in parentheses are based on standard errors following Newey and West (1987) using six lags.

| | BETA | SIZE | PRC | AGE | IVOL | DISP | VCF | OSCR | FP | DB | ILLIQ | HLS |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $\text{RISK}_{\text{DHS}}$ | 0.46 | 0.74 | 0.75 | 0.62 | 0.37 | 0.10 | 0.61 | 0.54 | 0.21 | 0.52 | 0.68 | 0.30 |
| | (1.68) | (3.39) | (2.42) | (5.04) | (1.63) | (0.46) | (3.83) | (2.76) | (0.84) | (2.18) | (3.43) | (1.24) |
| $\text{RISK}_{\text{SY}}$ | 0.72 | 0.80 | 0.91 | 1.01 | 0.70 | 0.42 | 0.84 | 0.88 | 0.58 | 0.73 | 0.74 | 0.72 |
| | (2.43) | (3.32) | (2.92) | (5.36) | (2.61) | (2.07) | (4.27) | (4.38) | (2.60) | (3.01) | (3.50) | (3.25) |
| $\text{RISK}_{\text{AFP}}$ | 0.36 | 0.70 | 0.64 | 0.56 | 0.16 | 0.46 | 0.42 | 0.64 | 0.33 | 0.43 | 0.61 | 0.45 |
| | (1.63) | (3.46) | (2.54) | (3.62) | (0.79) | (2.69) | (2.25) | (4.22) | (1.38) | (1.88) | (3.50) | (2.21) |
| $\text{MP}_{\text{DHS}}$ | -0.41 | -0.44 | -0.71 | -0.56 | -0.79 | -0.38 | -0.68 | -0.50 | -0.49 | -0.47 | -0.32 | -0.40 |
| | (-1.30) | (-3.76) | (-3.06) | (-2.97) | (-2.68) | (-1.93) | (-3.41) | (-3.29) | (-2.16) | (-1.60) | (-2.87) | (-1.38) |
| $\text{MP}_{\text{SY}}$ | -0.67 | -0.50 | -0.87 | -0.96 | -1.12 | -0.69 | -0.90 | -0.84 | -0.86 | -0.68 | -0.38 | -0.83 |
| | (-1.67) | (-3.87) | (-3.63) | (-3.50) | (-3.02) | (-2.66) | (-3.54) | (-4.72) | (-2.69) | (-1.79) | (-3.10) | (-2.62) |
| $\text{MP}_{\text{AFP}}$ | -0.31 | -0.40 | -0.60 | -0.50 | -0.58 | -0.73 | -0.49 | -0.60 | -0.61 | -0.38 | -0.25 | -0.56 |
| | (-1.16) | (-2.72) | (-2.24) | (-2.45) | (-2.04) | (-2.95) | (-2.67) | (-2.83) | (-2.57) | (-1.38) | (-2.05) | (-2.13) |

Table 7. Risk and Mispricing Components of Decile Portfolios
This table reports the monthly average risk and mispricing components of value-weighted decile portfolio returns. For each decile portfolio, we generate the risk and mispricing components by regressing the portfolio returns on FIN and PEAD (DHS-model of Daniel et al., 2020), MGMT and PERF (SY-model of Stambaugh and Yuan, 2017), or QMJ (AFP-model of Asness et al., 2019). The intercept plus the residual corresponds to the risk component, and the remainder of the fitted value corresponds to the mispricing component. We average the risk and mispricing components across the 12 strategies. For $\text{RISK}_{\text{all}}$ and $\text{MP}_{\text{all}}$, we also average the risk and mispricing components across the three factor models. The sample period is July 1974 to December 2016. For DISP, the sample period starts in February 1976. The $t$-statistics in parentheses refer to the difference portfolio and are based on standard errors following Newey and West (1987) using six lags.

| Decile | BOTH | $\text{RISK}_{\text{all}}$ | $\text{MP}_{\text{all}}$ | $\text{RISK}_{\text{DHS}}$ | $\text{MP}_{\text{DHS}}$ | $\text{RISK}_{\text{SY}}$ | $\text{MP}_{\text{SY}}$ | $\text{RISK}_{\text{AFP}}$ | $\text{MP}_{\text{AFP}}$ |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 0.54 | 0.92 | -0.38 | 0.94 | -0.41 | 1.02 | -0.48 | 0.79 | -0.25 |
| 2 | 0.57 | 1.01 | -0.43 | 1.04 | -0.47 | 1.11 | -0.54 | 0.87 | -0.29 |
| 3 | 0.61 | 1.09 | -0.49 | 1.15 | -0.55 | 1.19 | -0.59 | 0.93 | -0.33 |
| 4 | 0.60 | 1.16 | -0.56 | 1.23 | -0.63 | 1.27 | -0.67 | 0.97 | -0.37 |
| 5 | 0.60 | 1.19 | -0.60 | 1.27 | -0.68 | 1.31 | -0.71 | 1.00 | -0.40 |
| 6 | 0.66 | 1.31 | -0.66 | 1.39 | -0.74 | 1.44 | -0.79 | 1.10 | -0.45 |
| 7 | 0.64 | 1.36 | -0.72 | 1.46 | -0.81 | 1.50 | -0.86 | 1.14 | -0.50 |
| 8 | 0.67 | 1.48 | -0.81 | 1.58 | -0.92 | 1.63 | -0.96 | 1.23 | -0.56 |
| 9 | 0.56 | 1.51 | -0.95 | 1.62 | -1.06 | 1.70 | -1.13 | 1.23 | -0.67 |
| 10 | 0.42 | 1.59 | -1.18 | 1.70 | -1.28 | 1.82 | -1.40 | 1.26 | -0.85 |
| 10-1 | -0.12 | 0.68 | -0.80 | 0.76 | -0.88 | 0.80 | -0.92 | 0.47 | -0.59 |
| $t$(10-1) | (-0.59) | (5.87) | (-5.67) | (5.02) | (-6.16) | (5.96) | (-5.89) | (3.90) | (-3.41) |
| 5-1 | 0.06 | 0.27 | -0.22 | 0.33 | -0.27 | 0.29 | -0.23 | 0.20 | -0.15 |
| $t$(5-1) | (0.91) | (5.40) | (-6.28) | (5.58) | (-8.44) | (5.62) | (-5.56) | (3.96) | (-3.41) |
| 10-6 | -0.24 | 0.28 | -0.52 | 0.31 | -0.55 | 0.38 | -0.62 | 0.16 | -0.40 |
| $t$(10-6) | (-1.59) | (3.21) | (-5.44) | (2.91) | (-5.39) | (3.63) | (-5.94) | (1.73) | (-3.40) |
| (10-6)-(5-1) | -0.30 | 0.01 | -0.31 | -0.02 | -0.28 | 0.09 | -0.38 | -0.04 | -0.25 |
| $t$((10-6)-(5-1)) | (-2.38) | (0.09) | (-4.84) | (-0.19) | (-3.64) | (0.84) | (-5.91) | (-0.44) | (-3.40) |

Table 8. Sentiment Sensitivity of Long-Short Risk and Mispricing Components
This table reports the sentiment sensitivity of risk and mispricing components of value-weighted long-short portfolio returns. We allocate stocks to decile portfolios based on each of the 12 strategies at the end of each month using NYSE breakpoints. The long-short returns are the difference between extreme decile portfolio returns in the following month. We generate the risk and mispricing components by regressing the long-short returns on FIN and PEAD (DHS-model of Daniel et al., 2020), MGMT and PERF (SY-model of Stambaugh and Yuan, 2017), or QMJ (AFP-model of Asness et al., 2019). The intercept plus the residual corresponds to the risk component, and the remainder of the fitted value corresponds to the mispricing component. This table shows slope coefficients from regressions of the risk and mispricing components on the one-month-lagged investor sentiment index of Baker and Wurgler (2006). The sample period is July 1972 to December 2016. For DISP, the sample period starts in February 1976. The $t$-statistics in parentheses are based on standard errors following Newey and West (1987) using six lags.

| | BETA | SIZE | PRC | AGE | IVOL | DISP | VCF | OSCR | FP | DB | ILLIQ | HLS |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $\text{RISK}_{\text{DHS}}$ | 0.06 | -0.25 | -0.74 | -0.25 | -0.70 | -0.15 | -0.13 | -0.55 | -0.34 | -0.08 | -0.31 | -0.57 |
| | (0.29) | (-0.81) | (-1.94) | (-1.92) | (-2.94) | (-0.60) | (-0.76) | (-3.02) | (-1.50) | (-0.44) | (-1.15) | (-2.60) |
| $\text{RISK}_{\text{SY}}$ | 0.32 | -0.21 | -0.36 | -0.14 | -0.39 | 0.09 | 0.00 | -0.39 | 0.22 | 0.18 | -0.22 | -0.30 |
| | (1.71) | (-0.67) | (-0.85) | (-1.25) | (-1.83) | (0.38) | (0.02) | (-1.97) | (0.99) | (1.06) | (-0.77) | (-1.59) |
| $\text{RISK}_{\text{AFP}}$ | 0.22 | 0.03 | -0.14 | -0.13 | -0.30 | 0.18 | -0.01 | -0.12 | 0.08 | 0.09 | -0.02 | -0.17 |
| | (0.93) | (0.09) | (-0.40) | (-0.74) | (-1.31) | (1.07) | (-0.06) | (-0.80) | (0.35) | (0.38) | (-0.09) | (-0.72) |
| $\text{MP}_{\text{DHS}}$ | -0.49 | -0.20 | -0.37 | -0.41 | -0.63 | -0.59 | -0.47 | -0.25 | -0.22 | -0.55 | -0.11 | -0.54 |
| | (-2.24) | (-2.34) | (-1.92) | (-2.38) | (-2.27) | (-3.44) | (-2.34) | (-2.34) | (-1.16) | (-2.29) | (-2.09) | (-2.24) |
| $\text{MP}_{\text{SY}}$ | -0.75 | -0.24 | -0.76 | -0.52 | -0.94 | -0.82 | -0.60 | -0.41 | -0.78 | -0.82 | -0.20 | -0.82 |
| | (-2.92) | (-3.02) | (-3.12) | (-2.75) | (-2.94) | (-3.78) | (-2.72) | (-3.10) | (-3.04) | (-2.80) | (-3.10) | (-3.05) |
| $\text{MP}_{\text{AFP}}$ | -0.65 | -0.48 | -0.98 | -0.53 | -1.02 | -0.92 | -0.59 | -0.68 | -0.65 | -0.73 | -0.39 | -0.95 |
| | (-5.02) | (-5.02) | (-5.02) | (-5.02) | (-5.02) | (-4.65) | (-5.02) | (-5.02) | (-5.02) | (-5.02) | (-5.02) | (-5.02) |

Table 9. Risk and Mispricing Components: Subperiods

This table reports risk and mispricing components of value-weighted long-short portfolio returns for three different subperiods. We allocate stocks to decile portfolios based on each of the 12 strategies at the end of each month using NYSE breakpoints. The long-short returns are the difference between extreme decile portfolio returns in the following month. We generate the risk and mispricing components by regressing the long-short returns on FIN and PEAD (DHS-model of Daniel et al., 2020), MGMT and PERF (SY-model of Stambaugh and Yuan, 2017), or QMJ (AFP-model of Asness et al., 2019). The intercept plus the residual corresponds to the risk component, and the remainder of the fitted value corresponds to the mispricing component. The sample period is July 1972 to December 2016. For DISP, the sample period starts in February 1976. The $t$-statistics in parentheses are based on standard errors following Newey and West (1987) using six lags.

Panel A: July 1972 – April 1987

| | BETA | SIZE | PRC | AGE | IVOL | DISP | VCF | OSCR | FP | DB | ILLIQ | HLS |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $\text{RISK}_{\text{DHS}}$ | 0.51 | 0.86 | 1.19 | 0.29 | 0.46 | -0.06 | 0.86 | 0.43 | 1.21 | 0.53 | 1.11 | 0.46 |
| | (1.36) | (1.79) | (1.66) | (1.34) | (0.79) | (-0.13) | (2.34) | (1.16) | (2.16) | (1.29) | (1.96) | (1.14) |
| $\text{RISK}_{\text{SY}}$ | 0.71 | 0.96 | 1.23 | 0.66 | 0.70 | 0.27 | 1.03 | 0.94 | 1.01 | 0.90 | 1.15 | 0.54 |
| | (2.32) | (2.25) | (2.26) | (3.47) | (1.61) | (0.63) | (3.19) | (3.13) | (2.61) | (3.01) | (2.66) | (1.53) |
| $\text{RISK}_{\text{AFP}}$ | -0.48 | 0.73 | 0.67 | 0.12 | -0.20 | 0.18 | 0.17 | 0.60 | 0.08 | -0.20 | 0.93 | 0.19 |
| | (-1.25) | (2.14) | (1.65) | (0.51) | (-0.53) | (0.65) | (0.47) | (2.59) | (0.19) | (-0.50) | (2.87) | (0.66) |
| $\text{MP}_{\text{DHS}}$ | -1.12 | -0.50 | -1.09 | -0.35 | -1.13 | -0.35 | -0.95 | -0.32 | -1.33 | -0.92 | -0.58 | -0.57 |
| | (-4.24) | (-7.18) | (-8.06) | (-3.49) | (-6.27) | (-6.36) | (-5.41) | (-4.73) | (-7.97) | (-3.77) | (-8.16) | (-7.86) |
| $\text{MP}_{\text{SY}}$ | -1.33 | -0.60 | -1.13 | -0.72 | -1.37 | -0.68 | -1.12 | -0.83 | -1.13 | -1.29 | -0.63 | -0.65 |
| | (-3.83) | (-5.87) | (-5.56) | (-5.42) | (-5.58) | (-5.39) | (-4.82) | (-5.80) | (-4.51) | (-3.65) | (-5.08) | (-5.76) |
| $\text{MP}_{\text{AFP}}$ | -0.13 | -0.36 | -0.58 | -0.17 | -0.48 | -0.59 | -0.26 | -0.49 | -0.20 | -0.19 | -0.41 | -0.30 |
| | (-2.07) | (-2.07) | (-2.07) | (-2.07) | (-2.07) | (-2.55) | (-2.07) | (-2.07) | (-2.07) | (-2.07) | (-2.07) | (-2.07) |

Panel B: May 1987 – February 2002

| | BETA | SIZE | PRC | AGE | IVOL | DISP | VCF | OSCR | FP | DB | ILLIQ | HLS |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $\text{RISK}_{\text{DHS}}$ | 1.49 | 0.13 | 0.86 | 0.39 | 0.26 | 0.26 | 0.55 | -0.08 | 1.60 | 1.27 | 0.07 | 0.64 |
| | (3.87) | (0.34) | (1.07) | (1.51) | (0.62) | (0.62) | (1.82) | (-0.19) | (3.32) | (3.72) | (0.18) | (1.58) |
| $\text{RISK}_{\text{SY}}$ | 1.79 | 0.18 | 0.65 | 0.87 | 0.58 | 0.58 | 0.97 | 0.22 | 0.87 | 1.74 | 0.02 | 1.05 |
| | (4.95) | (0.45) | (1.13) | (3.05) | (1.33) | (1.47) | (3.85) | (0.59) | (2.45) | (5.46) | (0.07) | (2.30) |
| $\text{RISK}_{\text{AFP}}$ | 1.22 | 0.60 | 0.51 | 0.87 | 0.42 | 0.67 | 0.76 | 0.55 | 0.06 | 1.21 | 0.28 | 0.88 |
| | (2.68) | (1.29) | (0.97) | (2.37) | (0.88) | (2.14) | (2.05) | (2.28) | (0.09) | (2.68) | (0.83) | (1.68) |
| $\text{MP}_{\text{DHS}}$ | -0.92 | -0.28 | -1.59 | -0.78 | -1.54 | -0.78 | -0.84 | -0.36 | -2.23 | -1.02 | -0.23 | -1.20 |
| | (-3.16) | (-1.50) | (-5.99) | (-1.86) | (-2.86) | (-2.82) | (-2.14) | (-1.85) | (-9.27) | (-2.61) | (-3.16) | (-2.57) |
| $\text{MP}_{\text{SY}}$ | -1.22 | -0.32 | -1.37 | -1.25 | -1.86 | -1.10 | -1.26 | -0.65 | -1.50 | -1.48 | -0.19 | -1.61 |
| | (-3.54) | (-3.12) | (-4.06) | (-3.44) | (-3.66) | (-4.02) | (-3.31) | (-4.05) | (-3.80) | (-3.46) | (-4.04) | (-3.74) |
| $\text{MP}_{\text{AFP}}$ | -0.65 | -0.74 | -1.24 | -1.25 | -1.69 | -1.19 | -1.05 | -0.98 | -0.69 | -0.96 | -0.45 | -1.44 |
| | (-3.25) | (-3.25) | (-3.25) | (-3.25) | (-3.25) | (-3.25) | (-3.25) | (-3.25) | (-3.25) | (-3.25) | (-3.25) | (-3.25) |

*(continued)*

Table 9. Continued

| Panel C: March 2002 – December 2016 | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | BETA | SIZE | PRC | AGE | IVOL | DISP | VCF | OSCR | FP | DB | ILLIQ | HLS |
| $RISK_{DHS}$ | 0.54 | 0.46 | 1.02 | 0.57 | 0.78 | 0.58 | 0.22 | 0.52 | 0.54 | 0.70 | 0.47 | 0.70 |
| | (1.35) | (1.63) | (1.90) | (3.26) | (1.94) | (1.35) | (1.10) | (1.92) | (1.19) | (1.86) | (1.78) | (1.58) |
| $RISK_{SY}$ | 0.51 | 0.52 | 1.03 | 0.57 | 0.83 | 0.62 | 0.17 | 0.58 | 0.52 | 0.69 | 0.55 | 0.70 |
| | (1.33) | (1.99) | (2.19) | (3.67) | (2.43) | (2.23) | (0.71) | (2.45) | (1.75) | (1.85) | (2.45) | (1.91) |
| $RISK_{AFP}$ | 0.44 | 0.51 | 0.99 | 0.52 | 0.70 | 0.55 | 0.12 | 0.55 | 0.42 | 0.58 | 0.54 | 0.57 |
| | (1.24) | (2.19) | (2.20) | (3.42) | (2.11) | (1.74) | (0.60) | (3.18) | (1.07) | (1.86) | (2.54) | (1.68) |
| $MP_{DHS}$ | -0.70 | -0.15 | -0.63 | -0.23 | -0.62 | -0.51 | -0.39 | -0.29 | -0.66 | -0.69 | -0.12 | -0.75 |
| | (-1.76) | (-1.46) | (-1.84) | (-1.43) | (-1.71) | (-1.81) | (-1.55) | (-1.52) | (-1.78) | (-1.72) | (-1.53) | (-1.76) |
| $MP_{SY}$ | -0.67 | -0.21 | -0.64 | -0.23 | -0.67 | -0.55 | -0.33 | -0.35 | -0.64 | -0.68 | -0.19 | -0.74 |
| | (-1.41) | (-1.47) | (-1.35) | (-1.53) | (-1.51) | (-1.43) | (-1.54) | (-1.46) | (-1.23) | (-1.51) | (-1.44) | (-1.47) |
| $MP_{AFP}$ | -0.61 | -0.20 | -0.61 | -0.17 | -0.54 | -0.49 | -0.29 | -0.33 | -0.54 | -0.57 | -0.18 | -0.62 |
| | (-1.13) | (-1.13) | (-1.13) | (-1.13) | (-1.13) | (-1.13) | (-1.13) | (-1.13) | (-1.13) | (-1.13) | (-1.13) | (-1.13) |

# Appendix: Tables

Table A1. Correlation Coefficients of Mispricing Factors
This table shows correlation coefficients of the monthly mispricing factors FIN and PEAD (DHS-model of Daniel et al., 2020), MGMT and PERF (SY-model of Stambaugh and Yuan, 2017), and QMJ (AFP-model of Asness et al., 2019). The sample period is July 1972 to December 2016.

| | FIN | PEAD | MGMT | PERF | QMJ |
|---|---|---|---|---|---|
| FIN | 1.0000 | | | | |
| PEAD | -0.0381 | 1.0000 | | | |
| MGMT | 0.7944 | 0.0025 | 1.0000 | | |
| PERF | 0.1795 | 0.3842 | 0.0186 | 1.0000 | |
| QMJ | 0.5412 | 0.1462 | 0.3549 | 0.6590 | 1.0000 |

Table A2. Persistence of Factor Loadings

This table presents mispricing factor loadings of value-weighted portfolios based on pre-estimated mispricing factor loadings. We allocate stocks using NYSE breakpoints. In Panel A, for each month, we allocate stocks to decile portfolios based on the estimated slope coefficients from time-series regressions of monthly excess returns in the preceding 24 months (minimum 12 months) on FIN and PEAD (DHS-model of Daniel et al., 2020), MGMT and PERF (SY-model of Stambaugh and Yuan, 2017), or QMJ (AFP-model of Asness et al., 2019). In Panel B, we estimate slope coefficients based on daily excess returns in the preceding month (minimum 15 days). In addition, the table shows post-portfolio formation factor loadings, that is, the slope coefficients from time-series regressions of the subsequent monthly portfolio returns on PEAD and FIN, MGMT and PERF, or QMJ. The sample period is July 1974 to December 2016. The $t$-statistics in parentheses refer to the difference portfolio and are based on standard errors following Newey and West (1987) using six lags.

Panel A: Factor Loadings Based on Monthly Returns of Two Years

| | $\beta_{FIN}$ | | $\beta_{PEAD}$ | | $\beta_{MGMT}$ | | $\beta_{PERF}$ | | $\beta_{QMJ}$ | |
|---|---|---|---|---|---|---|---|---|---|---|
| Decile | pre | post | pre | post | pre | post | pre | post | pre | post |
| low | -2.73 | -1.51 | -3.13 | -0.65 | -3.47 | -1.93 | -2.32 | -0.94 | -4.49 | -2.57 |
| 2 | -1.72 | -1.05 | -1.72 | -0.49 | -2.18 | -1.33 | -1.40 | -0.72 | -2.84 | -1.88 |
| 3 | -1.31 | -0.71 | -1.14 | -0.45 | -1.67 | -1.04 | -1.03 | -0.59 | -2.20 | -1.56 |
| 4 | -1.02 | -0.58 | -0.73 | -0.42 | -1.31 | -0.84 | -0.77 | -0.48 | -1.77 | -1.27 |
| 5 | -0.79 | -0.48 | -0.40 | -0.40 | -1.02 | -0.74 | -0.55 | -0.37 | -1.42 | -1.04 |
| 6 | -0.58 | -0.38 | -0.09 | -0.33 | -0.75 | -0.60 | -0.35 | -0.29 | -1.10 | -0.89 |
| 7 | -0.37 | -0.33 | 0.24 | -0.19 | -0.48 | -0.53 | -0.15 | -0.26 | -0.80 | -0.69 |
| 8 | -0.15 | -0.25 | 0.60 | -0.12 | -0.20 | -0.38 | 0.06 | -0.17 | -0.47 | -0.59 |
| 9 | 0.13 | -0.18 | 1.09 | -0.08 | 0.16 | -0.28 | 0.35 | -0.13 | -0.07 | -0.44 |
| high | 0.64 | -0.13 | 2.26 | 0.06 | 0.86 | -0.31 | 0.96 | -0.13 | 0.69 | -0.35 |
| 10-1 | 3.36 | 1.38 | 5.39 | 0.71 | 4.33 | 1.62 | 3.28 | 0.81 | 5.18 | 2.22 |
| $t$-stat | (39.06) | (26.29) | (42.15) | (2.75) | (45.99) | (13.24) | (49.41) | (4.34) | (54.35) | (23.98) |

Panel B: Factor Loadings Based on Daily Returns of One Month

| | $\beta_{FIN}$ | | $\beta_{PEAD}$ | | $\beta_{MGMT}$ | | $\beta_{PERF}$ | | $\beta_{QMJ}$ | |
|---|---|---|---|---|---|---|---|---|---|---|
| Decile | pre | post | pre | post | pre | post | pre | post | pre | post |
| low | -3.10 | -1.42 | -3.68 | -0.91 | -4.08 | -1.88 | -2.90 | -1.00 | -5.25 | -2.40 |
| 2 | -1.81 | -0.88 | -1.74 | -0.62 | -2.33 | -1.19 | -1.46 | -0.66 | -2.99 | -1.71 |
| 3 | -1.30 | -0.64 | -1.01 | -0.56 | -1.65 | -0.94 | -0.92 | -0.59 | -2.13 | -1.39 |
| 4 | -0.97 | -0.51 | -0.51 | -0.44 | -1.19 | -0.77 | -0.54 | -0.44 | -1.55 | -1.17 |
| 5 | -0.70 | -0.42 | -0.10 | -0.34 | -0.82 | -0.61 | -0.22 | -0.37 | -1.08 | -0.97 |
| 6 | -0.45 | -0.36 | 0.30 | -0.31 | -0.48 | -0.56 | 0.07 | -0.29 | -0.66 | -0.83 |
| 7 | -0.21 | -0.28 | 0.71 | -0.17 | -0.15 | -0.51 | 0.39 | -0.22 | -0.25 | -0.65 |
| 8 | 0.05 | -0.26 | 1.20 | -0.09 | 0.22 | -0.48 | 0.75 | -0.11 | 0.22 | -0.57 |
| 9 | 0.41 | -0.23 | 1.90 | 0.01 | 0.72 | -0.43 | 1.27 | -0.08 | 0.86 | -0.52 |
| high | 1.29 | -0.34 | 3.67 | 0.20 | 1.96 | -0.56 | 2.51 | -0.05 | 2.32 | -0.56 |
| 10-1 | 4.39 | 1.08 | 7.35 | 1.11 | 6.04 | 1.32 | 5.41 | 0.95 | 7.57 | 1.84 |
| $t$-stat | (41.46) | (13.29) | (65.94) | (6.10) | (47.49) | (12.94) | (28.57) | (8.60) | (33.21) | (12.61) |

Table A3. Risk and Mispricing Components of Beta-Sorted Long-Short Portfolios
This table reports risk and mispricing components of value-weighted long-short portfolio returns. We allocate stocks to decile portfolios based on their market betas at the end of each month using NYSE breakpoints. BETA is used in the main analyses and is based on daily returns of the previous year. $\text{BETA}_{\text{FF}}$ follows Fama and French (1992) and is based on monthly returns of the previous five years using one Dimson (1979) lag. $\text{BETA}_{\text{LSY}}$ follows Liu et al. (2018) and is based on monthly returns of the previous five years using one Dimson (1979) lag and Vasicek (1973) shrinkage. $\text{BETA}_{\text{HS}}$ follows Hong and Sraer (2016) and is based on daily returns of the previous year using five Dimson (1979) lags. Following Frazzini and Pedersen (2014), $\text{BETA}_{\text{FP}}$ is based on rolling three-day return correlations of the previous five years and daily return volatility estimates of the previous year. $\text{BETA}_{\text{D}}$ is the Dimson (1979) beta as defined by Hou et al. (2020) using daily returns of the previous month. $\text{BETA}_{\text{m}}$ corresponds to a simple market beta based on daily returns of the previous month. The long-short returns are the difference between extreme decile portfolio returns in the following month. We generate the risk and mispricing components by regressing the long-short returns on FIN and PEAD (DHS-model of Daniel et al., 2020), MGMT and PERF (SY-model of Stambaugh and Yuan, 2017), or QMJ (AFP-model of Asness et al., 2019). The intercept plus the residual corresponds to the risk component, and the remainder of the fitted value corresponds to the mispricing component. The sample period is July 1972 to December 2016. The $t$-statistics in parentheses are based on standard errors following Newey and West (1987) using six lags.

| | BETA | $\text{BETA}_{\text{FF}}$ | $\text{BETA}_{\text{LSY}}$ | $\text{BETA}_{\text{HS}}$ | $\text{BETA}_{\text{FP}}$ | $\text{BETA}_{\text{D}}$ | $\text{BETA}_{\text{m}}$ |
|---|---|---|---|---|---|---|---|
| $\text{RISK}_{\text{DHS}}$ | 0.99 | 1.46 | 1.41 | 1.34 | 0.96 | 0.81 | 0.87 |
| | (3.90) | (4.32) | (4.24) | (4.04) | (3.52) | (3.47) | (3.46) |
| $\text{RISK}_{\text{SY}}$ | 1.07 | 1.47 | 1.43 | 1.50 | 0.95 | 0.86 | 0.90 |
| | (4.71) | (5.36) | (5.48) | (5.59) | (3.73) | (3.98) | (4.27) |
| $\text{RISK}_{\text{AFP}}$ | 0.48 | 0.84 | 0.81 | 0.83 | 0.33 | 0.46 | 0.43 |
| | (1.90) | (3.17) | (3.09) | (3.03) | (1.25) | (2.20) | (2.02) |
| $\text{MP}_{\text{DHS}}$ | -1.06 | -1.40 | -1.32 | -1.31 | -1.35 | -0.83 | -0.94 |
| | (-5.87) | (-6.09) | (-6.11) | (-5.52) | (-6.11) | (-5.92) | (-6.47) |
| $\text{MP}_{\text{SY}}$ | -1.14 | -1.41 | -1.34 | -1.47 | -1.34 | -0.87 | -0.96 |
| | (-5.92) | (-5.90) | (-5.90) | (-5.86) | (-5.93) | (-5.91) | (-5.89) |
| $\text{MP}_{\text{AFP}}$ | -0.55 | -0.79 | -0.72 | -0.80 | -0.71 | -0.48 | -0.50 |
| | (-3.40) | (-3.40) | (-3.40) | (-3.40) | (-3.40) | (-3.40) | (-3.40) |

Table A4. Market-Risk-Adjusted Risk and Mispricing Components of Decile Portfolios

This table reports the monthly average risk and mispricing components of value-weighted decile portfolio returns. We allocate stocks to decile portfolios based on each of the 12 strategies at the end of each month using NYSE breakpoints. We generate the risk and mispricing components by regressing the decile portfolio returns on FIN and PEAD (DHS-model of Daniel et al., 2020), MGMT and PERF (SY-model of Stambaugh and Yuan, 2017), or QMJ (AFP-model of Asness et al., 2019). The intercept plus the residual corresponds to the risk component, and the remainder of the fitted value corresponds to the mispricing component. We average the risk and mispricing components across the 12 strategies. For $RISK_{all}$ and $MP_{all}$, we also average the risk and mispricing components across the three factor models. For this analysis, we orthogonalize the mispricing factors with respect to the market factor by regressing each mispricing factor on the market excess return. The intercept plus the residual constitutes the orthogonalized mispricing factor. The sample period is July 1972 to December 2016. For DISP, the sample period starts in February 1976. The *t*-statistics in parentheses refer to the difference portfolio and are based on standard errors following Newey and West (1987) using six lags.

| Decile | BOTH | $RISK_{all}$ | $MP_{all}$ | $RISK_{DHS}$ | $MP_{DHS}$ | $RISK_{SY}$ | $MP_{SY}$ | $RISK_{AFP}$ | $MP_{AFP}$ |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 0.54 | 0.37 | 0.17 | 0.35 | 0.19 | 0.33 | 0.21 | 0.42 | 0.12 |
| 2 | 0.57 | 0.41 | 0.16 | 0.38 | 0.19 | 0.38 | 0.19 | 0.48 | 0.10 |
| 3 | 0.61 | 0.49 | 0.11 | 0.48 | 0.13 | 0.45 | 0.16 | 0.55 | 0.06 |
| 4 | 0.60 | 0.54 | 0.06 | 0.54 | 0.06 | 0.51 | 0.09 | 0.58 | 0.02 |
| 5 | 0.60 | 0.58 | 0.02 | 0.58 | 0.01 | 0.55 | 0.04 | 0.61 | -0.01 |
| 6 | 0.66 | 0.70 | -0.04 | 0.70 | -0.04 | 0.68 | -0.02 | 0.72 | -0.06 |
| 7 | 0.64 | 0.76 | -0.11 | 0.77 | -0.13 | 0.74 | -0.10 | 0.76 | -0.12 |
| 8 | 0.67 | 0.87 | -0.20 | 0.88 | -0.22 | 0.86 | -0.20 | 0.86 | -0.19 |
| 9 | 0.56 | 0.91 | -0.35 | 0.92 | -0.36 | 0.94 | -0.38 | 0.88 | -0.32 |
| 10 | 0.42 | 1.05 | -0.63 | 1.05 | -0.64 | 1.13 | -0.71 | 0.97 | -0.55 |
| 10-1 | -0.12 | 0.68 | -0.81 | 0.71 | -0.83 | 0.80 | -0.92 | 0.55 | -0.67 |
| *t*(10-1) | (-0.59) | (4.15) | (-9.54) | (3.77) | (-9.21) | (4.55) | (-9.51) | (3.40) | (-5.63) |
| 5-1 | 0.06 | 0.21 | -0.16 | 0.24 | -0.18 | 0.22 | -0.16 | 0.19 | -0.13 |
| *t*(5-1) | (0.91) | (3.66) | (-9.22) | (3.73) | (-10.35) | (3.77) | (-6.91) | (3.22) | (-5.67) |
| 10-6 | -0.24 | 0.35 | -0.59 | 0.35 | -0.59 | 0.45 | -0.69 | 0.26 | -0.50 |
| *t*(10-6) | (-1.59) | (2.98) | (-9.32) | (2.70) | (-8.09) | (3.48) | (-9.76) | (2.15) | (-5.61) |
| (10-6)-(5-1) | -0.30 | 0.14 | -0.44 | 0.12 | -0.42 | 0.23 | -0.52 | 0.07 | -0.37 |
| *t*((10-6)-(5-1)) | (-2.38) | (1.36) | (-8.63) | (1.12) | (-6.09) | (2.01) | (-9.66) | (0.64) | (-5.59) |

Table A5. Market-Risk-Adjusted Risk and Mispricing Components of Long-Short Portfolios This table reports risk and mispricing components of value-weighted long-short portfolio returns. We allocate stocks to decile portfolios based on each of the 12 strategies at the end of each month using NYSE breakpoints. The long-short returns are the difference between extreme decile portfolio returns in the following month. We generate the risk and mispricing components by regressing the long-short returns on FIN and PEAD (DHS-model of Daniel et al., 2020), MGMT and PERF (SY-model of Stambaugh and Yuan, 2017), or QMJ (AFP-model of Asness et al., 2019). The intercept plus the residual corresponds to the risk component, and the remainder of the fitted value corresponds to the mispricing component. For this analysis, we orthogonalize the mispricing factors with respect to the market factor by regressing each mispricing factor on the market excess return. The intercept plus the residual constitutes the orthogonalized mispricing factor. The sample period is July 1972 to December 2016. For DISP, the sample period starts in February 1976. The $t$-statistics in parentheses are based on standard errors following Newey and West (1987) using six lags.

| | BETA | SIZE | PRC | AGE | IVOL | DISP | VCF | OSCR | FP | DB | ILLIQ | HLS |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $\text{RISK}_{\text{DHS}}$ | 0.61 | 0.66 | 1.16 | 0.63 | 0.69 | 0.43 | 0.59 | 0.34 | 1.06 | 0.69 | 0.59 | 1.01 |
| | (1.84) | (2.72) | (2.57) | (3.70) | (1.95) | (1.36) | (2.52) | (1.53) | (3.05) | (2.08) | (2.60) | (3.03) |
| $\text{RISK}_{\text{SY}}$ | 0.65 | 0.68 | 1.10 | 0.92 | 0.89 | 0.56 | 0.74 | 0.55 | 0.88 | 0.90 | 0.61 | 1.08 |
| | (1.86) | (2.72) | (2.94) | (4.74) | (2.74) | (2.02) | (3.12) | (2.69) | (3.47) | (2.52) | (3.06) | (3.38) |
| $\text{RISK}_{\text{AFP}}$ | 0.19 | 0.82 | 1.02 | 0.48 | 0.37 | 0.71 | 0.27 | 0.74 | 0.31 | 0.33 | 0.78 | 0.74 |
| | (0.63) | (3.55) | (3.14) | (2.53) | (1.24) | (3.14) | (1.27) | (4.70) | (0.91) | (1.12) | (4.18) | (2.57) |
| $\text{MP}_{\text{DHS}}$ | -0.68 | -0.48 | -1.24 | -0.66 | -1.29 | -0.71 | -0.77 | -0.37 | -1.35 | -0.73 | -0.35 | -1.24 |
| | (-8.65) | (-7.26) | (-11.10) | (-5.57) | (-8.27) | (-8.58) | (-6.65) | (-6.48) | (-9.53) | (-7.30) | (-10.17) | (-8.70) |
| $\text{MP}_{\text{SY}}$ | -0.72 | -0.50 | -1.18 | -0.95 | -1.49 | -0.84 | -0.92 | -0.59 | -1.17 | -0.94 | -0.37 | -1.32 |
| | (-9.76) | (-9.74) | (-7.66) | (-9.09) | (-9.75) | (-7.89) | (-8.81) | (-8.58) | (-6.04) | (-9.17) | (-7.76) | (-9.46) |
| $\text{MP}_{\text{AFP}}$ | -0.26 | -0.64 | -1.10 | -0.51 | -0.96 | -0.99 | -0.45 | -0.78 | -0.60 | -0.37 | -0.54 | -0.97 |
| | (-5.61) | (-5.61) | (-5.61) | (-5.61) | (-5.61) | (-5.96) | (-5.61) | (-5.61) | (-5.61) | (-5.61) | (-5.61) | (-5.61) |