Arbitrage Asymmetry, Mispricing Gap, and Momentum Prediction

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Abstract

I introduce a measure called mispricing gap (Mgap), which is the mispricing score gap between overpriced winners and underpriced losers. I find that Mgap predicts stock momentum because it can intuitively measure the level of persistence in trading behaviors of both sentiment investors and arbitrageurs. This predictability is statistically and economically significant both in-sample and out-of-sample. The in-sample predictability remains even when accounting for various state-of-the-art common risk factors and existing predictors. A one standard deviation increase in Mgap boosts next month's momentum returns by 1.10%, which is over 90% of the historical 1.16% return.

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Recent studies indicate that momentum profit hinges on the persistent trading behaviors of two investor groups: sentiment investors and arbitrageurs. On the one hand, Ehsani and Linnainmaa (2022) (EL 2022) claim that auto-correlation in factor returns stems from persistent investor sentiment (PIS), leading to "factor momentum". On the other hand, Li et al. (2023) (LZY 2023) reveal that the autocorrelation in the "risk component" of stock returns is due to Persistent Mispricing Correction (PMC). They argue that because of limits-to-arbitrage, arbitrageurs have to correct mispricing progressively, resulting in "risk momentum". These two empirical findings imply the predictability of momentum profit, as both studies emphasize the importance of persistent trading behaviors. Put differently, the absence of PIS eliminates factor momentum, and without PMC, risk momentum attenuates. Consequently, it is tempting to forecast stock momentum, if one can devise a signal that gauges the persistence of such trading behaviors.

In this paper, I introduce a measure called mispricing gap (Mgap), which is the mispricing score[1] gap between overpriced winners and underpriced losers. By using Mgap and arbitrage asymmetry, I segment investors into two types: sentiment investors and arbitrageurs. I then examine the relationship between these investors' trading dynamics and future momentum profits, quantifying this relationship through Mgap. I find that Mgap predicts stock momentum because it can intuitively measure the level of persistence in trading behaviors of both sentiment investors and arbitrageurs. Overall, the predictability of Mgap is statistically and economically significant, both in and out-of-sample. Specifically, a one standard deviation increase in Mgap formed on the past 36 months raises the next month's momentum returns[2]

[1]Stambaugh and Yuan (2016) introduce their mispricing score, which is a mispricing measure for stocks. It is devised by aggregating its monthly rankings across 11 identified anomaly variables. Each stock is ranked based on its performance relative to a specific anomaly, where the highest rank is attributed to stocks exhibiting the lowest average abnormal return. The stock's overall mispricing measure, termed MISP and scaled from 0 to 100, represents the average of its percentile rankings across all anomalies. Under this metric, stocks with the highest MISP scores are deemed the most overpriced, while those with the lowest are considered the most underpriced. More information is available on Robert Stambaugh's website https://finance.wharton.upenn.edu/ stambaug/)

[2]To calculate monthly momentum returns, I follow the method proposed by Carhart (1997). At the

by 1.10%, which represents over 90% of the historical average monthly return of 1.16%. Furthermore, this in-sample predictability remains robust even after adjusting for a range of state-of-the-art common risk factors and existing predictors. More importantly, the out-of-sample R^2 statistics ranges from 0.01 to 0.02, all of which exceed the 0.5% threshold for economic significance suggested by Campbell and Thompson (2008). In addition, I show that Mgap predicts momentum crashes, with the major contribution coming from overpriced winners. To corroborate the underlying mechanism and analyze the determinants of Mgap, I use variables such as fund flows, macroeconomic factors, investor sentiment indices, and market friction proxies to explain both its long and short legs. My analysis reveals that sentiment investors determine mispricing score of the overpriced winners, while arbitrageurs influence the score of underpriced losers.

To define overpriced winners and underpriced losers in the formation period[3], I first sort stocks into quintile portfolios based on past returns. Within each quintile, I further sort stocks based on their mispricing scores. I define Overpriced Winners (OW) as stocks in the top quintile for past returns and the top decile for mispricing scores, and Underpriced Losers (UL) as those in the bottom quintile for past returns and the bottom decile for mispricing scores. Similarly, I generate the remaining two corner portfolios: overpriced losers (OL) and underpriced winners (UW). I define Mgap as the difference in average mispricing scores between OW and UL portfolios.

What can we infer about the trading dynamics of sentiment investors and arbitrageurs from Mgap observed over a long formation period? I first match these two investors with different types of stocks, then use Mgap to analyze the magnitude and direction of the impact

beginning of month t, I sort stocks into deciles based on their cumulative returns from $t-12$ to $t-2$ and calculate the decile spread between winners and losers.

[3]To simplify the dimensions of the results, I set the formation period (look-back window) for past returns from $t-12$ to $t-2$, matching the window used to construct the momentum portfolio. I allow the formation period for calculating the average mispricing score to vary from 11 ($t-12$ to $t-2$) to 72 ($t-73$ to $t-2$) months.

that trading dynamics have on momentum returns. I now consider a market where both arbitrageurs and sentiment investors face limits-to-arbitrage (Shleifer and Vishny (1997)), and each group trades on distinct signals persistently. Specifically, these assumptions are:

1. Sentiment investors persistently do trend-chasing tradings while arbitrageurs do not.

2. Arbitrageurs persistently trade on the mispricing level of a stock while sentiment investors do not.

3. Short-selling constraint.

The direct implication based on these assumptions is that sentiment investors engage in trend-chasing by persistently buying winner stocks, while arbitrageurs focus on the mispricing correction by persistently purchasing undervalued stocks. I visualize these trading dynamics in Figure 1, where I map the stock universe into a two-dimensional space characterized by mispricing score and past returns. In this space, I identify potential investors for each type of stock. For example, when classifying a stock as an overpriced winner, I investigate which investor is most likely to have made the overpriced stock a winner. When short-selling constraint applies, sentiment investors focus solely on buying winner stocks. This places sentiment investors (pure momentum traders) in the first and fourth quadrants. On the other hand, arbitrageurs, unable to short overpriced stocks, mainly correct underpriced stocks, positioning themselves in the first and second quadrants. Therefore, in month t, sentiment investors typically exacerbate the overpricing of past winners, bringing in positive returns for overpriced winners. Arbitrageurs, focus on correcting underpricing, securing positive returns for underpriced losers. If their trading behaviors are persistent, we will observe a strong momentum effect in the overpriced group. However, in the underpriced group, due to stronger mispricing correction from the underpriced losers, we would expect a stronger reversal effect for these stocks, resulting in a much weaker momentum effect in the underpriced stock group overall. In other words, these two types of returns create a counterbalance at the aggregate level of momentum profit in month t.

After establishing a direct relationship between trading dynamics and future momentum returns, I now propose using Mgap to measure the magnitude and direction of the impact that trading dynamics have on momentum returns. To provide simple intuition, I analyze two scenarios: In the first scenario, past winners consist of underpriced stocks, and losers consist of overpriced stocks, resulting in a narrow Mgap. This composition reflects a market where PMC is more dominant than PIS, because past winner is primarily driven by underpricing correction. In the second scenario, past winners consist of overpriced stocks and losers consist of underpriced stocks, leading to a wide Mgap. This reflects a market where PIS is more dominant than PMC, with past winners primarily driven by persistent winner-chasing. In other words, in markets where PIS outweighs PMC, trend-chasing strategies are likely to dominate, generating positive returns even for overpriced winners throughout the formation period. Consequently, these winner stocks will show high scores (overpriced stocks become more overpriced) at the end of the formation period, indicating a wide Mgap. Conversely, in markets where PMC prevails over PIS, the focus on mispricing correction leads to persistent positive returns for underpriced losers. These losers stocks, too, will exhibit high scores (underpriced stocks become less underpriced) by the end of the period, but with a narrower Mgap.

Put another way, PIS and PMC act as two horses each pulling in their unique directions when determining the expected return for different types of stocks. When PIS prevails, whether stocks are overpriced or underpriced, as long as they are winners, they will continue to achieve higher returns in the next period. Hence, the above analysis suggests that a wide Mgap signals strong and persistent investor sentiment, while indicating an ineffective and impersistent mispricing correction. If these trading behaviors persist into subsequent periods, we can expect to observe a pronounced momentum effect preceded by a wide Mgap. Therefore, by analyzing the scores of overpriced winners and underpriced losers, we can determine PIS and PMC during the formation period, thereby predicting the momentum profit in month t.

The motivation for adopting arbitrage asymmetry to identify investors is based on many previous studies (see, e.g., Stambaugh et al. (2012), Stambaugh et al. (2015)). These studies suggest that due to arbitrage asymmetry, different types of investors encounter different barriers when trading stocks. For example, Da et al. (2014) investigate whether liquidity shocks and investor sentiment have distinct roles in driving short-term reversals. Their findings suggest that investor sentiment, particularly in recent winners, aligns with the presence of short-sale constraints. These constraints curtail the capacity of arbitrageurs to immediately correct overpricing.[4] The use of mispricing score to identify investors is anchored in the common belief that sentiment investors are less concerned about a stock's mispricing level compared to arbitrageurs, often due to their perceived lower rationality. Hence, sentiment investors are more inclined to bet on past winners regardless of mispricing levels. Arbitrageurs, on the other hand, primarily focus on correcting mispricing, giving more weight to mispricing levels rather than just return signals. Loosely speaking,

Besides the above empirical motivation, I also provide theoretical support for using a mispricing signal to predict momentum profit. Dong et al. (2021) suggest that short legs of anomaly returns can predict market return, because part of the market return is related to PMC, especially from the short leg. Given that a portion of momentum profits may also be attributable to PMC, it's tempting to use a mispricing signal to forecast momentum. I now combine empirical and theoretical motivations to formulate three main testable hypotheses:

1. Momentum return is predictable based on a mispricing signal associated with temporal dynamics of sentiment investors and arbitrageurs.

[4]Likewise, Pontiff (2006) empirically demonstrates that stocks with greater arbitrage risk have higher expected returns, suggesting that arbitrage asymmetry could affect asset pricing. D'avolio (2002) and Ofek and Richardson (2003) provide empirical evidence showing that short-selling constraints contribute significantly to the presence of arbitrage asymmetry, influencing the speed and extent of mispricing correction.

2. Sentiment investors influence momentum return in a positive direction.

3. Arbitrageurs influence momentum return in a negative direction.

To demonstrate how sentiment investors influence the mispricing level of OW and how arbitrageurs affect the mispricing level of UL, I present direct evidence from fund flows, macro-financial state variables, and market friction measures. The underlying intuition is that these two distinct investor types respond differently to such factors. I first study the role of fund flows. In alignment with Akbas et al. (2015), I explore if mutual fund flows relate to mispricing score of overpriced winners and if hedge fund flows align with mispricing score of UL. My findings reveal that mutual funds propel pure momentum trades contributing to the overpriced winner, while hedge funds drive the correction of mispricing in the underpriced loser. This corroborates the finding in Grinblatt et al. (2020), which assert that the majority of hedge fund managers are not momentum traders, while mutual fund managers tend to pursue momentum strategies. Second, I use an array of macroeconomic variables and proxies for market frictions to explain both overpriced winners and UL. The conjecture here is that sentiment investors are more susceptible to the variation of market state variables, while arbitrageurs are more sensitive to fluctuations in market frictions. My finding indeed confirms this. First, sentiment investors are more vulnerable to economic fluctuations, as macro-finance factors only affect the score of overpriced winners. Second, arbitrageurs are more sensitive to market frictions, as market friction factors only affect scores in UL.

Why do we need a new predictor Mgap to forecast momentum? Momentum stands as perhaps the most challenging anomaly to reconcile with the efficient market hypothesis. Numerous studies have attempted to explain momentum from specific perspectives, yet none have achieved broad consensus (see e.g., Jegadeesh and Titman (1993), Barberis et al. (1998), Hong and Stein (1999), Daniel et al. (1998)). In momentum research, scholars often differentiate between cross-sectional return and time-series predictability. In this paper, I contend that part of the cross-sectional momentum profit arises from the trading dynamics of sentiment investors and arbitrageurs.[5] Furthermore, I argue that the dynamics of these two investor types are influenced by distinct variables. As such, it's imperative to demonstrate that the time-series predictability of momentum is indeed anchored in the interplay between sentiment investors and arbitrageurs.

My paper contributes to the extensive literature on the underlying mechanisms of momentum. Prior studies focus on explaining stock momentum from a behavioral aspect, attempting to attribute it either to arbitrageurs or sentiment investors (see, e.g., Ehsani and Linnainmaa (2022), Li et al. (2023)). My paper shows that momentum profit is determined by both types of investors. Second, my paper contributes to the literature on factor timing, especially on predicting momentum. While some existing studies touch upon the predictability of momentum profit, they often fall short of elucidating the underlying mechanism. For instance, Huang (2022) shows that "momentum gap" can predict momentum profit. However, Huang (2022) does not establish a direct connection between stock mispricing and momentum. Moreover, Huang (2022) does not demonstrate the underlying mechanism of how two different types of investors who trade on different signals create momentum profit. In contrast, this paper identifies these two investor categories and employs mispricing score as a direct predictor for momentum. Moreover, when controlling for mispricing gap, the predictability of the momentum gap no longer exists.

The remainder of the paper is organized as follows. Section 2.1 discusses the motivation and the data. Section 2.2 presents the main results of time-series prediction. Section 2.3

[5]Similar to my study, Asness et al. (2013) investigate the relationship between time-series momentum and value, providing further evidence of the interaction between investor sentiment and momentum strategies. Their findings suggest that sentiment investors may play a role in driving the observed patterns in both value and momentum returns. More recently, Kokkonen and Suominen (2015) determines the degree of market mis-valuation (or market inefficiency) by using the mis-valuation spread, which is the disparity between the most overvalued and undervalued stocks. They illustrate that this mis-valuation spread is a potent forecaster of the returns from a long-short portfolio based on mis-valuation. This lends support to the conjecture that it serves as an indicator of the degree of mispricing in the equity market.

examines the determinants of Mgap. Section 2.4 explores robustness. Section 2.5 concludes.

I. Theoretical Motivating Evidence

To provide theoretical support for my argument, I adapt the data-generating process from Dong et al. (2021). This study explores the use of long-short anomaly returns to predict next-month market returns, suggesting that this predictability likely arises from asymmetric limits of arbitrage and Persistent Mispricing Correction. I maintain all their notations unless specified otherwise[6]. In their model, they assume that the prices for the long and short legs of an anomaly portfolio contain a common martingale component with period t increment F_t. Additionally, the price of the long (short) leg includes stationary components, denoted $u_{L,t} \leq 0$ ($u_{S,t} \geq 0$). These components reflect the levels of underpricing and overpricing, respectively, and are uncorrelated with the common component. I assume that the returns of the momentum strategy is given by:

$$r_{mom,t} = winner_t - loser_t. \tag{1}$$

Dong et al. (2021) assume that the mispricing eventually corrects, because any mispricing shock affects the price only temporarily. Therefore, in their model, they only consider arbitrageurs. While this might be true for aggregate market returns, it does not apply to momentum strategy. Based on the previous analysis, I see that during the formation period, winner stocks may include both underpriced and overpriced stocks. Thus, in a more efficient market, "good momentum" prevails when winner stocks predominantly consist of underpriced stocks, reflecting PMC of such stocks. Conversely in a less efficient market, when winner stocks largely consist of overpriced stocks, "bad momentum" prevails. Therefore, given different types of investors focus on different types of stocks, both good and bad momentum

[6]I assume that the readers are familiar with their Section I.

may simultaneously exist. Hence, I define the winner and loser portfolios as follows:

$$winner_t = F_t + 0.5 * (\Delta u^{bad}_{S,t} + \Delta u^{good}_{L,t}) \tag{2}$$

$$loser_t = F_t + 0.5 * (\Delta u^{good}_{S,t} + \Delta u^{bad}_{L,t}) \tag{3}$$

$$\Delta u^{type}_{l,t} = \sum_{j=1}^{\infty} \tilde{\psi}_{l,j} * \nu_{l,t-j}, \quad \text{for} \quad l = L, S \quad \text{and} \quad type = good, bad. \tag{4}$$

This configuration[7] suggests that the winner's portfolio, for example, may simultaneously reflect both the exacerbation of overpricing $\Delta u^{bad}_{S,t}$ and the correction of underpricing $\Delta u^{good}_{L,t}$. Specifically, an overpriced stock has to be a past winner ($\Delta u^{\text{bad}}_{S,f} > 0$)[8] to show up at the end of month $t-1$ when constructing winner portfolio, thus the return generated by an overpriced stock in month t is $\Delta u^{\text{bad}}_{S,t}$. This trading mechanism means that overpricing is exacerbated in the formation period f. Hence, this OW represents bad momentum. Similarly, if an underpriced stock is a past winner ($\Delta u^{\text{good}}_{L,f} > 0$), the return generated in month t is $\Delta u^{\text{good}}_{L,t}$. This means that underpricing is mitigated in the formation period f. Hence, this underpriced winner represents good momentum. Together, the winner portfolio may comprise both types of momentum. The same reasoning applies to the loser portfolios.

Dong et al. (2021) suggest that the stationary component in each leg related to mispricing can be expressed as:

$$u_{l,f} = \sum_{j=1}^{\infty} \psi_{l,j} \cdot \nu_{l,t-j}, \quad \text{for} \quad l = L, S, \tag{5}$$

where $\psi_{1,0} = 1$, $\nu_{L,t-j} \leq 0$ (representing a serially uncorrelated underpricing shock) and $\nu_{S,t-j} \geq 0$ (representing an overpricing shock). Dong et al. (2021) argue that due to PMC, the correction of mispricing, $\Delta u_{L,f}$, must be non-negative for a previous underpricing shock

[7] I use the equal weight for simplicity

[8] I use the f-period to denote formation period return.

and non-positive for a previous overpricing shock. This implies that the aggregate change in response $\psi_{l,j}$ of $\nu_{l,t-j}$, defined as $\tilde{\psi}_{l,j} = \psi_{l,j} - \psi_{l,j-1}$, must be non-positive. This is to ensure that arbitrage is sufficiently active to prevent the exacerbation of mispricing associated with a period t mispricing shock in any subsequent period.

However, my Assumption 1, which posits that sentiment investors can exacerbate mispricing, differs from Dong et al. (2021) as it explicitly allows for persistent exacerbation by sentiment investors. In other words, for sentiment investors, instead of correcting mispricing like arbitrageurs, they can further amplify mispricing shocks in future periods. In this case, the change in response of the mispricing shock for sentiment investors can be non-negative:

$$\tilde{\psi}^{\text{sent}}_{l,j} = \psi^{\text{sent}}_{l,j} - \psi^{\text{sent}}_{l,j-1} \geq 0, \quad \text{for} \quad l = L, S. \tag{6}$$

Therefore, the mispricing shocks exacerbate in the formation period:

$$\Delta u^{\text{bad}}_{l,f} = \sum_{j=1}^{\infty} \tilde{\psi}^{\text{sent}}_{l,j} \cdot \nu_{l,t-j}, \quad \text{for} \quad l = L, S. \tag{7}$$

Since $\nu_{L,t-j} \leq 0$ and $\nu_{S,t-j} \geq 0$, I have exacerbation of mispricing of the formation period to be $\Delta u^{\text{bad}}_{L,f} \leq 0$ (underpriced loser), and $\Delta u^{\text{bad}}_{S,f} \geq 0$ (overpriced winner). However, sentiment investors do not observe the true mispricing signals, so their trading strategy is based on formation period return signals. Thus in the month t, the bad momentum is generated:

$$\Delta u^{\text{bad}}_{l,t} = \tilde{\psi}^{\text{sent}}_{l,j} \cdot \Delta u^{\text{bad}}_{l,f}, \quad \text{for} \quad l = L, S. \tag{8}$$

Now, turning to arbitrageurs, I have the change in response of the mispricing shock:

$$\tilde{\psi}^{\text{arb}}_{l,j} = \psi^{\text{arb}}_{l,j} - \psi^{\text{arb}}_{l,j-1} \leq 0, \quad \text{for} \quad l = L, S. \tag{9}$$

Assumption 2 posits that arbitrageurs correct mispricing irrespective of the formation period return. In this case,

$$\Delta u_{l,f}^{\text{good}} = \sum_{j=1}^{\infty} \tilde{\psi}_{l,j}^{\text{arb}} \cdot \nu_{l,t-j}, \quad \text{for} \quad l = L, S. \tag{10}$$

Since $\nu_{L,t-j} \leq 0$ and $\nu_{S,t-j} \geq 0$, I have good momentum (persistent mispricing correction) of the formation period to be $\Delta u_{L,f}^{\text{good}} \geq 0$ (underpriced winner), and $\Delta u_{S,f}^{\text{good}} \leq 0$ (overpriced loser).

A. Returns of the Four Types of Stocks in Month t

A.1. Overpriced Winner

Based on the above analysis, I derive the expect returns of four corner portfolios in month t. At the end of formation period f, the aggregate mispricing shock of overpriced winner (OW) is

$$\nu_{S,f}^{OW} = \nu_{S,t-f} + \alpha \cdot \Delta u_{S,f}^{\text{bad}} \geq \nu_{S,t-f}. \tag{11}$$

The return due to exacerbation of overpriced stocks in the formation period, denoted by $\Delta u_{S,f}^{\text{bad}}$, contributes positively[9] to the aggregate mispricing score of the OW at the end of the formation period. Because due to asymmetric limits-to-arbitrage, only sentiment investors would buy OW. Therefore, the return of OW in month t is non-negative:

$$\Delta u_{S,t}^{\text{bad}} = (\psi_{S,1}^{\text{sent}} - \psi_{S,0}^{\text{sent}}) \cdot \Delta u_{S,f}^{\text{bad}} \geq 0. \tag{12}$$

[9]The coefficient α, which represents the coefficient between formation period return and mispricing score at the end of formation period, is positive.

A.2. Overpriced Loser

At the end of formation period f, the aggregate mispricing shock of overpriced loser is:

$$\nu_{S,f}^{OL} = \nu_{S,t-f} + \alpha \cdot \Delta u_{S,f}^{\text{good}} \leq \nu_{S,t-f}. \tag{13}$$

This is because the return in the formation period, denoted by $\Delta u_{S,f}^{\text{good}}$, is negative for overpriced loser. Because no investors would trade overpriced loser due to asymmetric limits-to-arbitrage, the return in month t for overpriced loser should be zero:

$$\Delta u_{S,t}^{\text{good}} = 0. \tag{14}$$

A.3. Underpriced Winner

At the end of the formation period f, the aggregate mispricing shock of underpriced winner is

$$\nu_{L,f}^{UW} = \nu_{L,t-f} + \alpha \cdot \Delta u_{L,f}^{\text{good}}. \tag{15}$$

The determination of the sign for equation (15) is challenging because the correction of underpricing does not necessarily guarantee a complete correction of the initial underpricing. In month t, both sentiment investors and arbitrageurs tend to buy the underpriced winner:

$$\Delta u_{L,t}^{\text{good}} = (\psi_{l,1}^{\text{sent}} - \psi_{l,0}^{\text{sent}}) \cdot \Delta u_{L,f}^{\text{good}} + (\psi_{l,1}^{\text{arb}} - \psi_{l,0}^{\text{arb}}) \cdot \nu_{L,f}^{UW}[10]. \tag{16}$$

Since sentiment investors trade on past return signals, I have $(\psi_{l,1}^{\text{sent}} - \psi_{l,0}^{\text{sent}}) \cdot \Delta u_{L,f}^{\text{good}} \geq 0$. For arbitrageurs, the sign of $\nu_{L,f}^{UW}$ is uncertain, so prudent arbitrageurs will refrain from trading it. Even if some arbitrageurs believe they are overly corrected, due to short-selling restrictions,

[10]Note that sentiment investors trade on return signals $\Delta u_{L,f}^{\text{good}}$ while arbitraguers trade on mispricing signals $\nu_{L,f}^{UW}$.

they will refrain from shorting it. Hence, $(\psi^{\text{arb}}_{l,1} - \psi^{\text{arb}}_{l,0}) \cdot \nu^{UW}_{L,f} \geq 0$. Consequently, equation (16) remains nonnegative[11]:

$$\Delta u^{\text{good}}_{L,t} \geq 0. \tag{17}$$

A.4. Underpriced Loser

At the end of the formation period f, the aggregate mispricing shock of underpriced loser is

$$\nu^{UL}_{L,f} = \nu_{L,t-f} + \alpha \cdot \Delta u^{\text{bad}}_{L,f} \leq \nu_{L,t-f}. \tag{18}$$

For UL, only arbitrageurs would buy them, while sentiment investors cannot sell them due to short-selling constraints. This leads to:

$$\Delta u^{\text{bad}}_{L,t} = (\psi^{\text{arb}}_{l,1} - \psi^{\text{arb}}_{l,0}) \cdot \nu^{UL}_{L,f} \geq 0, \tag{19}$$

which suggests that UL will result in a positive return in month t.

I now summarize my findings for the winner and loser portfolios:

$$winner_t = F_t + 0.5 \times (\Delta u^{\text{bad}}_{S,t} + \Delta u^{\text{good}}_{L,t}) \geq F_t, \tag{20}$$

$$loser_t = F_t + 0.5 \times (\Delta u^{\text{good}}_{S,t} + \Delta u^{\text{bad}}_{L,t}) = F_t + 0.5 \times \Delta u^{\text{bad}}_{L,t} \geq F_t. \tag{21}$$

Therefore, in the winner portfolio, there will be a momentum effect because of the exacerbation of overpricing fueled by sentiment investors alone. Whereas for the loser group, I should observe a reversal effect due to arbitrageurs correcting the underpricing of losers in month t.[12]

[11] Considering $\nu_{L,t} \leq 0$, a positive shock implies that $-\nu_{L,t} \geq 0$.

[12] To better illustrate my analysis, I propose a behavioral quadrant. As shown in Figure 1, the first quadrant includes both sentiment investors and arbitrageurs, as these stocks are underpriced winners. The

In summary, the above analysis provides testable hypotheses:

1. Overpriced winners generate positive returns in month t, while overpriced losers generate zero return.[13]

2. Both underpriced winners and losers generate positive returns in month t.[14]

To test these hypotheses and provide motivating empirical evidence, I first sort stocks on formation period return, and then within each portfolio, I further sort stocks on their mispricing score. I here underscore the necessity of dependent sort because first, I measure the influence of mispricing within momentum groups. Second, it's more reasonable to treat stock momentum as ex-post evidence of how the market trades stocks. In contrast, mispricing scores are more like ex-ante proxies that can predict cross-sectional stock returns. Assuming the market is overall efficient in the long term, one should expect that overpriced stocks should appear in the loser decile group in the next period, while underpriced stocks in the winner group. Therefore, sorting stocks first on formation period return and then on mispricing score enables us to better understand how the market efficiently and effectively corrects mispricing.

Panel A of Table 1 reveals significant variations in momentum based on mispricing scores (momentum balanced). The most overpriced group displays an average monthly return of 1.14%, with a t value exceeding 4.98. So there is a strong momentum effect in the overpriced stock group. In contrast, the underpriced group exhibits no momentum. The disparity between the overpriced and underpriced groups is due to the unusually high positive return compensating the underpriced loser in the subsequent period. Thus, my two hypotheses are all testified, supporting my previous assumptions.

The takeaway here is that even though we may not fully understand the true nature of

second quadrant contains only arbitrageurs, as these stocks are UL. The third quadrant is empty due to short-selling constraints. The fourth quadrant includes only sentiment investors, as these stocks are OW.

[13]The first hypothesis corresponds to a momentum effect in the overpriced stock groups

[14]The second hypothesis implies a reversal effect for the underpriced loser group due to the correction effect brought by underpriced losers, and thus no overall momentum effect within underpriced stock groups.

a pure momentum effect, it's clear that the "winner minus loser" strategy varies quite a bit across different groups. Specifically, for overpriced stocks, this strategy requires some time to start bringing in positive returns, while in underpriced stocks, we do not really see a momentum effect. As illustrated in Figure 2, which plots the t values corresponding to these two strategies, the momentum strategy starts yielding significant positive returns as the window expands from 1 to 11 within the overpriced group. However, in the underpriced group, because underpriced loser stocks already bring high returns even when the window is 1 month, the momentum strategy does not contribute any additional significant return. This pattern is consistent across all time windows, suggesting that potential corrections for mispricing can handle both short and long-term mispricing signals. In contrast, however, sentiment investors seem to primarily focus on short to mid-term signals. In the long term, momentum does not seem to generate significant returns. Thus, these two variants of momentum exhibit substantial discrepancies, particularly in terms of their return-generating processes.

Furthermore, to demonstrate that the returns from these four corner portfolios are fundamentally different, I conduct a time-series regression of these returns on DHS factors. As demonstrated by Daniel et al. (2020), their behavioral model exhibits a strong ability to price stock momentum, outperforming the Fama-French 3 and 5-factor models significantly. Additionally, according to their arguments, the PEAD (post-earning announcement drift) factor is specifically associated with investors' underreaction to firm-specific news. Therefore, if any of these returns are due to investor underreaction, they should exhibit significant loadings on this factor. The results from panel B reveal that the OW portfolio differs significantly from the other three portfolios, as its loading on the PEAD factor is not significant. This suggests that the OW portfolio is not subject to investor underreaction. Moreover, the DHS factor model is presumed to capture behavior-related returns more effectively than those returns not related to behavior. If the return is indeed driven by sentiment investors, the DHS model should predict that the risk-adjusted return would be significantly lower. Given my argument that there are no arbitrage activities in overpriced stocks, the intercept term should be statistically insignificant. Indeed, the OW portfolio does not yield a significant risk-adjusted return.

In short, those findings highlight several key implications. Firstly, my first assumption appears valid. Otherwise, we wouldn't observe variation in the momentum strategy across different groups. The positive return from OW suggests that sentiment investors indeed chase winners irrespective of the mispricing level, which aligns with the first assumption. Secondly, formation period return may not be one of the mispricing measures. If it were the same as other mispricing measures, we would expect momentum traders and mispricing traders to theoretically trade in the same direction and momentum to pervade all groups sorted by mispricing scores. However, this is not the case here, especially for the underpriced loser group[15]. In this group, a momentum trader would consistently short the losers regardless of their mispricing level, while arbitrageurs seeking to correct mispricing would long these underpriced stocks regardless of their formation period return. Thirdly, no significant return from overpriced losers implies that short-sell constraints indeed affect both types of investors, which aligns with my third assumption.

Now, the above evidence suggests that momentum profit in month t depends on the momentum of the overpriced winner and the reversal effect of the underpriced loser. Therefore, I consider a predictive regression,

$$r_{mom,t} = \alpha_{LS} + \beta_{LS} \cdot Mgap_{t-2,t-12} + \epsilon_{LS,t}, \tag{22}$$

[15]This reasoning extends to other scenarios as well. In the overpriced winner group, momentum traders tend to long the stocks, while arbitrageurs tend to short them. Hence, in the overpriced winner and underpriced loser groups, momentum traders and arbitrageurs invariably trade in opposing directions. This argument seems to be in line with many previous studies such as EL 2022. However, this is not always the case. In other groups, such as overpriced losers, both types of traders tend to short the stock, while in underpriced winners, they both lean towards long the stock.

where

$$Mgap_{t-2,t-12} = Mgap_f = \nu^{OW}_{S,f} - \nu^{UL}_{L,f}. \tag{23}$$

The standardized slope coefficient in the equation is then given by[16]

$$\tilde{\beta}_{LS} = \frac{\text{cov}(Mgap_f, r_{LS,t})}{\text{var}(Mgap_f)} = \frac{0.5 \cdot [\tilde{\psi}^{\text{sent}}_{l,1} * var(\Delta u^{bad}_{S,f}) + \tilde{\psi}^{\text{arb}}_{l,1} * var(\nu^{UL}_{L,f})]}{\text{var}(\nu^{OW}_{S,f} - \nu^{UL}_{L,f})}. \tag{24}$$

This implies that the strong continuation of past overpricing by sentiment investors in winners and the weak correction of past underpricing by arbitrageurs in losers enable us to positively predict momentum profit for month t. Specifically, if sentiment investors strongly exacerbate mispricing ($\tilde{\psi}^{\text{sent}}_{l,1}$ is highly positive), and arbitrageurs are ineffective at correcting mispricing ($\tilde{\psi}^{\text{arb}}_{l,j}$ is slightly negative), this leads to a wider mispricing gap, resulting in stronger momentum profits for month t. Moreover, since the formation period for stock momentum is relatively long (e.g., 11 months for standard stock momentum), this requires that investor sentiment be persistently strong during this period. Thus, a high mispricing score in OW during the formation period indicates stronger momentum profits in the subsequent period. Similarly, a low mispricing score for UL also indicates stronger momentum profits.

B. Noise Reduction

I do not include mispricing score of underpriced winners when predicting next month's momentum profits, as the mispricing scores of OW and UL already contain the purest information about sentiment investors and arbitrageurs. Moreover, consider the covariance

[16]Detailed proof see Internet Appendix

between $\nu_{L,f}^{UW}$ and $r_{LS,t}$,

$$\text{cov}(\nu_{L,f}^{UW}, r_{LS,t}) = 0.5 * (\tilde{\psi}_{l,1}^{\text{sent}}/\alpha + \tilde{\psi}_{l,1}^{\text{arb}}) \times \text{var}(\nu_{L,f}^{UW}). \tag{25}$$

It's challenging to determine the sign of equation (25)[17] due to the opposing signs posited by the assumptions $\tilde{\psi}_{l,1}^{\text{sent}} \geq 0$ and $\tilde{\psi}_{l,1}^{\text{arb}} \leq 0$. Similar to Dong et al. (2021), incorporating mispricing score of the underpriced winner is likely to amplify the noise within Mgap[18], thus diminishing its predictive power regarding momentum profit.

Therefore, based on above analysis, I show that Mgap between OW and UL can positively predict momenutm profit in month t. If I use the absolute mispricing score (Stambaugh et al. (2012)) to represent this gap,

$$Mgap = Misp\_OW - Misp\_UL. \tag{26}$$

In summary, based on both theoretical and empirical evidence, I argue that Mgap should positively predict momentum profit.

C. Data

I obtain the momentum decile spread, Fama-French 3, and 5 factors from the French Data Library[19], and DHS factors from Kent Daniel's Website [20]. For mispricing score, I obtain the dataset from Stambaugh's website[21].

For both mutual fund flow and hedge fund flow, I strictly follow Akbas et al. (2015). I obtain monthly total net assets and returns from the CRSP Survivor Bias-Free U.S. Mutual

[17]See Internet Appendix for proof
[18]var($Mgap$) increases if I include mispricing score of underpriced winner
[19]`https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html`
[20]`http://www.kentdaniel.net/data.php`
[21]`https://finance.wharton.upenn.edu/~stambaug/`

Fund and the Lipper TASS Hedge Fund databases. For mutual fund flow, I refine my sample by selecting only those funds classified under the "equity objective" category, following the details provided in Huang et al. (2011). To keep a fund in my sample for a particular month, it must have non-missing values for all the variables that are used to build the aggregate measure. For hedge fund flow, my study mainly concerns hedge funds that predominantly trade U.S. equities. I begin with hedge funds denominated in U.S. dollars, which report returns on a monthly basis. In line with the approach of Cao et al. (2013), I exclude funds with strategies that are not primarily based on U.S. equities. For example, funds whose core strategy is identified as fixed income arbitrage, managed futures, or emerging markets are removed. I also exclude funds whose principal strategy is classified as a fund of funds to prevent duplication. To remain in the sample for a particular month, it is mandatory for each fund to have non-missing values for every variable used in creating the aggregate measure. My hedge fund sample comprises both active and terminated funds and starts from January 1994 to minimize the risk of survivorship bias.

Monthly aggregate fund flows to mutual funds (MF) and to hedge funds (HF) are computed as:

$$MF_t(orHF_t) = \frac{\sum_{i=1}^{N}(TNA_{i,t} - TNA_{i,t-1}(1 + R_{i,t}))}{\sum_{i=1}^{N} TNA_{i,t-1}} \tag{27}$$

where $TNA_{i,t}$ represents the total net assets of fund i in month t and $R_{i,t}$ is the return on fund i over month t. I obtain monthly total net assets and returns from the CRSP Survivor Bias-Free U.S. Mutual Fund and the Lipper TASS Hedge Fund databases.

II. Predicting Momentum Using Mispricing Gap

A. Summary Statistics of Mgap

Panel A of Table 2 presents the summary statistics for Mgap. For the standard momentum formation period, defined from month $t-12$ to $t-2$, the mean of $Mgap_{t-12,t-2}$ is 34.84 with a standard deviation of 3.25. This relatively small standard deviation compared to the mean results from using a combined percentile rank of 11[22] firm characteristics and a time-series average of the stock's mispricing score over the previous 11 months. Put differently, a shorter formation period should correspond to a larger standard deviation. However, if the formation period is excessively short, it could introduce too much randomness into the mispricing signal, potentially undermining its capability to predict momentum. Conversely, an overly extended formation period may also be suboptimal, as it could pick up stale information and reduce sensitivity in detecting time-series variations in mispricing signals.

If the market is more efficient in the long term compared to the short term, I would expect Mgap to narrow as the formation window extends. This occurs because arbitrageurs have more time to correct mispricing, resulting in lower scores for overpriced winners and higher scores for underpriced losers, which indicate substantial correction efforts by arbitrageurs. Indeed, $Mgap$ decreases from 34.84 to 29.19 as the window extends from 11 to 72 months.

If arbitrageurs target stocks in the more extreme deciles, I would expect lower scores for winners than for losers. In the case of underpriced stocks, this implies that arbitrageurs primarily buy the most underpriced ones. Consequently, as a result of mispricing correction, the past winners among underpriced stocks should exhibit lower scores than past losers. For overpriced stocks, in the absence of short-selling constraints, arbitrageurs would likely focus on shorting the most overpriced stocks. This mispricing correction would lead to past losers of overpriced stocks having higher scores than past winners. Panel B of Table 2 corroborates

[22]See Internet Appendix for Mgap net of momentum rank

this analysis. It shows that mispricing score of overpriced winners is lower than that of overpriced losers. Conversely, in the underpriced loser group, the score is higher than in the underpriced winner group, suggesting a relatively efficient market.

B. In-sample Predictive Regression

To test Hypothesis 1, that momentum profit should be predictable based on a mispricing signal, I use the $Mgap_{t-i,t-2}$ to predict momentum profit in month t. In addition to raw return, I also control for common risk factors such as the Fama-French three and five factors, and the HXZ q-factors. I exclude behavioral-based models like Stambaugh and Yuan (2016) and Daniel et al. (2020) to focus just on risk-based models.

I now estimate the following predictive regression:

$$MOM_t = \alpha + \beta \cdot \mathrm{Mgap}_{t-i,t-2} + \mathbf{\Gamma} \cdot \mathbf{F_t} + \epsilon_t, \tag{28}$$

where $\mathbf{F_t}$ is the vector of common risk factors. The models encompass the following configurations:

- **Model 0:** No additional risk factors.
- **Model 1:** $[\mathrm{Mkt.RF}, \mathrm{SMB}, \mathrm{HML}]$.
- **Model 2:** $[\mathrm{Mkt.RF}, \mathrm{SMB}, \mathrm{HML}, \mathrm{RMW}, \mathrm{CMA}]$.
- **Model 3:** $[\mathrm{Mkt.RF}, \mathrm{R_{ME}}, \mathrm{R_{IA}}, \mathrm{R_{ROE}}, \mathrm{R_{EG}}]$.

Table 3 presents the results of my predictive regression. Across a range of formation windows for mispricing scores (11 to 72 months), the coefficients for Mgap are all statistically significant, even after controlling for common risk factors. Interestingly, as the formation window extends, the coefficients increase. This trend implies that a longer window mitigates the effects of random stock appearances in the mispriced stock group and some fast mispricing signals, thus offering a more accurate and "stubborn" measure of a stock's mispricing level. This finding is also of substantial economic significance. For example, a one standard deviation increase in $Mgap_{t-37,t-2}$ raises the next month's momentum returns by 1.10%, which represents over 90% of the historical average monthly return of 1.16%.

B.1. Residual-based Mispricing Gap

A number of studies underline a significant overlap between momentum and other anomalies. For instance, an extensive body of existing research attributes the momentum effect to investor underreaction or overreaction (e.g., Hong and Stein (1999), Barberis et al. (1998)). Consequently, any anomalies based on similar investor behavior may also correlate with momentum. Therefore, one concern with using $Mgap$ is that it might covary with the momentum rank of a stock, which suggests that my predictability could stem from momentum rather than a mispricing score. For example, Huang (2022) argues that the gap between cumulative return during the formation period can predict momentum profit. Thus, one may suspect that the predictability of $Mgap$ may stem from the momentum rank. In this section, I delve deeper into this issue.

Firstly, if momentum significantly contributes to predictability, I would expect this effect to diminish as the windows lengthen. This expectation is based on the decreasing correlation between a stock's rolling average mispricing score and its momentum rank as the window extends, as observed in Panel A of Table 2 However, contrary to expectations, Table 3 shows the opposite trend: the estimate of $Mgap$ does not decrease but instead increases monotonically. This divergence indicates that the predictability of $Mgap$ does not rely on momentum rank.

Moreover, to minimize the momentum effect within mispricing scores, I adopt two approaches. The first approach involves simply excluding the momentum rank from the calculation of mispricing scores. However, this method does not fully address the concern that a portion of the mispricing may correlate with momentum. To effectively control for any effects correlated with momentum, I regress the average mispricing score on the momentum rank for each stock and extract the intercepts and residuals of this regression. Specifically, I use a recursive expanding window approach to extract the intercept and error terms. Thus, both intercepts and residuals are free from look-ahead bias.

The results in Table 4 reveal that my findings qualitatively remain, compared to those in Table 3[23]. This suggests that the predictive power of Mgap primarily emanates from the mispricing level of a stock independent of the return signal. More importantly, I observe that as the window expands, the coefficient of Mgap increases almost monotonically. These findings strongly imply that persistent mispricing potentially exerts a greater impact on momentum profit. Therefore, these results not only affirm Hypothesis 1 but also suggest the potential for strong out-of-sample performance in this predictive regression.

B.2. Which Leg?

To test Hypothesis 2, I conduct separate predictive regressions using different legs. Based on my analysis, I expect only the score of overpriced winners and the score of underpriced losers to predict future momentum profits. Other legs should not exhibit significant predictive power. Panel A of Table 5 confirms my conjecture, with overpriced winner scores positively predicting momentum and underpriced loser scores negatively predicting momentum. This finding is consistent with both theoretical motivation and cross-sectional evidence, as a reversal effect from the underpriced loser is expected if arbitrageurs truly disregard the formation period return. Thus, these results lend strong support to Hypothesis 2 that sentiment investors and arbitrageurs influence momentum profits in opposite directions.

[23] In an unreported analysis, when I use only the intercept, I find no such evidence.

B.3. Mean-reverting Mispricing Correction?

Existing literature suggests that strong and persistent investor sentiment will generate higher momentum profit in the subsequent month. Therefore, I expect a positive sign before the score of the overpriced winner in predictive regression, and this is corroborated by both Table 1 and Panel A of Table 5. However, the negative sign before the score of underpriced losers in the predictive regression warrants further exploration, despite its alignment with theoretical prediction. In other words, this suggests that a lower score may amplify the overall momentum effect by predicting a weaker reversal effect from the underpriced loser group.

First, unlike momentum traders who depend on historical returns to formulate their portfolios, arbitrageurs should not require a formation period for accumulation. Indeed, as shown in Panel A of Table 5, the coefficient of the overpriced winner increases with the expansion of the window, while the coefficient of the underpriced loser almost remains constant. Hence, I expect that returns from underpriced losers are predictable, with this predictability being more prominent than that of overpriced winners. If mispricing correction is mean-reverting, a lower score for an underpriced loser would signal a weaker past mispricing correction and a more potent mispricing correction in the subsequent month and therefore, a stronger reversal effect. However, according to LZY 2023, risk momentum should not be mean-reverting, at least in a short period. Furthermore, Panel B demonstrates that the score of the underpriced loser positively predicts the portfolio return for the following month. That is, a higher score for the underpriced loser indicates a more powerful reversal effect from that group, implying that a more potent mispricing correction can persist into the subsequent month. Thus, mispricing correction is not mean-reverting, and a negative contribution from the score of an underpriced loser should be expected.

B.4. Predicting Momentum Crashes

Next, I delve into the predictability of momentum crashes. Daniel and Moskowitz (2016) highlight that momentum strategies, while yielding high average profits, also experience sporadic severe crashes. They note that the 10 most significant downturns for the benchmark momentum strategy span from a drop of 30.54% in August 2009 to a staggering 74.36% in August 1932. Given this context, I adopt a logistic approach to assess the predictability of these downturns.

Panel A of Table 6 and Table A.5 indicate that $Mgap$ exhibits strong predictability. The z values of the $Mgap$ are almost all significant for both $Mgap$ and residual-based $Mgap$. Panel B of both tables further shows that this predictability stems mainly from overpriced winners rather than underpriced losers. This is because arbitrageurs appear to be considerably less influenced by macroeconomic shifts[24]. Put differently, compared to sentiment investors, arbitrageurs do not seem to discern between the market's good and bad times. Indeed, LZY 2023 also shows that their risk momentum strategy does not suffer from momentum crashes. This suggests that historical momentum crashes can be primarily attributed to sentiment investors.

C. Out-of-sample Prediction

I now turn to out-of-sample prediction. Given the relatively low variance of Mgap, one may question its out-of-sample predictive power. I alleviate these concerns by varying the window for averaging mispricing scores. This practice has significant economic significance and is not a result of data snooping. As suggested in previous literature such as SYY 2012 and Akbas et al. (2015), noise in mispricing score can be mitigated by averaging scores across different anomalies. Here I mainly consider how averaging time-varying score affects my results.

[24]further evidence can be found in section 6

Therefore, in addition to this cross-sectional mean measure, I use rolling means to mitigate this issue. The rationale is straightforward: the fewer windows used to estimate a stock's mispricing level, the more randomness is introduced, leading to less robust profits for arbitrageurs. By using the rolling mean of mispricing scores, I not only reduce the randomness issue, but also tend to retain those mispriced stocks whose mispricing levels are more persistent, or "stubborn", as described by Daniel et al. (2020). Daniel et al. (2020) argue that certain biases should lead to more persistent, longer-horizon mispricing. For instance, overconfident investors overreacting to private information signals can create a value effect wherein firms with high stock valuations relative to fundamental measures subsequently experience low returns. Their short behavioral factors tend to exhibit a much higher turnover rate than their long behavioral factors. They attribute this to PEAD reflecting high-frequency systematic mispricing caused by limited investor attention to earnings-related information and use a PEAD factor to capture comovement associated with high-frequency mispricing. Thus, by expanding my rolling window to estimate the time-varying mean of the mispricing scores of stocks, I filter out high-frequency, short-term oriented mispricing signals.

I evaluate the out-of-sample forecasting performance based on the widely used Campbell and Thompson (2008) R^2_{oos} statistic

$$R^2_{oos} = 1 - \frac{\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{N}(y_i - \bar{y})^2}, \tag{29}$$

where y_i represents the actual month return of momentum strategy, $\hat{y}_i$ represents the predicted values from the baseline model of equation (24), $\bar{y}$ is the mean of the historical return, and N is the number of observations in the out-of-sample dataset. Besides Campbell and Thompson (2008) R^2_{oos} statistic, I also report p_value of MSE-F statistic by McCracken (2007) that tests for equal MSE of the unconditional forecast and the conditional forecast.

Table 7 confirms this conjecture. Overall, the oos R^2 beats the benchmark historical average return by at least 1% when the window ranges from 11 to 72 months. As we transition from an 11-month window to a 42-month window, the R^2_{oos} increases. However, it begins to decrease beyond that point. This finding aligns with the results in Daniel et al. (2020)[25]. The p_value of MSE-F statistic shows that the majority of the F-statistics are significant at the 1% level. In summary, Table 7 reveals that my mispricing gap exhibits robust out-of-sample predictive power. Properly expanding the window yields higher out-of-sample R^2 values.

III. Determinants of Mispricing Gap

The above analysis centers on the conjecture that mispricing score of OW represents PIS, while that of UL represents PMC. To test this hypothesis, I conduct three experiments.

A. Fund Flows

My previous analysis points to distinct driving forces for different portfolios. Akbas et al. (2015) employ mutual fund flows and hedge fund flows to investigate their separate effects on long-short returns based on mispricing scores. They find that aggregate flows to mutual funds (dubbed "dumb money") appear to exacerbate cross-sectional mispricing, especially for growth, accrual, and momentum anomalies. In contrast, hedge fund flows (termed "smart money") seem to attenuate aggregate mispricing.

According to their analysis, both mutual fund flows and hedge fund flows should primarily reside within overvalued stocks. However, since I argue that momentum traders and arbitrageurs who operate on true mispricing do not trade in the same direction for overpriced

[25]Employing an event time approach, they investigate the buy-and-hold returns of short-horizon anomaly portfolios in each of the 12 months following portfolio formation. For long-horizon anomaly portfolios, they examine the buy-and-hold returns in each of the 12 quarters post-formation. Their results indicate that the premiums earned by short-horizon anomaly portfolios become statistically insignificant after 6 to 9 months. In contrast, most long-horizon anomaly portfolios continue to earn statistically significant abnormal returns for 1 to 3 years after a portfolio's formation.

winners and underpriced losers, I expect mutual fund flows to predominantly reside in overpriced winners, while hedge fund flows should primarily reside in underpriced losers.

As Akbas et al. (2015) demonstrate neither mutual fund flows nor hedge fund flows have superior forecasting power for next-period returns, and given that my measures average out the time-varying variations of mispricing scores, we would expect neither fund flow to predict portfolio returns. Indeed, I find no evidence of such predictive power.

Instead of using fund flows to predict returns, I opt for a different approach. As previously discussed, a high score in the overpriced winner category indicates that some momentum traders are indifferent to potential reversals in such a portfolio. These traders behave akin to sentiment-driven investors, focusing on trends rather than fundamental stock values. Hence, I expect "dumb money" (mutual fund flows) to positively predict mispricing scores in the next period. Conversely, for arbitrageurs, a higher hedge fund flow would suggest higher scores in the underpriced loser category, leading us to expect positive predictability from hedge fund flows. Apart from the mispricing scores in these two portfolios, I do not expect predictive power from either mutual or hedge funds.

Table 8 confirms my conjecture. Mutual funds positively predict mispricing score in the overpriced winners, while hedge funds positively predict mispricing score in the underpriced losers. My findings partially corroborate the conclusions of Akbas et al. (2015) in that I observe "dumb money" solely in overvalued stocks. However, these funds do not appear in overpriced losers, which form the short-leg of the momentum strategy. As for "smart money," while one would expect them to correct overvalued stocks, I find them present in underpriced losers, where they correct the mispricing, leading to a higher score in the next period. Thus, the findings of previous literature do not explicitly express the importance of arbitrage asymmetry, as sentiment investors and arbitrageurs target on different stocks. In sum, my findings here lend conditional support to many previous studies (e.g., Grinblatt et al. (1995) Carhart (1997) Grinblatt et al. (2020)), positing mutual funds as trend-chasers and hedge funds as contrarians.

My results here are critical as they suggest a distinction between momentum and other mispricing anomalies. If momentum is of the same type as these anomalies, investors will trade them in the same direction. Yet, I find momentum to be distinct, appearing more as a mixed result, composed of pure momentum traders and pure arbitrageurs operating in opposite directions.

B. Macro-Economic Variables and Sentiment

Prior literature underscores the influence of certain macroeconomic factors and market sentiment on the time-series profitability of momentum strategies (e.g., Cooper et al. (2004) and Huang et al. (2015)). In my analysis, I delve further into the possible determinants of variables such as $TERM$, DEF, DIV, and $SENT$ on Mgap identified in my model. DIV is the dividend yield of the CRSP value-weighted index, DEF is the yield spread between Baa-rated bonds and Aaa-rated bonds, $TERM$ is the yield spread between ten-year Treasury bonds and six-month Treasury bills, and SENT is the Huang et al. (2015) PLS-based and orthogonalized sentiment index[26]. In addition, I add the formation period return gap ($Fgap$) in Huang (2022) as a control variable. Specifically, I run the following regression:

$$Leg_{i,t} = \alpha + \beta_1 * cum\_MKT_t + \beta_2 * Fgap_t + \beta_3 * ma\_DIV_t + \tag{30}$$

$$\beta_4 * ma\_DEF_t + \beta_5 * ma\_TERM_t + \beta_6 * sd\_SENT_t + \epsilon_t. \tag{31}$$

Here my idea is based on the different ways sentiment investors and arbitrageurs behave when they trade. Notably, sentiment investors, unlike arbitrageurs, tend to exhibit trend-chasing behavior. Thus, I hypothesize that macroeconomic activities or indicators such as market sentiment that affect market trends might also influence Mgap. Moreover, I posit

[26] $PLS\_SENTothogonalized$ in their data

that such impacts may be more pronounced in determining mispricing score within overpriced winners than underpriced losers. This is primarily because arbitrageurs, as discussed earlier, appear capable of correcting mispricing irrespective of the fluctuation of macroeconomic factors.

My findings, as shown in Table 9, lend strong support to this conjecture. Although Mgap is indeed dependent on these macroeconomic variables, their explanatory power diverges between overpriced winners and underpriced losers. This discrepancy implies that momentum traders are more susceptible to economic volatility. Specifically, all variables, except for $Fgap$ and ma_DIV, are statistically significant in explaining mispricing score of overpriced winners. In contrast, for arbitrageurs operating in the underpriced loser category, only cumulative market return exhibits significant explanatory power in terms of its score. This outcome suggests that arbitrageurs tend to be considerably less influenced by macro-economic volatility, which is consistent with many previous studies that study how retail investors can be influenced by psychological biases and other factors that might make them more susceptible to macroeconomic events (Barberis and Thaler (2003) and Malmendier and Nagel (2011)).

Moreover, my analysis here reveals a significant relationship between Mgap and the volatility of market sentiment. Notably, this relationship manifests significantly in the overpriced winners but remains insignificant for the underpriced losers. This distinction provides empirical support to the theoretical predictions of EL 2022, which postulates that a requisite level of sentiment persistence is essential for factor momentum generation. Consequently, I emphasize the importance of shifting from the absolute level of market sentiment to its volatility. In the unreported analysis, I find no similar relationship when examining the investor sentiment index. This underscores the premise that pure sentiment-driven momentum is predicated upon a less volatile and persistent sentiment environment.

C. Market Frictions

In this section, I investigate if Mgap and scores covary differently with market friction variables.

To construct proper measures for market friction, I heavily rely on previous studies. For example, Dong et al. (2021) explore various proxies for market frictions as suggested by numerous studies. First, they consider the aggregate liquidity and liquidity shocks from Pástor and Stambaugh (2003). Secondly, they examine idiosyncratic volatility, a significant factor commonly associated with the execution costs of short arbitrage, as evidenced by studies such as Pontiff (2006). Their approach to measuring aggregate idiosyncratic risk involves calculating the idiosyncratic volatility of individual stocks as per Ang et al. (2006) for a particular month, and then determining the value-weighted average of these volatilities. Other factors they consider include trading noise from Hu et al. (2013), which serves as an indicator of arbitrage capital scarcity by examining noise in Treasury security prices, and short fees, as explored by Asness et al. (2018), which quantify the expenses associated with shorting stocks.

In this section, I focus on five proxies - aggregate liquidity, liquidity shocks, aggregate idiosyncratic volatility, VIX, and trading noise. Numerous studies confirm the importance of these five variables in determining the degree of limits-to-arbitrage.

Contrasting with macroeconomic variables, I hypothesize that these limits-to-arbitrage or market frictions variables significantly affect pure arbitrageurs more than they do sentiment investors. Thus, I predict that all coefficients of these five proxies will be significant. However, given that these five variables are explicitly designed to capture the time-series variation in limits-to-arbitrage, I anticipate a substantial degree of correlation among them. Examining Panel A in Table 10, I indeed find severe cross-correlations among these variables. For instance, the correlation between VIX and trading noise exceeds 0.74, potentially leading to multicollinearity issues when using traditional OLS regressions.

To address this concern, I turn to Principal Component Analysis (PCA) to reduce dimensionality before conducting regressions. Hence, I extract five principal components and examine the variance explained by each. I discover that the first three components can account for approximately 90% of the total variance, confirming severe multicollinearity amongst the five variables. Having extracted the first three components, I proceed with my regression as follows:

$$Leg_{i,t} = \alpha_i + \beta_{1,i} * PC1_{i,t} + \beta_{2,i} * PC2_{i,t} + \beta_{3,i} * PC3_{i,t} + \epsilon_{i,t}, \tag{32}$$

Consistent with my hypothesis, I observe a significant influence of the limits-to-arbitrage proxies on arbitrageurs, as the first three principal components substantially impact mispricing within the underpriced loser category. However, they appear insignificant within the overpriced winner category, largely populated by sentiment investors. Notably, Mgap is significantly influenced by only the first principal component, given the divergent trading directions of these trader groups. In addition, the R^2 for UL is 0.23, which is significantly higher than that of OW. Thus, findings from Table 10 strengthen my conjecture: arbitrageurs predominantly operate within the underpriced loser group, and their mispricing correction efforts heavily hinge on the dynamics of trading frictions.

IV. Robustness

In my previous discussions, I refer to similar research like Huang (2022), where the author argues that the formation period return spread between winner and loser can negatively predict momentum profit. Yet, Guo (2019) contests that the momentum gap introduced by Huang (2022) lacks significant predictive power. Therefore, I investigate whether the predictability of Mgap remains robust after accounting for the formation period gap, termed here as $Fgap$.

As evident in Table 11, $Fgap$ fails to offer any significant predictive power across all windows, while $Mgap$ consistently predicts momentum profit positively for every window examined. Furthermore, Huang (2022) posits that his result stems from stock level mispricing but falls short of drawing a direct link between $Fgap$ and stock level mispricing. In contrast, my approach begins with theoretical evidence and the cross-sectional difference of momentum within different stock groups, sorted by mispricing score, and delivers compelling economic rationale: the existence of at least two types of traders who can generate different types of momentum at the stock level, and their interactions counterbalance each other.

In my above experiments, I employ the 25th and 75th percentiles to cut the formation period return, while using the 10th and 90th percentiles to cut mispricing score. In Table 12, I further apply the 25th and 75th percentiles to both return signals and mispricing scores, yielding results that are quantitatively similar. However, the implications extend beyond a mere robustness check. As previously discussed, arbitrageurs are more likely to trade extreme stocks found in the top and bottom decile portfolios. This preference will inevitably influence my results. Indeed, compared to Table 3, even though the result still qualitatively remains, the statistical significance of $Mgap$ mildly reduces in Table 13.

Furthermore, as indicated by prior studies (e.g., Daniel et al. (2020)), different levels of mispricing require varying durations to correct. In this study, I set the first formation period to be 11 months, while allowing for different windows to average out mispricing score. This configuration somewhat constrains the predictability of my model, as both the mispricing level of stocks and the time required for arbitrageurs to correct these mispricings are time-varying. Consequently, I estimate that my above model offers a conservative approach to forecasting momentum profit.

V. Conclusion

Momentum profit hinges on the dynamics of both sentiment investors and arbitrageurs during the formation periods. Using mispricing scores and short-selling constraints, I demonstrate that the momentum strategy is largely confined to overpriced stock groups. This is due to the fact that underpriced losers are likely to generate a positive return in month t, as arbitrageurs are more focused on the mispricing level of a stock rather than past return signals. Therefore, a reversal effect will offset the momentum effect in month t.

To capture this effect, I construct a "mispricing gap", which is the difference in mispricing scores between overpriced winners and underpriced losers. I show that this gap can positively and significantly predict momentum profit both in-sample and out-of-sample. The rationale is that a high mispricing score for overpriced winners (indicating a high level of overpricing) suggests a strong, uncorrected investor sentiment in the formation period, likely leading to further mispricing exacerbation and continued investment in overpriced winners in the subsequent month. Conversely, a low score for underpriced losers (indicating a high level of underpricing) signifies a weak, inconsistent correction by arbitrageurs, leading to continued underperformance for underpriced losers in the next month. Together, a wider gap suggests stronger momentum profit in the subsequent month.

The predictability of momentum profit implies that sentiment investors determine the score of overpriced winners, while arbitrageurs determine the score of underpriced losers. To support this argument, I find that mutual fund flows primarily contribute to the score of overpriced winners, while hedge fund flows contribute to that of underpriced losers. Additionally, the scores of overpriced winners are more sensitive to macro-finance factors and volatility of the sentiment index, while the scores of underpriced losers are more sensitive to market frictions. This indicates that these two groups are fundamentally different.

The predictability of momentum suggests that momentum might be attributable to both persistent mispricing exacerbation and correction simultaneously. Thus, the debate about whether momentum is a result of either overreaction or underreaction seems to be resolved empirically.

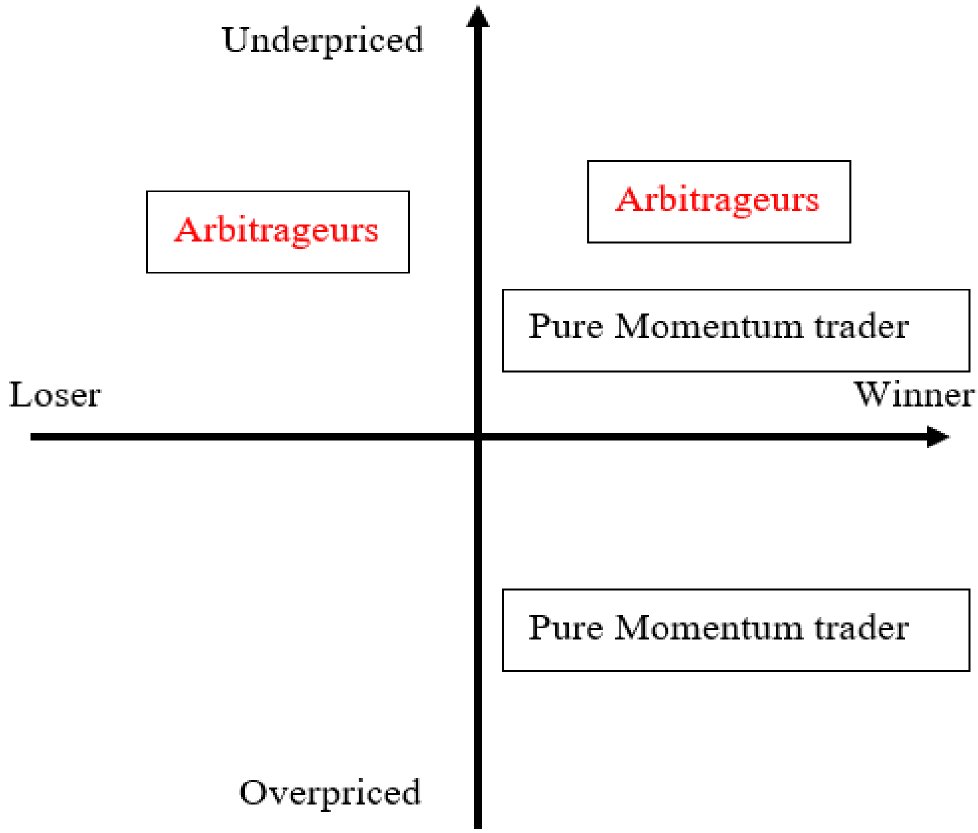

Fig. 1 Behavioral Matrix
This figure represents a behavioral matrix, composed of arbitrageurs and pure momentum traders (sentiment investors). When short-selling constraints are present, pure momentum traders, who primarily trade based on return signals rather than mispricing signals, predominantly occupy quadrants I and IV. Conversely, arbitrageurs, who focus more on mispricing signals than return signals, mainly reside in quadrants I and II.

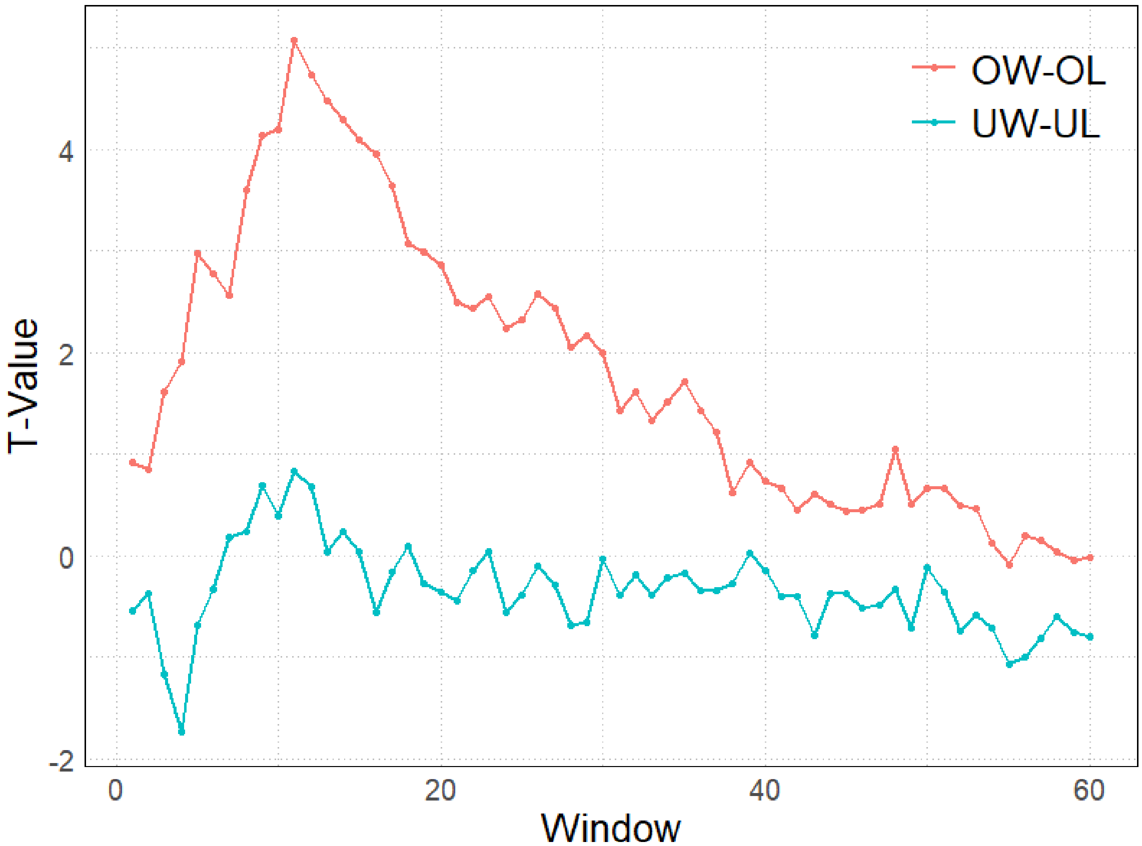

Fig. 2 Winner-Minus-Loser Strategy in Overpriced and Underpriced Stock Groups t-stats Plot

This figure illustrates the t-stats of two winner-minus-loser strategies derived from the overpriced and underpriced stock groups. To compute these t-stats, I implement a dependent double sorting strategy: first sorting on formation period return and then on mispricing scores. Specifically, stocks are sorted based on the $t-12$ to $t-2$ returns and the formation window for calculating the average mispricing score (for momentum balance) spanning from 1 to 60 months. I then determine the return spreads as the difference between the overpriced winners and overpriced losers (OW-OL), and between the underpriced winners and underpriced losers (UW-UL).

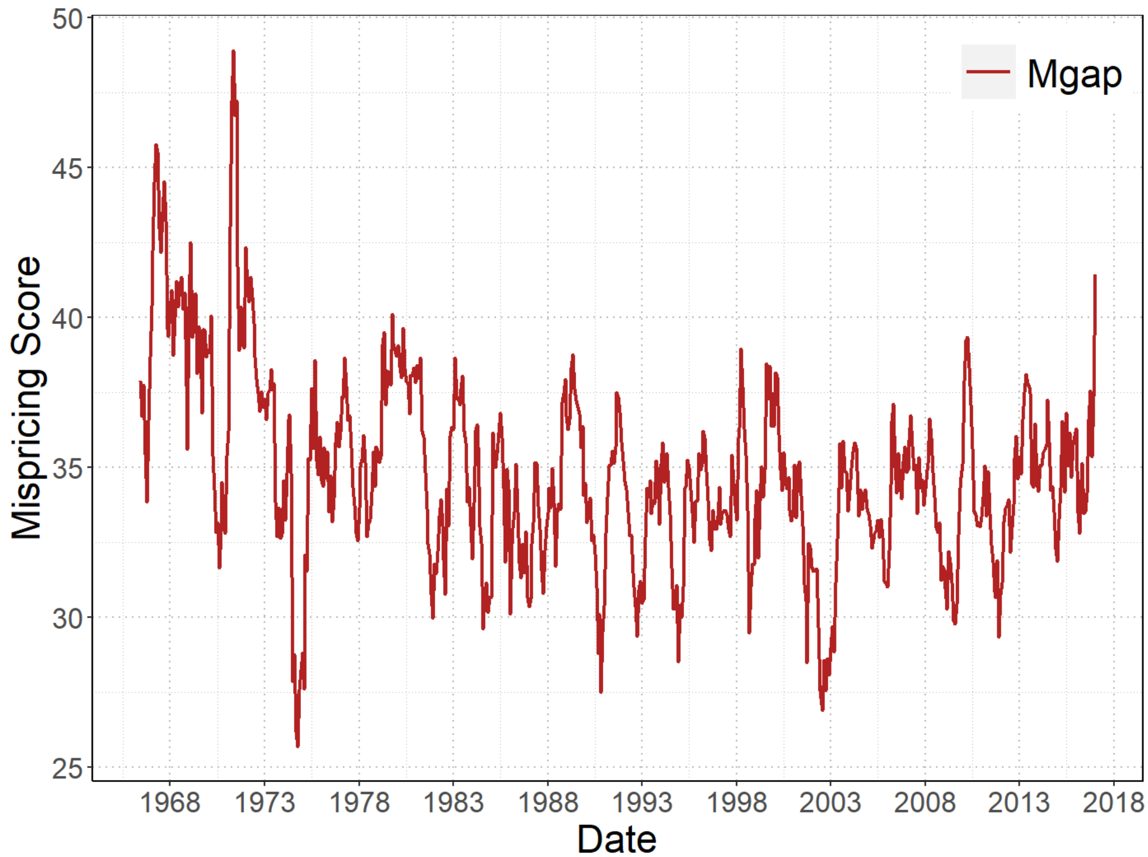

Fig. 3 Time-series Plot of Mgap

This figure plots Mgap against date. The $Mgap$ is constructed as mispricing score difference between the overpriced winner and the underpriced loser. Portfolios are constructed by double-sorting stocks first on formation period return and then on mispricing score (dependent sort), and both measures are based on the past 11-month observations: 11-month cumulative return and 11-month average mispricing score (momentum balanced) from month t-12 to t-2.

Table 1 Momentum Profit Sorted by Mispricing Score

Panel A outlines momentum profits organized by mispricing scores. Stocks are categorized into three groups based on formation period returns (month $t-12$ to $t-2$) at the NYSE 25th and 75th percentiles. Portfolios include top stocks above the 75th percentile and bottom stocks below the 25th percentile, further sorted by mispricing scores at the 10th and 90th percentiles. 'W' denotes winners, 'M' median, and 'L' losers in each portfolio, with 'O' for overpriced, 'N' for neutrally priced, and 'U' for underpriced stocks. It reports value-weighted returns, t-stats (in brackets), and the return spread between the top and bottom deciles. Panel B covers risk-adjusted returns of four corner portfolios using DHS factors, with t-statistics calculated using Newey-West standard errors.

Panel A. Momentum profit sorted by Mispricing Score

	W	M	L	W-L	Mom Effect
O	1.11	0.66	-0.05	1.14	Yes
	[4.67]	[3.21]	[-0.16]	[4.98]	
N	1.10	0.82	0.60	0.53	Yes
	[5.10]	[4.45]	[2.29]	[2.53]	
U	1.20	0.99	1.03	0.12	No
	[5.96]	[5.95]	[4.41]	[0.57]	
U-O	0.07	0.31	1.09		
	[0.59]	[2.92]	[6.51]		

Panel B. Risk-adjusted Return of Four Corner Porfolios

	OW			OL		
	Estimate	t-stat	adj_R^2	Estimate	t-stat	adj_R^2
Intercept	0.24	1.41	0.70	0.00	0.00	0.61
Mkt.RF	1.12	23.42		1.21	14.71	
PEAD	0.14	1.34		-0.68	-4.90	
FIN	0.10	1.41		-0.11	-0.71	

	UW			UL		
	Estimate	t-stat	adj_R^2	Estimate	t-stat	adj_R^2
Intercept	0.48	3.40	0.64	1.00	4.68	0.60
Mkt.RF	0.95	20.65		1.01	20.76	
PEAD	0.45	4.23		-0.63	-4.50	
FIN	0.09	1.22		0.07	0.74	

Table 2 Summary Statistics of Mgap

Panel A of this table documents the summary statistics for Mgap ($Mgap_{t-i,t-2}$), with i ranging from 12 to 73 months and a fixed 11-month momentum formation period. This gap indicates the difference in mispricing scores between overpriced winners and underpriced losers, derived from double-sorting stocks by formation period return and mispricing score. Breakpoints for momentum and mispricing scores use NYSE 25th/75th and 10th/90th percentiles, respectively. Mgaps are the difference in scores between overpriced winners and underpriced losers. Panel B reports the average mispricing score across different stock groups. I set the formation window for both return and mispricing score to be 11 months. Specifically, "W" stands for winners, "M" median, "L" losers, "O" overpriced, "N" neutral-priced, and "U" underpriced. The last column "Corr," represents the correlation between the rolling mispricing score of a stock and its momentum rank. The t-statistics are computed using Newey-West standard errors.

Panel A. Summary statistics for $Mgap$

Window	Mean	SD	Skew	Kurt	Corr
11	34.84	3.25	0.58	4.54	0.23
24	33.44	2.87	0.74	5.33	0.16
30	32.57	2.62	0.63	4.70	0.15
36	31.87	2.49	0.56	4.60	0.13
42	31.26	2.37	0.48	4.35	0.12
48	30.71	2.30	0.52	4.43	0.11
54	30.24	2.24	0.50	4.06	0.11
60	29.86	2.22	0.44	4.00	0.10
66	29.55	2.17	0.30	3.81	0.09
72	29.19	2.08	0.08	3.49	0.09

Panel B. Average mispricing score across groups

	W	M	L
O	68.38	69.88	75.48
N	47.02	48.69	54.28
U	27.72	29.25	33.55

Table 3 Predictive Regression

This table documents the estimates of $Mgap$ from the following predictive regression:

$$MOM_{\mathrm{t}} = \alpha + \beta * \mathrm{Mgap}_{\mathrm{t-i,t-2}} + \mathbf{\Gamma} * \mathbf{F_t} + \epsilon_{\mathrm{t}}, \tag{34}$$

MOM_t represents the momentum decile return spread for month t, obtained from the French Data Library. Mgaps, denoted by $Mgap_{t-i,t-2}$, where i varies from 12 to 73 months, reflect mispricing score differences between overpriced winners and underpriced losers over different formation periods. Stocks are double-sorted by formation period return and then by mispricing score. Breakpoints for momentum and mispricing scores are set at the 25th/75th and 10th/90th percentiles, respectively. $\mathbf{F_t}$ is the vector of common risk factors, encompassing models from Raw to Q5: $\mathbf{0}$ (Raw), $[\mathrm{Mkt.RF}, \mathrm{SMB}, \mathrm{HML}]$ (FF3), $[\mathrm{Mkt.RF}, \mathrm{SMB}, \mathrm{HML}, \mathrm{RMW}, \mathrm{CMA}]$ (FF5) , and $[\mathrm{Mkt.RF}, \mathrm{R_{ME}}, \mathrm{R_{IA}}, \mathrm{R_{ROE}}, \mathrm{R_{EG}}]$ (Q5). R^2 is adjusted R^2, and t-statistics are computed using Newey-West standard errors.

	Raw			FF3		
Window	Estimate	t-stat	R^2	Estimate	t-stat	R^2
11	0.29	3.03	0.02	0.26	3.03	0.09
24	0.34	2.95	0.02	0.30	3.01	0.09
30	0.40	3.05	0.02	0.38	3.29	0.09
36	0.44	3.21	0.02	0.42	3.48	0.10
42	0.47	3.06	0.02	0.45	3.37	0.10
48	0.46	2.86	0.02	0.44	3.20	0.10
54	0.46	2.73	0.02	0.47	3.22	0.10
60	0.47	2.76	0.02	0.48	3.22	0.10
66	0.46	2.53	0.02	0.51	3.14	0.10
72	0.53	2.60	0.02	0.60	3.25	0.10

	FF5			Q5		
Window	Estimate	t-stat	R^2	Estimate	t-stat	R^2
11	0.27	3.21	0.12	0.22	3.29	0.31
24	0.30	2.99	0.12	0.22	2.63	0.31
30	0.36	3.18	0.12	0.26	2.75	0.31
36	0.40	3.37	0.13	0.28	2.77	0.31
42	0.44	3.32	0.13	0.31	2.70	0.31
48	0.44	3.29	0.13	0.31	2.65	0.31
54	0.48	3.40	0.13	0.34	2.73	0.31
60	0.49	3.41	0.13	0.35	2.77	0.31
66	0.51	3.31	0.13	0.38	2.74	0.30
72	0.60	3.43	0.13	0.45	2.84	0.31

Table 4 Predictive Regression: Look-ahead Bias-free Residuals as Mispricing Score

This table presents estimates of the Mgap ($Mgap^*_{t-i,t-2}$) from the predictive regression:

$$MOM_{\mathrm{t}} = \alpha + \beta \times \mathrm{Mgap}^*_{\mathrm{t-i,t-2}} + \mathbf{\Gamma} \times \mathbf{F_t} + \epsilon_{\mathrm{t}}, \tag{36}$$

where MOM_t, the momentum decile return spread for month t, is obtained from the French Data Library. The $Mgap^*_{t-i,t-2}$ is the residual-based Mgap at month $t-2$, calculated over formation periods ranging from 12 to 73 months through a time-series regression using average mispricing scores versus momentum ranks. This gap is the differential in residual plus intercept scores between overpriced winners and underpriced losers, with stocks double-sorted by return and mispricing score. Breakpoints are set at the 25th/75th percentiles for momentum and 10th/90th percentiles for mispricing. $\mathbf{F_t}$ indicates the common risk factors. R^2 is adjusted R^2, and t-statistics are computed using Newey-West standard errors.

	Raw			FF3		
Window	Estimate	t-stat	R^2	Estimate	t-stat	R^2
11	0.29	1.93	0.01	0.29	2.09	0.08
24	0.50	2.54	0.02	0.53	3.01	0.10
30	0.54	2.74	0.03	0.57	3.22	0.10
36	0.52	2.69	0.02	0.57	3.10	0.09
42	0.57	2.88	0.03	0.64	3.23	0.10
48	0.61	2.86	0.03	0.65	3.19	0.10
54	0.61	2.83	0.03	0.65	3.22	0.10
60	0.56	2.73	0.02	0.61	3.14	0.10
66	0.57	2.94	0.03	0.65	3.47	0.11
72	0.52	2.79	0.02	0.61	3.37	0.11

	FF5			Q5		
Window	Estimate	t-stat	R^2	Estimate	t-stat	R^2
11	0.33	2.32	0.11	0.21	1.77	0.30
24	0.53	3.35	0.14	0.31	2.15	0.33
30	0.57	3.45	0.15	0.34	2.40	0.33
36	0.55	3.27	0.14	0.30	1.99	0.32
42	0.60	3.27	0.14	0.32	1.99	0.32
48	0.59	3.03	0.15	0.31	1.90	0.33
54	0.59	3.16	0.15	0.31	1.91	0.33
60	0.57	3.14	0.15	0.31	2.01	0.33
66	0.60	3.39	0.16	0.36	2.44	0.33
72	0.56	3.21	0.16	0.32	2.24	0.33

Table 5 Predictive Regression: Which Leg?

Panel A presents results from the predictive regression: $\text{MOM}_t = \alpha + \beta \times Leg_{t-i,t-2} + \epsilon_t$, where $Leg_{t-i,t-2}$ denotes the time series mean mispricing score of four portfolios, calculated using a window from $t-i$ to $t-2$. Panel B discusses a predictive regression using mispricing scores as independent variables against subsequent period returns. t-statistics are calculated using Newey-West standard errors.

Panel A. Four Legs Predicting Next-Period Momentum

	OW		OL	
Window	Estimate	t-stat	Estimate	t-stat
11	0.33	2.64	0.18	1.60
24	0.41	2.52	0.14	0.95
30	0.47	2.44	0.13	0.81
36	0.50	2.48	0.04	0.28
42	0.53	2.43	0.02	0.10
48	0.48	2.20	-0.02	-0.14
54	0.46	2.13	-0.04	-0.22
60	0.42	2.01	0.02	0.11
66	0.39	1.91	0.05	0.26
72	0.48	2.21	0.02	0.13

	UW		UL	
Window	Estimate	t-stat	Estimate	t-stat
11	0.14	0.88	-0.54	-2.60
24	0.19	1.08	-0.48	-2.65
30	0.15	0.88	-0.55	-2.83
36	0.17	0.99	-0.58	-2.98
42	0.15	0.85	-0.53	-2.67
48	0.19	1.04	-0.49	-2.54
54	0.22	1.11	-0.45	-2.30
60	0.23	1.15	-0.49	-2.48
66	0.13	0.64	-0.50	-2.27
72	0.16	0.72	-0.49	-2.10

Panel B. Mispricing Score Predicting Next-Period Return

Leg	Estimate	t-stat	R^2
OW	0.13	1.04	0.00
OL	-0.02	-0.19	0.00
UW	-0.18	-1.07	0.00
UL	0.35	2.19	0.01

Table 6 Predicting Momentum Crashes

Panel A presents the results of logistic regressions using $Mgap$ to predict momentum crashes. In both Panels A and B, a momentum crash indicator is set to one if the return to the momentum strategy is less than or equal to -10%, and 0 otherwise. The Pseduo R^2 is Nagelkerke et al. (1991) Pseudo R-squared (R^2), and t-statistics are computed using Newey-West standard errors.

Panel A. Predicting Momentum Crashes Using Mgap

Window	Estimate	z value	Pseudo R^2
11	-0.17	-3.19	0.05
24	-0.14	-2.10	0.03
30	-0.16	-2.10	0.03
36	-0.17	-2.17	0.03
42	-0.17	-2.04	0.03
48	-0.18	-2.08	0.03
54	-0.19	-2.05	0.03
60	-0.21	-2.26	0.03
66	-0.19	-2.06	0.03
72	-0.23	-2.52	0.04

Panel B. Predicting Momentum Crashes Using OW and UL

Window	Leg	Estimate	z value	Pseudo R^2
11	OW	-0.05	-0.63	0.06
	UL	0.37	3.09	
24	OW	-0.17	-1.66	0.03
	UL	0.09	0.81	
30	OW	-0.24	-1.92	0.03
	UL	0.05	0.49	
36	OW	-0.27	-2.09	0.03
	UL	0.05	0.45	
42	OW	-0.29	-2.20	0.03
	UL	0.03	0.27	
48	OW	-0.27	-2.11	0.03
	UL	0.08	0.76	
54	OW	-0.28	-2.26	0.04
	UL	0.08	0.68	
60	OW	-0.27	-2.28	0.04
	UL	0.13	1.08	
66	OW	-0.25	-2.22	0.03
	UL	0.12	0.91	
72	OW	-0.29	-2.72	0.04
	UL	0.15	1.14	

Table 7 Out-of-Sample Prediction

This table provides the result of out-of-sample prediction. The training result is obtained using: $MOM_t = \alpha + \beta \times Leg_{t-i,t-2} + \epsilon_t$, where MOM_t represents the momentum decile return spread for month t, obtained from the French Data Library. Mgaps, denoted by $Mgap_{t-i,t-2}$, where i varies from 12 to 73 months, reflect mispricing score differences between overpriced winners and underpriced losers over different formation periods. I set the initial window of the estimation period to be 120 months, and I use the recursive expanding window approach to estimate R^2_{oos}. The first column is the window I use to average mispricing score. The second column is Campbell and Thompson (2008) R^2_{oos}. The third column is the ΔRMSE is the root-mean-square error (RMSE) difference between the unconditional forecast and the conditional forecast for the same sample/forecast period. The fourth column p-value of F-test in McCracken (2007).

Window	R^2_{oos}	ΔRMSE	p_value
11	0.01	0.05	0.01
24	0.01	0.05	0.01
30	0.02	0.06	0.01
36	0.02	0.07	0.00
42	0.02	0.06	0.01
48	0.01	0.05	0.02
54	0.01	0.04	0.03
60	0.01	0.05	0.02
66	0.01	0.06	0.01
72	0.02	0.07	0.01

Table 8 Determinants of Mgap: Fund Flows
This table documents the result of the following predictive regression:

$$\mathrm{Leg_{i,t}} = \alpha_\mathrm{i} + \beta_{1,\mathrm{i}} * \mathrm{MFFLOW_{t-1}} + \beta_2 * \mathrm{HFFLOW_{t-1}} + \epsilon_{\mathrm{i,t}}, \tag{38}$$

The $Leg_{i,t}$ is mispricing score of four portfolios at month t (OW as overpriced winner, OL as overpriced loser, UW as underpriced winner, UL as underpriced loser). Portfolios are constructed by double-sorting stocks first on formation period return and then on mispricing score (dependent sort), and the formation period for momentum is based on the past 11-month observations: 11-month cumulative return. For mispricing score and formation period return, the formation window is 11 months. The breakpoints for momentum and mispricing score are 25th and 75th percentile and 10th and 90th percentile, respectively. The $MFFLOW_t$ is the mutual fund flow in month t, while $HFFLOW_t$ is the hedge fund flow in month t. OW stands for the overpriced winner, OL Overpriced loser, UW underpriced winner, and UL underpriced loser. The R^2 is adjusted R-squared. T-statistics are computed using Newey-West standard errors.

	OW				OL		
	Estimate	t-stat	R^2		Estimate	t-stat	R^2
Intercept	64.29	733.26	0.05	Intercept	69.29	442.88	0.02
MFFLOW	41.57	2.19		MFFLOW	30.70	0.87	
HFFLOW	1.60	1.14		HFFLOW	-1.41	-0.62	

	UW				UL		
	Estimate	t-stat	R^2		Estimate	t-stat	R^2
Intercept	33.34	429.91	0.03	Intercept	37.06	369.09	0.05
MFFLOW	-11.70	-0.73		MFFLOW	29.34	1.47	
HFFLOW	-2.80	-1.75		HFFLOW	2.32	2.15	

Table 9 Determinants of Mgap: Macro-economic Variables and Sentiment
This table documents the result of the contemporaneous time-series regressions. The estimated coefficients appear in the first column of the table. OW stands for the overpriced winner, OL Overpriced loser, UW underpriced winner, and UL underpriced loser. The t-statistics are computed using Newey-West standard errors.

	Mgap		OW		UL	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Intercept	39.65	28.30	69.52	95.59	29.87	29.47
cum_MKT	7.97	4.40	5.78	4.69	-2.19	-2.12
$Fgap$	0.03	1.00	0.03	0.94	0.00	-0.18
ma_DIV	-0.64	-1.51	-0.25	-1.09	0.39	1.14
ma_DEF	1.29	1.51	1.35	3.75	0.06	0.09
ma_TERM	-0.53	-2.45	-0.30	-2.29	0.23	1.70
sd_SENT	-3.12	-3.41	-2.02	-2.14	1.10	1.39
adj_R^2	0.42		0.43		0.22	

Table 10 Determinants of Mgap: Market Frictions

This table documents the result of the following contemporaneous time-series regression:

$$\mathrm{Leg}_{\mathrm{i,t}} = \alpha_{\mathrm{i}} + \beta_{1,\mathrm{i}} * \mathrm{PC1}_{\mathrm{t}} + \beta_{2,\mathrm{i}} * \mathrm{PC2}_{\mathrm{t}} + \beta_{3,\mathrm{i}} * \mathrm{PC3}_{\mathrm{t}} + \epsilon_{\mathrm{i,t}}, \tag{40}$$

The $Leg_{i,t}$ is mispricing score of two portfolios at month t (OW as the overpriced winner and UL as an underpriced loser). OW stands for the overpriced winner, OL Overpriced loser, UW underpriced winner, and UL underpriced loser. The first three principal components, PC1, PC2, and PC3, are extracted from five variables representing moving average values of market frictions. These variables include aggregate liquidity, liquidity shocks, the VIX (Volatility Index), trading noise, and idiosyncratic volatility. The t-statistics are computed using Newey-West standard errors.

Panel A. Cross-correlations: Market Frictions Measures

	Noise_ma	aggLIQ	LIQshock_ma	aggIV_ma	VIX_ma
Noise_ma	1.00				
aggLIQ_ma	-0.12	1.00			
LIQshock_ma	-0.10	0.75	1.00		
aggIV_ma	0.45	-0.32	-0.23	1.00	
VIX_ma	0.74	-0.17	-0.10	0.43	1.00

Panel B. Variance Explained by Principal Components

	PC1	PC2	PC3	PC4	PC5
Variance Explained	0.48	0.30	0.12	0.06	0.05

Panel C. Determinants of Mgap

	$Mgap$		OW		UL	
	Estimate	t-stat	Estimate	t-stat	Estimate	t-stat
Intercept	39.33	122.36	70.57	306.94	31.24	224.74
PC1	0.49	2.52	0.20	1.49	-0.28	-3.67
PC2	-0.22	-1.89	0.03	0.32	0.25	5.27
PC3	0.21	0.61	-0.06	-0.22	-0.27	-2.08
adj_R^2	0.11		0.03		0.23	

Table 11 Robustness: $Fgap$ as Control Variable

This table documents the result of the following contemporaneous time-series regression:

$$MOM_{\mathrm{t}} = \alpha + \beta_1 * \mathrm{Mgap}_{\mathrm{t-i,t-2}} + \beta_2 * \mathrm{Fgap}_{\mathrm{t-11,t-2}} + \epsilon_{\mathrm{t}}, \tag{42}$$

The MOM_t is the decile return spread at month t. I obtain it from French Data Library. In addition to Table3 first scenario, where Mgapis the only dependent variable, here I add $Fgap$ as another dependent variable. The $Fgap$ is the formation period return spread between the winner portfolio and the loser portfolio. The t-statistics are computed using Newey-West standard errors.

Window	Variables	Estimate	t-stat	R^2
11	$Mgap$	0.26	2.93	0.01
	$Fgap$	-0.04	-1.07	0.01
24	$Mgap$	0.32	3.14	0.02
	$Fgap$	-0.06	-1.33	0.02
30	$Mgap$	0.36	3.20	0.02
	$Fgap$	-0.06	-1.23	0.02
36	$Mgap$	0.40	3.34	0.02
	$Fgap$	-0.06	-1.26	0.02
42	$Mgap$	0.42	3.23	0.02
	$Fgap$	-0.06	-1.36	0.02
48	$Mgap$	0.41	3.00	0.02
	$Fgap$	-0.06	-1.26	0.02
54	$Mgap$	0.40	2.79	0.02
	$Fgap$	-0.05	-1.11	0.02
60	$Mgap$	0.42	2.81	0.02
	$Fgap$	-0.05	-1.11	0.02
66	$Mgap$	0.41	2.61	0.02
	$Fgap$	-0.05	-1.03	0.02
72	$Mgap$	0.48	2.69	0.02
	$Fgap$	-0.05	-1.00	0.02

Table 12 Robustness: 25th and 75th Percentile as Breakpoint
This table documents the result of the following contemporaneous time-series regression:

$$MOM_{\mathrm{t}} = \alpha + \beta_1 * \mathrm{Mgap}_{\mathrm{t-i,t-2}} + \beta_2 * \mathrm{Fgap}_{\mathrm{t-11,t-2}} + \epsilon_{\mathrm{t}}, \tag{44}$$

The MOM_t is the decile return spread at month t. I obtain it from French Data Library. In addition to Table 3 first scenario, where Mgapis the only dependent variable, here I add $Fgap$ as another dependent variable. The $Fgap$ is the formation period return spread between the winner portfolio and the loser portfolio. The t-statistics are computed using Newey-West standard errors.

	Raw			FF3		
Window	Estimate	t-stat	R^2	Estimate	t-stat	R^2
11	0.27	2.43	0.01	0.24	2.44	0.08
24	0.37	2.70	0.02	0.36	2.92	0.09
30	0.39	2.58	0.02	0.39	2.86	0.09
36	0.38	2.44	0.01	0.39	2.75	0.09
42	0.37	2.36	0.01	0.39	2.73	0.09
48	0.38	2.34	0.01	0.40	2.69	0.09
54	0.37	2.30	0.01	0.42	2.89	0.09
60	0.41	2.41	0.01	0.47	3.08	0.09
66	0.42	2.38	0.01	0.53	3.17	0.10
72	0.43	2.39	0.01	0.53	3.05	0.10

	FF5			Q5		
Window	Estimate	t-stat	R^2	Estimate	t-stat	R^2
11	0.26	2.72	0.11	0.19	2.50	0.31
24	0.36	2.99	0.12	0.24	2.46	0.31
30	0.39	2.94	0.12	0.26	2.35	0.31
36	0.39	2.83	0.12	0.25	2.17	0.31
42	0.39	2.81	0.12	0.26	2.14	0.31
48	0.39	2.75	0.12	0.25	2.11	0.31
54	0.40	2.90	0.12	0.28	2.28	0.30
60	0.46	3.08	0.12	0.32	2.47	0.30
66	0.52	3.22	0.12	0.35	2.53	0.31
72	0.51	3.04	0.12	0.33	2.34	0.31

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Internet Appendix

A. Proof of equation 24

$$
\begin{aligned}
2 \times \operatorname{cov}(\nu_{L,f}^{UW}, r_{LS,t}) &= 2 \times \operatorname{cov}\left(\nu_{L,f}^{UW}, 0.5 \times (\Delta u_{S,t}^{\text{bad}} + \Delta u_{L,t}^{\text{good}}) - 0.5 \times \Delta u_{L,t}^{\text{bad}}\right) \\
&= \operatorname{cov}\left(\nu_{L,f}^{UW}, \Delta u_{L,t}^{\text{good}}\right) \\
&= \operatorname{cov}\left(\nu_{L,f}^{UW}, (\psi_{l,1}^{\text{sent}} - \psi_{l,0}^{\text{sent}}) \cdot \Delta u_{L,f}^{\text{good}} + (\psi_{l,1}^{\text{arb}} - \psi_{l,0}^{\text{arb}}) \cdot \nu_{L,f}^{UW}\right) \\
&= \operatorname{cov}\left(\nu_{L,f}^{UW}, \tilde{\psi}_{l,1}^{\text{sent}} \times (\nu_{L,f}^{UW} - \nu_{L,0})/\alpha + \tilde{\psi}_{l,1}^{\text{arb}} \cdot \nu_{L,f}^{UW}\right) \\
&= \operatorname{cov}\left(\nu_{L,f}^{UW}, (\tilde{\psi}_{l,1}^{\text{sent}}/\alpha + \tilde{\psi}_{l,1}^{\text{arb}}) \times \nu_{L,f}^{UW}\right) \\
&= (\tilde{\psi}_{l,1}^{\text{sent}}/\alpha + \tilde{\psi}_{l,1}^{\text{arb}}) \times \operatorname{var}(\nu_{L,f}^{UW})
\end{aligned}
\tag{45}
$$

B. Proof of equation 25

$$\tilde{\beta}_{LS} = \frac{\mathrm{cov}(Mgap_f, r_{LS,t})}{\mathrm{var}(Mgap_f)} \tag{46}$$

The numerator $\mathrm{cov}(Mgap_f, r_{LS,t})$ can be further decomposed into:

$$\begin{aligned}
2 \times \mathrm{cov}(Mgap_f, r_{LS,t}) =& 2 \times [\mathrm{cov}(\nu^{OW}_{S,f} - \nu^{UL}_{L,f}, 0.5 \times (\Delta u^{bad}_{S,t} + \Delta u^{good}_{L,t}) - \\
& 0.5 \times (\Delta u^{good}_{S,t} + \Delta u^{bad}_{L,t}))] \\
=& 2 \times [\mathrm{cov}(\nu^{OW}_{S,f} - \nu^{UL}_{L,f}, 0.5 \times (\Delta u^{bad}_{S,t} + \Delta u^{good}_{L,t}) - \\
& 0.5 \times \Delta u^{bad}_{L,t})] \\
=& \mathrm{cov}(\nu^{OW}_{S,f}, \Delta u^{bad}_{S,t}) + \mathrm{cov}(\nu^{OW}_{S,f}, \Delta u^{good}_{L,t}) - \mathrm{cov}(\nu^{OW}_{S,f}, \Delta u^{bad}_{L,t}) \\
& - \mathrm{cov}(\nu^{UL}_{L,f}, \Delta u^{bad}_{S,t}) - \mathrm{cov}(\nu^{UL}_{L,f}, \Delta u^{good}_{L,t}) + \mathrm{cov}(\nu^{UL}_{L,f}, \Delta u^{bad}_{L,t}) \\
=& \mathrm{cov}(\nu^{OW}_{S,f}, \Delta u^{bad}_{S,t}) + \mathrm{cov}(\nu^{UL}_{L,f}, \Delta u^{bad}_{L,t}) \\
=& \tilde{\psi}^{\mathrm{sent}}_{l,j} \times var(\Delta u^{bad}_{S,f}) + \tilde{\psi}^{\mathrm{arb}}_{l,j} \times var(\nu^{UL}_{L,f})
\end{aligned} \tag{47}$$

C. Tables

Table A.1 Momentum Profit Sorted by Mispricing Score (residual-based)
Panel A of This table documents the momentum profit sorted by mispricing scores (residual-based). The mispricing scores (residual-based) is constructed as the mispricing score difference between the overpriced winner and the underpriced loser. To obtain residuals, I run the time-series regression for each stock. The independent variable is the average mispricing score, and the independent variable is the momentum rank. I then extract the residuals from this regression. To calculate the return for each portfolio, I first sort all available stocks on formation period return (month t-12 to t-2) into 3 groups. The breakpoints for formation period return is NYSE 25 and 75 percentile. The top portfolio contains all the stocks whose formation period return is above the 75 percentile, and the bottom portfolio contains all the stocks whose formation period return is below the 25 percentile. Within each of the 3 portfolios, I then sort stocks on the mispricing score. The breakpoints for mispricing scores are 10 and 90 percentile. W stands for all winner stocks from the top portfolio, M stands for median stocks from the middle portfolio, and L stands for losers stocks from the bottom portfolio. Similarly, O stands for overpriced stocks from the top portfolio, N stands for neutral-priced stocks from the middle portfolio, and U stands for underpriced stocks from the bottom portfolios. I report the value-weighted return and t-stats (in brackets) for each portfolio. Besides portfolio return, I also report the return spread between top and bot deciles. For example, I report all winner-minus-loser strategy returns within each portfolio sorted by mispricing scores. The t-statistics are computed using Newey-West standard errors.

Panel A. Momentum profit sorted by Mispricing Score

	W	M	L	W-L
O	0.01	0.01	0.00	0.90
	[4.10]	[3.14]	[0.40]	[3.39]
N	0.01	0.01	0.01	0.47
	[5.62]	[4.90]	[2.80]	[2.21]
U	0.01	0.01	0.01	0.14
	[6.06]	[5.73]	[4.56]	[0.57]
O-U	-0.32	-0.40	-1.07	
	[-1.69]	[-2.74]	[-4.77]	

Table A.2 Summary Statistics of Mispricing Gap (residual-based)

This table documents the summary statistics of the mispricing gap (Mgap) based on different formation periods while holding momentum formation period fixed at 11-month. The Mispricing Gap (residual-based) is constructed as the mispricing score difference between the overpriced winner and the underpriced loser. To obtain residuals, I run the time-series regression for each stock. The independent variable is the average mispricing score, and the independent variable is the momentum rank. I then extract the residuals from this regression. Similar to the previous Mispricing Gap, this residual-based Mispricing Gap is also constructed as the mispricing score difference between the overpriced winner and the underpriced loser. Portfolios are constructed by double-sorting stocks first on formation period return and then on the mispricing score (dependent sort), and the formation period for momentum is based on the past 11-month observations: 11-month cumulative return. For the mispricing score, the formation window ranges from 11-month to 72-month, and I average the mispricing score (momentum balanced) with respect to their rolling formation window. The breakpoints for momentum and mispricing score are 25th and 75th percentile and the 10th and 90 percentile, respectively. The mispricing score differences are then calculated as the equal-weighted average score in the overpriced winner minus the equal-weighted average score in underpriced losers. The *t*-statistics are computed using Newey-West standard errors.

Panel A. Summary statistics for Mgap

Window	Mean	SD	Skew	Kurt
11	38.85	2.69	0.41	3.85
24	35.46	2.27	-0.22	3.81
30	34.51	2.26	-0.18	3.76
36	33.77	2.21	-0.15	3.56
42	33.09	2.15	-0.15	3.39
48	32.50	2.05	-0.17	3.33
54	32.07	2.06	-0.04	3.66
60	31.78	2.11	0.22	4.06
66	31.41	2.16	0.36	4.38
72	31.11	2.23	0.35	4.41

Panel B. Average mispricing score across groups

	W	M	L
O	60.91	61.21	63.99
N	40.85	40.22	42.23
U	22.78	21.48	22.07

Table A.3 Summary Statistics of Mispricing Gap (Net of Momentum Rank)
Panel A of this table documents the summary statistics for the Mispricing Gap ($Mgap_{t-i,t-2}$), with i ranging from 12 to 73 months and a fixed 11-month momentum formation period. This gap indicates the difference in mispricing scores between overpriced winners and underpriced losers, derived from double-sorting stocks by formation period return and mispricing score. Breakpoints for momentum and mispricing scores use NYSE 25th/75th and 10th/90th percentiles, respectively. Mispricing Gaps are the difference in scores between overpriced winners and underpriced losers. Panel B reports the average mispricing score across different stock groups. I set the formation window for both return and mispricing score to be 11 months. Specifically, "W" stands for winners, "M" median, "L" losers, "O" overpriced, "N" neutral-priced, and "U" underpriced. The t-statistics are computed using Newey-West standard errors.

Panel A. Summary statistics for Mgap

Window	Mean	SD	Skew	Kurt
11	40.55	3.58	0.53	4.08
24	37.35	3.15	0.77	4.88
30	36.18	2.90	0.67	4.41
36	35.31	2.78	0.62	4.30
42	34.57	2.66	0.59	4.18
48	33.91	2.58	0.64	4.35
54	33.35	2.52	0.63	4.18
60	32.89	2.49	0.59	4.23
66	32.52	2.43	0.38	3.98
72	32.10	2.33	0.14	3.68

Panel B. Average mispricing score across groups

	W	M	L
O	71.56	71.60	75.77
N	48.71	48.96	53.17
U	27.89	28.09	31.01

Table A.4 Predictive Regression: Net of Momentum Rank
This table documents the estimates of Mgap from the following predictive regression:

$$\mathrm{MOM_t} = \alpha + \beta * \mathrm{Mgap_{t-i,t-2}} + \mathbf{\Gamma} * \mathbf{F_t} + \epsilon_{\mathrm{t}}, \tag{49}$$

MOM_t represents the momentum decile return spread for month t, obtained from the French Data Library. The Mispricing Gaps (net of momentum rank), denoted by $Mgap_{t-i,t-2}$, where i varies from 12 to 73 months, reflect the mispricing score differences between overpriced winners and underpriced losers over different formation periods. Stocks are double-sorted by formation period return and then by mispricing score. Breakpoints for momentum and mispricing scores are set at the 25th/75th and 10th/90th percentiles, respectively. $\mathbf{F_t}$ is the vector of common risk factors, encompassing models from Raw to Q5: $\mathbf{0}$ (Raw), $[\mathrm{Mkt.RF}, \mathrm{SMB}, \mathrm{HML}]$ (Q1), $[\mathrm{Mkt.RF}, \mathrm{SMB}, \mathrm{HML}, \mathrm{RMW}, \mathrm{CMA}]$ (Q3), and $[\mathrm{Mkt.RF}, \mathrm{R_{ME}}, \mathrm{R_{IA}}, \mathrm{R_{ROE}}, \mathrm{R_{EG}}]$ (Q5). R^2 is adjusted R^2, and t-statistics are computed using Newey-West standard errors.

	Raw			FF3		
Window	Estimate	t-stat	R^2	Estimate	t-stat	R^2
11	0.25	2.84	0.01	0.22	2.83	0.09
24	0.29	2.87	0.01	0.25	2.86	0.09
30	0.34	2.94	0.02	0.31	3.10	0.09
36	0.37	3.07	0.02	0.34	3.26	0.09
42	0.38	2.91	0.02	0.36	3.16	0.09
48	0.37	2.72	0.02	0.35	3.01	0.09
54	0.37	2.58	0.01	0.38	3.04	0.09
60	0.38	2.62	0.01	0.40	3.08	0.09
66	0.38	2.46	0.01	0.43	3.09	0.09
72	0.45	2.55	0.02	0.52	3.23	0.10

	FF5			Q5		
Window	Estimate	t-stat	R^2	Estimate	t-stat	R^2
11	0.23	3.02	0.12	0.18	2.99	0.31
24	0.25	2.97	0.11	0.18	2.48	0.31
30	0.30	3.11	0.12	0.22	2.57	0.31
36	0.34	3.26	0.12	0.23	2.53	0.31
42	0.36	3.19	0.12	0.24	2.39	0.31
48	0.36	3.15	0.12	0.24	2.32	0.31
54	0.39	3.26	0.13	0.26	2.36	0.31
60	0.40	3.27	0.12	0.28	2.46	0.31
66	0.44	3.29	0.12	0.31	2.55	0.30
72	0.52	3.44	0.13	0.38	2.73	0.31

Table A.5 Predicting Momentum Crashes using $Mgap^*_{t-i,t-2}$: Logistic Regression
In both Panels A and B, a momentum crash indicator is set to one if the return to the momentum strategy is less than or equal to -10%. The $Mgap^*_{t-i,t-2}$ denotes the residual-based mispricing gap at month $t-2$ for different formation periods. The Pseduo R^2 is Nagelkerke et al. (1991) Pseudo R-squared (R^2), and t-statistics are computed using Newey-West standard errors.

Panel A. Predicting Momentum Crashes Using Mispricing Gap

Window	Estimate	z value	Pseudo R^2
11	-0.10	-1.61	0.01
24	-0.19	-2.75	0.04
30	-0.21	-2.99	0.04
36	-0.20	-2.67	0.04
42	-0.20	-2.57	0.03
48	-0.23	-2.83	0.04
54	-0.26	-3.17	0.05
60	-0.28	-3.30	0.06
66	-0.28	-3.25	0.06
72	-0.26	-3.08	0.06

Panel B. Predicting Momentum Crashes Using OW and UL

Window	Variable	Estimate	z value	Pseudo R^2
11	OW	-0.11	-1.59	0.01
	UL	0.08	0.77	
24	OW	-0.26	-3.34	0.05
	UL	0.12	1.11	
30	OW	-0.28	-3.52	0.06
	UL	0.08	0.72	
36	OW	-0.27	-3.09	0.05
	UL	0.04	0.34	
42	OW	-0.26	-2.95	0.05
	UL	0.00	-0.02	
48	OW	-0.26	-2.87	0.05
	UL	-0.01	-0.11	
54	OW	-0.25	-2.97	0.04
	UL	0.02	0.14	
60	OW	-0.27	-3.12	0.04
	UL	0.06	0.45	
66	OW	-0.25	-2.90	0.04
	UL	0.09	0.69	
72	OW	-0.23	-2.75	0.03
	UL	0.08	0.61	