Firm-Specific Information and Anomalies.

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ABSTRACT

I develop a price inefficiency regarding firm-specific information (PIFI) measure and examine its relation with 144 momentum and other anomalies. The crossover interaction term between the anomaly variable and PIFI completely subsumes the return predictability of more than 70 percent of anomaly variables and significantly weakens the return predictability for an additional 10 percent. PIFI is high when more firm-relevant news is produced and when the firm-specific information is difficult to interpret and value. The results suggest that incorrect incorporation of firm-specific information into prices lies at the core of the return predictability of the most prevalent asset market anomalies.

Keywords: Momentum, Asset Returns, Firm-Specific Information, Price Inefficiency

JEL Classification: G11, G12, G14

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THE RETURN PREDICTABILITY of anomaly variables in asset markets has puzzled researchers for decades. The finance literature finds that predictability generally lies where firm-specific information is hard to incorporate into prices, such as in complicated, ambiguous, opaque, or hard-to-value firms.[1] Recently, Engelberg, McLean, and Pontiff (2018) further say that most anomalies are related to firm-specific information. These findings imply that the incorrect incorporation of firm-specific information into prices is probably at the core of return predictability.

Behavioral studies have found that both overreaction and underreaction to information are pervasive in the market.[2] The wrong and untimely incorporation of firm-specific information into prices, namely price inefficiency regarding firm-specific information, is the common theme among theoretical and empirical studies around anomalies. Even the most savvy group of financial players whose primary job is to analyze information, such as analysts, cannot process the firm-specific information correctly (Engelberg, McLean, and Pontiff (2020)). However, no measure precisely determines the semi-strong form price inefficiency regarding firm-specific information. This study fills that gap with PIFI and provide strong empirical evidence of incorrect incorporation of firm-specific information into prices as one possible mechanism behind hundreds of asset market anomalies, including momentum.

PIFI quantifies semi-strong form price inefficiency, particularly regarding firm-specific information. Further validation exercises to determine the potential drivers of PIFI at the firm and at the aggregate economy level corroborate. As momentum is found to be the most persistent anomaly (Fama and French (2008)), I use four conventional momentum anomalies as my laboratory anomalies but provide ample

[1]See Cohen and Lou (2012), Daniel and Titman (1999), Kumar (2009), Jin and Myers (2006)

[2]See Cutler, Poterba, and Summers (1991), Bernard and Thomas (1989), Chan, Jegadeesh, and Lakonishok (1996) De Bondt and Thaler (1985), Lakonishok, Shleifer, and Vishny (1994), La Porta (1996), etc.

empirical evidence regarding close to hundred and fifty other anomalies.

I find that controlling for PIFI and its crossover interaction with a stock's past returns, even the most persistent market anomaly, namely momentum 6/6 (portfolio formed based on past six-month returns with a six-month holding period) anomaly, completely loses its statistical power to predict future six-month holding period returns. I find similar results on other conventional momentum anomalies, such as residual return, firm-specific return, and 52-week-high prices. Results are robust accross a battery of tests.

Using the data provided by Chen and Zimmermann (2022), I further study more than 200 other anomalies. Out of more than 200 anomalies that I examine, 140 anomaly variables still significantly predict returns in recent data. A fascinating result is that the crossover interaction term between PIFI and the anomaly condition variable subsumes the return predictability of the anomaly variables among 70 percent of asset market anomalies that still predict returns in recent data and significantly weakens for another 10 percent. If I zoom my analysis for the last two decades, nearly 80 percent of anomaly variables lose statistical significance after augmenting the interaction term.

The anomaly group that loses the return predictability the most is Intangibles (e.g., Asset Tangibility); eighty-six percent of anomalies in this group lose return predictability. The result is intuitive as, at any point in time, it is more likely that prices are inefficient regarding to the value of a firm's intangibles since the firm-specific information related to intangibles is ambiguous and very hard to value (Kumar (2009),Daniel and Titman (1999)). On the other hand, the anomaly group that loses the least return predictability is Value vs. Growth; Only forty-seven percent of anomalies in this group lose return predictability. Value vs. growth information such as Book-to-Market or Total Assets to Market directly comes from the firm's reported financials and does not require investors to process the complex firm-specific information. The overall empirical evidence strongly suggests that price inefficiency related to firm-specific information plays a crucial role in the return predictability of most asset market anomalies.

Considering the results that PIFI and its interaction term with anomaly variables subsume momentum and hundreds of other anomalies, it is critical to understand what drives PIFI.

Kumar (2009) finds that behavioral bias is higher where valuation uncertainty is higher and stocks are more difficult to value. Pástor and Pietro (2003) state that when a firm has higher uncertainty around average profitability, investors have difficulty valuing the firm. They find their results even more true for firms that pay low dividends. Jin and Myers (2006) provide evidence that investors rely more on aggregate market information to value opaque firms that are less transparent to outsiders, meaning that firm-specific announcement signals carry less precision. When a firm has higher uncertainties around its fundamentals and is more opaque, investors will have difficulty determining the value of newly arrived firm-specific information, resulting in incorrect incorporation of that information into security prices. And, Zhang (2006) says, "...the degree of incompleteness of the market reaction increases monotonically with the level of information uncertainty.". The literature suggests that the higher the uncertainty around the firms' fundamentals higher the chances that prices incorrectly incorporate new information.

Consistent with these strands literature, I find that high-PIFI firms are slightly larger growth firms with higher profitability volatility. They have higher asset growth and perform more material corporate events (e.g., M&As, SEOs, share repurchases, and stock splits). Fewer analysts cover them on average, but there is a higher dispersion among these analysts about the firms' future earnings. High PIFI firms are also more sensitive to aggregate economy level uncertainty, proxied by professional forecasters' dispersion on inflation forecasts, for example. These firms pay meager dividends and are more opaque. Empirical evidence strongly supports that uncertainties around a firm's fundamentals drive its PIFI. Furthermore, since high-PIFI firms have a lower bid-ask spread, lower illiquidity, higher dollar volume, and higher institutional ownership, the limits to arbitrage might not be hindering firm-specific information from being reflected in prices correctly and quickly.

Furthermore, I find a robust relation between the volume of past six months of firm-related news production and PIFI. PIFI is very strongly related to the overall firm-relevant news production over the past six months, especially to the value-relevant new such as the news about products and services, stock prices, and earnings and revenues. The results further strengthen the story that PIFI captures the inefficiency of prices regarding firm-specific information.

Similarly, at the aggregate economy level, I find that aggregate PIFI (APIFI) is very much correlated with Economic Policy Uncertainty (Baker, Bloom, and Davis (2016)), which again suggests PIFI and uncertainty story.

The correlation between PIFI and the variance, skewness, and kurtosis of monthly returns are 0.009, -0.008, and 0.020, respectively. These very low correlations tell us that PIFI is not just capturing the higher-order moments of returns. Also, the correlation between a stock's PIFI and $\text{BHR6M}_{-1,-6}$ and PIFI and β_{UMD}[1] are 0.003 and 0.004, respectively, reducing the concern that PIFI is somehow a repacking of momentum. Furthermore, since the PIFI interaction terms subsume return predictability of hundreds of anomaly variables, it is highly unlikely that PIFI is correlated with one particular anomaly variable.

An investors' behavioral bias can causes some stock prices to be abnormally high while at the same time others to be abnormally low. For example, if investors are under-weighting a firm's public signal due to being overconfident in their private signals[Daniel, Hirshleifer, and Subrahmanyam (1998)], they are equally likely to be overconfident in their positive as well as negative private signals. And, the higher the investors' behavioral bias, the higher the price inefficiencies with respect to firm-specific information or PIFI. As PIFI oppositely impacts positive (long legs of anomalies) and negative (short legs of anomalies) abnormal returns, in the sample that comprises stocks belonging to both legs, the slope coefficient and statistical significance of PIFI are muted. Hence, investigating the crossover interaction term between PIFI and anomaly variables is more meaningful.

The primary contribution of my paper is two-fold: the introduction of the PIFI measure and a plausible explanation of the hundreds of anomalies, including momentum. Even though I use PIFI to explain momentum and other anomalies in this paper, the measure could be used in various settings where the efficient incorporation of firm-specific information into prices plays an important role.

The remainder of the paper is organized as follows. Section I discusses the data sources, motivation for PIFI, and PIFI calculation. Section II discusses the results. I discuss the various robustness exercises in Section III. Section IV talks about the drivers of PIFI and the characteristics of high- versus low-PIFI firms. Finally, Section V concludes the article.

I. Data and PIFI Calculation

A. Data

Most information, such as stock returns, company fundamentals, and corporate events, come from typical CRSP, COMPUSTAT, and SDC sources. Market dividend yield, term spread, and default spread information are obtained from Professor Amit Goyal's website. Information on professional forecasters' dispersion on government purchases of products and services and inflation and tax code expiration data is obtained from *http://www.policyuncertainty.com/*. I present the summary statistics of a few selected variables in Table I.

B. Motivation for PIFI

Both overreaction and underreaction to information are pervasive in financial markets. Return predictability arises as prices deviate from true fundamental value and slowly move towards the true value. Cohen and Lou (2012) find that return predictability is more pronounced in complicated firms, in which complicated analysis is required to incorporate pieces of information into prices. Engelberg et al. (2018) further say that most anomalies related to firm-specific information.

Barberis, Shleifer, and Vishny (1998) develop a model based on psychological evidence that produces both under- and over-reaction. In the model of Barberis et al. (1998), the representative agent, whose beliefs affect prices and returns, suffers from conservatism bias. Conservatism is defined as the slow updating of models in the face of new evidence (Edwards (1968)). Hence, when firm-specific information hits the market, the agent updates the model only partially, resulting in initial underreaction.

Daniel et al. (1998) say that investor overconfidence causes the market to deviate from the rightful incorporation of relevant information. In their model, investors collect information (e.g., by interviewing management, verifying rumors, and analyzing financial statements). The assumption here is that investors overestimate their skills in collecting information and, therefore, are overconfident in the accuracy of the information they generate, causing an overreaction.

Regardless of whether investors overreact or underreact to information, their wrongful and untimely reaction to firm-specific information slows down the process of prices quickly and rightfully reflecting firm-specific information. Semi-strong form price inefficiencies regarding firm-specific information estimate the inefficiencies of prices regarding to a particular source of information, namely firm-specific. As firms' characteristics and nature dictate the ability of prices to incorporate information correctly (Cohen and Lou (2012), Kumar (2009),Daniel and Titman (1999)), literature implies that PIFI can be expected to impact the return predictability in the market in general.

C. PIFI Calculation

I develop the PIFI measure using the methodology introduced by Hou and Moskowitz (2005) (hereafter HM).[3]

As RHS returns used to calculate the HM measure are US market returns, the

[3] Using a rolling 12-month window, they first estimate the following models for each firm for each month: $Base: r_{i,w} = \alpha_i + \gamma_i^0 r_{m,w} + \epsilon_{i,t}$ and $Extended: r_{i,w} = \alpha_i + \beta_i^0 r_{m,w} + \sum_{n=1}^{4} \beta_i^n r_{m,w-n} + \epsilon_{i,t}$, where, $r_{i,w}$ is the weekly return of stock i in week w and $r_{m,w}$ is the weekly CRSP value-weighted market returns in week w. One of their semi-strong form price inefficiency measures then is calculated as:

$$D3 = \frac{\sum_{n=1}^{4} n \, \frac{abs(\beta_i^n)}{se(\beta_i^n)}}{\frac{abs(\gamma_i^0)}{se(\gamma_i^0)} + \sum_{n=1}^{4} \frac{abs(\beta_i^n)}{se(\beta_i^n)}} \tag{1}$$

measure only captures the information delay specific to the US market. If we want to capture the information delay from other sources such as global markets, the RHS returns used to calculate the measure must be the international market returns. In my setting, as I want to capture information delay (both underreaction or overreaction) of firm-specific information, I use the firm's returns as my RHS variable.

Second, the time lag of RHS returns dictates the time horizon for which the measure captures the information delay (both underreaction or overreaction). For example, if it takes about t+12 time to correctly incorporate all the firm-specific information into prices and if our RHS variables only lags to t-6, then we can confidently say that the measure does not fully capture the information delay.

How long does it take for the prices to rightfully incorporate all firm-specific information into prices is an open question. For example, if momentum is driven by firm-specific information (Hong and Stein (1999)) and if we can generate abnormal returns using the trading strategy that uses the past six months' information, then the phenomena suggests that it probably takes more than six months for prices to fully reflect firm-specific information. Furthermore, an abundance of studies in finance suggests that information can take months, if not years, to be fully incorporated into prices. The primary and most straightforward examples are post-earning announcement drift (PEAD) anomalies. Analyzing 216 published and eight working papers on PEAD, Fink (2021) suggests that it is still a global phenomenon and has not disappeared yet, even after 50 years since the publication of the seminal paper Ball and Brown (1968). It exists in both highly- and less-developed markets (Griffin, Kelly, and Nardari (2010)). Even recent literature such as Ali, Chen, Yao, and Yu (2020) confirms a declining but multi-quarter PEAD. So, I chose a six-month time horizon to calculate the PIFI. The calculation of PIFI is as follows:

First, using a rolling window of 60 months, I estimate the following two models for each firm for each month:

$$Base\ \ Model:\ r_{i,t} = \alpha_i + \gamma_i^1\, r_{i,t-1} + \sum_{n=0}^{6} \xi_i^n\, r_{m,t-n} + \sum_{n=0}^{6} \phi_i^n\, r_{ind,t-n} + \epsilon_{i,t} \tag{2}$$

$$Extended\,Model:\ r_{i,t} = \alpha_i + \beta_i^1\, r_{i,t-1} + \sum_{n=2}^{6} \beta_i^n\, r_{i,t-n} + \sum_{n=0}^{6} \xi_i^n\, r_{m,t-n} + \sum_{n=0}^{6} \phi_i^n\, r_{ind,t-n} + \epsilon_{i,t} \tag{3}$$

where, $r_{i,t}$ is the monthly return of stock i in month t, and $r_{m,t}$ is the monthly return of the CRSP value-weighted index in month t, and $r_{ind,t}$ is the value-weighted monthly industry (to which a firm belongs) return in month t. Using the Fama-French 49 industry classification to group firms into an industry, PIFI is then calculated as:

$$PIFI = \frac{\sum_{n=2}^{6} n\, \frac{abs(\beta_i^n)}{se(\beta_i^n)}}{\frac{abs(\gamma_i^1)}{se(\gamma_i^1)} + \sum_{n=2}^{6} \frac{abs(\beta_i^n)}{se(\beta_i^n)}} \tag{4}$$

PIFI measure uses monthly returns and six months of information to calculate the price inefficiency. To extract the price inefficiency regarding firm-specific information not contaminated by the price inefficiency regarding US market-specific information or industry-specific information, I include contemporaneous and the past six months of market and industry returns in both base and extended models.

The PIFI above gives more weight to the more precise coefficients and to the $t-stat$s that belong to more lagged returns.[4] Secondly, since I am interested in the price inefficiency regardless of the sign of the β coefficients of past returns, I use

[4] One of the price inefficiency measures (D1) that HM use is calculated as 1 minus the ratio of R^2 (R^2 of the base model divided by R^2 of the extended model). Because the D1 does not distinguish between precision or lags, I use a D3 style price inefficiency measure in my analysis.

absolute βs. Whether prices initially underreact and then correct (negative βs) or initially overreact and then correct (positive βs), both are incorrect incorporation of information into prices. The $t-stat$ weighting mechanism is somewhat arbitrary, but the results are robust to different weighting mechanisms, as discussed in robustness checks.

Even though I use the lag of 6, results are robust to varying the lags. In my sample, PIFI numbers range from 0.101 to 2.157, with a mean of 1.347 and a standard deviation of 0.251. The fifth and 95th percentiles are 0.903 and 1.725, respectively.

To examine the economy-wide PIFI, I also calculate the equal-weighted (APIFI_EQ) and the market-cap-weighted PIFI (APIFI_VW) in the cross-section of firms for each month. The minimum, maximum, mean, and standard deviation of APIFI_EQ are 1.302, 1.393, 1.34314, and 0.019, respectively; those of PIFI_VW are 1.284, 1.407, 1.348, and 0.029, respectively. As I show in Figure 1, both of the consolidated economy-wide PIFIs have become significantly more volatile since 2008.

D. PIFI & Auto-Correlation Coefficients

As multiple-order auto-correlation coefficients are used to calculate PIFI, a concern can be raised that I am just capturing momentum through PIFI in a disguised form. In fact, from the surface, momentum and positive auto-correlation sound synonymous.

First, I want to clarify that momentum and auto-correlation are not the same: one is a cross-sectional phenomenon, while the other is a time series. Lewellen (2002) says, “It is well known that momentum is not the same as positive autocorrelation: momentum is a cross-sectional result (winners beat losers), while autocorrelation is a time-series phenomenon (a stock’s past and future returns are correlated).” For example, momentum can still be significant if both winners and losers lose but losers lose more, or if both winners and losers win, but winners win more. Lo and MacKinlay (1990) show that lead-lag relations among stocks, cross-sectional dispersion in unconditional means, or autocorrelation in returns might cause momentum. While Lewellen (2002) finds strong momentum in industry size and BM portfolios, he also finds that the industry's annual return and its future returns are slightly negatively correlated (-0.005 and -0.064 by two and ten months later, respectively). The paper finds that lead-lag relations among stocks play an important role in momentum phenomenon of industry, size and BM portfolios.

Second, in Table II, I show the correlations between PIFI, stocks' momentum loadings (β_{UMD}), and β^1 through β^6 from equation 3. No correlation number is alarmingly high. The correlation between PIFI and β_{UMD} and $BHR6M_{-1,-6}$ are 0.004 and 0.003, respectively. The very low correlations reduce the concerns that PIFI is somewhat related to a stock's past returns or its momentum loading. With PIFI, β^1 (first-degree autocorrelation coefficient controlling for second- to sixth-degree autocorrelation coefficients) has the highest correlation of 0.152 and β^6 has the lowest correlation of -0.059. Scatter plots of PIFI and each of the β^1 to β^6 in Figure 3 and 2 also shows that all the plots are big bulbs centered around zero.

As I discuss in III.B, the first-degree autocorrelation coefficient has statistically significant (at 1% level) negative loading in the Fama-MacBeth cross-sectional regression. Both first-degree autocorrelation coefficients without controlling for any other degree auto-correlation coefficients (γ^1) or the one with controlling for second- to sixth-degree autocorrelation coefficients (β^1) produces similar results; They have no impact on the loading of past returns ($BHR6M_{-1,-6}$), and they themselves have significant negative loadings.

II. Results

In Columns (1) and (2) of Table III, I show that strong price momentum exists in my sample. The sample is limited to observations where price at the beginning of the portfolio formation month was at least \$1, and where the PIFI and other controls (e.g., $D3\_HM$) at month $t-1$ are non-missing. Results show that controlling for D3_HM and its interaction with past returns makes momentum stronger, while controlling for PIFI and its with past returns takes the momentum away.

A. *PIFI & Vanilla Momentum Strategy*

In Table III, I show the results of cross-sectional Fama-MacBeth regressions. For the cross-sectional regressions, two variables of interest are the dependent variable $\mathrm{BHR6M}_{0,5}$, the six-month buy and hold returns from month $t=0$ to month $t=5$, and $\mathrm{BHR6M}_{-1,-6}$, the six-month buy and hold returns from month $t=-1$ to month $t=-6$. Controls are usual empirical regularities such as size, book-to-market ratio, asset growth, return on assets, and price inefficiency measure of HM, D3_HM.

The first two models in the table confirm strong momentum in my sample even after controlling for well-known size, book-to-market ratio, asset growth, and return on assets. Model 3 controls for the price inefficiency measure of HM (D3_HM) and model 4 controls for D3_HM and its interaction with past returns. Controlling for well-known predictors of returns lowers the coefficient of $\mathrm{BHR6M}_{-1,-6}$, but adding D3_HM and PIFI has almost no effect on the coefficient.

Only when I introduce the interaction term between PIFI and past returns ($\mathrm{BHR6M}_{-1,-6}$) in the cross-sectional regressions, momentum loses its statistical significance (Column 6) to predict future returns. The interaction term between PIFI and past returns

(BHR6M$_{-1,-6}$) takes away momentum effects even after controlling for typical controls such as size, book-to-market ratio, asset growth, and return on assets.

The results in Table III provide very strong evidence that the interaction between past return information and PIFI is what possibly explains momentum. Thus, very high momentum exists among firms whose firm-specific information is reflected in prices relatively incorrectly, and very minimal momentum exists among firms whose firm-specific information is baked into prices relatively correctly.

B. PIFI and Other Conventional Return Momentum Strategies

A couple of other momentum strategies that are closely related to price momentum are the 52-high momentum strategy (George and Hwang (2004)), residual-return momentum strategy (Blitz, Huij, and Martens (2011)), and firm-specific-return momentum strategy (Grundy and Martin (2001)). George and Hwang (2004) find that nearness to the 52-week high dominates and improves upon the forecasting power of past returns for future returns. Blitz et al. (2011) rank stocks on residual stock returns instead of total returns and find that residual momentum earns risk-adjusted profits that are twice as large as those associated with the total return momentum. And, Grundy and Martin (2001) find that momentum strategies that define winner or loser status on stock-specific return components are more profitable than those based on total returns.

Here, I study the relation between these momentum strategies and PIFI. The prior is that since these momentum strategies are closely related to price momentum, controlling for the interaction between PIFI and information on which stocks are ranked in each of these momentum strategies, the return predictability of these momentum strategies should weaken. I look at each residual-return momentum and firm-specific-return momentum separately because even though residuals and firm-specific returns are sometimes synonymously viewed, the residual returns strategies unavoidably contain bets against the betas of the factor model used to estimate them and hence are not pure bets on firm-specific return momentum (Ehsani and Linnainmaa (2022)).

I calculate the condition variables following each of the corresponding papers. The condition variable for the 52-high strategy is calculated as the maximum price of a stock from month $t-12$ to $t-1$ divided by the price in month $t-1$. The condition variable for firm-specific-return strategy is the α of the Fama-French three-factor model estimated using the monthly returns from the month $t-12$ to month $t-2$. And, the conditional variable on the residual-return strategy is the six-month cumulative residual returns of the Fama-French three-factor model estimated on a 36-month rolling window basis.

I present the result of this analysis in Table IV. Consistent with the findings of the original papers, all three condition variables predict future returns, and all three coefficients (Columns 1, 3, and 5) are significant at a 1% level. However, when I control for the interaction terms between each of the condition variables particular to the momentum strategy and PIFI, all three momentum strategies, High-52 (Column (2)), FF3α (Column (4)), and RRet (Column (6)), return predictability of these momentum strategies get subsumed. The ability to subsume the momentum returns predictability of the momentum strategies beyond just plain vanilla strategy of Jegadeesh and Titman (1993), strongly validates the paper's finding that PIFI might be behind the momentum phenomena and anomaly return predictability in general.

C. PIFI and 201 Other Financial Market Anomalies

For this this analysis, I use the anomaly data set provided by Chen and Zimmermann (2022). For 201 anomalies (predictors set of Chen and Zimmermann (2022) less the anomalies that I already examined very closely above), first, using the Fama-MacBeth regression, I look at whether the anomaly variables predict the next month returns statistically significantly within my sample period. Out of 201 that were examined, 140 anomaly variables statistically significantly predict the subsequent month's returns. Then, for each of the 140 anomaly variables, I again estimate the Fama-MacBeth cross-sectional regression controlling for one month-lagged PIFI, and its interaction with each of the anomaly variables at month $t-1$ and examine whether the anomaly variable still predicts next month's return statistically significantly. I present the results in Table V.

Out of 140 anomaly variables that significantly predict returns in the recent sample, after I introduce the PIFI and its interaction term, 103 anomaly variables completely lose their statistical power to predict next month's returns, and the return predictability of another 13 anomaly variables significantly weakens.

Anomalies related to intangibles (86%) are the ones that most often lose their statistical power to predict returns after I augment their interaction term with PIFI. The result helps corroborate the findings that price inefficiencies regarding firm-specific information plays a very important role in generating financial market anomalies. At any point in time, prices are more likely to be inefficient related to firm-specific information with regard to intangibles because estimating the precise value of intangibles is difficult for investors. On the other hand, assigning a firm into value vs growth based on variables such as book-to-market or total-assets-to-market is fairly simple using the financials reported by a firm. The value vs. growth anomaly group loses the least return predictability (47%). This evidence validates that PIFI captures price inefficiencies regarding a firm's firm-specific information.

III. Robustness Tests

In this Section, I talk about few selected robustness tests. I explain on additional robustness exercises in Section B.A in the Internet Appendix.

A. PIFI and Momentum Strategies Other Than 6/6

As mentioned in the original momentum paper of Jegadeesh and Titman (1993) and found by several follow-up papers, the 6/6 momentum strategy produces the strongest momentum results. Hence, I use this strategy as a guinea pig for all my studies.

However, as a robustness check, I also run the analysis on several other momentum strategies. In Table VI, I show the cross-sectional Fama-MacBeth regression results on 3/3, 6/3, 12/3, 1/6, 12/6, and 6/12 momentum strategies. Holding period returns are calculated from the month $t = 0$ for all momentum strategies.

The results show that, in general, regardless of the length of the holding period or the length of the period of returns that we use to form the momentum portfolios, my results are robust. Once I control for the interaction between PIFI and past returns (corresponding to each momentum strategy), all momentum effects lose statistical significance in the context of Fama-MacBeth cross-sectional regressions (except 12/3 whose statistical significance decreases to 5% level but does not go away).

The results in Table VI further provide strong evidence that the price inefficiency regarding firm-specific information is behind the momentum phenomenon; hence, when controlling for PIFI and its interaction with past returns, momentum does not exist.

B. Controlling for Various-Order Auto-correlation Coefficients

One primary concern about PIFI is that it may just capture the autocorrelation structure of the stocks. Literature has established that cross-correlation and not auto-correlation are behind the momentum (Lewellen (2002)). Nonetheless, it is a valid concern as auto-correlation coefficients mechanically come into the formula of PIFI (equation 2). Among all the correlations between PIFI and multiple-order auto-correlation coefficients, the PIFI and first-order auto-correlation of a firm's stock returns has the highest positive correlation of about 0.34 (Table II).

To address this concern, I replicate my analysis by replacing PIFI with a first-order auto-correlation coefficient without controlling for other degree autocorrelations (γ_i^1). As we can see in Table VII,Columns 1, 2, and 3, momentum stays very strong even after controlling for a stock's past first-order auto-correlation and its interaction with a firm's past six-month cumulative returns. γ_i^1 loads significantly negatively. Using β^1 (first-degree autocorrelation coefficient after controlling for second- to sixth-degree autocorrelation coefficient) also produce almost exact results. As shown in Column (3) in Table VII, momentum goes away only after controlling for PIFI and its interaction terms with past six-month cumulative returns while controlling for the stock's past first-order auto-correlation and its interaction term. The results strongly support that the information that PIFI captures, namely the speed of diffusion of firm-specific information, is significantly different than that captured by stock's first-order auto-correlation.

C. Controlling for Other Explanations for Momentum

Over time, since 1992, when momentum was first documented, researchers have found different firm characteristics associated with momentum. Here, I control the most prominent explanation for momentum with and without PIFI. The bottom-line result is that none of the explanations completely takes statistical significance away from the past returns, and every single time, while controlling for each of the explanatory variables, PIFI and its interaction term with past returns take away the statistical significance of past returns.

As I mentioned above, many researchers, including Jegadeesh and Titman (e.g., Jegadeesh and Titman (1993), Hong and Stein (1999)), suggest that momentum profits are due to underreaction to firm-specific information. One proxy finance literature uses for firm-specific information is a firm's idiosyncratic volatility (IVOL). I control for IVOL calculated with respect to the Fama-French three-factor model (Ang, Hodrick, Xing, and Zhang (2006)) in my analysis. Hong, Lim, and Stein (2000) find that within a size group momentum strategies work better among stocks with low analyst coverage. The paper uses analyst coverage as a proxy for information diffusion contemplated by Hong and Stein (1999). Analyst count can be thought of as a proxy for firm-specific information delay in that we can expect to see a very strong negative relation between the information delay of a firm and the number of analysts covering a firm.

Sadka (2006) shows that about half of the time-variation in momentum profits can be explained by the liquidity risk exposure. I control for the illiquidity measure of Amihud (2002) as a proxy for liquidity risk exposure. Chordia, Subrahmanyam, and Tong (2014) show that momentum profits are sensitive to trading costs. I control for bid-ask spread as a proxy for trading costs. Lee and Swaminathan (2000) find a strong link between volume turnover and momentum. I control for stock turnover to control for their findings. Avramov, Chordia, Jostova, and Philipov (2007) show that momentum profits are stronger in more distressed companies. I control for leverage as a proxy for the financial distress of the firms. Chordia and Shivakumar (2006) find that price momentum is captured by the systematic component of earnings momentum. I control for standardized unexpected earnings (SUE) to capture the component of earnings momentum.

Moskowitz and Grinblatt (1999) document a strong momentum effect in the industry component of stock returns. To examine the industry effect on momentum, I calculate the price inefficiency regarding Industry-specific Information (PEII) measure (Section B.A.2). Lastly, Da, Gurun, and Warachka (2014) test the frog-in-the-pan (FIP) hypothesis and find that continuous information induces strong, persistent return continuation. They test their FIP hypothesis using information discreteness or ID. Following the paper, I calculate the ID measure as the sign of the past twelve-month returns times the percentage of negative returns days minus the percentage of positive returns days over the last twelve months. I present the analysis of all these robustness tests in Table VIII, Panels A and B.

D. *Controlling for Stock's Loadings on UMD (Momentum Factor)*

One concern with using PIFI to study momentum is a claim that PIFI might only be capturing the stocks' loadings on UMD (up minus down momentum factor). To address such concerns, I first run 60-month rolling window regressions of stock returns on the UMD factor to obtain the time series of β_{UMD} coefficients for each stock for each month. In the cross-section of firms, I find that PIFI and β_{UMD} has a negative correlation of only about 0.004, very close to zero.

To examine whether using β_{UMD} instead of PIFI in the cross-sectional regressions gives similar results, I run the Fama-MacBeth cross-sectional regression, in which I control for β_{UMD} and its interaction with the past six months' cumulative returns ($\text{BHR6M}_{-1,-6}$) rather than controlling for PIFI and its interaction with $\text{BHR6M}_{-1,-6}$. In Table IA4, I present the results of these regressions. Columns (1) and (2) show that $\text{BHR6M}_{-1,-6}$ is still statistically significant at the 1% level in predicting the next six months' cumulative returns, even after controlling for β_{UMD} and/or its interaction with $\text{BHR6M}_{-1,-6}$, momentum gets stronger, controlling for β_{UMD} and/or its interaction with $\text{BHR6M}_{-1,-6}$. The results provide evidence that information captured by PIFI is very different from and unrelated to that captured by β_{UMD}.

E. Controlling for Fama-French and Investment-Based Asset Pricing Factors

In this section, I perform a robustness exercise to see whether my results are robust to controlling for the factors of the most widely used asset pricing models. The two most widely used asset pricing models currently are the Fama-French five-factor asset pricing model (Fama and French (1993), Fama and French (2015)) and investment-based q-factor models (Hou, Xue, and Zhang (2015), Hou, Mo, Xue, and Zhang (2021)). In this exercise, besides controlling for the various firm characteristics such as size and book-to-market, I also control for these factors.

I present the results of this analysis in Table IX. Results in Column are almost identical to the main results (Column (6) of the Table III). As we can see in Column three, past returns significantly predict future returns even after controlling for both Fama-French and Q factors. Once I introduce the PIFI and its interaction term with past returns, the return predictability of the primary independent variable - $\text{BHR6M}_{-1,-6}$ - goes away. Again, results suggest that PIFI can explain momentum very well.

F. *Controlling for Information Uncertainties, Material Corporate Events and their Interactions*

Zhang (2006) introduces information uncertainty proxies and finds that momentum is stronger among stocks that have higher information uncertainty. The paper finds that in the presence of higher information uncertainty, the good news (bad news) results in more pronounced positive (negative) price drifts. It is intuitive and seems plausible that in the presence of higher information uncertainty, the incorporation of firm-specific information into prices will be hampered, causing PIFI to increase. Thus, I next scrutinize whether my results are driven by the presence of information uncertainty and not the PIFI, per se.

The six information uncertainty proxies of Zhang (2006) are the reciprocal of firm age (RES_AGE), the reciprocal of firm market value (RES_MV), the reciprocal of analyst count (RES_ANLST), cash flow volatility (SDCF), stock volatility (VLTY), and analyst dispersion (ANLSTDISP).

In Zhang (2006), news has a multiplier effect on the drift. Drifts are stronger if followed by news. Thus, to capture the major news events of firms that have the potential to move prices or events that investors consider material, I look into the seven major corporate events that the finance event study literature finds to produce post-event abnormal returns: the announcements of mergers and acquisitions (where the deal value is at least 2.5% of the market value), stock splits, debt issuances, dividend initiations or material changes (at least 20% absolute change), secondary equity offerings, share repurchases, and joint ventures. My three news variables (MAT_EVENT_6M, MAT_EVENT_12M, and MAT_EVENT_24M) are simply the number of material corporate events announced by the firm in the past 6, 12, and 24 months, respectively. Next, I study the relation between PIFI and momentum, controlling for the information uncertainty proxies of Zhang (2006) and the material corporate events.

First, I study whether controlling for either the major corporate material events or its interaction with past returns takes away the predictive power of PIFI in the cross-section by including my material corporate events variables and their interaction terms with past returns within Fama-MacBeth cross-sectional regression models. I present the results of this analysis in Table IA5. The overall result is that controlling for the proxy of material news production does impact much the predictability of $BHAR6M_{-1,-6}$ to predict future returns.

Second, I perform a similar exercise using the information uncertainty proxies of Zhang (2006). Because Zhang (2006) does not create a single consolidated information uncertainty proxy, I normalize each of the information uncertainty proxies to have a mean of 1 and average them to create a single consolidated information uncertainty proxy (IU_Z). I present the result of this analysis in Table IA6.

The model in the first column includes only IU_Z, and the second column includes IU_Z and its interaction term with past returns ($BHR6M_{-1,-6}$); Compared to the model in the second column of Table III, the result in Column (2) is much stronger, meaning momentum is stronger after controlling for IU_Z and its interaction term with past returns. Results show that including the IU_Z and its interaction term with past returns do not impact the statistical significance or the coefficients of PIFI or its interaction term with past returns.

Overall, the results in Tables IA5 and IA6 confirm that information uncertainty, material corporate events, and their interaction terms with past returns cannot take away the momentum effect in the cross-section. On the contrary, when controlling for these variables, momentum becomes slightly stronger. The results suggest that the information captured by PIFI is very different than what is captured by information uncertainty variables of Zhang (2006) or news variables.

IV. Plausible Determinants of PIFI

In this section, I examine the possible drivers of PIFI. Daniel and Titman (1999) suggest that the momentum effect is likely to be strongest in those firms whose valuations require the interpretation of ambiguous information. When there is high uncertainty around a firm's fundamentals, interpretation of information about the firm, firm-specific or otherwise, becomes difficult and ambiguous. When the interpretation of the information becomes hard, it is very plausible that the price inefficiency regarding firm-specific information increases. Therefore, I dig a little deeper into the firm characteristics of low- versus high-PIFI firms concerning the uncertainties around their fundamentals.

I test whether PIFI is high if there is higher uncertainty around the fundamentals of a firm or if a firm is hard to value. Zhang (2006) finds a stronger momentum effect when there is higher information uncertainty. Pástor and Pietro (2003) state that when a firm has higher uncertainty around the average profitability, investors will have difficulty valuing the firm. They find their results to be even more true for firms that pay low dividends. Jin and Myers (2006) provide evidence that investors would rely more on aggregate market information to value opaque firms that are less transparent to outsiders and hence, firm-specific announcement signals would carry less precision. Here, I study the relation between PIFI and some of the variables suggested by the above literature.

The overall results suggest that higher firm-level uncertainty around the fundamentals is what might be behind higher PIFI. Even though higher sensitivity to economy-wide uncertainty does not directly translate into higher firm-level uncertainty, it is more likely that firms with higher firm-level uncertainty show more sensitivity to aggregate economy-wide uncertainty. My results support that hypothesis; the results suggest that high-PIFI firms are more sensitive to economy-wide uncertainty. I also show that limits of arbitrage probably are not the reason behind the variation of PIFI across firms.

A. Characteristics of Low- versus High-PIFI Firms

In Table I, I present a summary of firm characteristics of ten groups of firms divided based on their PIFI values and the statistical significance of the difference between 10th-decile PIFI firms and first-decile PIFI firms. A top-level summary tells us that high-PIFI firms are larger growth firms with higher year-over-year asset growth and lower return on assets. This summary is consistent with Daniel and Titman (1999), who also found stronger momentum among growth firms. Compared to low-PIFI firms, high-PIFI firms have lower profitability, higher cost of goods sold as a percentage of total assets, and experience higher sales volatility on average.

Higher PIFI firms not only have a slow diffusion of firm-specific information but also perform a higher number of material corporate events than low-PIFI firms. The variables MAT_EVENT_24M, MAT_EVENT_12M, and MAT_EVENT_6M are simply the number of material corporate events announced by the firm in the past 6, 12, and 24 months, respectively. The seven major corporate events that I look into are the announcements of mergers and acquisitions (where the deal value is at least 2.5% of the market value), stock splits, debt issuances, dividend initiations, or material changes (at least 20% absolute change), secondary equity offerings, share repurchases, and joint ventures. Summary statistics suggest that high PIFI firms also produce more material news.

To understand the higher PIFI firms' sensitivity to the aggregate economy-wide uncertainty, I rely on the data from Baker et al. (2016). Three aggregate uncertainty measures for which I studied the sensitivity of firms are dispersion among professional forecasters' about CPI (CPIDIS), purchase of goods and services by the government (GOVDIS), and tax code expiration (TAXEXP). I estimate the 60-month rolling window regression of individual firms' returns on each uncertainty measures to obtain their respective β coefficients. Table I shows that higher PIFI firms are significantly more sensitive to economy-wide uncertainty than lower PIFI firms.

A.1. News Production

My hypothesis in this paper is that PIFI captures the inefficiency of prices in rightfully incorporating the firm-specific information. So, in this section, I look at the relation between the volume of firm-relevant news production and PIFI. I hypothesize that PIFI should be higher when firm-specific news production is higher. To test my hypothesis I use Ravenpack's news database.

Ravenpack compiles news items from various sources and provides the relevancy score of the news item for a specific firm. It categorizes news items into over fifty groups such as Stock Prices, Products & Services, Investors Relations, Taxes etc. Products and Services group include news such as “China grants conditional approval for Merck’s COVID-19 drug.” Earnings and Revenues group are news such as “Li Auto delivered 46,319 vehichles in Q4.” Stock Prices group include news such as “Tesla stock to surge 394% in next 12 months.” And, “Green Thumb will host a conference call on Tuesday, February 28, 2023 at 5:00 pm ET.” is an example of Investor Relation group. The conjecture here is that, even among news groups, PIFI should be strongly related to firm-value relevant news compared to the other news such as investor-relation news.

The results in Table X very strongly support my hypothesis above. Each of the news variables is the natural logarithm of relevancy weighted monthly news items averaged over the months $t-7$ to $t-1$, and the dependent variable, PIFI, is at month t. The monthly Fama-Macbeth regression shows that the news production in the past six months very strongly predicts the PIFI in month t. The results further support my claim in the paper that PIFI captures the inefficiency of prices in rightfully incorporating firm-specific information.

A.2. Level and Variance of Profitability

Pástor and Pietro (2003) find that when uncertainty about the firm’s average profitability or the idiosyncratic volatility of profitability increases, so does the idiosyncratic return volatility. They find that firms’ market-to-book ratio increases with uncertainty about average profitability. Their results were stronger, especially for non-dividend payers.

Furthermore, Pan, Parajuli, and Sinagl (2021) theoretically show that when uncertainty around profitability is high, investors cannot disentangle systematic from idiosyncratic information signals. As firm-specific information and systematic information are mixed up, it is plausible that the price inefficiency increases. My hypothesis here is that higher profitability variability increases the PIFI.

I examine firms' operating margin (O_MARGIN), net income margin (NI_MARGIN), gross margin (G_MARGIN), earning before interest tax and depreciation and amortization margin and their respective variance (SD_OM, SD_NIM, SD_GPM, and SD_EBITA). I also calculate a firm's dividend payout ratio and returns solely coming from dividends.

I present the result in Table XI. The table presents the slope coefficient, t-stat, and R^2 of the Fama-MacBeth regression $PIFI_{t,i} = \alpha_i + \beta\, Variable_{t,i} + \epsilon_{t,i}$ where the $Variable$ can be any of the level or variance profitability or payout variables. Compared to low-PIFI firms, high-PIFI firms have lower profitability across the board. Also, high-PIFI firms have higher variances around profitability margins. Their payout ratio is low, and their dividend returns are smaller than that of low-PIFI firms. Overall, the evidence suggests that higher uncertainties around their profitability potentially drives PIFI.

A.3. High PIFI Firms, Information Uncertainties, Opaqueness

Zhang (2006) finds a stronger momentum effect when there is higher information uncertainty, and it is very plausible that higher information uncertainty obstructs the firm-specific information to be rightfully incorporated into the prices. Also, as Jin and Myers (2006) point out, firm-specific information carries less precision among opaque firms. I hypothesize that the PIFI should be higher among opaque firms as the firm-specific information carries less precision. I present my analysis using the information uncertainty variables proposed by Zhang (2006) and Jiang, Lee, and Zhang (2005) and opaqueness variables suggested by Jin and Myers (2006) in Table XII.

The table presents the slope coefficient, t-stat, and R^2 of the Fama-MacBeth regression $PIFI_{t,i} = \alpha_i + \beta\, Variable_{t,i} + \epsilon_{t,i}$ where the $Variable$ can be any of the information uncertainty or opaqueness variables.

The returns of high-PIFI firms are more volatile, and there is high dispersion among analysts in their forecasts about firms' future earnings, even though fewer analysts cover the high-PIFI firms on average. High PIFI firms also experience higher turnover and have higher equity duration. Overall, the results provide very strong evidence that high-PIFI firms are the firms with higher information uncertainty. The only information uncertainty variable that suggests otherwise is the reciprocal of market value, one of the information uncertainty variables of Zhang (2006). The negative coefficient here is perfectly in line because high-PIFI firms are larger growth firms.

Concerning opaqueness, high PIFI firms have higher market-to-book, higher intangible assets scaled by total assets, and higher research and development scaled by assets. Again, results strongly suggest that the high PIFI firms are more opaque. Overall, high-PIFI firms have higher uncertainties around their fundamentals and are hard to value.

A.4. High PIFI Firms and Limits of Arbitrage

If investors are prohibited from acting due to market constraints on new information when they receive it, that new information will not be reflected in the price rightfully. The proxies of limits of arbitrage are generally used to understand the extent to which arbitrageurs can not correct mispricing in the market due to various reasons. Next, I look at the characteristics of high-PIFI versus low-PIFI firms concerning limits of arbitrage proxies to understand whether some economic constraints cause the PIFI to increase among high-PIFI firms.

Based on Amihud (2002) and Lam and Wei (2011), my variable for limits of arbitrage are illiquidity (AILLIQ), dollar trading volume (DOLLAR_VOL), and bid-ask spread (BA_SPREAD). In Panel B of Table XII, I present the slope coefficients of each of the proxies from the Fama-MacBeth regression of $PIFI_{t,i} = \alpha_i + \beta_i Variable_{t,i} + \epsilon_{t,i}$ where $Variable$ can be any of the three measures.

Compared to low-PIFI firms, high-PIFI firms, on average, have a lower bid-ask spread and illiquidity and higher dollar volume. Overall, the results suggest that limits of arbitrage probably are not the reason why firm-specific information diffuses slowly among high-PIFI firms. Columns (7) and (8) of Panel B of Table XII also show that compared to low-PIFI firms high-PIFI firms have higher institutional ownership, another suggestive evidence that limits of arbitrage are probably lower among high-PIFI firms.

B. Plausible Determinants of Economy-wide PIFI

In this section, I study the relation between aggregate economy-wide PIFI variables and economic and business cycle variables. For this purpose, I calculate two consolidated market-level PIFI variables - APIFI_EQ (aggregate equal-weighted PIFI) and PIFI_VW (aggregate market-cap-weighted PIFI) - of all firms in the cross-section for the month. In Figure 1, I plot APIFI_EQ and APIFI_VW with the EPU Index of Baker et al. (2016) as a proxy for economy-wide uncertainty. Visually, the plot suggests that aggregate economy-wide PIFI generally is increasing in recent times and is higher when EPU is high. I find the correlation between the EPU index and APIFI_EQ to be about 40%, suggesting that when economy-wide uncertainty increases, the price inefficiency regarding firm-specific information is higher on average across firms. Models 7 of Table XIII confirm the results in the regression setting. The results support the view that PIFI increases in periods of higher economic uncertainty.

In Table XIII, I show the results of a few univariate regressions of the business cycle and other economic variables on APIFI_EQ in contemporaneous time. Most business cycle variables are from Welch and Goyal (2008). DIVIDEND_YIELD is defined as the total dividend payments accruing to the CRSP value-weighted index over the previous 12 months, divided by the current level of the index level. TERM_SPREAD is the difference between the average yield of Treasury bonds with more than ten years to maturity and the average yield of T-bills that mature in three months. PRICE-To-EARNINGS is the total sum of earnings by S&P 500 companies divided by the S&P 500 index value. DEFAULT_RSPREAD is the default return spread, which is the difference between corporate returns and long-term government bond yield. DEFAULT_YSPREAD is the default yield spread, which is the difference in yield between AAA bonds and BAA bonds. STOCK_VARIANCE is computed as the sum of squared daily returns on the S&P500. EPU is the consolidated economic policy uncertainty index from Baker et al. (2016). Lastly, REALIZED_VARIANCE is realized stock variance from Zhou (2018).

The results show that term spread, default return and yield spread, price-to-earning ratio, economic political uncertainty, and stock variance and realized stock variance are significantly positively associated with APIFI_EQ, and the dividend yield is significantly negatively associated. Individual univariate regressions of each of the determinants of APIFI_EQ provide evidence that again supports the view that PIFI generally is higher during uncertain times.

V. Conclusion

In this paper, I study the relationship between price inefficiency regarding firm-specific information (PIFI) and 144 asset market anomalies, including momentum. The finance literature finds that return predictability generally lies where firm-specific information is hard to incorporate into prices, such as in complicated, ambiguous, opaque, and hard-to-value firms, suggesting that the incorrect incorporation of firm-specific information probably is at the core of return predictability of anomalies in general.

Motivated by this line of thought, I develop a price inefficiency regarding firm-specific information (PIFI) measure to capture only the price inefficiency regarding firm-specific information and for a relatively longer horizon, six months. The six-month time horizon is motivated by the PEAD literature. PIFI also controls for the contamination of the price inefficiencies regarding US market-specific information and a firm's industry-specific information.

Analyzing the firm characteristics of low- versus high-PIFI firms, I find evidence that high uncertainties around firms' fundamentals, on average, drive PIFI. PIFI is strongly related to the volume of a firm's value-relevant news. I find that high-PIFI firms are generally slightly larger growth firms with higher profitability volatility. These firms have higher asset growth, and fewer analysts cover them on average; however, there is higher dispersion among these analysts about their future earnings. These firms have a higher cost of goods sold and pay very low dividends.

I find that controlling the interaction between PIFI and anomaly variables subsumes the return predictability of conventional momentum anomaly variables such as past returns, residual return, firm-specific returns, 52-week-high-prices as well as the return predictability of more than 70% of prevalent asset market anomalies that still predicts returns in recent data and weakens the predictability of another 10%. The empirical evidence suggests that incorrect incorporation of firm-specific information into prices lies at the core of the return predictability of most asset market anomalies, including momentum.

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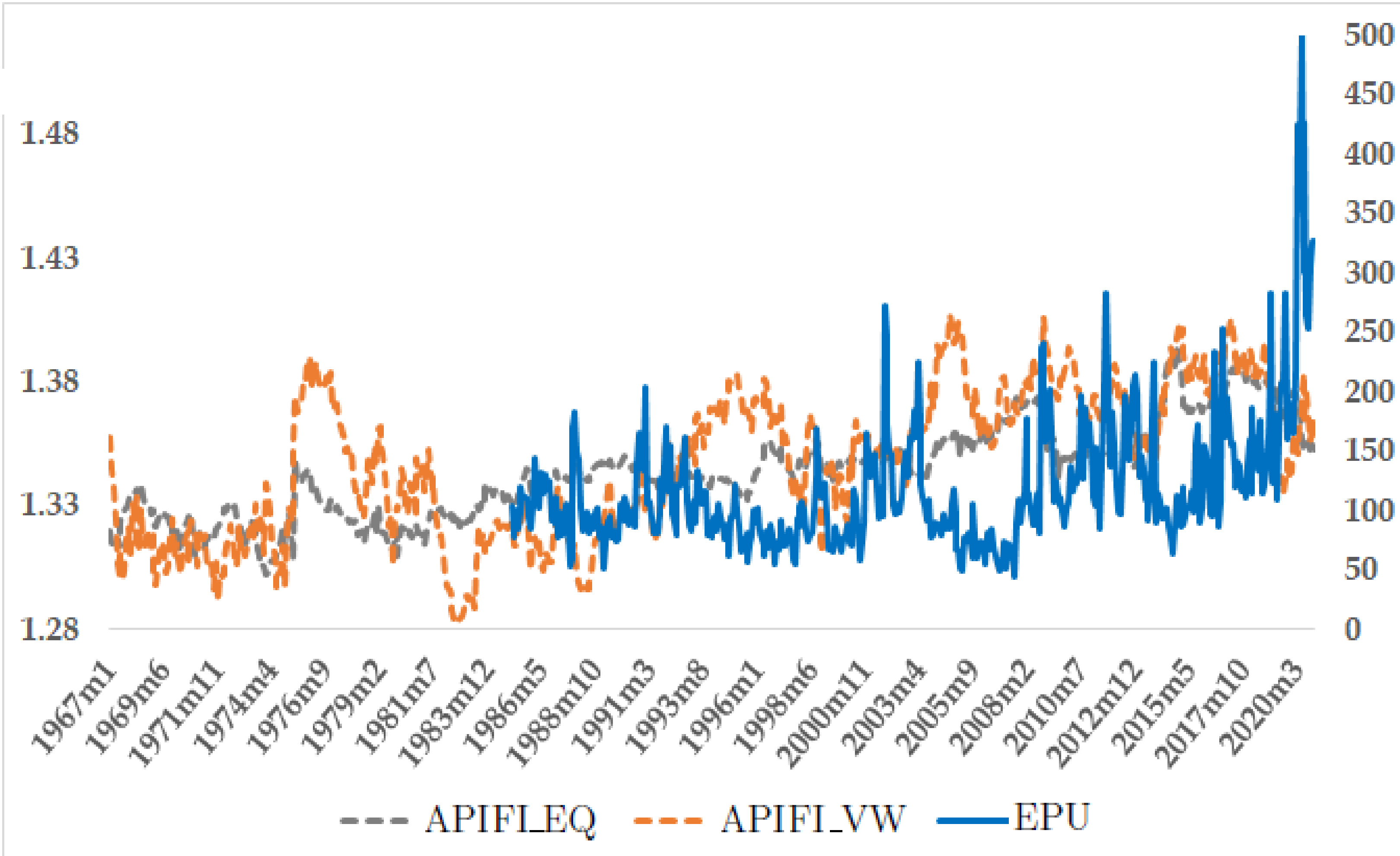
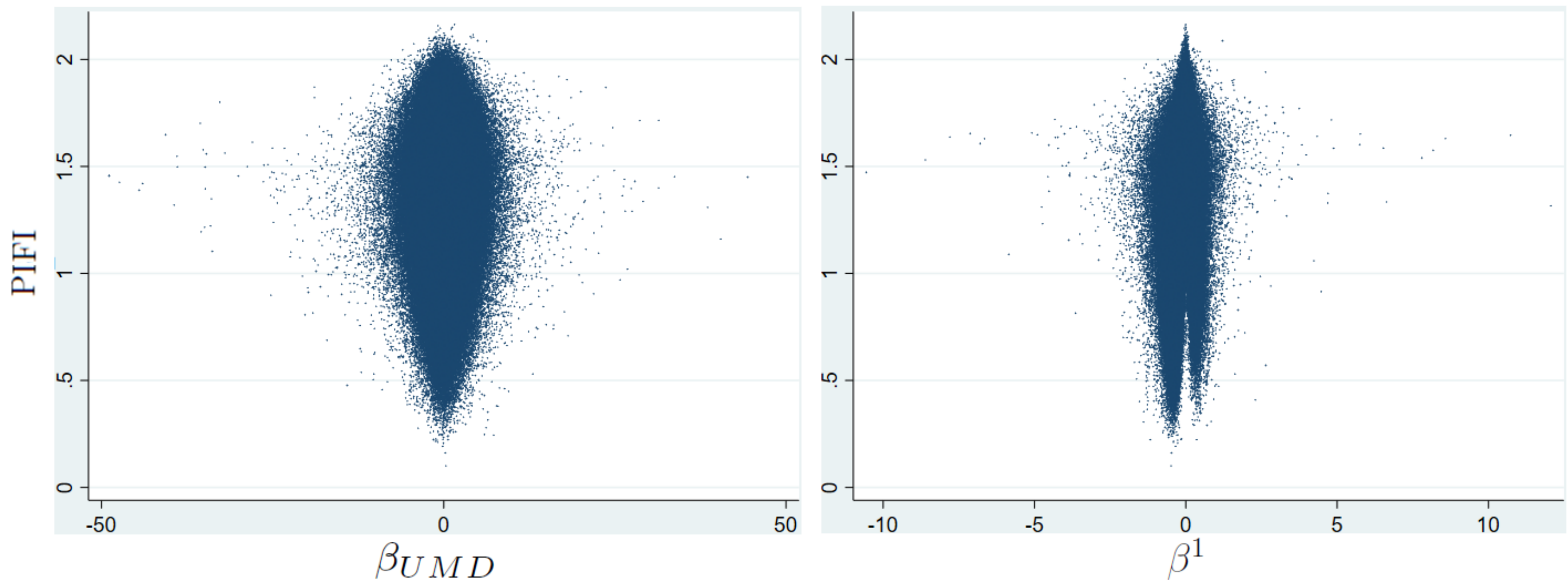


Figure 1: Economic Policy Uncertainty & PIFI. The plots show that both aggregate PIFI measures are increasing in recent times with EPU. EPU is the Economic Policy Uncertainty Index developed by Baker et al. (2016). APIFI_EQ is the equal-weighted PIFI of all firms in the cross-section for the month. Similarly, APIFI_VW is the market-cap-weighted average of the PIFI of all firms in the cross-section for the month. The price filter used is $1.



2: Auto-correlation Coefficient, Carhart MOM Factor loading, and PIFI. The left-hand side plot shows the scatter plot of stocks' PIFI and Carhart Momentum Factor loading (β_{UMD}) and the right-hand side plot shows the scatter plot of stocks' PIFI and first-order auto-correlation coefficient (β^1 from equation 3) of monthly returns. The plots show very little relation between a stock's PIFI, first-order autocorrelation coefficient, and its loading to the Carhart Momentum Factor.

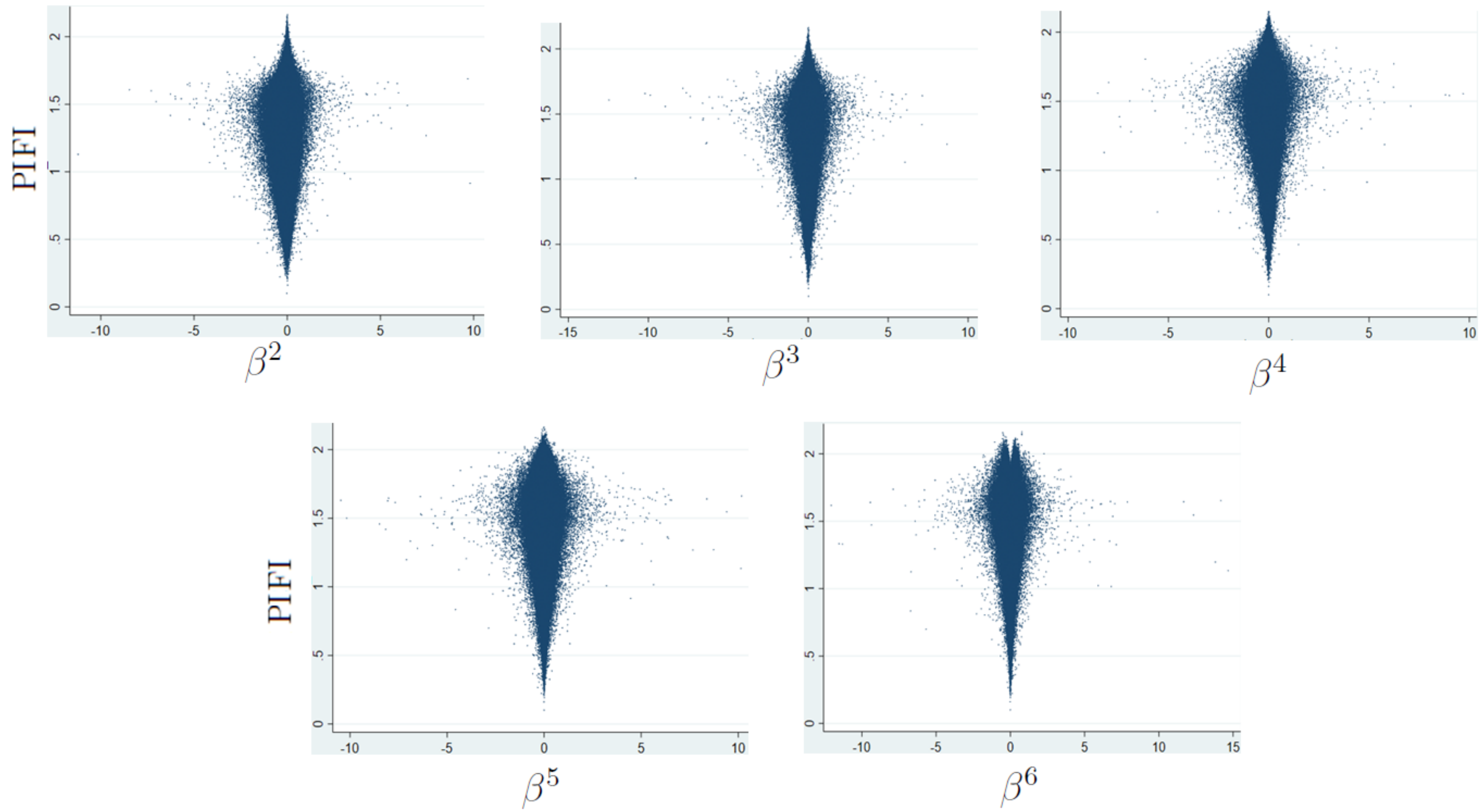


Figure 3: PIFI and β coefficients. This figure shows the scatter plots between PIFI and each of the β^2 through β^6 coefficient from the extended model (equation 3) used to calculate PIFI. Plots show that PIFI has very little correlation, if any, with any of the βs from the extended model.

Table I: Summary Statistics

This table shows the mean value of firm fundamental characteristics within each PIFI decile. PIFI is the price inefficiency wrt firm-specific information as defined by equation 4. I sort the firm-month observations into 10 PIFI deciles every month based on the firms' PIFI values at the end of month $t-1$. I then take the simple average of the characteristics (winsorized (1,99) to reduce the impact of outliers on the mean) for the whole sample period within each decile. LMCAP is the natural logarithm of price times the shares outstanding. LBM is the the natural logarithm of the book-to-market ratio calculated following Davis, Fama, and French (2000). AG is year-over-year asset growth. ROA is the return on assets, calculated as the current year's net income divided by the previous year's total assets. MAT_EVENT_6M, MAT_EVENT_12M, and MAT_EVENT_12M are the number of material events announced over 6, 12, and twenty 24, respectively. IU_Z is a consolidated information uncertainty variable, and β variables are slope coefficients of each of the variables, GOV_DIS, CPI_DIS, and TAXEXP. All variables are defined in Appendix A. The sample period runs from January 1967 through December 2020, and the price filter used is $1.

	PIFI Deciles										
	1	2	3	4	5	6	7	8	9	10	10-1 $t-stat$
PIFI	0.881	1.078	1.183	1.263	1.332	1.396	1.459	1.526	1.604	1.735	
LMCAP	5.060	5.077	5.074	5.063	5.088	5.074	5.086	5.09	5.084	5.096	6.015
LBM	-0.466	-0.483	-0.491	-0.496	-0.505	-0.512	-0.521	-0.522	-0.531	-0.54	-27.804
AG	0.082	0.085	0.084	0.086	0.086	0.085	0.087	0.089	0.091	0.094	15.588
ROA	-0.007	-0.010	-0.010	-0.012	-0.012	-0.014	-0.014	-0.015	-0.016	-0.016	-16.527
MAT_EVENT_6M	1.213	1.237	1.242	1.234	1.237	1.224	1.224	1.219	1.215	1.219	1.016
MAT_EVENT_12M	2.417	2.465	2.47	2.465	2.47	2.444	2.441	2.43	2.418	2.43	1.185
MAT_EVENT_24M	4.823	4.911	4.929	4.918	4.934	4.871	4.87	4.845	4.835	4.862	1.968
IU_Z	0.710	0.713	0.720	0.728	0.727	0.732	0.735	0.737	0.745	0.745	20.174
β_{GOVDIS}	0.022	0.023	0.023	0.023	0.024	0.024	0.024	0.024	0.025	0.025	7.172
β_{CPIDIS}	0.002	0.014	0.0256	0.020	0.014	0.023	0.031	0.025	0.024	0.011	1.815
β_{TAXEXP}	0.014	0.013	0.014	0.013	0.014	0.014	0.014	0.015	0.015	0.017	4.321

Table II:
Correlation Among PIFI, β_{UMD}, and β^2 to β^6 from the Extended Model

This table shows the correlation among stocks' past returns, PIFI, stocks' momentum loading, moments of stocks' past returns, and slope coefficients of base and extended models. BHR6M$_{-1,-6}$ is the cumulative returns from month $t-6$ to month $t-1$. PIFI is the price inefficiency regarding firm-specific information calculated using equation 4. β_{UMD} is the slope coefficient of the regression $r_{i,t} = \alpha_i + \beta_{UMD(i,t)}\, UMD_t + \epsilon_{i,t}$, where UMD is the Carhart momentum factor obtained from Kenneth French's website. Return Variance, Skewness, and Kurtosis are calculated using daily returns on a rolling 12-month window basis. And, β^1 through β^6 used to calculate PIFI come from the extended model (equation 3). The sample period runs from January 1966 through December 2016. All variables are defined in Appendix A. The price filter used is $1.

	BHR6M$_{-1,-6}$	PIFI	β_UMD	RetVar	RetSkew	RetKurt	β^1	β^2	β^3	β^4	β^5	β^6
BHR6M$_{-1,-6}$	1.000											
PIFI	0.003	1.000										
β_UMD	0.112	0.004	1.000									
RetVar	0.097	0.009	-0.035	1.000								
RetSkew	0.185	-0.008	0.023	0.272	1.000							
RetKurt	0.044	0.020	-0.004	0.319	0.440	1.000						
β^1	0.019	0.152	-0.001	0.016	-0.008	0.031	1.000					
β^2	0.018	0.063	-0.004	0.002	-0.016	0.005	0.186	1.000				
β^3	0.012	0.016	-0.011	0.001	-0.017	0.000	0.160	0.190	1.000			
β^4	0.005	-0.024	0.003	0.006	-0.004	0.000	0.072	0.164	0.162	1.000		
β^5	0.008	-0.035	0.004	0.009	-0.004	-0.002	0.110	0.063	0.119	0.174	1.000	
β^6	0.002	-0.059	0.011	-0.002	-0.004	-0.005	0.025	0.065	0.035	0.122	0.157	1.000

Table III:
Momentum (6/6) and Price Inefficiency wrt Firm-Specific Information (PIFI)

This table shows the results of Fama-MacBeth cross-sectional regressions of future six-month buy-and-hold returns ($BHR6M_{0,5}$) on past six-month buy and hold returns ($BHR6M_{-1,-6}$) after controlling for well-known empirical regularities, the price inefficiency measure of Hou and Moskowitz (2005), and PIFI and its interactions with the past six-month buy and hold returns. The primary independent variable $BHR6M_{-1,-6}$ is the buy and hold returns from month $t-1$ to month $t-6$, whereas dependent variable $BHR6M_{0,5}$ is the buy and hold returns from t to $t+5$. To avoid having negative values, $BHR6M_{-1,-6}$ is adjusted to 1 minus $BHR6M_{-1,-6}$. $BHR6M_{-1,-6}$, PIFI and their interaction term are standardized to have σ of 1 for easy interpretation. PIFI is the price inefficiency wrt firm-specific information as defined by equation 4, and D3_HM is the semi-strong form price inefficiency measure of Hou and Moskowitz (2005) as defined by equation 1. The sample period runs from January 1967 through December 2020, and the price filter used is $1 (The price filter of $5 also produces similar results.). All variables are defined in Appendix A. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively. Standard errors are Newey adjusted with six lags.

	(1)	(2)	(3)	(4)	(5)	(6)
$BHR6M_{-1,-6}$	1.926***	1.727***	1.736***	2.652***	1.729***	0.616
	(3.834)	(3.876)	(3.900)	(4.720)	(3.884)	(0.972)
$LMCAP_{-12}$		-0.351	-0.368	-0.363	-0.352	-0.352
		(-1.621)	(-1.633)	(-1.620)	(-1.628)	(-1.630)
LBM_{-12}		0.840**	0.834**	0.846**	0.835**	0.837**
		(2.162)	(2.174)	(2.213)	(2.152)	(2.159)
AG_{-12}		-4.884***	-4.908***	-4.927***	-4.888***	-4.892***
		(-8.830)	(-9.007)	(-9.041)	(-8.845)	(-8.867)
ROA_{-12}		5.745***	5.727***	5.719***	5.734***	5.722***
		(3.429)	(3.451)	(3.425)	(3.422)	(3.410)
$D3\_HM_{-1}$			-0.191	3.708***		
			(-0.373)	(3.584)		
$D3\_HM_{-1}$ x $BHR6M_{-1,-6}$				-3.373***		
				(-3.793)		
$PIFI_{-1}$					-0.069	-0.546***
					(-1.112)	(-3.020)
$PIFI_{-1}$ x $BHR6M_{-1,-6}$						1.235***
						(2.646)
Constant	6.750***	9.038***	9.029***	8.911***	9.044***	9.061***
	(5.395)	(4.118)	(3.797)	(3.762)	(4.118)	(4.128)
Months	648	648	648	648	648	648
Observations	1,788,942	1,788,942	1,788,942	1,788,942	1,788,942	1,788,942

Table IV:
Price Inefficiency regarding Firm-specific Information (PIFI) and High-52, Abnormal-Return, Residual-Return Momentum Strategies

This table shows the results of Fama-MacBeth cross-sectional regressions of future six-month buy-and-hold returns ($BHR6M_{0,5}$) on various past return information measures after controlling for well-known empirical regularities, and PIFI and its interactions with the past return information measure based on which the particular momentum strategy is formed. Dependent variable $BHR6M_{0,5}$ is the buy and hold returns from t to $t+5$. PIFI is the price inefficiency wrt firm-specific information as defined by equation 4. *High_52* is the maximum price of a stock from month $t-12$ to $t-1$ divided by the price in month $t-1$ (George and Hwang (2004)). *FF3_α* is the intercept of the time series regression of a firm's monthly returns from the month $t-12$ to month $t-2$ on Fama-French three factors (Grundy and Martin (2001)). And, *RRet* is the past six-month cumulative residual returns of the Fama-French three-factor model where the regression is estimated using a 36-month rolling window (Blitz et al. (2011)). The sample period runs from January 1967 through December 2020, and the price filter used is $1 (The price filter of $5 also produces similar results.). All variables are defined in Appendix A. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively. Standard errors are Newey adjusted with six lags.

	(1)	(2)	(3)	(4)	(5)	(6)
$High\_52_{-1}$	8.418***	3.897				
	(4.901)	(1.445)				
$FF3\alpha_{-1}$			23.471***	9.424		
			(6.478)	(1.302)		
$RRet_{-1,-6}$					3.104***	0.391
					(3.729)	(0.303)
$PIFI_{-1}$		-2.606**		-0.305		-0.270
		(-2.484)		(-1.232)		(-1.013)
$PIFI_{-1}$ x $High\_52_{-1}$		3.388**				
		(2.528)				
$PIFI_{-1}$ x $FF3\alpha_{-1}$				10.474**		
				(2.166)		
$PIFI_{-1}$ x $RRret_{-1}$						2.054***
						(2.879)
Controls	YES	YES	YES	YES	YES	YES
Constant	2.667	6.154*	9.190***	9.618***	8.793***	9.165***
	(0.911)	(1.823)	(4.046)	(4.540)	(3.913)	(4.429)
Months	645	645	645	645	645	645
Observations	1,789,726	1,789,726	1,786,045	1,786,045	1,786,045	1,786,045

Table V:
All Anomalies

This table shows the slope coefficient, β , and its t-stat from the Fama-MacBeth cross-sectional regression $ret_{i,t} = \alpha + \beta\, AVar_{i,t-1} + \sum_{i=1}^{5} \gamma_i\, X_{i,t-n} + \epsilon$ in Columns (1) and (2) and the regression $ret_{i,t} = \alpha + \beta\, AVar_{i,t-1} + \gamma_1\, PIFI_{i,t-1} + \gamma_2\, PIFI_{i,t-1} * AVar_{i,t-1} + \sum_{i=3}^{8} \gamma_i\, X_{i,t-n} + \epsilon_i$ in Columns (3) and (4). $AVar_{i,t-1}$ is one of the 201 anomaly variables provided by Chen and Zimmermann (2022) and $X_{i,t-n}$ are lagged control variables MCAP, BM, Asset Growth, ROA, and D3_HM. n is 1 for D3_HM and 12 for the rest. The sample period runs from January 1967 through December 2020, and the price filter used is $1. All variables are defined in Appendix A. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively. Results show that controlling for PIFI and its interaction terms with the anomaly variable subsumes the return predictability of the anomaly variable for the majority of asset-market anomalies.

	Without PIFI Interaction		With PIFI Interaction	
Anomaly Description	β (1)	t-stat (2)	β (3)	t-stat (4)
Abnormal Accruals	-0.012	(-8.027)***	-0.008	(-0.983)
Accruals	-0.013	(-6.516)***	-0.011	(-1.470)
EPS forecast revision	0.001	(2.146)**	0.003	(1.025)
Tail risk beta	0.002	(1.762)*	0.002	(0.682)
Systematic volatility	-0.090	(-2.389)**	0.063	(0.439)
Cash to assets	0.015	(5.452)***	-0.011	(-1.109)
Cash-based operating profitability	0.012	(8.472)***	0.007	(1.172)
Operating Cash flows to price	0.003	(2.994)***	0.004	(0.828)
Change in recommendation	0.002	(6.752)***	0.001	(0.562)
Growth in book equity	-0.001	(-2.47)**	-0.001	(-0.866)
Change in Forecast and Accrual	0.008	(11.47)***	0.004	(1.641)
Inventory Growth	-0.021	(-6.51)***	-0.006	(-0.443)
Change in capital inv (ind adj)	0.001	(-4.831)***	0.001	(0.397)
Decline in Analyst Coverage	-0.015	(-1.746)*	0.044	(0.800)
Change in Net Noncurrent Op Assets	-0.006	(-4.178)***	0.006	(0.803)
Change in Net Working Capital	-0.007	(-3.447)***	-0.003	(-0.265)
Citations to RD expenses	0.002	(2.415)**	0.005	(1.477)
Composite debt issuance	0.001	(-2.408)**	0.001	(0.354)
Consensus Recommendation	-0.010	(-5.785)***	0.001	(0.064)
Convertible debt indicator	-0.002	(-4.104)***	-0.001	(-0.842)
Coskewness using daily returns	-0.004	(-2.107)**	-0.005	(-1.080)
Customer momentum	0.030	(4.312)***	-0.027	(-0.456)
Debt Issuance	-0.002	(-3.437)***	-0.001	(-1.166)

Table V:
All Anomalies Continued...

Anomaly Description	Without PIFI Interaction		With PIFI Interaction	
	β (1)	t-stat (2)	β (3)	t-stat (4)
Breadth of ownership	0.001	(2.767)***	0.001	(0.111)
Change in current operating assets	-0.012	(-6.137)***	-0.012	(-1.609)
Change in current operating liabilities	-0.006	(-2.456)**	-0.012	(-1.057)
Change in equity to assets	-0.008	(-4.273)***	-0.009	(-1.254)
Change in financial liabilities	-0.011	(-7.05)***	-0.008	(-1.526)
Change in net financial assets	0.007	(6.308)***	0.004	(0.750)
Dividend Omission	-0.007	(-3.564)***	0.023	(1.423)
Down forecast EPS	-0.003	(-5.306)***	-0.001	(-0.403)
Long-vs-short EPS forecasts	0.001	(-1.9)*	0.001	(-0.477)
Earnings surprise streak	0.038	(3.882)***	0.027	(0.543)
Enterprise component of BM	0.001	(1.853)*	0.001	(0.127)
Equity Duration	0.001	(-4.446)***	0.001	(-0.834)
Exchange Switch	-0.006	(-4.259)***	-0.021	(-0.487)
Analyst earnings per share	0.001	(3.121)***	0.001	(1.626)
Firm Age - Momentum	0.02	(7.062)***	0.001	(-0.007)
gross profits / total assets	0.003	(2.274)**	0.003	(1.039)
Change in capex (two years)	0.001	(-3.906)***	0.001	(1.285)
Change in capex (three years)	0.001	(-5.106)***	-0.001	(-1.505)
Sales growth over inventory growth	0.001	(2.562)**	0.001	(0.966)
Industry concentration (sales)	-0.002	(-2.402)**	-0.001	(-0.469)
Industry concentration (assets)	-0.002	(-2.275)**	0.001	(-0.151)
Employment growth	-0.003	(-4.164)***	-0.002	(-0.559)
Idiosyncratic risk	-0.234	(-8.213)***	-0.089	(-1.528)
Idiosyncratic risk (3 factor)	-0.265	(-7.943)***	-0.100	(-1.475)
Idiosyncratic risk (AHT)	-0.148	(-2.911)***	-0.055	(-0.717)
Amihud's illiquidity	245.349	(5.189)***	219.313	(1.279)
Industry Momentum	0.024	(5.736)***	0.008	(1.042)
Intermediate Momentum	0.005	(4.147)***	0.002	(0.714)
Investment to revenue	-0.002	(-7.211)***	-0.002	(-1.344)
change in ppe and inv/assets	-0.006	(-6.758)***	-0.005	(-1.422)

Table V:
All Anomalies Continued...

Anomaly Description	Without PIFI Interaction		With PIFI Interaction	
	β (1)	t-stat (2)	β (3)	t-stat (4)
Inventory Growth	-0.001	(-6.24)***	-0.001	(-0.865)
Customers momentum	0.005	(3.167)***	0.003	(0.721)
Suppliers momentum	0.005	(3.135)***	0.008	(1.590)
Revenue Growth Rank	0.001	(2.161)**	0.001	(0.117)
Junk Stock Momentum	0.006	(2.701)***	0.006	(1.340)
Momentum (12 month)	0.007	(5.005)***	0.003	(1.527)
Momentum without the seasonal part	0.072	(5.389)***	0.027	(1.116)
Off season reversal years 16 to 20	-0.034	(-1.793)*	-0.028	(-0.377)
Return seasonality years 6 to 10	0.014	(5.076)***	0.015	(1.311)
Return seasonality years 11 to 15	0.009	(2.693)***	0.007	(0.590)
Return seasonality years 16 to 20	0.010	(2.605)***	-0.004	(-0.244)
Return seasonality last year	0.009	(4.259)***	0.010	(1.547)
Momentum in high volume stocks	0.001	(2.916)***	0.001	(1.055)
Mohanram G-score	0.001	(4.717)***	-0.001	(-0.438)
Net debt financing	-0.012	(-6.363)***	-0.009	(-1.096)
Net debt to price	-0.001	(-2.375)**	0.001	(0.609)
Earnings streak length	0.001	(8.694)***	0.001	(1.324)
Change in order backlog	0.002	(1.849)*	0.003	(0.567)
Organizational capital	0.002	(7.501)***	0.002	(1.484)
Patents to RD expenses	0.001	(2.897)***	0.002	(1.057)
Probability of Informed Trading	0.041	(4.309)***	0.019	(0.437)
Piotroski F-score	0.001	(2.998)***	0.001	(-0.229)
R&D over market cap	0.034	(5.355)***	0.021	(0.854)
IPO and no R&D spending	-0.005	(-3.333)***	0.029	(1.105)
Real estate holdings	0.003	(2.415)**	0.010	(1.643)
Analyst Recommendations and Short-Interest	0.007	(2.821)***	0.007	(0.663)
Earnings forecast revisions	0.043	(3.701)***	-0.088	(-1.129)
Revenue Surprise	0.001	(6.488)***	0.001	(0.436)
Inst Own and Forecast Dispersion	0.002	(4.618)***	0.002	(1.448)
Inst Own and Market to Book	0.003	(6.894)***	0.001	(0.654)

Table V:
All Anomalies Continued...

Anomaly Description	Without PIFI Interaction		With PIFI Interaction	
	β (1)	t-stat (2)	β (3)	t-stat (4)
Inst Own and Turnover	0.003	(5.105)***	0.002	(1.227)
Inst Own and Idio Vol	0.003	(6.243)***	0.001	(-0.170)
Share issuance (1 year)	-0.001	(-3.437)***	-0.001	(-0.612)
Share repurchases	0.002	(3.764)***	0.001	(1.264)
Share Volume	-0.003	(-1.867)*	0.001	(-0.003)
Short Interest	0.001	(-4.495)***	0.001	(0.310)
Volatility smirk near the money	-0.022	(-4.041)***	-0.017	(-0.686)
Put volatility minus call volatility	-0.037	(-10.193)***	-0.017	(-0.974)
Spinoffs	0.006	(3.515)***	0.012	(0.346)
Unexpected R&D increase	0.001	(2.716)***	-0.003	(-1.483)
Tangibility	0.010	(5.206)***	0.010	(1.545)
Total accruals	-0.003	(-3.385)***	-0.004	(-0.821)
Up Forecast	0.003	(5.898)***	0.002	(0.681)
Volume to market equity	-0.025	(-3.547)***	-0.025	(-1.305)
Volume Variance	-0.003	(-1.848)*	-0.001	(-0.447)
Net external financing	-0.007	(-4.366)***	-0.011	(-1.617)
change in net operating assets	-0.006	(-7.743)***	-0.004	(-1.678)*
Momentum and LT Reversal	0.013	(6.169)***	0.011	(1.852)*
Operating leverage	0.001	(4.591)***	0.001	(1.894)*
Medium-run reversal	-0.005	(-4.867)***	-0.005	(-1.749)*
Off season reversal years 6 to 10	-0.039	(-3.228)***	-0.067	(-1.688)*
Earnings surprise of big firms	0.002	(3.26)***	0.003	(1.768)*
Intangible return using Sale2P	-0.001	(-2.644)***	-0.001	(-1.924)*
Asset growth	-0.005	(-7.691)***	-0.005	(-2.543)**
Dividend seasonality	0.002	(9.925)***	0.003	(2.428)**
Maximum return over month	-0.083	(-12.064)***	-0.045	(-2.572)**
Net equity financing	-0.017	(-6.159)***	-0.026	(-2.189)**
Conglomerate return	0.077	(7.227)***	0.095	(2.394)**
Return on assets (qtrly)	0.078	(4.728)***	0.082	(2.005)**
Coskewness	-0.004	(-3.954)***	-0.006	(-2.202)**

Table V:
All Anomalies Continued...

Anomaly Description	Without PIFI Interaction		With PIFI Interaction	
	β (1)	t-stat (2)	β (3)	t-stat (4)
Idiosyncratic skewness (3F model)	-0.002	(-7.169)***	-0.002	(-2.604)***
Return skewness	-0.002	(-9.223)***	-0.002	(-2.862)***
Days with zero trades	0.001	(4.061)***	0.002	(3.038)***
Volume Trend	-0.090	(-5.431)***	-0.111	(-2.918)***
Book-to-market and accruals	0.017	(5.799)***	0.026	(3.768)***
Total assets to market	0.001	(2.684)***	0.001	(2.63)***
Earnings announcement return	0.044	(18.056)***	0.031	(3.151)***
Off season long-term reversal	-0.123	(-8.26)***	-0.111	(-2.894)***
Book to market using most recent ME	0.004	(4.545)***	0.006	(4.851)***
Change in Taxes	0.112	(10.255)***	0.134	(3.164)***
Composite equity issuance	-0.001	(-3.319)***	-0.002	(-2.495)**
Past trading volume	-0.001	(-3.08)***	-0.002	(-3.443)***
Earnings Surprise	0.001	(8.659)***	0.001	(3.426)***
Efficient frontier index	0.004	(4.574)***	0.006	(3.147)***
Growth in long term operating assets	0.006	(3.726)***	0.016	(2.339)**
Days with zero trades(Alt1)	0.001	(3.137)***	0.001	(2.036)**
Industry return of big firms	0.136	(11.709)***	0.174	(6.082)***
Intangible return using BM	-0.003	(-3.588)***	-0.005	(-2.838)***
Long-run reversal	-0.002	(-4.351)***	-0.002	(-2.058)**
Return seasonality years 2 to 5	0.010	(3.425)***	0.029	(2.659)***
Net Payout Yield	0.009	(1.859)*	0.033	(1.886)*
Net Operating Assets	-0.004	(-6.908)***	-0.005	(-2.54)**
Sales-to-price	0.001	(3.961)***	0.001	(3.894)***
Share turnover volatility	-0.044	(-4.034)***	-0.125	(-3.085)***
Trend Factor	0.480	(10.979)***	0.702	(6.021)***
Days with zero trades (Alt12)	0.001	(5.192)***	0.002	(3.188)***
Predicted div yield next month	0.001	(9.368)***	0.002	(2.968)***

Table VI:
Price Inefficiency wrt Firm-Specific Information (PIFI) and Several Other Momentum Strategies

This table shows the results of Fama-MacBeth cross-sectional regressions of future buy-and-hold returns on past buy-and-hold returns controlling for well-known empirical regularities, the price inefficiency measure of HM, and PIFI and its interaction with past buy-and-hold returns. Dependent variables, $BHR3M_{0,2}$, $BHR6M_{0,5}$, and $BHR12M_{0,11}$ are 3-month, 6-month, and 12-month buy and hold returns, respectively, starting from month t. Likewise, the independent variables $BHR3M_{-1,-3}$, $BHR6M_{-1,-6}$ and $BHR12M_{-1,-12}$ are buy-and-hold returns going back 3, 6, and 12 months, respectively, starting from month $t-1$. PIFI is the price inefficiency wrt firm-specific information as defined by equation 4. D3_HM is the semi-strong form price inefficiency measure of Hou and Moskowitz (2005) as defined by equation 1. The sample period runs from January 1967 through December 2020, and the price filter used is $1. All variables are defined in Appendix A. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively. Standard errors are Newey adjusted with six lags.

	3/6	12/6	3/3	6/3	12/3	3/12	6/12	12/12
	$BHR3M_{0,2}$ (1)	$BHR12M_{0,11}$ (2)	$BHR3M_{0,2}$ (3)	$BHR6M_{0,5}$ (4)	$BHR12M_{0,11}$ (5)	$BHR3M_{0,2}$ (6)	$BHR6M_{0,5}$ (7)	$BHR12M_{0,11}$ (8)
$BHR6M_{-1,-6}$	-0.306	0.677						
	(-0.890)	(0.614)						
$BHR3M_{-1,-3}$			-0.084	0.503	1.398**			
			(-0.431)	(1.409)	(2.201)			
$BHR12M_{-1,-12}$						0.360	0.340	-0.693
						(0.830)	(0.396)	(-0.487)
$LMCAP_{-12}$	-0.168	-0.917**	-0.159	-0.366	-0.899**	-0.181	-0.396*	-0.928**
	(-1.424)	(-2.315)	(-1.318)	(-1.608)	(-2.270)	(-1.526)	(-1.725)	(-2.302)
LBM_{-12}	0.321	2.131***	0.313	0.791**	2.073***	0.414**	0.941***	2.111***
	(1.540)	(3.362)	(1.485)	(2.001)	(3.162)	(2.112)	(2.612)	(3.392)
AG_{-12}	-2.265***	-9.727***	-2.304***	-4.956***	-9.697***	-2.431***	-5.179***	-9.893***
	(-7.360)	(-10.468)	(-7.349)	(-8.975)	(-10.541)	(-8.000)	(-9.482)	(-10.572)
ROA_{-12}	3.463***	10.250***	3.634***	5.906***	10.453***	3.155***	5.473***	10.383***
	(3.848)	(3.274)	(3.971)	(3.528)	(3.370)	(3.491)	(3.257)	(3.239)
$D3\_HM_{-1}$	-0.072	-0.213	-0.014	-0.113	-0.148	-0.124	-0.225	-0.231
	(-0.266)	(-0.246)	(-0.052)	(-0.220)	(-0.171)	(-0.468)	(-0.449)	(-0.265)
$PIFI_{-1}$	-0.460***	-0.827**	-0.300***	-0.431***	-0.584***	-0.253***	-0.412***	-0.624***
	(-4.051)	(-2.562)	(-3.797)	(-3.257)	(-2.719)	(-3.886)	(-3.935)	(-3.117)
$PIFI_{-1}$ x $BHR6M_{-1,-6}$	1.094***	1.734**						
	(3.858)	(2.049)						
$PIFI_{-1}$ x $BHR3M_{-1,-3}$			0.423***	0.601***	0.767**			
			(3.246)	(2.607)	(2.139)			
$PIFI_{-1}$ x $BHR12M_{-1,-12}$						0.776***	1.422***	2.186***
						(3.040)	(3.203)	(2.808)
Constant	4.243***	20.033***	4.187***	9.046***	19.956***	4.448***	9.286***	19.953***
	(3.388)	(4.994)	(3.246)	(3.736)	(4.970)	(3.550)	(3.875)	(4.944)
Months	645	645	645	645	645			

Table VII: PIFI, Auto-correlation Coefficients, and Momentum

This table shows the results of Fama-MacBeth cross-sectional regressions of future six-month buy and hold returns ($BHR6M_{0,5}$) on past six-month buy and hold returns ($BHR6M_{-1,-6}$) controlling for usual empirical regularities, stocks' monthly autocorrelation coefficients from equations 2 and 3, PIFI, and their interactions with the past six-month buy and hold returns. Both γ_i^1 (equation 2) and β (Equation 3) coefficients are obtained using 60-month rolling window regressions. The independent variable $BHR6M_{-1,-6}$ is the past buy and hold returns from month $t-1$ to month $t-6$. PIFI is the price inefficiency wrt firm-specific information as defined by equation 4. The sample period runs from January 1967 through December 2020, and the price filter used is $1. All variables are defined in Appendix A. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively. Standard errors are Newey adjusted with six lags.

	BHR6M_0, 5 (1)	BHR6M_0, 5 (2)	BHR6M_0, 5 (3)	BHR6M_0, 5 (4)	BHR6M_0, 5 (5)	BHR6M_0, 5 (6)
$BHR6M_{-1,-6}$	1.734***	0.608	1.735***	0.626	1.719***	0.678
	(3.900)	(0.975)	(3.898)	(1.001)	(3.863)	(1.093)
$LMCAP_{-12}$	-0.375*	-0.375*	-0.373*	-0.372*	-0.375*	-0.375*
	(-1.667)	(-1.667)	(-1.653)	(-1.653)	(-1.671)	(-1.673)
LBM_{-12}	0.817**	0.820**	0.824**	0.825**	0.819**	0.821**
	(2.136)	(2.146)	(2.151)	(2.157)	(2.142)	(2.151)
AG_{-12}	-4.875***	-4.883***	-4.893***	-4.903***	-4.880***	-4.887***
	(-8.995)	(-9.013)	(-9.055)	(-9.077)	(-9.107)	(-9.121)
ROA_{-12}	5.667***	5.666***	5.698***	5.685***	5.753***	5.754***
	(3.413)	(3.415)	(3.430)	(3.425)	(3.452)	(3.453)
$D3\_HM_{-1}$	-0.196	-0.190	-0.185	-0.182	-0.181	-0.177
	(-0.387)	(-0.377)	(-0.365)	(-0.360)	(-0.360)	(-0.352)
γ^1_{-1}	-1.381***	-1.456***			-0.932	-0.986
	(-2.916)	(-3.160)			(-1.392)	(-1.495)
β^1_{-1}			-0.927***	-0.930***	-0.391	-0.393
			(-2.726)	(-2.903)	(-0.881)	(-0.888)
β^2_{-1}					-0.018	-0.012
					(-0.062)	(-0.042)
β^3_{-1}					-0.299	-0.288
					(-1.163)	(-1.114)
β^4_{-1}					-0.892***	-0.905***
					(-3.857)	(-3.905)
β^5_{-1}					-0.206	-0.201
					(-0.772)	(-0.749)
β^6_{-1}					0.009	0.043
					(0.032)	(0.147)
$PIFI_{-1}$		-0.458**		-0.486***		-0.430**
		(-2.548)		(-2.704)		(-2.394)
$PIFI_{-1}$ x $BHR6M_{-1,-6}$		1.250***		1.233***		1.159**
		(2.726)		(2.688)		(2.545)
Constant	8.926***	8.932***	8.945***	8.960***	8.862***	8.869***
	(3.706)	(3.716)	(3.721)	(3.735)	(3.679)	(3.690)
Months	645	645	645	645	645	645

Table VIII:
Other Explanations for Momentum and PIFI

This table shows the replications of the main result (Column 6 of Table III) after controlling various explanations of momentum put together by the literature. Many researchers, including Jegadeesh and Titman (e.g., Jegadeesh and Titman (1993), Hong and Stein (1999)), suggest that momentum profits are due to underreaction to firm-specific information. One proxy finance literature uses for firm-specific information is a firm's idiosyncratic volatility (IVOL). Chordia et al. (2014) show that momentum profits are sensitive to trading costs. I use bid-ask spread as a proxy for trading costs. Hong et al. (2000) find that within a size group, momentum strategies work better among stocks with low analyst coverage. Avramov et al. (2007) show that momentum profits are stronger in more distressed companies. I use leverage as a proxy for the financial distress of the firms. PIII is price inefficiency wrt industry-specific information to address the findings of Moskowitz and Grinblatt (1999), which document a strong momentum effect in the industry component of stock returns. I use the Illiquidity measure of Amihud (2002) to control for the findings of Sadka (2006), which shows that about half of the time-variation in momentum profits can be explained by the liquidity risk exposure. And, I control for standardized unexpected earnings (SUE), turnover, and information discreteness (ID) measures to address the findings of Chordia and Shivakumar (2006), Lee and Swaminathan (2000), and Da et al. (2014), respectively. The sample period runs from January 1967 through December 2020, and the price filter used is $1. All variables are defined in Appendix A. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively. Standard errors are Newey adjusted with six lags.

Panel A: Other Explanations for Momentum II

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$BHR6M_{-1,-6}$	1.783***	0.666	1.879***	0.784	1.744***	0.637	1.752***	0.638
	(4.033)	(1.044)	(4.494)	(1.301)	(3.952)	(1.018)	(3.916)	(1.010)
$IVOL_{-1}$	-742.738***	-739.263***						
	(-5.005)	(-5.018)						
$BASpread_{-1}$			-2.898***	-2.897***				
			(-2.672)	(-2.687)				
$AnlstCount_{-1}$					0.258	0.261		
					(1.158)	(1.173)		
$Leverage_{-12}$							-0.629	-0.626
							(-0.977)	(-0.974)
$PIFI_{-1}$		-0.544***		-0.535***		-0.548***		-0.529***
		(-3.075)		(-3.039)		(-3.072)		(-2.979)
$PIFI_{-1}$ x $BHR6M_{-1,-6}$		1.240***		1.220***		1.230***		1.232***
		(2.678)		(2.678)		(2.649)		(2.635)
Constant	9.113***	9.131***	9.309***	9.331***	9.052***	9.071***	9.200***	9.230***
	(4.202)	(4.208)	(4.104)	(4.114)	(3.785)	(3.796)	(3.893)	(3.906)
Months	645	645	645	645	645	645	645	645

Table VIII:
Other Explanations for Momentum and PIFI Contd...

Panel B: Other Explanations for Momentum I

	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
BHR6M_−1, −6	2.069**	0.941	1.756***	0.547	1.375***	0.453	2.065***	0.944	1.711***	0.591
	(2.378)	(0.940)	(3.903)	(0.855)	(3.043)	(0.689)	(4.583)	(1.500)	(3.965)	(0.962)
PEII_{-1}	0.464	0.471								
	(0.837)	(0.852)								
PEII_{-1} x $\text{BHR6M}_{-1,-6}$	-0.247	-0.253								
	(-0.435)	(-0.450)								
AhILLIQ_{-1}			9.7e+04***	9.7e+04***						
			(3.658)	(3.656)						
SUE_{-3}					2.096***	2.094***				
					(25.771)	(25.877)				
Turnover_{-1}							-12.489***	-12.645***		
							(-4.975)	(-5.075)		
ID_{-2}									-2.162	-2.207
									(-1.160)	(-1.186)
PIFI_−1		-0.548***		-0.593***		-0.457**		-0.525***		-0.550***
		(-3.073)		(-3.333)		(-2.529)		(-2.930)		(-3.085)
PIFI_−1 x $\text{BHR6M}_{-1,-6}$		1.249***		1.345***		1.026**		1.244***		1.245***
		(2.707)		(2.887)		(2.159)		(2.710)		(2.692)
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	
Constant	8.606***	8.624***	7.363***	7.380***	9.018***	9.030***	9.566***	9.591***	9.010***	9.028***
	(3.271)	(3.274)	(3.287)	(3.297)	(3.779)	(3.787)	(4.170)	(4.178)	(3.842)	(3.852)
Months	645	645	634	634	645	645	643	643	645	645

Table IX:
Momentum (6/6), Fama-French Five and Q5 Factors, and PIFI

This table shows the results of Fama-MacBeth cross-sectional regressions of future six-month buy and hold returns ($BHR6M_{0,5}$) on past six-month buy and hold returns ($BHR6M_{-1,-6}$) after controlling for well-known empirical regularities, Fama-French five and Q5 factors, price inefficiency measure of HM, and PIFI and its interactions with the past six-month buy and hold returns. Dependent variable ($BHR6M_{0,5}$) is buy-and-hold returns from month t to month $t+5$. The sample period runs from January 1967 through December 2020, and the price filter used is $1. All variables are defined in Appendix A. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively. Standard errors are Newey adjusted with six lags.

	(1)	(2)	(3)	(4)
$BHR6M_{-1,-6}$	1.725***	1.725***	1.725***	0.596
	(3.861)	(3.861)	(3.861)	(0.944)
$LMCAP_{-12}$	-0.348	-0.348	-0.348	-0.366
	(-1.607)	(-1.607)	(-1.607)	(-1.625)
LBM_{-12}	0.826**	0.826**	0.826**	0.817**
	(2.127)	(2.127)	(2.127)	(2.137)
AG_{-12}	-4.878***	-4.878***	-4.878***	-4.909***
	(-8.784)	(-8.784)	(-8.784)	(-8.985)
ROA_{-12}	5.747***	5.747***	5.747***	5.702***
	(3.426)	(3.426)	(3.426)	(3.428)
MKTRF	0.792***	0.374**	0.852***	0.911***
	(3.795)	(2.556)	(5.534)	(5.433)
SMB	0.634***		0.239**	0.235*
	(2.967)		(2.118)	(1.940)
HML	0.053		-0.002	-0.011
	(0.395)		(-0.017)	(-0.108)
RMW	-0.092		-0.026	-0.034
	(-0.888)		(-0.620)	(-0.709)
CMA	0.024		0.098	0.105
	(0.182)		(0.824)	(0.818)
Q5_MKT		0.419***		
		(3.926)		
Q5_MER		0.463***	0.206**	0.211*
		(3.111)	(2.081)	(1.918)
Q5_IA		0.191*	0.083	0.061
		(1.805)	(1.514)	(1.292)
Q5_ROE		-0.088	-0.002	0.006
		(-0.696)	(-0.014)	(0.051)
Q5_EG		0.109	0.125	0.120
		(0.933)	(1.391)	(1.264)
$D3\_HM_{-1}$				-0.181
				(-0.357)
$PIFI_{-1}$				-0.557***
				(-3.118)
$PIFI_{-1}$ x $BHR6M_{-1,-6}$				1.264***
				(2.722)
Constant	0.033	0.108	-0.010	-0.014
	(0.463)	(0.877)	(-0.240)	(-0.313)
Months	645	645	645	645

Table X:
PIFI and News Production

This table shows the results of Fama-MacBeth cross-sectional regressions of PIFI on the firms' various measures of news production. The dependent variable, PIFI, is the price inefficiency regarding firm-specific information as defined by equation 4. Each news variable is a natural logarithm of relevancy weighted news count averaged over the months $t-7$ to $t-1$. Due to the availability of Ravenpack News Data, the sample period runs from January 2001 through December 2020, and the price filter used is $1. All variables are defined in Appendix A. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively. Standard errors are Newey adjusted with six lags.

	PIFI	PIFI	PIFI	PIFI	PIFI	PIFI
Stock Price News$_{-1,-7}$	0.966***					0.940***
	(12.383)					(8.330)
Products & Services News$_{-1,-7}$		0.763***				0.388***
		(15.108)				(5.380)
Earnings & Revenues News$_{-1,-7}$			1.219***			0.387*
			(9.633)			(1.804)
Other News$_{-1,-7}$				0.668***		-0.705***
				(6.750)		(-3.988)
All Relevant News$_{-1,-7}$					0.743***	
					(6.488)	
Constant	135.841***	136.089***	132.220***	134.104***	132.960***	136.670***
	(713.245)	(603.445)	(459.969)	(593.225)	(327.971)	(253.664)
Months	240	240	240	240	240	240
Observations	392,420	362,515	455,626	487,616	508,522	322,591

Table XI:
PIFI and Level and Variance of Profitability

This table shows the results of Fama-MacBeth cross-sectional regressions of PIFI on various measures of level and variance of profitability. Cross-sectional regression takes the form $PIFI_t = \alpha + \beta\ Variable_t\ + \epsilon$, where the variable can be any of the twelve variables presented in the table. PIFI is the price inefficiency wrt firm-specific information as defined by equation 4. The results show that high PIFI firms have relatively lower profitability but higher uncertainty around profitability. The higher PIFI firms have a very low payout ratio, and dividends make up a smaller percentage of returns. Results are consistent with Pástor and Pietro (2003) that lower dividend payers have higher uncertainty around profitability. The sample period runs from January 1967 through December 2020, and the price filter used is $1. All variables are defined in Appendix A. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Panel A: Profitability

	O_MARGIN (1)	NI_MARGIN (2)	G_MARGIN (3)	EBITA_MARGIN (4)	ROA (5)
β	-.0222	-.0212	-.0014	-.0054	-.0097
T Stat	-10.096***	-8.9991***	-2.041**	-4.3429***	-2.7425***
R^2 Adjusted	.0005	.0006	.0008	.0003	.0005

Panel B: Payouts & Variance of Profitability

	Payouts		Profitability Variance				
	PAYOUT_RATIO (1)	DIV_RET (2)	SD_OM (3)	SD_NIM (4)	SD_GPM (5)	SD_EBITA (6)	SD_SALES (7)
β	-.0174	-1.9702	.005	.0085	.0023	.004	.0135
T Stat	-16.8991***	-28.2027***	7.2608***	6.2974***	1.342	3.3007***	21.3275***
R^2 Adjusted	.0005	.0015	0	.0001	-.0005	.0001	.0003

Table XII:
PIFI, Information Uncertainty, Limits of Arbitrage, and Opaqueness

This table shows the results of Fama-MacBeth cross-sectional regressions of PIFI on various firm characteristics measures of information uncertainty, limits of arbitrage, firm opaqueness, and institutional holdings variables. Cross-sectional regression takes the form $PIFI_t = \alpha + \beta \; Variable_t + \epsilon$, where the variable can be any of the sixteen variables presented in the tables. PIFI is the price inefficiency wrt firm-specific information as defined by equation 4. The results show that high PIFI firms are slightly bigger, younger firms with lower analyst counts, higher dispersion among analysts on their future forecast, higher turnover, equity duration, cash flow volatility, and overall volatility. The higher PIFI firms have lower limits of arbitrage; they are more opaque and more held by institutions. Results show that high-PIFI firms have a higher information uncertainty and lower limits of arbitrage. The sample period runs from January 1967 through December 2020, and the price filter used is $1. All variables are defined in Appendix A. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Panel C: Information Uncertainty Variables of Zhang (2006) & Jiang et al. (2005)

	Information Uncertainty							
	RES_MV (1)	RES_AGE (2)	RES_ACOUNT (3)	ADISP (4)	TURNOVER (5)	EQ_DURATION (6)	CF_SD (7)	VOLATILITY (8)
β	-2.7874	1.1952***	.0225***	.0276***	.0058***	.0041***	.0791***	.4407***
T Stat	-.5718	26.4402	2.6206	11.23	22.4368	7.2394	28.0302	27.2714
R^2 Adjusted	.0003	.0023	-.0025	.0007	.0041	.0022	.0019	.0035

Panel D: Limits of Arbitrage & Opaqueness

	Limits of Arbitrage			Opaqueness			INST Holders	
	AILLIQ (1)	DOLLAR_VOL (2)	BA_SPREAD (3)	MB (4)	INTAN_AT (5)	RND_AT (6)	INST_HOLD (7)	INST_NUM (8)
β	-.9905***	0.0127***	-.2904***	.006***	.017***	.0747***	.0016***	.0088***
T Stat	-17.1659	11.5416	-6.4118	18.722	4.2146	9.3108	7.621	1.9203
R^2 Adjusted	.0004	.0007	.0011	.0007	.0005	.0002	.0006	.0007

Table XIII:
Economic Determinants of Aggregate Economy-Wide PIFI

This table shows the results of univariate and multivariate pooled OLS regressions of APIFI_EQ on potential economy-wide determinants of price inefficiency wrt firm-specific Information such as business cycle variables. The dependent variable APIFI_EQ is the economy-wide aggregate equally-weighted average PIFI of all firms in the cross-section whose closing price for the month was at least $1. DIVIDEND_YIELD is defined as the total dividend payments accruing to the CRSP value-weighted index over the previous 12 months, divided by the current index level. TERM_SPREAD is the difference between the average yield of Treasury bonds with more than ten years to maturity and the average yield of T-bills that mature in three months. PRICE-To-EARNINGS is the total sum of earnings by S&P 500 companies divided by the S&P 500 index value. DEFAULT_RSPREAD is the default return spread, which is the difference between corporate returns and long-term government bond yield. DEFAULT_YSPREAD is the default yield spread which is the difference in yield between AAA bonds and BAA bonds. STOCK_VARIANCE is the sum of squared daily returns on the S&P500. EPU is the consolidated economic policy uncertainty index from Baker et al. (2016). Most of the business cycle variables are from Welch and Goyal (2008). Finally, REALIZED_VARIANCE is realized stock variance from Zhou (2018). The sample period runs from January 1967 through December 2020, and the price filter used is $1. All variables are defined in Appendix A. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively. Standard errors are robust standard errors.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
DIVIDEND_YIELD	-1.061***								-1.126***	-0.384***
	(-27.990)								(-22.166)	(-4.145)
TERM_SPREAD		0.277***							0.103***	-0.200***
		(6.438)							(3.331)	(-4.906)
PRICE-To-EARNIGNS			0.049***						-0.015***	-0.015***
			(4.881)						(-4.600)	(-3.846)
DEFAULT_RSPREAD				0.228***					0.070***	0.124***
				(14.443)					(4.701)	(4.880)
DEFAULT_YSPREAD					0.673***				-0.844***	-0.694***
					(3.585)				(-6.637)	(-2.799)
STOCK_VARIANCE						0.449***			0.178**	-1.607**
						(3.408)			(2.251)	(-2.186)
EPU							0.046***			-0.010
							(4.493)			(-0.762)
REALIZED_VARIANCE								0.000***		0.000**
								(4.297)		(2.457)
Constant	1.374***	1.338***	1.334***	1.357***	1.351***	1.343***	1.348***	1.355***	1.372***	1.371***
	(1023.087)	(1085.210)	(675.078)	(1107.392)	(621.616)	(1668.558)	(990.699)	(1741.000)	(714.547)	(489.699)
Observations	648	648	648	648	648	648	432	372	648	372
R^2 Adjusted	0.462	0.047	0.108	0.240	0.023	0.015	0.035	0.014	0.521	0.238

Appendix A. Variable Definitions

AG: Year-over-year asset growth.

AILLIQ: The illiquidity measure of Amihud (2002) is the absolute value of daily stock returns divided by daily dollar trading volume; this captures the impact of order flow on the stock price.

ANLST_DISP: Analyst forecast dispersion, calculated as the standard deviation of analyst forecasts scaled by the prior year-end stock price.

BA_SPREAD: Following Lam and Wei (2011), Bid-ask spread calculated as the time-series average of $2 \times \frac{|Price - \frac{(Ask+Bid)}{2}|}{Price}$ at the end of each month over the 12 months ending in June of year t. Here, Price is the closing stock price, and Ask (Bid) is the ask (bid) quote

β_{UMD}: Slope coefficient obtained by running a regression of stock i's returns on UMD (up minus down momentum factor) on a 60-month rolling window basis.

COST: Cost is calculated as the cost of goods sold for the quarter divided by the total assets for the quarter.

DOLLAR_VOL: Following Lam and Wei (2011), Dollar trading volume is the time-series average of monthly share trading volume multiplied by the monthly closing price over the past 12 ending June of the year t.

PIFI: The price inefficiency regarding firm-specific information as defined by equation 4.

γ_i^1: The slope coefficient of the 60-month rolling window regression of $Ret_{t,i} = \alpha + \gamma\, ret_{t-1,i} + \epsilon$

GM_SD: The volatility of the gross margin; the standard deviation of the last five years' quarterly gross margin numbers, where gross margin is gross income (income before interest charges) for the quarter divided by the total sales for the quarter.

IU_Z: The average of information uncertainty (IU) proxies RES_AGE, VLTY, RES_MV, ANLST_DISP, SD_CF, and RES_ANLST as defined by Zhang (2006), each normalized to a mean of 1.

LBM: The log of the book-to-market ratio, calculated following Davis et al. (2000).

LMCAP: The log of market cap, where market cap is the stock price at the end of the previous calendar year times the shares outstanding.

MAT_EVENT_6M: The number of material events (mergers and acquisitions, dividend initiations or at least 20% absolute change, stock splits, share repurchases, debt issuances, and joint ventures) announced over months $t-1$ through $t-6$.

MAT_EVENT_12M: The number of material events (mergers and acquisitions, dividend initiations or at least 20% absolute change, stock splits, share repurchases, debt issuances, and joint ventures) announced over months $t-1$ through $t-12$.

MAT_EVENT_24M: The number of material events (mergers and acquisitions, dividend initiations or at least 20% absolute change, stock splits, share repurchases, debt issuances, and joint ventures) announced over months $t-1$ through $t-24$.

RES_AGE: The reciprocal of firm age, where firm age is defined as the number of months between event month t and the first month that stock appears in CRSP.

RES_ANLST: The reciprocal of analyst count.

RES_MV: The reciprocal of market value, where market value is stock price times the shares outstanding.

ROA: Return on assets, calculated as income before extraordinary items divided by total assets.

ROA_SD: The volatility of ROA; the standard deviation of the last five years' quarterly ROA numbers.

SD_CF: Cash flow volatility, calculated as the standard deviation of cash flow from operations in the last five years.

VLTY: Return volatility, defined as the standard deviation of weekly market excess returns over the year ending in month t.

Appendix B. Internet Appendix

Appendix A. Other Robustness Exercises

Appendix A.1. Size, PIFI, and Past Returns Sorted Portfolios

To analyze the impact of PIFI on momentum (winner minus loser) returns, I form triple-sorted and hedged portfolios. First, at the beginning of each month, I sort firms whose price was at least \$1 at the end of month $t-1$ into two groups based on their market cap at the end of month $t-1$ (below median MCAP vs above median). Second, within each of those two size groups, I sort firms into ten deciles based on their PIFI values at the end of month $t-1$. Finally, within each size and PIFI double-sorted group, I further sort firms into ten deciles based on their BHR6M$_{-1,-6}$ (buy and hold returns from month $t-6$ to month $t-1$) at the end of month $t-1$.

At the beginning of each month t, after I sort all firms into 200 triple-sorted groups, I form 200 portfolios, 100 in each size-based sub-sample - small and large - that go long the stocks that fall in each of those 200 buckets. In addition, I form 20 hedged portfolios, ten in each size-based sub-sample - small and large - that go long the winner and short the loser within each size and PIFI double-sorted group. Then, for each month t and for each of the 220 portfolios, I calculate the six-month value-weighted and equal-weighted buy and hold returns from month $t = 0$ to the month $t = 5$.

Panels A and B of Table IA1 show the value-weighted returns of the size, PIFI, and BHR6M$_{-1,-6}$ triple-sorted portfolios and the hedged portfolios (winner minus loser within the size and PIFI double-sorted group) in the sub-samples of the large and small firms, respectively. Table IA2 presents the equal-weighted returns of those same 220 portfolios.

Panel A of Table IA1 shows that there is a significant difference in the value-weighted momentum (winner minus loser return spread) returns between low-PIFI firms and high-PIFI firms within the sub-samples of larger firms. Within the sub-sample of big firms, high-PIFI firms, on average, earn value-weighted momentum (winner minus loser) returns of about 7.06% (13.6% vs 6.56%) per year more than low-PIFI firms. Within small firms, the value-weighted return differential decreases to about 6.22% per year (Panel B). In the context of equal-weighted returns, return differentials between low-PIFI and high-PIFI are slightly lower but similar to the value-weighted returns. The return differential among big and small firms are about 5.40% and about 5.66% per year, respectively.

In the previous section, in the context of Fama-MacBeth cross-sectional regression, I show that the interaction of PIFI and BHR6M$_{-1,-6}$ is what explains the momentum returns. Triple-sorted portfolio returns strongly agree with that result. If we glance at the average returns of winner and loser portfolios, we can see that the interaction effect of PIFI is almost symmetrical for both groups, especially evident in equal-weighted returns. In other words, as PIFI values increase, winners become extreme winners and losers become extreme losers.

Hence, higher PIFI predicts higher returns for winners while at the same time predicting lower returns for losers, strong evidence that the interaction between PIFI and past returns is what explains the momentum returns. Even though momentum is generally considered a small firm phenomenon, PIFI results are significantly stronger among bigger firms and with value-weighted portfolios, which reduces the concerns that my results are driven by microcap firms.

Appendix A.2. Price Inefficiency regarding Industry-Specific Information (PEII)

Hou and Moskowitz (2005) find that their semi-strong form price inefficiency regarding US market information has no relation with momentum. Here, I test whether price inefficiency regarding industry-specific information (PEII) has any explanatory power over momentum. To calculate PEII, similar to that of PIFI, I estimate the following two regressions on a 60-month rolling window basis.

$$Base\ \ Model:\ r_{i,t} = \alpha_i + \gamma_i^1\, r_{ind,t} + \epsilon_{i,t} \tag{B1}$$

$$Extended\ \ Model:\ r_{i,t} = \alpha_i + \beta_i^n \sum_{n=0}^{6} r_{ind,t-n} + \epsilon_{i,t} \tag{B2}$$

where, $r_{i,t}$ is the monthly return of stock i and $r_{ind,t}$ is the value-weighted monthly return of stock i's industry (excluding stock i). I use the Fama-French 49 industry classification to group firms into an industry. Similar to that of PIFI, PEII then is calculated as:

$$PEII = \frac{\sum_{n=1}^{6}\ n\ \frac{abs(\beta_i^n)}{se(\beta_i^n)}}{\frac{abs(\gamma_i^1)}{se(\gamma_i^1)} + \sum_{n=1}^{6}\ \frac{abs(\beta_i^n)}{se(\beta_i^n)}} \tag{B3}$$

I present the results using PEII in Columns (4) through (6) in Table VIII. PEII and its interaction with past returns do not have any explanatory power over the momentum; Contrarily, The coefficient of $BHR6M_{-1,-6}$ increases when controlling for PEII and its interaction terms with past returns (Column 5). Again, after augmenting the model with PIFI and its interaction with past returns, the slope coefficient of $BHR6M_{-1,-6}$ turns statistically insignificant. Overall, results suggest that the crossover interaction term between PIFI and past returns can explain momentum.

Appendix A.3. Alternative Definitions of PIFI

As I mentioned above, I include both market and industry returns in both base and extended models to control for the price inefficiency regarding US market-specific information and a firm's industry-specific information. However, in this section, I am studying how critical it is to control for such information.

Appendix A.4. PIFI without Controlling for Industry-specific Information

Even though including industry returns in both base and extended models reduces the contamination effect of the price inefficiency regarding industry-specific information, it complicates the calculation of PIFI. Here, I test whether taking the industry returns out of the models and calculating PIFI from those reduced models impact the explanatory power of PIFI. I calculate the revised PIFI_WOI (PIFI without industry returns) in the following way:

First, using a rolling window of 60 months, I estimate the following two models for each firm for each month:

$$Base\ \ Model:\ r_{i,t} = \alpha_i + \gamma_i^1\, r_{i,t-1} + \sum_{n=0}^{6} \xi_i^n\, r_{m,t-n} + \epsilon_{i,t} \tag{B4}$$

$$Extended\ \ Model:\ r_{i,t} = \alpha_i + \beta_i^1\, r_{i,t-1} + \sum_{n=2}^{6} \beta_i^n\, r_{i,t-n} + \sum_{n=0}^{6} \xi_i^n\, r_{m,t-n} + \epsilon_{i,t} \qquad \text{(B5)}$$

where, $r_{i,t}$ is the monthly return of stock i in month t and $r_{m,t}$ is the monthly return of the CRSP value-weighted index in month t . PIFI_WOI then is calculated as:

$$PIFI\_WOI = \frac{\sum_{n=2}^{6} n\, \frac{abs(\beta_i^n)}{se(\beta_i^n)}}{\frac{abs(\gamma_i^1)}{se(\gamma_i^1)} + \sum_{n=2}^{6} \frac{abs(\beta_i^n)}{se(\beta_i^n)}} \qquad \text{(B6)}$$

Appendix A.5. PIFI without Controlling for Market-specific Information

In this exercise, I exclude the market returns from the base (2) and extended (3) models and calculate the PIFI_WOM (PIFI without market returns) in the following way:

First, using a rolling window of 60 months, I estimate the following two models for each firm for each month:

$$Base\ \ Model:\ r_{i,t} = \alpha_i + \gamma_i^1\, r_{i,t-1} + \sum_{n=0}^{6} \phi_i^n\, r_{ind,t-n} + \epsilon_{i,t} \qquad \text{(B7)}$$

$$Extended\ \ Model:\ r_{i,t} = \alpha_i + \beta_i^1\, r_{i,t-1} + \sum_{n=2}^{6} \beta_i^n\, r_{i,t-n} + \sum_{n=0}^{6} \phi_i^n\, r_{ind,t-n} + \epsilon_{i,t} \qquad \text{(B8)}$$

where, $r_{i,t}$ is the monthly return of stock i in month t and $r_{ind,t}$ is the value-weighted monthly industry (to which a firm belongs) return in month t. PIFI_WOM then is calculated as:

$$PIFI\_WOM = \frac{\sum_{n=2}^{6} n \frac{abs(\beta_i^n)}{se(\beta_i^n)}}{\frac{abs(\gamma_i^1)}{se(\gamma_i^1)} + \sum_{n=2}^{6} \frac{abs(\beta_i^n)}{se(\beta_i^n)}} \tag{B9}$$

My results are very similar even if I use the above-revised PIFI measures. I present the main results of Table III but with the replacement PIFI with PIFI_WOI in Panel A of Table IA7 and by replacing PIFI with PIFI_WOM in Panel B of Table IA7. It seems like contamination of price inefficiency regarding market-specific information or industry-specific information does not materially harm the explanatory power of PIFI when explaining momentum.

Appendix A.6. Different Weighting Schemes

Also, something to note about the price inefficiency measure of HM defined by equation 1 is that the $t-stat$ weighting mechanism is somewhat arbitrary, although it makes intuitive sense to give greater weight to the $t-stat$ of more lagged RHS variables. Hence, as a robustness test, I vary my $t-stat$ weighting mechanism. Some of the alternative PIFI measures that I used in my analysis are as follows:

$$PIFI_{Alt_2} = \frac{\sum_{n=2}^{6} n \frac{abs(\beta_i^n)}{se(\beta_i^n)}}{\frac{abs(\gamma_i^0)}{se(\gamma_i^0)} + \sum_{n=2}^{6} n \frac{abs(\beta_i^n)}{se(\beta_i^n)}} \qquad PIFI_{Alt_3} = \frac{\sum_{n=2}^{6} \sqrt{n} \frac{abs(\beta_i^n)}{se(\beta_i^n)}}{\frac{abs(\gamma_i^0)}{se(\gamma_i^0)} + \sum_{n=2}^{6} \frac{abs(\beta_i^n)}{se(\beta_i^n)}}$$

$$PIFI_{Alt_4} = \frac{\sum_{n=2}^{6} \sqrt{n} \frac{abs(\beta_i^n)}{se(\beta_i^n)}}{\frac{abs(\gamma_i^0)}{se(\gamma_i^0)} + \sum_{n=2}^{6} \sqrt{n} \frac{abs(\beta_i^n)}{se(\beta_i^n)}} \qquad PIFI_{Alt_5} = \frac{\sum_{n=2}^{6} \frac{abs(\beta_i^n)}{se(\beta_i^n)}}{\frac{abs(\gamma_i^0)}{se(\gamma_i^0)} + \sum_{n=2}^{6} \frac{abs(\beta_i^n)}{se(\beta_i^n)}}$$

Even though the $PIFI_{Alt_5}$ gives comparatively weaker results than other $PIFI_{Alt}$ measures, my results are robust to all the alternative definitions of $PIFI$. The fact that $PIFI_{Alt_5}$ gives comparatively weaker results and supports the intuition that information provided by more lagged returns is more informative about PIFI than information from less lagged returns.

Table IA1:
PIFI and Value-Weighted Momentum (High - Low) Portfolio Returns

This table shows the average value-weighted six-month buy-and-hold returns of 200 size, PIFI, and $BHR6M_{-1,-6}$ triple-sorted portfolios and 20 momentum (winner minus loser) hedged portfolios. Panel A and B show results among big and small firms, respectively. PIFI is the price inefficiency wrt firm-specific information as defined by equation 4. First, using market capital at the end of month $t-1$, I sort firms into two groups (below median and above median). Within each group, I sort firms into ten deciles based on their PIFI values at the end of month $t-1$. Then, within each of those size and PIFI double-sorted groups, I sort firms into ten deciles based on their buy and hold returns from month $t-6$ to $t-1$. For each month t, I calculate the six-month ($t=0$ to $t=5$) value-weighted buy and hold returns of each of the 200 (2x10x10) portfolios. The momentum portfolio returns for each of the 20 size and PIFI double-sorted groups is the six-month buy and hold returns of the winner portfolio (decile 10) minus the returns of the loser portfolio (decile 1) within each size-PIFI group. The panels below show the returns averaged over 648 months. The sample period runs from January 1967 through December 2020. The price filter used is $1.

Panel A: Big Firms - Six-Month Momentum Returns in Ten PIFI Deciles

	Loser	Dec 2	Dec 3	Dec 4	Dec 5	De 6	Dec 7	Dec 8	Dec 9	Winner	W - L	t-stat
Low PIFI	4.19	5.43	5.98	6.02	5.54	5.71	6.03	6.10	6.60	7.46	3.28	4.35
Decile 2	3.49	5.54	5.37	6.17	6.10	6.10	6.08	5.97	6.49	8.36	4.87	5.97
Decile 3	3.45	5.48	5.56	5.65	5.92	5.98	6.76	6.13	6.58	8.45	5.00	5.73
Decile 4	3.69	5.70	5.62	5.97	5.63	5.7	5.14	5.54	7.05	9.24	5.55	6.46
Decile 5	4.30	5.36	6.11	5.80	5.63	6.16	5.94	6.52	6.68	7.81	3.51	4.03
Decile 6	4.23	5.38	5.17	6.03	5.38	6.04	5.92	6.53	6.64	7.62	3.39	3.92
Decile 7	4.09	4.97	5.77	6.08	6.06	5.92	5.74	6.02	7.13	7.80	3.71	4.46
Decile 8	4.21	4.25	5.60	5.11	5.70	6.20	5.98	6.31	6.55	8.04	3.83	4.38
Decile 9	4.16	4.60	5.21	5.75	5.72	6.10	5.89	5.66	6.81	8.36	4.20	4.67
High PIFI	3.42	4.57	5.73	5.2	5.85	5.95	5.49	6.33	6.22	10.22	6.80	6.72
(H-L) PIFI											3.53	4.26

Panel A: Small Firms - Six-Month Momentum Returns in Ten PIFI Deciles

	Loser	Dec 2	Dec 3	Dec 4	Dec 5	De 6	Dec 7	Dec 8	Dec 9	Winner	W - L	t-stat
Low PIFI	3.60	5.27	6.47	7.16	6.86	7.66	8.98	8.00	9.51	11.76	7.97	5.50
Decile 2	2.80	4.40	5.82	6.16	7.34	7.21	6.94	8.04	9.37	9.71	6.21	4.60
Decile 3	1.57	3.97	5.00	6.02	6.85	6.86	6.89	7.86	9.52	10.15	8.65	7.72
Decile 4	0.77	3.13	5.05	6.64	6.99	5.96	7.10	9.59	8.12	9.74	8.16	6.88
Decile 5	1.99	3.40	5.15	6.07	7.21	7.33	7.95	8.37	9.38	10.53	8.53	6.68
Decile 6	3.65	4.38	5.51	4.81	6.21	7.17	8.3	8.09	8.39	10.77	6.95	4.64
Decile 7	1.82	4.24	5.28	6.48	7.12	7.77	7.23	7.65	8.45	9.73	7.44	6.55
Decile 8	2.77	4.06	5.33	5.32	7.83	7.79	8.35	7.93	8.51	10.13	7.15	6.30
Decile 9	0.61	4.72	4.09	5.73	6.4	7.16	7.32	8.47	8.99	10.00	8.93	7.82
High PIFI	0.90	3.55	5.35	6.41	6.62	7.73	7.98	8.7	10.06	12.01	11.10	9.01
(H-L) PIFI											3.11	1.85

Table IA2:
PIFI and Equal-Weighted Momentum (High - Low) Portfolio Returns

This table shows the average equal-weighted six-month buy-and-hold returns of 200 size, PIFI, and $BHR6M_{-1,-6}$ triple-sorted portfolios and 20 momentum (winner minus loser) hedged portfolios. Panel A and B show results among big and small firms, respectively. PIFI is the price inefficiency wrt firm-specific information as defined by equation 4. First, using market capital at the end of month $t-1$, I sort firms into two groups (below median and above median). Within each group, I sort firms into ten deciles based on their PIFI values at the end of month $t-1$. Then, within each of those size and PIFI double-sorted groups, I sort firms into ten deciles based on their buy and hold returns from month $t-6$ to $t-1$. For each month t, I calculate the six-month ($t=0$ to $t=5$) equal-weighted buy and hold returns of each of the 200 (2x10x10) portfolios. The momentum portfolio returns for each of the 20 size and PIFI double-sorted groups is the six-month buy and hold returns of the winner portfolio (decile 10) minus the returns of the loser portfolio (decile 1) within each size-PIFI group. The panels below show the returns averaged over 648 months. The sample period runs from January 1967 through December 2020. The Price filter used is $1.

Panel A: Big Firms - Six-Month Momentum Returns in Ten PIFI Deciles

	Loser	Dec 2	Dec 3	Dec 4	Dec 5	De 6	Dec 7	Dec 8	Dec 9	Winner	W - L	t-stat
Low PIFI	4.28	6.13	6.4	6.37	6.36	6.38	6.61	6.56	7.00	8.21	3.93	5.70
Decile 2	3.51	6.13	6.23	6.65	6.77	6.28	6.50	6.95	7.81	8.83	5.32	7.32
Decile 3	3.86	5.92	6.25	6.52	6.45	6.71	6.65	7.24	7.55	9.45	5.58	8.16
Decile 4	3.70	5.74	5.95	6.22	6.54	6.64	6.44	6.82	7.40	8.80	5.10	7.35
Decile 5	3.59	5.69	6.39	6.33	6.36	6.46	6.81	6.72	7.46	8.93	5.34	6.88
Decile 6	3.03	5.10	5.77	6.72	6.24	6.35	6.63	6.6	7.53	8.86	5.83	8.29
Decile 7	3.45	5.15	6.38	6.22	6.53	6.71	6.56	6.94	7.66	8.47	5.02	6.99
Decile 8	3.38	5.13	5.75	5.95	6.23	6.47	6.50	7.07	7.29	8.66	5.27	7.45
Decile 9	3.34	4.92	5.75	6.31	6.46	6.74	6.82	7.05	7.10	9.24	5.90	7.72
High PIFI	3.09	4.97	5.87	5.75	6.05	6.5	6.68	7.05	7.49	9.72	6.63	8.42
(H-L) PIFI											2.70	5.00

Panel A: Small Firms - Six-Month Momentum Returns in Ten PIFI Deciles

	Loser	Dec 2	Dec 3	Dec 4	Dec 5	De 6	Dec 7	Dec 8	Dec 9	Winner	W - L	t-stat
Low PIFI	3.85	6.43	7.1	7.26	7.15	8.12	9.26	8.79	10.48	11.3	7.28	5.47
Decile 2	3.69	5.54	6.56	6.89	8.07	7.47	7.7	8.62	9.61	9.98	5.67	4.81
Decile 3	2.51	5.03	5.87	6.63	7.48	7.44	7.61	8.4	10.1	9.84	7.47	6.95
Decile 4	1.56	4.14	5.75	7.21	7.69	6.81	7.58	9.51	9.04	10.36	8.11	7.26
Decile 5	3.29	4.96	5.71	7.14	7.62	8.08	8.36	8.57	10.04	10.52	7.27	6.16
Decile 6	4.34	5.38	6.16	5.98	6.86	7.33	8.63	8.57	9.11	10.52	5.94	4.65
Decile 7	2.71	4.84	6.22	6.97	7.58	8.29	7.52	8.17	9.32	10.78	7.73	7.17
Decile 8	3.58	4.26	6.02	6.13	8.68	8.47	8.69	8.42	9.23	10.2	6.60	6.28
Decile 9	2.22	5.92	4.54	6.2	7.31	7.34	7.50	8.68	9.87	9.96	7.32	6.89
High PIFI	2.35	3.67	5.31	7.19	7.53	8.28	8.50	9.76	10.24	12.31	10.04	8.81
(H-L) PIFI											2.83	2.00

Table IA3:
List of Anomalies Examined in this Paper

This table lists the 205 financial markets anomalies I examined in this paper. Except for the first four rows, the acronym shows the acronym used by Chen and Zimmermann (2022). The long description details on the anomaly variable; The author shows the authors of the the original paper that discovered the anomaly; the year shows the year the paper was published; The journal shows the journal in which the research paper was published. Finally, the Column "Subsumed?" shows whether the interaction term between the anomaly variable and PIFI subsumes the return predictability of the anomaly variable.

Acronym	Long Description	Author	Year	Journal	Subsumed?
Self-Calculated	Momentum (6 month)	Jegadeesh and Titman	1993	JF	Yes
Self-Calculated	Momentum based on FF3 residuals	Blitz, Huij and Martens	2011	JEmpFin	Yes
Self-Calculated	52 week high	George and Hwang	2004	JF	Yes
Self-Calculated	Firm-Specific-Return	Grundy and Martin	2001	RFS	Yes
AbnormalAccruals	Abnormal Accruals	Xie	2001	AR	Yes
Accruals	Accruals	Sloan	1996	AR	Yes
AnalystRevision	EPS forecast revision	Hawkins, Chamberlin, Daniel	1984	FAJ	Yes
BetaTailRisk	Tail risk beta	Kelly and Jiang	2014	RFS	Yes
betaVIX	Systematic volatility	Ang et al.	2006	JF	Yes
Cash	Cash to assets	Palazzo	2012	JFE	Yes
CBOperProf	Cash-based operating profitability	Ball et al.	2016	JFE	Yes
cfp	Operating Cash flows to price	Desai, Rajgopal, Venkatachalam	2004	AR	Yes
ChangeInRecommendation	Change in recommendation	Jegadeesh et al.	2004	JF	Yes
ChEQ	Growth in book equity	Lockwood and Prombutr	2010	JFR	Yes
ChForecastAccrual	Change in Forecast and Accrual	Barth and Hutton	2004	RAS	Yes
ChInv	Inventory Growth	Thomas and Zhang	2002	RAS	Yes
ChInvIA	Change in capital inv (ind adj)	Abarbanell and Bushee	1998	AR	Yes
ChNAnalyst	Decline in Analyst Coverage	Scherbina	2008	ROF	Yes
ChNNCOA	Change in Net Noncurrent Op Assets	Soliman	2008	AR	Yes
ChNWC	Change in Net Working Capital	Soliman	2008	AR	Yes
CitationsRD	Citations to RD expenses	Hirschleifer, Hsu and Li	2013	JFE	Yes
CompositeDebtIssuance	Composite debt issuance	Lyandres, Sun and Zhang	2008	RFS	Yes
ConsRecomm	Consensus Recommendation	Barber et al.	2002	JF	Yes
ConvDebt	Convertible debt indicator	Valta	2016	JFQA	Yes
CoskewACX	Coskewness using daily returns	Ang, Chen and Xing	2006	RFS	Yes
CustomerMomentum	Customer momentum	Cohen and Frazzini	2008	JF	Yes
DebtIssuance	Debt Issuance	Spiess and Affleck-Graves	1999	JFE	Yes
DelBreadth	Breadth of ownership	Chen, Hong and Stein	2002	JFE	Yes
DelCOA	Change in current operating assets	Richardson et al.	2005	JAE	Yes
DelCOL	Change in current operating liabilities	Richardson et al.	2005	JAE	Yes
DelEqu	Change in equity to assets	Richardson et al.	2005	JAE	Yes
DelFINL	Change in financial liabilities	Richardson et al.	2005	JAE	Yes
DelNetFin	Change in net financial assets	Richardson et al.	2005	JAE	Yes
DivOmit	Dividend Omission	Michaely, Thaler and Womack	1995	JF	Yes
DownRecomm	Down forecast EPS	Barber et al.	2002	JF	Yes
EarningsForecastDisparity	Long-vs-short EPS forecasts	Da and Warachka	2011	JFE	Yes
EarningsStreak	Earnings surprise streak	Loh and Warachka	2012	MS	Yes
EBM	Enterprise component of BM	Penman, Richardson and Tuna	2007	JAR	Yes
EquityDuration	Equity Duration	Dechow, Sloan and Soliman	2004	RAS	Yes
ExchSwitch	Exchange Switch	Dharan and Ikenberry	1995	JF	Yes
FEPS	Analyst earnings per share	Cen, Wei, and Zhang	2006	WP	Yes
FirmAgeMom	Firm Age - Momentum	Zhang	2004	JF	Yes
GP	gross profits / total assets	Novy-Marx	2013	JFE	Yes
grcapx	Change in capex (two years)	Anderson and Garcia-Feijoo	2006	JF	Yes
grcapx3y	Change in capex (three years)	Anderson and Garcia-Feijoo	2006	JF	Yes
GrSaleToGrInv	Sales growth over inventory growth	Abarbanell and Bushee	1998	AR	Yes
Herf	Industry concentration (sales)	Hou and Robinson	2006	JF	Yes
HerfAsset	Industry concentration (assets)	Hou and Robinson	2006	JF	Yes
hire	Employment growth	Bazdresch, Belo and Lin	2014	JPE	Yes
IdioRisk	Idiosyncratic risk	Ang et al.	2006	JF	Yes
IdioVol3F	Idiosyncratic risk (3 factor)	Ang et al.	2006	JF	Yes
IdioVolAHT	Idiosyncratic risk (AHT)	Ali, Hwang, and Trombley	2003	JFE	Yes
Illiquidity	Amihud's illiquidity	Amihud	2002	JFM	Yes
IndMom	Industry Momentum	Grinblatt and Moskowitz	1999	JFE	Yes
IntMom	Intermediate Momentum	Novy-Marx	2012	JFE	Yes
Investment	Investment to revenue	Titman, Wei and Xie	2004	JFQA	Yes
InvestPPEInv	change in ppe and inv/assets	Lyandres, Sun and Zhang	2008	RFS	Yes
InvGrowth	Inventory Growth	Belo and Lin	2012	RFS	Yes
iomom_cust	Customers momentum	Menzly and Ozbas	2010	JF	Yes
iomom_supp	Suppliers momentum	Menzly and Ozbas	2010	JF	Yes
MeanRankRevGrowth	Revenue Growth Rank	Lakonishok, Shleifer, Vishny	1994	JF	Yes
Mom6mJunk	Junk Stock Momentum	Avramov et al	2007	JF	Yes
Mom12m	Momentum (12 month)	Jegadeesh and Titman	1993	JF	Yes
Mom12mOffSeason	Momentum without the seasonal part	Heston and Sadka	2008	JFE	Yes
MomOffSeason16YrPlus	Off season reversal years 16 to 20	Heston and Sadka	2008	JFE	Yes

Table IA3:
List of Anomalies Examined in this Paper Continued...

Acronym	Long Description	Author	Year	Journal	Subsumed?
MomSeason06YrPlus	Return seasonality years 6 to 10	Heston and Sadka	2008	JFE	Yes
MomSeason11YrPlus	Return seasonality years 11 to 15	Heston and Sadka	2008	JFE	Yes
MomSeason16YrPlus	Return seasonality years 16 to 20	Heston and Sadka	2008	JFE	Yes
MomSeasonShort	Return seasonality last year	Heston and Sadka	2008	JFE	Yes
MomVol	Momentum in high volume stocks	Lee and Swaminathan	2000	JF	Yes
MS	Mohanram G-score	Mohanram	2005	RAS	Yes
NetDebtFinance	Net debt financing	Bradshaw, Richardson, Sloan	2006	JAE	Yes
NetDebtPrice	Net debt to price	Penman, Richardson and Tuna	2007	JAR	Yes
NumEarnIncrease	Earnings streak length	Loh and Warachka	2012	MS	Yes
OrderBacklogChg	Change in order backlog	Baik and Ahn	2007	Other	Yes
OrgCap	Organizational capital	Eisfeldt and Papanikolaou	2013	JF	Yes
PatentsRD	Patents to RD expenses	Hirschleifer, Hsu and Li	2013	JFE	Yes
ProbInformedTrading	Probability of Informed Trading	Easley, Hvidkjaer and O'Hara	2002	JF	Yes
PS	Piotroski F-score	Piotroski	2000	AR	Yes
RD	R&D over market cap	Chan, Lakonishok and Sougiannis	2001	JF	Yes
RDIPO	IPO and no R&D spending	Gou, Lev and Shi	2006	JBFA	Yes
realestate	Real estate holdings	Tuzel	2010	RFS	Yes
Recomm_ShortInterest	Analyst Recommendations and Short-Interest	Drake, Rees and Swanson	2011	AR	Yes
REV6	Earnings forecast revisions	Chan, Jegadeesh and Lakonishok	1996	JF	Yes
RevenueSurprise	Revenue Surprise	Jegadeesh and Livnat	2006	JFE	Yes
RIO_Disp	Inst Own and Forecast Dispersion	Nagel	2005	JF	Yes
RIO_MB	Inst Own and Market to Book	Nagel	2005	JF	Yes
RIO_Turnover	Inst Own and Turnover	Nagel	2005	JF	Yes
RIO_Volatility	Inst Own and Idio Vol	Nagel	2005	JF	Yes
ShareIss1Y	Share issuance (1 year)	Pontiff and Woodgate	2008	JF	Yes
ShareRepurchase	Share repurchases	Ikenberry, Lakonishok, Vermaelen	1995	JFE	Yes
ShareVol	Share Volume	Datar, Naik and Radcliffe	1998	JFM	Yes
ShortInterest	Short Interest	Dechow et al.	2001	JFE	Yes
skew1	Volatility smirk near the money	Xing, Zhang and Zhao	2010	JFQA	Yes
SmileSlope	Put volatility minus call volatility	Yan	2011	JFE	Yes
Spinoff	Spinoffs	Cusatis, Miles and Woolridge	1993	JFE	Yes
SurpriseRD	Unexpected R&D increase	Eberhart, Maxwell and Siddique	2004	JF	Yes
tang	Tangibility	Hahn and Lee	2009	JF	Yes
TotalAccruals	Total accruals	Richardson et al.	2005	JAE	Yes
UpRecomm	Up Forecast	Barber et al.	2002	JF	Yes
VolMkt	Volume to market equity	Haugen and Baker	1996	JFE	Yes
VolSD	Volume Variance	Chordia, Subra, Anshuman	2001	JFE	Yes
XFIN	Net external financing	Bradshaw, Richardson, Sloan	2006	JAE	Yes
AssetGrowth	Asset growth	Cooper, Gulen and Schill	2008	JF	Weakens
DivSeason	Dividend seasonality	Hartzmark and Salomon	2013	JFE	Weakens
dNoa	change in net operating assets	Hirshleifer, Hou, Teoh, Zhang	2004	JAE	Weakens
EarnSupBig	Earnings surprise of big firms	Hou	2007	RFS	Weakens
MaxRet	Maximum return over month	Bali, Cakici, and Whitelaw	2010	JF	Weakens
MomOffSeason06YrPlus	Off season reversal years 6 to 10	Heston and Sadka	2008	JFE	Weakens
MomRev	Momentum and LT Reversal	Chan and Ko	2006	JOIM	Weakens
MRreversal	Medium-run reversal	De Bondt and Thaler	1985	JF	Weakens
NetEquityFinance	Net equity financing	Bradshaw, Richardson, Sloan	2006	JAE	Weakens
OPLeverage	Operating leverage	Novy-Marx	2010	ROF	Weakens
retConglomerate	Conglomerate return	Cohen and Lou	2012	JFE	Weakens
ReturnSkew3F	Idiosyncratic skewness (3F model)	Bali, Engle and Murray	2015	Book	Weakens
roaq	Return on assets (qtrly)	Balakrishnan, Bartov and Faurel	2010	JAE	Weakens
DivYieldST	Predicted div yield next month	Litzenberger and Ramaswamy	1979	JF	Weakens
MomOffSeason	Off season long-term reversal	Heston and Sadka	2008	JFE	Weakens
ReturnSkew	Return skewness	Bali, Engle and Murray	2015	Book	No
VolumeTrend	Volume Trend	Haugen and Baker	1996	JFE	No
AccrualsBM	Book-to-market and accruals	Bartov and Kim	2004	RFQA	No
AM	Total assets to market	Fama and French	1992	JF	No
AnnouncementReturn	Earnings announcement return	Chan, Jegadeesh and Lakonishok	1996	JF	No
BM	Book to market using most recent ME	Rosenberg, Reid, and Lanstein	1985	JF	No
ChTax	Change in Taxes	Thomas and Zhang	2011	JAR	No
CompEquIss	Composite equity issuance	Daniel and Titman	2006	JF	No
Coskewness	Coskewness	Harvey and Siddique	2000	JF	No
DolVol	Past trading volume	Brennan, Chordia, Subra	1998	JFE	No
EarningsSurprise	Earnings Surprise	Foster, Olsen and Shevlin	1984	AR	No
Frontier	Efficient frontier index	Nguyen and Swanson	2009	JFQA	No
GrLTNOA	Growth in long term operating assets	Fairfield, Whisenant and Yohn	2003	AR	No
IndRetBig	Industry return of big firms	Hou	2007	RFS	No
IntanBM	Intangible return using BM	Daniel and Titman	2006	JF	No
IntanSP	Intangible return using Sale2P	Daniel and Titman	2006	JF	No
LRreversal	Long-run reversal	De Bondt and Thaler	1985	JF	No
MomSeason	Return seasonality years 2 to 5	Heston and Sadka	2008	JFE	No
NetPayoutYield	Net Payout Yield	Boudoukh et al.	2007	JF	No
NOA	Net Operating Assets	Hirshleifer et al.	2004	JAE	No
SP	Sales-to-price	Barbee, Mukherji and Raines	1996	FAJ	No
std_turn	Share turnover volatility	Chordia, Subra, Anshuman	2001	JFE	No
TrendFactor	Trend Factor	Han, Zhou, Zhu	2016	JFE	No
zerotrade	Days with zero trades	Liu	2006	JFE	No
zerotradeAlt1	Days with zero trades	Liu	2006	JFE	No
zerotradeAlt12	Days with zero trades	Liu	2006	JFE	No

Table IA4: Momentum (6/6) and UMD (UP Minus Down - Momentum Factor) Loadings

This table shows the results of Fama-MacBeth cross-sectional regressions of future six-month buy and hold returns ($BHR6M_{0,5}$) on past six-month buy and hold returns ($BHR6M_{-1,-6}$) after controlling for well-known empirical regularities, semi-strong form price inefficiency wrt market-specific information of Hou and Moskowitz (2005), and stock's loading on UMD (momentum factor) and its interactions with the past six-month buy and hold returns. I obtain the time series of β_{UMD} for each stock i for each month t by running a 60-month rolling regression of stock i's monthly returns on the UMD factor. The dependent variable $BHR6M_{0,5}$ is the buy-and-hold return from month $t+0$ to month $t+5$. The primary independent variable $BHR6M_{-1,-6}$ is the past buy and hold returns from month $t-1$ to month $t-6$. PIFI is the price inefficiency wrt firm-specific information as defined by equation 4. D3_HM is the semi-strong form price inefficiency measure of Hou and Moskowitz (2005) as defined by equation 1. The sample period runs from January 1967 through December 2020, and the price filter used is $1. All variables are defined in Appendix A. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively. Standard errors are Newey adjusted with six lags.

	(1)	(2)	(3)	(4)
$BHR6M_{-1,-6}$	1.909***	1.940***	1.738***	1.840***
	(4.225)	(4.641)	(4.349)	(5.236)
LMCAP_−12			-0.412*	-0.409*
			(-1.862)	(-1.857)
LBM_−12			0.736**	0.739**
			(2.065)	(2.077)
AG_−12			-4.785***	-4.761***
			(-9.128)	(-9.179)
ROA_−12			5.472***	5.446***
			(3.472)	(3.465)
D3_HM_−1			-0.090	-0.100
			(-0.193)	(-0.220)
β_UMD	-0.259	0.071	-0.408	-0.234
	(-0.393)	(0.075)	(-0.689)	(-0.266)
β_UMD x BHR6M		-0.224		-0.010
		(-0.207)		(-0.010)
Constant	6.816***	6.850***	9.089***	9.121***
	(5.983)	(6.153)	(4.166)	(4.242)
Months	648	648	648	648

Table IA5:
PIFI and Material Corporate Events

This table shows the results of Fama-MacBeth cross-sectional regressions of future six-month buy and hold returns ($\text{BHR6M}_{0,5}$) on past six-month buy and hold returns ($\text{BHR6M}_{-1,-6}$) after controlling for well-known empirical regularities, price inefficiency measure of Hou and Moskowitz (2005), and material corporate events variables and their interactions with the past six-month buy and hold returns. The dependent variable $\text{BHR6M}_{0,5}$ is the buy-and-hold return from month $t+0$ to month $t+5$. The primary independent variable $\text{BHR6M}_{-1,-6}$ is the past buy and hold returns from month $t-1$ to month $t-6$. PIFI is the price inefficiency wrt firm-specific information as defined by equation 4. D3_HM is the semi-strong form price inefficiency measure of Hou and Moskowitz (2005) as defined by equation 2. The sample period runs from January 1967 through December 2020, and the price filter used is $1. All variables are defined in Appendix A. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively. Standard errors are Newey adjusted with six lags.

	(1)	(2)	(3)	(4)	(5)	(6)
$\text{BHR6M}_{-1,-6}$	0.016***	0.016***	0.016***	0.016***	0.016***	0.016***
	(3.500)	(3.509)	(3.494)	(3.504)	(3.482)	(3.482)
LMCAP_−12	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002
	(-0.995)	(-1.015)	(-0.981)	(-0.977)	(-0.912)	(-0.865)
LBM_−12	0.008**	0.008**	0.008**	0.008**	0.008**	0.008**
	(2.108)	(2.094)	(2.109)	(2.108)	(2.119)	(2.131)
AG_−12	-0.050***	-0.050***	-0.050***	-0.050***	-0.049***	-0.049***
	(-9.358)	(-9.384)	(-9.332)	(-9.373)	(-9.310)	(-9.327)
ROA_−12	0.054***	0.054***	0.054***	0.055***	0.054***	0.055***
	(3.460)	(3.457)	(3.461)	(3.459)	(3.445)	(3.481)
D3_HM_−1	-0.003	-0.003	-0.003	-0.003	-0.003	-0.003
	(-0.547)	(-0.555)	(-0.538)	(-0.533)	(-0.567)	(-0.559)
MAT_EVENT_6M	-0.003	-0.000				
	(-1.624)	(-0.065)				
MAT_EVENT_6M x BHR6M		0.003				
		(0.298)				
MAT_EVENT_12M			-0.002	-0.002		
			(-1.304)	(-1.093)		
MAT_EVENT_12M x BHR6M				0.006		
				(0.656)		
MAT_EVENT_24M					-0.001	-0.002
					(-0.814)	(-1.029)
MAT_EVENT_24M x BHR6M						0.006
						(0.850)
Constant	0.083***	0.077***	0.083***	0.077***	0.080***	0.075***
	(3.546)	(3.558)	(3.525)	(3.528)	(3.542)	(3.441)
Months	612	612	612	612	612	612

Table IA6:
PIFI and Information Uncertainty

This table shows the results of Fama-MacBeth cross-sectional regressions of future six-month buy and hold returns ($BHR6M_{0,5}$) on past six-month buy and hold returns ($BHR6M_{-1,-6}$) after controlling for well-known empirical regularities, price inefficiency measure of Hou and Moskowitz (2005), and information uncertainty variable and its interactions with the past six-month buy and hold returns. IU_Z is the information uncertainty variable calculated using the six information uncertainty variables proposed by Zhang (2006). The dependent variable $BHR6M_{0,5}$ is the buy-and-hold return from month $t+0$ to month $t+5$. The primary independent variable $BHR6M_{-1,-6}$ is the past buy and hold returns from month $t-1$ to month $t-6$. PIFI is the price inefficiency regarding firm-specific information as defined by equation 4. D3_HM is the price inefficiency measure of Hou and Moskowitz (2005) as defined by equation 2. The sample period runs from January 1967 through December 2020, and the price filter used is $1. All variables are defined in Appendix A. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively. Standard errors are Newey adjusted with six lags.

	(1)	(2)	(3)	(4)
$BHR6M_{-1,-6}$	1.687***	2.096***	2.098***	0.973
	(3.816)	(3.705)	(3.715)	(1.397)
LMCAP_−12	-0.497**	-0.496**	-0.496**	-0.497**
	(-2.499)	(-2.554)	(-2.559)	(-2.560)
LBM_−12	0.720*	0.731**	0.727**	0.729**
	(1.932)	(1.980)	(1.970)	(1.977)
AG_−12	-4.866***	-4.863***	-4.866***	-4.865***
	(-8.981)	(-9.046)	(-9.057)	(-9.054)
ROA_−12	5.054***	4.951***	4.939***	4.933***
	(3.129)	(3.090)	(3.082)	(3.072)
D3_HM_−1	-0.181	-0.176	-0.176	-0.171
	(-0.353)	(-0.343)	(-0.345)	(-0.335)
IU_Z_0	-1.026***	-0.144	-0.143	-0.186
	(-2.604)	(-0.177)	(-0.177)	(-0.230)
IU_Z_0 x BHR6M_−1, −6		-0.713	-0.712	-0.676
		(-1.097)	(-1.101)	(-1.044)
PIFI_−1			-0.057	-0.523***
			(-0.976)	(-2.942)
PIFI_−1 x BHR6M_−1, −6				1.216***
				(2.628)
Constant	10.243***	10.156***	10.163***	10.179***
	(4.737)	(4.844)	(4.841)	(4.851)
Months	645	645	645	645

Table IA7:
Momentum (6/6) and Alternative Price Inefficiency regarding Firm-Specific Information (PIFI) Measures

This table shows the results of Fama-MacBeth cross-sectional regressions of future six-month buy and hold returns ($BHR6M_{0,5}$) on past six-month buy and hold returns ($BHR6M_{-1,-6}$) after controlling for well-known empirical regularities, the price inefficiency measure of Hou and Moskowitz (2005), and alternative PIFIs defined by equations B6 and B9 and their interactions with the past six-month buy and hold returns. Panel A and B present the results using PIFI_WOI and PIFI_WOM, respectively. The primary independent variable $BHR6M_{-1,-6}$ is the buy and hold returns from month $t-1$ to month $t-6$, whereas dependent variable $BHR6M_{0,5}$ is the buy and hold returns from t to $t+5$. PIFI is the price inefficiency regarding firm-specific information as defined by equation 4, and D3_HM is the semi-strong form price inefficiency measure of Hou and Moskowitz (2005) as defined by equation 1. The sample period runs from January 1967 through December 2020, and the price filter used is $1. All variables are defined in Appendix A. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively. Standard errors are Newey adjusted with six lags.

Panel A: Main Table Results with PIFI_WOI as the Variable of Interest

	(1)	(2)	(3)	(4)	(5)
$BHR6M_{-1,-6}$	1.926***	1.727***	1.736***	1.739***	0.783
	(3.835)	(3.876)	(3.900)	(3.910)	(1.392)
$D3\_HM_{-1}$			-0.191	-0.191	-0.182
			(-0.373)	(-0.376)	(-0.357)
$PIFI\_WOI_{-1}$				-0.079	-0.581***
				(-1.510)	(-3.151)
$PIFI\_WOI_{-1}$ x $BHR6M_{-1,-6}$					1.106***
					(2.669)
Controls	YES	YES	YES	YES	YES
Constant	6.750***	9.038***	9.029***	9.026***	9.038***
	(5.391)	(4.112)	(3.792)	(3.788)	(3.794)

Panel B: Main Table Results with PIFI_WOIM as the Variable of Interest

	(1)	(2)	(3)	(4)	(5)
BHR6M_$-1, -6$	1.926***	1.727***	1.736***	1.739***	0.510
	(3.835)	(3.876)	(3.900)	(3.917)	(0.797)
D3_HM_-1			-0.191	-0.189	-0.190
			(-0.373)	(-0.371)	(-0.372)
$PIFI\_WOM_{-1}$				0.036	-0.593***
				(0.655)	(-2.994)
$PIFI\_WOM_{-1}$ x $BHR6M_{-1,-6}$					1.451***
					(3.064)
Controls	YES	YES	YES	YES	YES
Constant	6.750***	9.038***	9.029***	9.038***	9.044***
	(5.391)	(4.112)	(3.792)	(3.792)	(3.799)