Price Delay Specific to Firm-Specific Information and Anomalies

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ABSTRACT

In this paper, I develop a measure that measures the price delay specific to firm-specific information (PD) and examine its relation with 210 anomalies. PD captures the speed at which prices incorporate the left-over firm-specific information not incorporated into prices contemporaneously. In Fama-MacBeth regressions, PD interaction term takes away the statistical significance of consolidated anomalies. PD is high when firm-specific information is difficult to interpret; a firm produces more price-relevant event news; and fundamental uncertainty is high. The results suggest that, on average, market anomalies primarily exist where PD is high.

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

JEL Classification: G11, G12, G14

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In asset markets, there is an overwhelming amount of return predictability by hundreds of anomaly variables (Chen and Zimmermann (2022), Jensen, Kelly, and Pedersen (2023)). For decades, the researchers in financial economics have been trying to uncover the source of return predictability of these anomalies. The 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 (e.g., Cohen and Lou (2012)). [1] Recently, Engelberg, McLean, and Pontiff (2018) further say that most anomalies' return predictability is related to firm-specific news. These findings imply that the incorrect incorporation of firm-specific information into prices is probably at the core of return predictability of anomalies.

On one hand, rational attention theories suggest that investors with limited cognitive ability process more market- or industry-specific shocks than firm-specific shocks (Peng and Xiong (2006), Schmidt (2012)). And on the other, 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)). Taken together, these literature strands imply that prices are more likely to be inefficient for firm-specific information compared to other sources of information. This study contributes with a price delay specific to firm-specific information (PD), and provides strong empirical evidence that price inefficiency about firm-specific information, especially the instantaneous aspect, is probably at the core of return predictability of all asset market anomalies.

Coining the term "efficient markets," Fama 1965 states "...on the average, competition will cause the *full effects* of new information on intrinsic value to be reflected *instantaneously* in actual price." In other words, instantaneity and unbiasedness are

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

the two sides of the same price efficiency coin. The PD primarily focuses on instantaneous aspect. Furthermore, as behavioral studies have found that both overreaction and underreaction to information are pervasive in the market, PD treats both equally.[2] Validation exercises to understand the PD find that the PD is related to higher fundamental and information uncertainty and lower profitability.

Using the framework of Engelberg et al. (2018), I create an anomaly long ranking variable (ALRank). ALRank is a composite measure that combines the information from all financial market anomalies into a single variable. It is probably one of the strongest predictors of future returns (t-stat of 12.2 in Fama-MacBeth regression). I find that controlling for PD and its interaction with ALRank, ALRank completely loses its statistical power to predict future returns. One interpretation of this result is that financial markets anomalies, in general, exist only among high PD firms. Results are robust across a battery of tests.

There are many seminal papers in finance that suggest that idiosyncratic volatility might be one of the biggest hindrance against market players not being able to correct anomalies[1]. So, I test whether an interaction term with IVOL produces the similar effect on ALRank as the PD does. None of the IVOLs calculated using various asset pricing models and their interactions with ALRank takes the return predictability away from the ALRank. Even in the presence of various types of IVOL and their interactions with ALRank, the return predictability of ALRank goes away only after augmenting the model with the interaction term between PD and ALRank.

Using the data provided by Chen and Zimmermann (2022), I further study more

[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.

[1]See Pontiff (1996), Pontiff (2006), Shleifer and Vishny (1997), Chu, Hirshleifer, and Ma (2020), Duan, Hu, and McLean (2010)

than 200 anomalies individually. Out of 210 anomalies that I examine, 147 anomaly variables significantly predict returns in my sample. A fascinating result is that the interaction term between PD and the anomaly condition variable drives out the return predictability of more than 88 percent of the anomaly variables and substantially weakens the return predictability of the remainder. The results, again, suggest that the return predictability of most asset market anomalies comes from prices that are inefficient concerning firm-specific information, especially on the instantaneous aspect.

The anomaly group that loses the return predictability the most is Investments; a hundred percent of anomalies in this group lose return predictability. With 96% and 95%, respectively, the next most affected groups that lose the predictability the most are Other (e.g., patents, spinoff, institutional ownership) and Intangibles. The result is consistent with my uncertainty story because, at any point in time, it is more likely that prices are inefficient regarding the value of a firm's intangibles and investments since the firm-specific information related to intangibles and investments 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 Trading Frictions; Only seventy-two percent of anomalies in this group lose return predictability. This, again is consistent with my fundamental uncertainty story as the speed of incorporation of firm-specific information into prices is less likely to play a role in increasing or decreasing the trading frictions such as liquidity. 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.

PD measures the instantaneous aspect of price inefficiency concerning firm-specific information. Given that there is some over or underreaction to the firm specific information in contemporaneous time, it measures the speed by which the prices incorporate the left over information in coming months. For example, suppose prices in both firm A and B incorporate 80% of the firm-specific information in contemporaneous time. So, on unbiasedness aspect, both firms are equally inefficient. If prices in firm A incorporate 50% of leftover information in month 1 and 50% in month 2, whereas the prices in firm B incorporate 70% in month 1 and 30% in month 2, then firm B prices, from the instantaneity perspective, are more efficient than firm A prices. My findings that the ALRank predicts next three month earning announcement returns only among high PD firms strongly supports my story that PD captures the price inefficiency specific to firm specific information.

PD does not capture the price inefficiency of firm-specific information in an absolute sense, meaning both the unbiased and instantaneous aspects. Just as the delay measures of Hou and Moskowitz (2005), it is an empirically motivated measure. Hou and Moskowitz (2005) compute price inefficiencies in market-specific information by comparing how much information is incorporated contemporaneously versus with delay. Within the framework of Hou and Moskowitz (2005), one cannot look at how much firm-specific information is incorporated in a contemporaneous manner. PD is more useful to compare the price inefficiency of firms rather than to look at a firm in isolation. Given that there is some market over- or under-reaction to firm-specific information in contemporaneous time, PD then measures how slowly or rapidly the leftover information is incorporated into prices. In theory, where one hundred percent of firm-specific information is incorporated into prices in contemporaneous times, PD is undefined (zero divided by zero).

Considering the results, understanding the drivers of PD is a natural next step.

The literature suggests that the higher the uncertainty around the firms' fundamentals, the higher the chances that prices incorrectly incorporate new information. Kumar (2009) finds that behavioral bias is higher where valuation uncertainty is higher, and stocks are more difficult to value. Pástor and Veronesi (2003) state that when a firm has higher uncertainty around average profitability, investors have difficulty valuing the firm. They find their results are especially 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. And Zhang (2006) finds incorrect market reactions when the level of information uncertainty is high. 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.

Consistent with these strands of literature, I find that high-PD firms are larger growth firms with highly volatile profitability. 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 regarding firms' future earnings. High PD firms are also more sensitive to aggregate economy-level uncertainty, proxied, for example, by professional forecasters' dispersion on government purchases of goods and services, for example. These firms pay meager dividends and are more opaque. Overall, empirical evidence strongly supports that uncertainties around a firm's fundamentals drive its PD. Furthermore, since high-PD firms have a lower bid-ask spread, lower illiquidity, and higher dollar volume, higher limits to arbitrage might not be the reason for higher

PD.

Furthermore, I find a robust relationship between the volume of a firm's frequency of key development events news and PD. Even though media play a role in propagating information among investors (Peress (2014)), category-learning by investors (Peng and Xiong (2006)), suggests that if a firm performs more value-relevant events, it is more likely that prices become more inefficient with respect to firm-specific information. The results help corroborate the conjecture that PD captures the inefficiency of prices regarding firm-specific information.

The correlation between PD and the variance, skewness, and kurtosis of monthly returns is 0.023, -0.010, and 0.018, respectively. These very low correlations tell us that PD is not just capturing the higher-order moments of returns. Furthermore, since the PD interaction terms subsume return predictability of hundreds of anomaly variables, it is highly unlikely that PD is correlated with one particular anomaly variable.

Investors' behavioral bias can cause some stock prices to be abnormally high while others are abnormally low. For example, if investors are overconfident in the private signal and under-weight a firm's public signal [Daniel, Hirshleifer, and Subrahmanyam (1998)], they are equally likely to be overconfident in their positive as well as negative private signals. The higher the investors' behavioral bias, the higher the price inefficiencies with respect to firm-specific information or PD. As PD 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 PD are muted. Hence, investigating the interaction term between PD and anomaly variables is more meaningful. However, in the sub-samples divided using the past six months' cumulative returns, PD strongly predicts negative returns for losers and, at the same time, positive returns for winners.

The primary contribution of my paper is two-fold: the introduction of an easy-to-calculate PD measure and plausible empirical evidence that the inefficiency of prices concerning firm-specific information, especially the instantaneous aspect, could be at the core of return predictability for hundreds of market anomalies. Even though I use PD to study anomalies, the measure could be used in various settings where semi-strong form price inefficiency about firm-specific information plays an important role. Secondly, as we try to understand the drivers of the anomalies in the financial markets, this paper adds to the understanding of the return predictability of the anomaly variables by providing the evidence that firm-specific information plays an important role in the return predictability of financial market anomalies.

The remainder of the paper is organized as follows. Section I discusses the data, motivation, and calculation of PD. Section II presents the results. Section III covers the robustness exercises. Section IV explores the information possibly captured by PD and the characteristics of high- versus low-PD firms. Finally, Section V concludes the article.

I. Data and PD 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 are obtained from Professor Goyal's website. I present the summary statistics of a few selected variables in Table I.

B. Motivation for PD

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, where complicated analysis is required to incorporate pieces of information into prices. Engelberg et al. (2018) further say that most anomalies are related to firm-specific information.

The literature has developed extensive theory suggesting various mechanisms by which both under- and over-reaction can occur in the market. For example, Barberis, Shleifer, and Vishny (1998) develop a model based on psychological evidence that produces both under- and over-reaction. Additionally, Daniel et al. (1998) state that investor overconfidence causes the market to deviate from the rightful incorporation of relevant information. 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.

Hence, theory suggests that there should be a relation between price inefficiencies with regard to firm-specific information and return predictability. A semi-strong form of price inefficiency regarding firm-specific information measure should estimate the inefficiencies of prices regarding a particular source of information, namely firm-specific. In this paper, I argue that PD can be a proxy for such a measure.

C. PD Calculation

My methodology for calculating PD is roughly motivated by the D3 measure of Hou and Moskowitz (2005). However, as I am interested in calculating the price inefficiency with respect to firm-specific information, I use the return predictability of its own past returns to estimate PD instead.

Consider the estimation of $r_{i,t} = \alpha + \beta_1 r_{i,t-1} + \beta_2 r_{i,t-2} + \beta_3 r_{i,t-3} + \beta_4 r_{i,t-4} + ... + \beta_n r_{i,t-n} + \epsilon$. If the stock prices immediately and correctly incorporate all firm-specific information and if firm-specific information comes to market randomly, then we can expect all the βs from β_1 to β_n to be zero. If the stock prices under- or over-react to the firm-specific information first and then slowly adjust to the true fundamental value, then we should see some of these βs to be non-zero. The longer the time prices take to incorporate the firm-specific information correctly, the higher the βs of longer lagged returns. The deviation of βs associated with lagged returns from zero provides significant insight into tells us a great deal about how efficiently prices incorporate firm-specific information.

In the above estimation, the sign of the βs depends on whether the market under- or over-reacts first, then corrects. Both price paths are the results of price inefficiencies concerning firm-specific information. Whether prices initially underreact and correct (positive higher-order βs) or initially overreact and then correct (negative higher-order βs), both are incorrect incorporation of information into prices. Hence, I treat overreaction and underreaction equally when calculating PD.

The next question is how many lags to use when estimating the above equation. How long it takes for the prices to rightfully incorporate all firm-specific information into prices is an open question. 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-earnings 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 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)). Other recent studies such as Ali, Chen, Yao, and Yu (2020) also confirm a declining but multi-quarter PEAD. If anomalies such as 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 n months' information, then the phenomena suggest that it probably takes something close to n months for prices to fully reflect firm-specific information.

Finally, the calculation of PD is as follows. First, using a rolling window of 60 months, I estimate the following regression for each firm for each month:

$$r_{i,t} = \alpha_i + \sum_{n=1}^{6} \beta_i^n \, r_{i,t-n} \; + f(r_{m,t}, r_{ind,t}) + \epsilon_{i,t} \tag{1}$$

where, $f(r_{m,t}, r_{ind,t}) = \sum_{n=0}^{6} \xi_i^n \, r_{m,t-n} + \sum_{n=0}^{6} \phi_i^n \, r_{ind,t-n}$ and $r_{i,t}$ is the monthly return of stock i in month t. Furthermore, $r_{m,t}$ 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. I use the Fama-French 49 industry classification to group firms into an industry. I include $f(r_m, r_{ind})$ in the regression to control for the market-specific and industry-specific information. PD is then calculated as:

$$\text{PD} = \frac{\sum_{n=1}^{6} \sqrt{n} \cdot |t\text{-stat}(\beta_n^i)|}{\sum_{n=1}^{6} |t\text{-stat}(\beta_n^i)|} \tag{2}$$

This method of calculating PD closely resembles how Hou and Moskowitz (2005) calculate their price inefficiency measure D3[1]. The authors calculate their inefficiency

[1]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

measure by comparing the t-stats associated with contemporaneous market returns versus the t-stats associated with more lagged market returns. In my context, as both the Y and X variables are the firm's own returns, I cannot calculate β_0 (or its *t-stat*) within the framework of Hou and Moskowitz (2005). Hence, my measure does not capture the contemporaneous time unbiasedness aspect of price inefficiency but rather captures the instantaneous aspect of the price inefficiency.

In equation 2, the higher the deviation from zero of higher βs (associated with higher lagged returns), the higher the severity of price inefficiencies. In other words, for the two firms A and B, if we have $\vec{\beta_A} = \{0, 0.2, 0, 0, 0, 0\}$ and $\vec{\beta_B} = \{0, 0, 0, 0, 0, 0.2\}$ then price inefficiency about firm-specific information is higher in B compared to that in firm A. While it is true that $\vec{\beta_A} = \{0.8, 0, 0, 0, 0, 0\}$ and $\vec{\beta_B} = \{0.001, 0, 0, 0, 0, 0\}$ produce the same PD, it is still interpretable in two ways. First, from the sole instantaneous perspective, they are equally efficient. Once any other βs of B get higher than zero, firm B will be considered more inefficient compared to A. Second, in the data, it is almost never the case that one but all betas are non-zero.

The PD formula gives more weight to more precise coefficients and to the t-statistics that belong to more lagged returns.[1] Secondly, since I am interested in the price inefficiency regardless of the sign of the β coefficients of past returns (related to both overreaction or underreaction), I use absolute βs. Just as it is for D3 of Hou and Moskowitz (2005), the t-statistic weighting mechanism is somewhat arbitrary,

market returns in week w. One of their semi-strong form price inefficiency measures is then calculated as:

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

[1]One of the price inefficiency measures (D1), which Hou and Moskowitz (2005) 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.

but the results are robust to different weighting mechanisms, as n.

PD is empirically motivated. PD calculates price inefficiency from an instantaneous perspective by looking at how immediately the information that was not incorporated contemporaneously gets baked into the prices. So, in theory, if the firm-specific information is incorporated into the prices immediately and all βs are zero, then PD is undefined. However, the literature (e.g., PEAD literature discussed above) suggests that this is not empirically the case in the financial markets. Second, hypothetically, if the market takes exactly one month to rightfully incorporate firm-specific information into the prices, then all the βs except β_1 will be zero, and PD will be 1, which is the lower bound of PD. Again, a firm with the lowest PD of 1 can be very price inefficient in an absolute sense (e.g., 0% of the information is incorporated contemporaneously). However, given at least some under- or over-reaction occurred in contemporaneous time, the firm has the lowest price inefficiency concerning the instantaneous aspect.

In my sample, PD numbers range from 1.06 to 2.41, with a mean of 1.77 and a standard deviation of 0.16. The fifth and 95th percentiles are 1.51 and 2.03, respectively.

D. PD, Other Price Inefficiency Measures, and Firm Characteristics

Before I study the relation between PD and anomaly returns, it is crucial to understand whether PD captures new information or is merely a repackaging of other price inefficiency measures already studied extensively in the literature. In this section, I look at the correlation between PD and other price inefficiency measures introduced by Hou and Moskowitz (2005), variance ratios (Lo and MacKinlay (1990)), and a few price informativeness measures such as the probability of informed trading (PIN) and return nonsynchronicity.

I present the results in Table II, Panel A. All the other price inefficiency and price informativeness measures are slightly negatively correlated with PD, with absolute correlations between 1.1 and 3.2 percent. These low correlations suggest that the information that PD captures is different than that captured by other price inefficiency and price informativeness measures.

The literature also suggests that certain anomalies are stronger among firms with certain characteristics (e.g. Chordia and Swaminathan (2000)). Furthermore, information related to analysts, such as the number of analysts covering the stocks or forecast dispersion among analysts, are also used in the literature (e.g. Hong and Stein (1999)) as proxies for price (in)efficiency. Hence, it is natural to understand whether PD is correlated with certain firm characteristics. I present the correlations between PD and various firm-characteristic measures in Table II, Panel B.

The table shows that correlations between PD and various firm-characteristic measures range from negative 3.6 percent (with book-to-market) to positive 4.6 percent (turnover). None of the correlation coefficients are alarming. The low correlation numbers suggest that PD is not highly influenced by firms with certain characteristics, again supporting the notion that PD is capturing a new set of information.

II. Results

A. PD and All Anomalies Put Together

My hypothesis in this paper is that PD should have a strong relation with the return predictability of anomalies in general. To test the hypothesis, I calculate a consolidated anomaly variable that consolidates the information from more than 200 anomalies. The variable is motivated from Engelberg et al. (2018) and use the data from Chen and Zimmermann (2022). For each month, for each anomaly variable, I assign the cross-section of firms into three groups - high, medium, low - based the value of the anomaly variable and sign of the return predictability. I ensure that higher terciles always correspond to higher predicted returns, irrespective of the anomaly's sign. For example, firms with the lowest asset growth (a negative-sign anomaly) and firms with the highest twelve-month cumulative returns (a positive-sign anomaly) are both placed in tercile three, while firms with the highest asset growth and the lowest twelve-month cumulative returns are assigned to tercile one. Finally, we define the variable *Anmly Rank* (Anomaly Long Ranking) as the firm's average tercile ranking across all two hundred plus anomalies.

I provide the results of this analysis in Table Table III. First column shows that the average tercile very strongly predicts next month's returns (t-stat of 11.02). As I show in Column 3, controlling for usual empirical regularities such as size, book-to-market, and ROA, the return predictability of the consolidated anomaly variables increases even further. However, after I augment the model with the PD and it's interaction term with the consolidated anomaly variable, the return predictability of the anomaly variable disappears (t-stat of 0.32). Controlling for PD and its interaction term with the anomaly variables results into interesting changes concerning how other well known firm characteristics load. Size becomes insignificant, book-to-market switches from positive significance from Column 2 to 5, and asset growth turns negative to positive significant. Significant positive coefficient of the interaction term between PD and the consolidated anomaly variable suggests that, on average, financial market anomalies exist among high PD firms. In another words, most anomalies exists where firms' prices are inefficient about firm-specific information, especially on the instantaneous aspect.

B. PD, Anomalies, and Idiosyncratic Volatility

Pontiff (1996) and Pontiff (2006) suggest that idiosyncratic volatility is one of the primary obstacle to arbitrage. Shleifer and Vishny (1997) shows how IVOL deter arbitrageurs. Furthermore, Duan et al. (2010) shows how reducing arbitrage constraints affects anomalies. And, recently, Chu et al. (2020) shows anomalies are stronger in high IVOL stocks. So, understanding relation between the IVOL and PD is important. I test whether an interaction term with IVOL produces the similar effect on anomaly ranking variable as the PD does. As IVOL is such an imporant variable when studying anomalies, I use IVOL from six very widely used asset pricing models - Fama-French three, four, five and six factor models (Fama and French (2015)) and Q4 and Q5 models (Hou, Mo, Xue, and Zhang (2021)) - in my analysis.

I present the results of this analysis in Table IV. I examine whether the interaction term between any of the IVOLs with consolidated anomaly variable takes the return predictability away from the consolidate anomaly variable. While it is very evident from the results that the IVOL interaction term significantly reduce the slope coefficient as well as the t-stat of consolidated anomaly variable, even after augmenting the model with the IVOL interaction term, the consolidated anomaly variable is still significant at 1% level in predicting future returns. Even in the presence of IVOL and it's interaction with the anomaly variable, the return predictability of consolidated anomaly variable only goes away after augmenting the model with the IVOL interaction term with PD. Results suggest that PD captures the inefficiency of prices concerning firm specific information above and beyond what IVOL contributes to the hindrance of arbitrage.

C. PD, Anomalies, Transaction Costs, and Liquidity

Studies such as Chen and Velikov (2023), Novy-Marx and Velikov (2016), and Patton and Weller (2020) find a strong relation between persistence of anomalies and transaction costs. Several other studies such as Lou and Sadka (2011), Bali, Peng, Shen, and Tang (2014), Hasbrouck (2009) points to the relation between liquidity and the anomaly returns or expected returns in general. So, it is important to understand the performance of PD in the model augmented with illiquidity and transaction costs and their interactions with the consolidated anomaly.

I present the results of this analysis in V. While it is generally true that return predictability of consolidated anomaly variable is generally stronger where bid-ask spread (a proxy for transaction costs) are high and or illiquidity is high, the interaction terms between these variable and consolidated anomaly variable do not take the statistical significance away from the consolidated anomaly variable. Controlling for illiquidity and its interaction term with consolidated anomaly variable makes the anomaly variable stronger. Bid-ask spread seems to more important when explaining some of the return predictability of the consolidated anomaly variable. Regardless whether I control for bid-ask spread, illiquidity and/or their interaction terms, the interaction term between PD and consolidated anomaly variable takes away the statistical significance of consolidated anomaly variable. The results the materiality of PD concerning anomalies, on average.

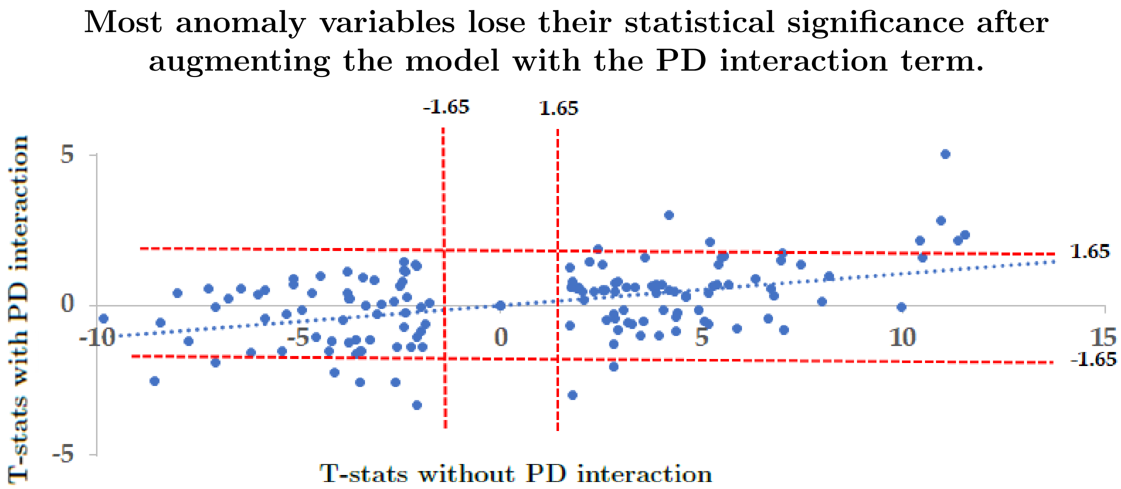
D. PD and 210 Individual Market Anomalies

For this analysis, I use the anomaly data set provided by Chen and Zimmermann (2022). For 209 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 and with price filter of \$5. Out of 210 that were examined, 147 anomaly variables statistically significantly predict the subsequent month's returns in my sample. Then, for each of the 147 anomaly variables, I again estimate the Fama-MacBeth cross-sectional regression controlling for one month-lagged PD 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 Figure 1 and in Table VI.

Out of 147 anomaly variables that significantly predict returns in the recent sample, after I introduce the PD and its interaction term, 130 anomaly variables completely lose their statistical power to predict next month's returns and the return predictability of another 12 anomaly variables significantly weakens[1].

Anomalies related to intangibles (95%) and investments (100%) are the ones that most often lose their statistical power to predict returns after I augment their interaction term with PD. The result helps corroborate the findings that price ineffi-

[1]Sixty-two anomalies that are insignificant in predicting returns in my sample stay insignificant (except a couple) even after I augment the model with the PD interaction term. One hundred and thirty includes two that reverses the sign after I augment the model with PD interaction term.



1: This figure shows the drop in the t-statistics of hundreds of anomaly variables after I introduce the PD interaction term into the regression. While the t-statistics range from -10 to +15 without the PD interaction term in the regression, with the interaction term, the t-statistics of most anomaly variables fall within the statistical insignificance band of $\pm$ 1.65.

ciencies regarding firm-specific information play a very important role in the return predictability of financial market anomalies. At any point in time, prices are more likely to be inefficient with regard to firm-specific information about intangibles and investments because estimating the precise value of intangibles or investments is difficult for investors. The anomaly group that loses the return predictability the least is Trading Frictions (72%). Trading frictions anomaly variables such as bid-ask spread are less likely to be influenced by the incorrect incorporation of firm-specific information into the prices than the intangibles anomaly variables. Results again corroborate that price inefficiency concerning firm-specific information plays an important role in anomaly return predictability, and PD rightfully captures such price inefficiency.

E. *Returns Predictability of PD*

Literature finds that price inefficiencies generally leads to price continuation[1]. As PD oppositely impacts past winners and losers, in the sample that comprises stocks belonging to both legs, the slope coefficient and statistical significance of PD are muted (e.g., in Column 5 of Table **??**). Hence, investigating the return predictability PD in the sub-samples that have experienced positive and negative return continuation in the past is more meaningful. In the five sub-samples divided using the past six months' cumulative returns, PD strongly negatively predicts returns among losers and, at the same time, strongly positively predicts returns among winners. I present the results in Table IA1.

F. *PD, All Anomalies Put Together & Announcement Returns*

Engelberg et al. (2018) shows that anomaly returns concentrate around earning announcements, which suggests that anomalies reflect mispricing information. So and Wang (2014) finds stronger anomaly returns around earning news and suggests that information affects anomaly profits. This literature suggests that the disclosure of firm-specific information is very critical for anomaly returns.

Firms earning announcements are one of the most important information disclosure event, especially the firm-specific information. These brings a huge amount of firm-specific information to investors for them to process. I hypothesize that if PD truly captures the inefficiencies of prices to reflect firm-specific information, we should return predictability around earnigns to be stronger for prices that are more inefficient concerning firm-specific information, meaning the firms with high PD.

[1] See Bernard and Thomas (1989), Hong and Stein (1999), Hong, Lim, and Stein (2000), Jegadeesh and Titman (1993), Zhang (2006)

To test this hypothesis I use the announcement returns data provide by Chen and Zimmermann (2022) for the announcement returns anomaly discovered by Chan et al. (1996). I present the results in Table VII. I find that anomaly ranking variable predicts next three-month average announcement returns only among the firms with high PD even after augmenting the model with PD and it's interaction term with anomaly ranking variable. The results help to validate my story that PD captures the inefficiency of prices concerning firm-specific information.

III. Information Captured by PD

In this section, I examine the possible drivers of PD to better understand the kind of information captured by PD. Even the professional financial players such as analysts are slow to update their forecast for complicated firms rather than for simple firms for the same information (Cohen and Lou (2012)). 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-PD firms concerning the uncertainties around their fundamentals.

I test whether PD 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 return continuation effect when there is higher information uncertainty. Pástor and Veronesi (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 PD and some of the variables suggested by the above literature.

The overall results suggest that higher firm-level uncertainty around the fundamentals might be behind higher PD. 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 the hypothesis that high-PD firms are also more sensitive to economy-wide uncertainty. I also show that limits of arbitrage probably are not the reason behind the variation of PD across firms.

A. Characteristics of Low- versus High-PD Firms

In Table I, I present a summary of firm characteristics of ten groups of firms divided based on their PD values and the statistical significance of the difference between 10th-decile PD firms and first-decile PD firms. A top-level summary tells us that high-PD firms are larger growth firms with higher year-over-year asset growth and lower return on assets. And PD in not related to the firm size at all. Compared to low-PD firms, high-PD firms have lower profitability and book-to-market and higher asset growth. High-PD firms also perform more material corporate events.

Higher PD firms not only have a slow diffusion of firm-specific information but also perform a higher number of material corporate events than low-PD 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 PD firms also produce more material news.

To understand the higher PD firms' sensitivity to the aggregate economy-wide uncertainty, I rely on the data from Baker, Bloom, and Davis (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 measure to obtain their respective β coefficients. Table I shows that higher PD firms are significantly more sensitive to economy-wide uncertainty than lower PD firms.

A.1. Key Corporate Events & News Production

Rational attention theory suggests that investors with limited cognitive ability choose to learn about the common shocks, such as shocks at the market or industry level, at the cost of the firm-specific shocks (Peng and Xiong (2006), Kacperczyk, Van Nieuwerburgh, and Veldkamp (2009)). This phenomenon suggests that prices are more likely to be inefficient concerning firm-specific shocks than market-specific shocks, for example. On top of that, if a firm performs more value-relevant actions, then some of the information will be overlooked by resource-constrained investors, and the information that is yet to be incorporated into the prices will pile up. Hence, PD should be high in those circumstances. While (Peress (2014)) suggests that media plays a role in propagating information among investors, performing more corporate events does not necessarily equate to having more media coverage. For example, for a given corporate event, glamorous and meme stocks get more media coverage than value stocks.

To test my hypothesis, I use the Key Developments database. The Key Developments database compiles a time series of two hundred thirty-four different types of key corporate events that are relevant to stock prices. Some of the key development types include the announcement of business expansions M&A rumors and discussions, client announcements, strategic alliances, dividend affirmations or decreases, board meetings, impairments and write-offs, potential buybacks, and fixed income calls.

The results in Table VIII very strongly support my hypothesis above. Each of the key development variables is the natural logarithm of the number of key development events the firm had in the month $t-1$, and the dependent variable, PD, is at month t. The monthly Fama-Macbeth regression shows that the key corporate events variables in the previous month very strongly predict the PD in month t. Coefficients are very intuitive. The coefficient for investments and financing developments is four times the coefficient of earnings-related announcements. It is intuitive as earnings-related news is expected, scheduled beforehand, and widely covered by analysts and media, while information about the value implications of investments and financing decisions is hard to decipher. Miscellaneous and other category is very close but not significant. It is probably because the category includes events such as inclusion or drop from indices such as S&P, which is less about the firm-specific shock. The results further support my claim in the paper that PD captures the inefficiency of prices about firm-specific information.

A.2. Level and Variance of Profitability

Pástor and Veronesi (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 conjecture here is that higher profitability variability should be related to higher PD.

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

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

A.3. High PD Firms, Information Uncertainties, & Opaqueness

Zhang (2006) finds a stronger return continuation 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 PD 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 X.

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

The returns of high-PD 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-PD firms on average. High PD firms also experience higher turnover and have higher equity duration. Overall, the results provide very strong evidence that high-PD firms are the firms with higher information uncertainty.

Concerning opaqueness, high PD 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 PD firms are more opaque. Overall, high-PD firms have higher uncertainties around their fundamentals and are hard to value.

A.4. High PD 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-PD versus low-PD firms concerning limits of arbitrage proxies to understand whether some economic constraints cause the PD to increase among high-PD firms.

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

Compared to low-PD firms, high-PD firms, on average, have a lower bid-ask spread, illiquidity, and higher dollar volume. Overall, the results suggest that limits of arbitrage probably are not why firm-specific information diffuses slowly among high-PD firms.

B. Plausible Determinants of Economy-wide PD

When aggregate economic uncertainty is high, on average, firm-level uncertainty should be high as well (Bloom, Bond, and Van Reenen (2007), Bloom (2009)). So, I hypothesize that PD and aggregate uncertainty should have some positive relation. In this section, I study the relation between aggregate economy-wide PD variables and economic and business cycle variables. For this purpose, I calculate two consolidated market-level PD variables - APD_EQ (aggregate equal-weighted PD) and PD_VW (aggregate market-cap-weighted PD) - of all firms in the cross-section for the month. In Figure 4, I plot APD_EQ and APD_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 PD has generally been increasing in recent times and is higher when EPU is high. I find the correlation between the EPU index and APD_EQ to be about 30%, suggesting that when economy-wide uncertainty increases, the price inefficiency regarding firm-specific information is higher on average across firms. Column (6) of Table XI confirm the results in the regression setting. The results support the view that PD increases in periods of higher economic uncertainty.

In Table XI, I show the results of a few univariate regressions of the business cycle and other economic variables on APD_EQ in contemporaneous time. 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. 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 APD_EQ, and the dividend yield is significantly negatively associated. Individual univariate regressions of each of the determinants of APD_EQ provide evidence that again supports the view that PD generally is higher during uncertain times.

IV. Conclusion

In this paper, I study the relationship between price inefficiency regarding firm-specific information (PD) and ALRank, a composite measure that captures the information from more than two hundred asset market anomalies. 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 on average.

Motivated by this line of thought, I develop a price delay (PD) regarding firm-specific information 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 anomaly literature such as PEAD and momentum. PD also controls for US market-specific information and a firm's industry-specific information.

Analyzing the firm characteristics of low- versus high-PD firms, I find evidence that high uncertainties around firms' fundamentals, on average, increase PD. PD is strongly related to the volume of a firm's value-relevant news. I find that high-PD firms are generally 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 PD and ALRank subsumes the return predictability of ALRank. Examining each anomaly individually, I find that the interaction term between PD and anomaly variable takes away the return predictability of more than 88% of prevalent asset market anomalies that still predicts returns in my sample and weakens the predictability of almost all the rest. The empirical evidence suggests that price inefficiencies specific to firm-specific information, especially on the instantaneous aspect, lies at the core of the return predictability of asset market anomalies in general.

REFERENCES

Ali, Ashiq, Xuanjuan Chen, Tong Yao, and Tong Yu, 2020, Can mutual funds profit from post earnings announcement drift? the role of competition, *Journal of Banking & Finance* 114, 105774.

Amihud, Yakov, 2002, Illiquidity and stock returns: cross-section and time-series effects, *Journal of financial markets* 5, 31–56.

Baker, Scott R, Nicholas Bloom, and Steven J Davis, 2016, Measuring economic policy uncertainty, *The Quarterly Journal of Economics* 131, 1593–1636.

Bali, Turan G, Lin Peng, Yannan Shen, and Yi Tang, 2014, Liquidity shocks and stock market reactions, *The Review of Financial Studies* 27, 1434–1485.

Ball, Ray, and Philip Brown, 1968, An empirical evaluation of accounting income numbers, *Journal of accounting research* 159–178.

Barberis, Nicholas, Andrei Shleifer, and Robert Vishny, 1998, A model of investor sentiment1, *Journal of financial economics* 49, 307–343.

Bernard, Victor L, and Jacob K Thomas, 1989, Post-earnings-announcement drift: delayed price response or risk premium?, *Journal of Accounting research* 27, 1–36.

Bloom, Nicholas, 2009, The impact of uncertainty shocks, *econometrica* 77, 623–685.

Bloom, Nick, Stephen Bond, and John Van Reenen, 2007, Uncertainty and investment dynamics, *The review of economic studies* 74, 391–415.

Chan, Louis KC, Narasimhan Jegadeesh, and Josef Lakonishok, 1996, Momentum strategies, *The Journal of Finance* 51, 1681–1713.

Chen, Andrew Y, and Mihail Velikov, 2023, Zeroing in on the expected returns of anomalies, *Journal of Financial and Quantitative Analysis* 58, 968–1004.

Chen, Andrew Y., and Tom Zimmermann, 2022, Open source cross-sectional asset pricing, *Critical Finance Review* 27, 207–264.

Chordia, Tarun, and Bhaskaran Swaminathan, 2000, Trading volume and cross-autocorrelations in stock returns, *The Journal of Finance* 55, 913–935.

Chu, Yongqiang, David Hirshleifer, and Liang Ma, 2020, The causal effect of limits to arbitrage on asset pricing anomalies, *The Journal of Finance* 75, 2631–2672.

Cohen, Lauren, and Dong Lou, 2012, Complicated firms, *Journal of financial economics* 104, 383–400.

Cutler, David M, James M Poterba, and Lawrence H Summers, 1991, Speculative dynamics, *The Review of Economic Studies* 58, 529–546.

Daniel, Kent, David Hirshleifer, and Avanidhar Subrahmanyam, 1998, Investor psychology and security market under-and overreactions, *the Journal of Finance* 53, 1839–1885.

Daniel, Kent, and Sheridan Titman, 1999, Market efficiency in an irrational world, *Financial Analysts' Journal* 55, 28–40.

Davis, James L, Eugene F Fama, and Kenneth R French, 2000, Characteristics, covariances, and average returns: 1929 to 1997, *The Journal of Finance* 55, 389–406.

De Bondt, Werner FM, and Richard Thaler, 1985, Does the stock market overreact?, *The Journal of finance* 40, 793–805.

Duan, Ying, Gang Hu, and R David McLean, 2010, Costly arbitrage and idiosyncratic risk: Evidence from short sellers, *Journal of Financial Intermediation* 19, 564–579.

Engelberg, Joseph, R David McLean, and Jeffrey Pontiff, 2018, Anomalies and news, *The Journal of Finance* 73, 1971–2001.

Engelberg, Joseph, R David McLean, and Jeffrey Pontiff, 2020, Analysts and anomalies, *Journal of Accounting and Economics* 69, 101249.

Fama, Eugene F, and Kenneth R French, 2015, A five-factor asset pricing model, *Journal of financial economics* 116, 1–22.

Fink, Josef, 2021, A review of the post-earnings-announcement drift, *Journal of Behavioral and Experimental Finance* 29, 100446.

Griffin, John M, Patrick J Kelly, and Federico Nardari, 2010, Do market efficiency measures yield correct inferences? a comparison of developed and emerging markets, *The Review of Financial Studies* 23, 3225–3277.

Hasbrouck, Joel, 2009, Trading costs and returns for us equities: Estimating effective costs from daily data, *The Journal of Finance* 64, 1445–1477.

Hong, Harrison, Terence Lim, and Jeremy C Stein, 2000, Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies, *The Journal of Finance* 55, 265–295.

Hong, Harrison, and Jeremy C Stein, 1999, A unified theory of underreaction, momentum trading, and overreaction in asset markets, *The Journal of finance* 54, 2143–2184.

Hou, Kewei, Haitao Mo, Chen Xue, and Lu Zhang, 2021, An augmented q-factor model with expected growth, *Review of Finance* 25, 1–41.

Hou, Kewei, and Tobias J Moskowitz, 2005, Market frictions, price delay, and the cross-section of expected returns, *The Review of Financial Studies* 18, 981–1020.

Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, *The Journal of finance* 48, 65–91.

Jensen, Theis Ingerslev, Bryan Kelly, and Lasse Heje Pedersen, 2023, Is there a replication crisis in finance?, *The Journal of Finance* 78, 2465–2518.

Jiang, Guohua, Charles MC Lee, and Yi Zhang, 2005, Information uncertainty and expected returns, *Review of Accounting Studies* 10, 185–221.

Jin, Li, and Stewart C Myers, 2006, R2 around the world: New theory and new tests, *Journal of financial Economics* 79, 257–292.

Kacperczyk, Marcin, Stijn Van Nieuwerburgh, and Laura Veldkamp, 2009, Rational attention allocation over the business cycle, Technical report, National Bureau of Economic Research.

Kumar, Alok, 2009, Hard-to-value stocks, behavioral biases, and informed trading, *Journal of Financial and Quantitative Analysis* 44, 1375–1401.

La Porta, Rafael, 1996, Expectations and the cross-section of stock returns, *The Journal of Finance* 51, 1715–1742.

Lakonishok, Josef, Andrei Shleifer, and Robert W Vishny, 1994, Contrarian investment, extrapolation, and risk, *The journal of finance* 49, 1541–1578.

Lam, FY Eric C, and KC John Wei, 2011, Limits-to-arbitrage, investment frictions, and the asset growth anomaly, *Journal of Financial Economics* 102, 127–149.

Lo, Andrew W, and A Craig MacKinlay, 1990, When are contrarian profits due to stock market overreaction?, *The review of financial studies* 3, 175–205.

Lou, Xiaoxia, and Ronnie Sadka, 2011, Liquidity level or liquidity risk? evidence from the financial crisis, *Financial Analysts Journal* 67, 51–62.

Novy-Marx, Robert, and Mihail Velikov, 2016, A taxonomy of anomalies and their trading costs, *The Review of Financial Studies* 29, 104–147.

Pan, Xuhui Nick, Bharat Raj Parajuli, and Petra Sinagl, 2021, The idiosyncratic volatility puzzle with learning and asymmetric signal precision, *Available at SSRN: https://ssrn.com/abstract=3574790* .

Pástor, L'uboš, and Pietro Veronesi, 2003, Stock valuation and learning about profitability, *The Journal of Finance* 58, 1749–1789.

Patton, Andrew J, and Brian M Weller, 2020, What you see is not what you get: The costs of trading market anomalies, *Journal of Financial Economics* 137, 515–549.

Peng, Lin, and Wei Xiong, 2006, Investor attention, overconfidence and category learning, *Journal of Financial Economics* 80, 563–602.

Peress, Joel, 2014, The media and the diffusion of information in financial markets: Evidence from newspaper strikes, *the Journal of Finance* 69, 2007–2043.

Pontiff, Jeffrey, 1996, Costly arbitrage: Evidence from closed-end funds, *The Quarterly Journal of Economics* 111, 1135–1151.

Pontiff, Jeffrey, 2006, Costly arbitrage and the myth of idiosyncratic risk, *Journal of Accounting and Economics* 42, 35–52.

Schmidt, Daniel, 2012, Investors' attention and stock covariation: Evidence from google sport searches .

Shleifer, Andrei, and Robert W Vishny, 1997, The limits of arbitrage, *The Journal of finance* 52, 35–55.

So, Eric C, and Sean Wang, 2014, News-driven return reversals: Liquidity provision ahead of earnings announcements, *Journal of Financial Economics* 114, 20–35.

Welch, Ivo, and Amit Goyal, 2008, A comprehensive look at the empirical performance of equity premium prediction, *The Review of Financial Studies* 21, 1455–1508.

Zhang, X Frank, 2006, Information uncertainty and stock returns, *The Journal of Finance* 61, 105–137.

Zhou, Hao, 2018, Variance risk premia, asset predictability puzzles, and macroeconomic uncertainty, *Annual Review of Financial Economics* 10, 481–497.

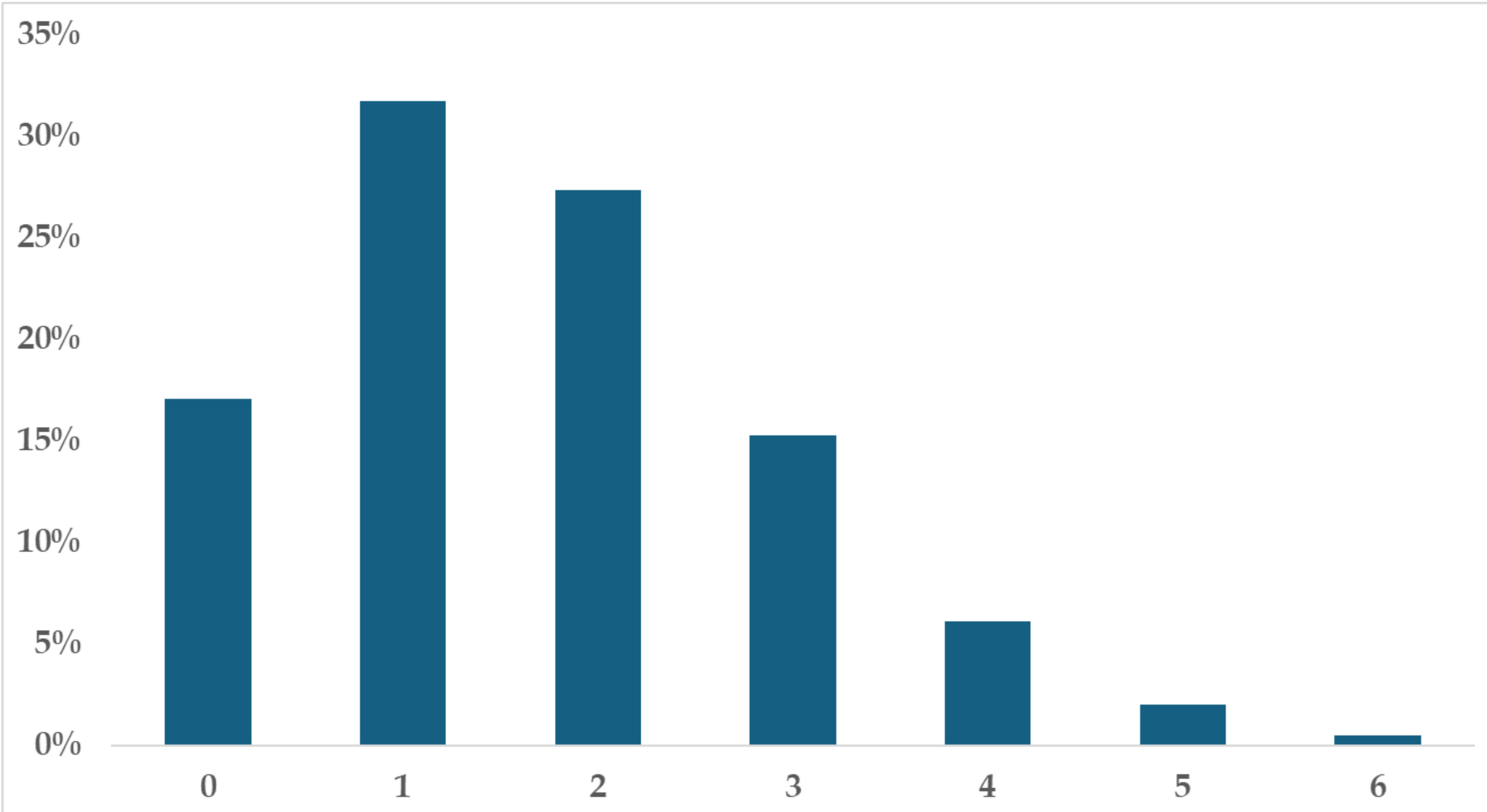


Figure 2: Statistical Significance of β Coefficients in Equation 1. The plots show the probability distribution curve for the number of β coefficients (out of all the six βs from β_1 thorough β_6) that are statistically significant at a 20% level. Plot shows that more than 83% of the time, at least one of the beta coefficients is significant. Even though the statistical significance level I am using is high, the results show that at least some of the beta coefficients are not purely noise and contain some valuable information. The price filter used is $5, and the minimum number of observations required for 60-month rolling regression is twenty-four.

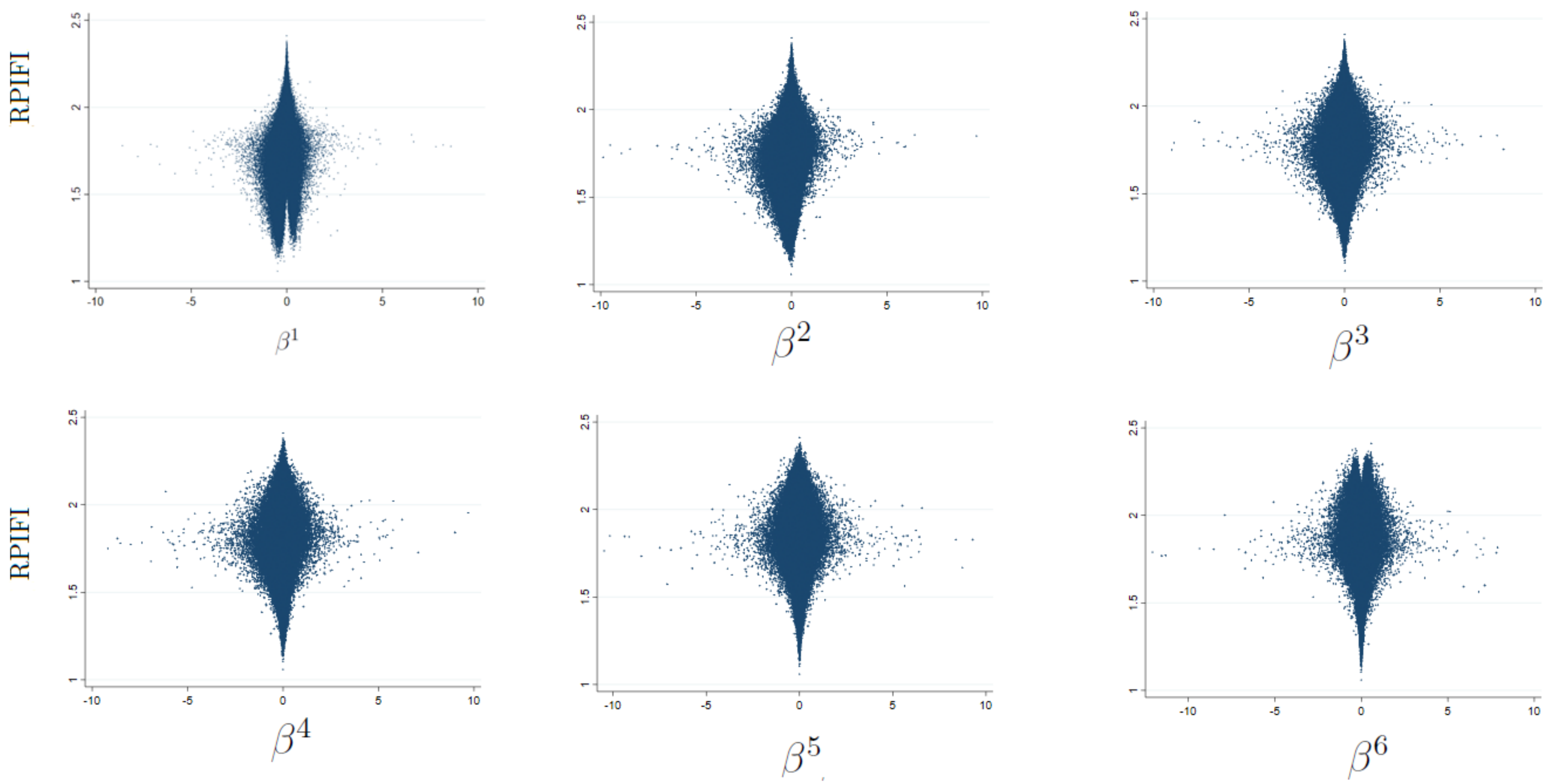


Figure 3: PD and β coefficients. This figure shows the scatter plots between PD and each of the β^2 through β^6 coefficient from the extended model (equation 1) used to calculate PD. Plots show that PD has very little correlation, if any, with any of the βs from the extended model.

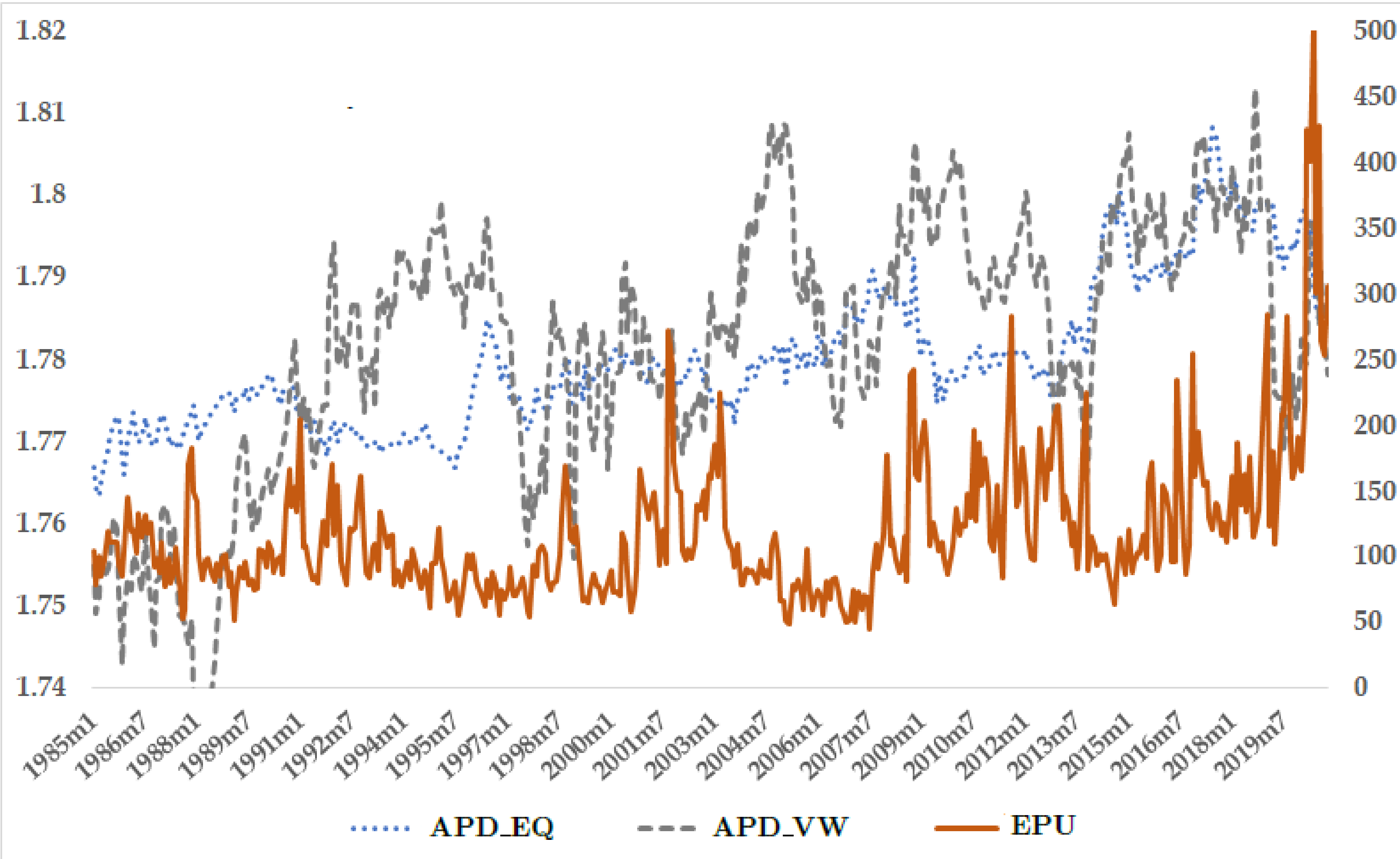


Figure 4: Economic Policy Uncertainty & PD. The plots show that both aggregate PD measures have increased in recent times with EPU. EPU is the Economic Policy Uncertainty Index developed by Baker et al. (2016). APD_EQ is the equal-weighted PD of all firms in the cross-section for the month. Similarly, APD_VW is the market-cap-weighted average of the PD of all firms in the cross-section for the month. The price filter used is $1.

Table I: Summary Statistics

This table shows the mean value of firm fundamental characteristics within each PD decile. PD is the price inefficiency concerning firm-specific information as defined by equation 2. I sort the firm-month observations into 10 PD deciles every month based on the firms' PD 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 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 $5.

	PD Deciles										
	1	2	3	4	5	6	7	8	9	10	10-1 $t-stat$
PD	1.496	1.607	1.668	1.716	1.759	1.8	1.841	1.886	1.941	2.039	.
LMCAP	5.801	5.82	5.827	5.815	5.813	5.808	5.811	5.81	5.798	5.830	2.868
LBM	-.549	-.57	-.58	-.586	-.591	-.593	-.593	-.606	-.61	-.609	21.278
AG	.112	.118	.119	.122	.123	.123	.124	.127	.128	.128	20.884
ROA	.042	.042	.042	.041	.041	.041	.041	.040	.040	.040	-7.584
MAT_EVENT_6M	1.361	1.388	1.406	1.402	1.393	1.385	1.379	1.374	1.375	1.379	3.073
MAT_EVENT_12M	2.704	2.771	2.807	2.801	2.786	2.767	2.759	2.745	2.745	2.75	2.966
MAT_EVENT_24M	5.368	5.521	5.591	5.567	5.539	5.501	5.488	5.464	5.462	5.464	3.11
IU_Z	.505	.515	.522	.528	.532	.534	.538	.541	.544	.544	-40.767

Table II:
Correlation Among PD, Other Price Efficiency Measures, Firm Characteristics, and βs from Equation 1

This table shows the correlation between PD and various measures of price efficiencies and informativeness (Panel A), firm characteristics (Panel B), return characteristics (Panel C), and βs from Equation 1 (Panel C). In Panel A, D1_HM and D3_HM are price inefficiency measures of Hou and Moskowitz (2005). VarRatio variables are variance ratio measures following Lo and MacKinlay (1990). PIN_EKO and PIN_VDJ are the probability of informed trading measures. And, Rsynchronicity is return synchronicity. In Panel B, LnMCAP, LnBM, AG, and ROA are the natural logarithm of market capital, the natural logarithm of book-to-market, asset growth, and return on assets, respectively. Then, Age, ILLIQ, Price, LnACount, and ANLST_DISP, are firm age, illiquidity measure of Amihud (2002), stock's closing price for the month, the natural logarithm of the number of analysts covering the firm, and analysts' dispersion. In Panel C, $\text{BHR6M}_{-1,-6}$ is the cumulative returns from month $t-6$ to month $t-1$. PD is the price inefficiency regarding firm-specific information calculated using equation 2. 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 PD come from the Equation 1). The sample period runs from January 1966 through December 2020. All variables are defined in Appendix A. The price filter used is \$5.

Panel A: Correlations between PD and Other
Price Efficiency and Price Informativeness Measures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
PD	1.000								
D1_HM	-0.013	1.000							
D3_HM	-0.011	0.842	1.000						
VarRatio 2W	-0.022	0.168	0.145	1.000					
VarRatio 4W	-0.021	0.153	0.132	0.834	1.000				
VarRatio 8W	-0.016	0.110	0.094	0.603	0.863	1.000			
PIN_EKO	-0.028	0.338	0.296	0.264	0.232	0.167	1.000		
PIN_VDJ	-0.032	0.378	0.330	0.284	0.252	0.182	0.801	1.000	
RSynchronicity	-0.013	0.484	0.446	0.186	0.170	0.126	0.429	0.466	1.000

Table II:
Correlation Among PD, Other Price Efficiency Measures, Firm Characteristics, and βs from Equation 1 Contd...

Panel B: Correlations between PD & Firm Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
PD	1.000										
LnMCAP	0.022	1.000									
LnBM	-0.036	-0.367	1.000								
AG	0.012	0.052	-0.155	1.000							
ROA	0.005	0.015	-0.084	0.013	1.000						
Turnover	0.046	0.187	-0.145	0.083	-0.006	1.000					
Age	-0.030	0.320	0.066	-0.121	0.011	-0.068	1.000				
ILLIQ	-0.010	-0.198	0.082	-0.009	-0.003	-0.028	-0.045	1.000			
Price	0.008	0.327	-0.149	0.041	0.020	0.036	0.151	-0.058	1.000		
LnACount	0.025	0.476	-0.189	0.004	-0.005	0.198	0.134	-0.086	0.143	1.000	
ANLST_DISP	-0.027	-0.433	0.204	-0.004	0.006	-0.181	-0.079	0.101	-0.112	-0.734	1.000

Panel C: Correlations between PD, Return Characteristics, and βs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$BHR6M_{-1,-6}$	1.000											
PD	0.007	1.000										
β_UMD	0.127	0.003	1.000									
RetVar	0.189	0.023	-0.015	1.000								
RetSkew	0.210	-0.010	0.039	0.206	1.000							
RetKurt	0.052	0.018	-0.001	0.262	0.373	1.000						
β^1	0.024	0.358	-0.002	0.034	-0.010	0.038	1.000					
β^2	0.018	0.215	-0.008	0.021	-0.019	0.002	0.192	1.000				
β^3	0.012	0.060	-0.016	0.012	-0.021	-0.003	0.167	0.199	1.000			
β^4	0.010	0.019	0.003	0.013	-0.005	-0.001	0.083	0.175	0.172	1.000		
β^5	0.013	-0.018	0.007	0.016	-0.006	-0.006	0.118	0.064	0.128	0.181	1.000	
β^6	0.008	-0.043	0.015	0.006	0.003	0.002	0.032	0.065	0.044	0.124	0.165	1.000

Table III:
ALRank (Anomaly Long Ranking) and Price Inefficiency Concerning Firm-Specific Information (PD)

This table shows the results of Fama-MacBeth cross-sectional regressions of monthly returns on the anomaly ranking variable after controlling for well-known empirical regularities, the price inefficiency measure of Hou and Moskowitz (2005), and PD and its interactions with the anomaly ranking variable. Using the data from Chen and Zimmermann (2022), each month, each firm, based on firm's the anomaly variable value for the month and sign of return predictability of the anomaly variable, I assign each firm in to three terciles - high, medium, and low. The ALRank (Anomaly Long Ranking) is the firm's average tercile ranking for the month across all two hundred plus anomalies. PD is the price inefficiency of firm-specific information as defined by equation 2, and D3_HM is the semi-strong form price inefficiency measure of Hou and Moskowitz (2005) as defined by equation 3. The sample period runs from January 1967 through December 2020, and the price filter used is $5. All variables are defined in Appendix A. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
ALRank	3.266***		3.376***	2.914***	0.237
	(11.017)		(12.189)	(7.206)	(0.324)
$MCAP_{-1}$		-0.052**	-0.008	-0.016	-0.017
		(-2.087)	(-0.314)	(-0.608)	(-0.622)
BM_{-12}		0.135***	-0.084**	-0.083**	-0.081**
		(2.891)	(-2.094)	(-2.114)	(-2.036)
$AsstGrowth_{-12}$		-0.755***	0.221**	0.212**	0.197**
		(-6.744)	(2.393)	(2.320)	(2.102)
ROA_{-12}		0.715**	0.330	0.300	0.333
		(2.308)	(1.055)	(0.985)	(1.017)
$BHR6M_{-1,-6}$		0.055	-0.200	-0.165	-0.164
		(0.296)	(-1.120)	(-0.947)	(-0.945)
$D3\_HM_{-1}$				-0.735*	-0.753**
				(-1.937)	(-1.987)
$D3\_HM_{-1}$ x $ALRank_{-1}$				0.337*	0.346*
				(1.775)	(1.825)
PD_{-1}					-2.793***
					(-3.797)
PD_{-1} x $ALRank_{-1}$					1.512***
					(3.976)
Constant	-5.070***	1.588***	-5.295***	-4.203***	0.745
	(-7.391)	(3.853)	(-6.312)	(-3.923)	(0.487)
Months	648	648	648	648	648
Observations	1,611,260	1,611,260	1,611,260	1,611,260	1,611,260

Table IV:
IVOL and PD

This table shows the results of Fama-MacBeth cross-sectional regressions of monthly returns on the anomaly ranking variable after controlling for well-known empirical regularities, the price inefficiency measure of Hou and Moskowitz (2005), and PD and its interactions with the anomaly ranking variable and PDs interaction with various idiosyncratic volatility measures. Using the data from Chen and Zimmermann (2022), each month, each firm, based on firm's the anomaly variable value for the month and the sign of return predictability of the anomaly variable, I assign each firm in to three terciles - high, medium, and low. The ALRank (Anomaly Long Ranking) is the firm's average tercile ranking for the month across all two hundred plus anomalies. IVOLFF3, IVOLFF4, IVOLFF5, IVOLFF6, IVOLQ4 and IVOLQ5, are monthly idiosyncratic volatility calculated using Fama-French three, four, five, and six factors and Q5 and Q4 asset pricing factors asset pricing models, respectively. PD is the price inefficiency of firm-specific information as defined by equation 2. Controls include the control variables controlled for in Table III. The sample period runs from January 1967 through December 2020, and the price filter used is $5. All variables are defined in Appendix A. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
ALRank	0.983***	-0.773	1.046***	-0.760	1.058***	-0.736
	(2.733)	(-1.084)	(2.891)	(-1.063)	(2.914)	(-1.030)
IVOLFF3$_{-1}$	-1.842***	-1.827***				
	(-10.982)	(-10.948)				
PD$_{-1}$ x IVOLFF3$_{-1}$	0.873***	0.865***				
	(10.072)	(10.013)				
IVOLFF4$_{-1}$			-1.867***	-1.852***		
			(-10.820)	(-10.782)		
PD$_{-1}$ x IVOLFF4$_{-1}$			0.885***	0.877***		
			(9.901)	(9.839)		
IVOLFF5$_{-1}$					-1.921***	-1.906***
					(-11.002)	(-10.970)
PD$_{-1}$ x IVOLFF5$_{-1}$					0.910***	0.901***
					(10.057)	(10.002)
PD$_{-1}$		-1.770**		-1.823**		-1.810**
		(-2.505)		(-2.578)		(-2.561)
PD$_{-1}$ x ALRank$_{-1}$		0.991***		1.018***		1.012***
		(2.716)		(2.787)		(2.772)
Controls	YES	YES	YES	YES	YES	YES
Constant	0.476	3.619**	0.338	3.578**	0.321	3.538**
	(0.535)	(2.497)	(0.379)	(2.464)	(0.358)	(2.437)
Months	648	648	648	648	648	648
Observations	1,611,260	1,611,260	1,611,260	1,611,260	1,611,260	1,611,260

Table IV:
IVOL and PD Contd...

	(Panel B: Fama-French-Carhart and Q Models)					
	(1)	(2)	(3)	(4)	(5)	(6)
ALRank	1.124***	-0.708	1.137***	-0.628	1.160***	-0.619
	(3.086)	(-0.989)	(3.044)	(-0.853)	(3.105)	(-0.842)
$IVOLFF6_{-1}$	-1.945***	-1.931***				
	(-10.739)	(-10.703)				
PD_{-1} x $IVOLFF6_{-1}$	0.921***	0.913***				
	(9.805)	(9.748)				
$IVOLQ4_{-1}$			-1.882***	-1.864***		
			(-11.222)	(-11.176)		
PD_{-1} x $IVOLQ4_{-1}$			0.890***	0.880***		
			(10.296)	(10.240)		
$IVOLQ5_{-1}$					-1.934***	-1.916***
					(-11.265)	(-11.214)
PD_{-1} x $IVOLQ5_{-1}$					0.914***	0.904***
					(10.328)	(10.265)
PD_{-1}		-1.852***		-1.820**		-1.837**
		(-2.615)		(-2.494)		(-2.518)
PD_{-1} x $ALRank_{-1}$		1.032***		0.999***		1.007***
		(2.824)		(2.649)		(2.672)
Controls	YES	YES	YES	YES	YES	YES
Constant	0.172	3.465**	0.086	3.305**	0.036	3.286**
	(0.191)	(2.381)	(0.092)	(2.199)	(0.039)	(2.187)
Months	648	648	648	648	648	648
Observations	1,611,260	1,611,260	1,611,260	1,611,260	1,611,260	1,611,260

Table V:
ALRank (Anomaly Long Ranking), Transaction Costs, Illiquidity, and PD

This table shows the results of Fama-MacBeth cross-sectional regressions of monthly returns on the anomaly ranking variable after controlling for well-known empirical regularities, the price inefficiency measure of Hou and Moskowitz (2005), and PD and its interactions with the anomaly ranking variable and PDs interaction with the measures of illiquidity and transaction costs. Using the data from Chen and Zimmermann (2022), each month, each firm, based on firm's the anomaly variable value for the month and the sign of return predictability of the anomaly variable, I assign each firm in to three terciles - high, medium, and low. The ALRank (Anomaly Long Ranking) is the firm's average tercile ranking for the month across all two hundred plus anomalies. Illiq is the illiquidity measure calculated following Amihud (2002), and BA_Spread is bid-ask spread calculated following Lam and Wei (2011). PD is the price inefficiency of firm-specific information as defined by equation 2. Controls include the control variables controlled for in Table III. The sample period runs from January 1967 through December 2020, and the price filter used is $5. All variables are defined in Appendix A. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
ALRank	3.293***	0.483	2.362***	-0.004	2.221***	-0.260
	(11.727)	(0.700)	(9.104)	(-0.006)	(8.341)	(-0.373)
BAS_{-1}			-13.516***	-13.456***	-13.785***	-13.626***
			(-5.976)	(-5.841)	(-6.143)	(-6.025)
BAS_{-1} x $ALRank_{-1}$			6.953***	6.896***	7.116***	6.994***
			(5.656)	(5.510)	(5.836)	(5.710)
$Illiq_{-1}$	-0.297	-0.355*			-0.310	-0.362*
	(-1.529)	(-1.844)			(-1.626)	(-1.914)
$Illiq_{-1}$ x $ALRank_{-1}$	0.140	0.169*			0.147	0.172*
	(1.456)	(1.765)			(1.553)	(1.833)
PD_{-1}		-2.901***		-2.467***		-2.573***
		(-3.931)		(-3.367)		(-3.514)
PD_{-1} x $ALRank_{-1}$		1.571***		1.342***		1.402***
		(4.115)		(3.533)		(3.690)
Controls	YES	YES	YES	YES	YES	YES
Constant	-4.804***	0.395	-3.034***	1.353	-2.657***	1.916
	(-5.098)	(0.268)	(-3.685)	(0.938)	(-3.112)	(1.317)
Months	648	648	648	648	648	648
Observations	1,611,260	1,611,260	1,611,260	1,611,260	1,611,260	1,611,260

Table VI: 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 $ret_{i,t} = \alpha + \beta\, AVar_{i,t-1} + \gamma_1\, PD_{i,t-1} + \gamma_2\, PD_{i,t-1} * AVar_{i,t-1} + \sum_{i=3}^{8} \gamma_i\, X_{i,t-n} + \epsilon_i$ 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 PD and its interaction terms with the anomaly variable subsumes the return predictability of the anomaly variable for the majority of asset-market anomalies.

	Without PD Interaction		With PD Interaction	
Anomaly Description	β (1)	t-stat (2)	β (3)	t-stat (4)
Share issuance (1 year)	-0.003	(-3.331)***	0.000	(-0.009)
Convertible debt indicator	-0.001	(-2.958)***	0.000	(0.024)
Change in put minus call vol	-0.020	(-7.049)***	-0.001	(-0.053)
Intangible return using Sale2P	-0.001	(-1.966)**	0.000	(-0.056)
Past trading volume	-0.001	(-1.766)*	0.000	(0.077)
Change in Forecast and Accrual	0.007	(9.97)***	0.000	(-0.078)
Call minus Put Vol	0.053	(7.999)***	0.009	(0.127)
Share issuance (5 year)	-0.001	(-2.616)***	0.000	(0.132)
Change in Net Noncurrent Op Assets	-0.007	(-4.91)***	-0.002	(-0.151)
Piotroski F-score	0.001	(3.052)***	-0.001	(-0.16)
Inst Own and Turnover	0.003	(4.937)***	0.000	(-0.165)
Growth in long term operating assets	0.007	(4.066)***	-0.002	(-0.178)
Analyst Rec. and Short-Interest	0.005	(2.091)**	0.003	(0.188)
Change in current operating assets	-0.008	(-3.756)***	0.003	(0.207)
Net Operating Assets	-0.003	(-6.749)***	0.001	(0.22)
Long-run reversal	-0.001	(-3.703)***	0.000	(0.224)
Coskewness using daily returns	-0.005	(-2.337)**	-0.002	(-0.253)
Debt Issuance	-0.001	(-2.324)**	0.001	(0.258)
Inst Own and Forecast Dispersion	0.002	(4.626)***	0.001	(0.266)
Cash to assets	0.012	(4.4)***	-0.006	(-0.268)
Change in capital inv (ind adj)	0.001	(-3.049)***	0.000	(-0.29)
Net debt financing	-0.009	(-5.313)***	-0.004	(-0.299)
Cash flow to market	0.004	(2.816)***	-0.004	(-0.311)

Table VI:
All Anomalies Continued...

Anomaly Description	Without PD Interaction β (1)	Without PD Interaction t-stat (2)	With PD Interaction β (3)	With PD Interaction t-stat (4)
Earnings streak length	0.001	(6.805)***	0.000	(0.326)
Share repurchases	0.002	(4.62)***	0.001	(0.328)
change in ppe and inv/assets	-0.006	(-5.992)***	0.003	(0.353)
Operating Cash flows to price	0.005	(4.349)***	-0.004	(-0.381)
change in net operating assets	-0.006	(-8.004)***	0.002	(0.402)
Industry Momentum	0.020	(5.191)***	0.006	(0.403)
Total accruals	-0.003	(-3.802)***	0.004	(0.406)
Customer momentum	0.039	(3.875)***	0.025	(0.41)
Earnings announcement return	0.045	(17.232)***	0.008	(0.434)
Medium-run reversal	-0.004	(-4.681)***	0.002	(0.436)
Inventory Growth	-0.001	(-5.833)***	-0.001	(-0.436)
Earnings surprise of big firms	0.001	(2.858)***	-0.001	(-0.442)
Days with zero trades	0.001	(2.332)**	0.000	(0.442)
Firm Age - Momentum	0.015	(6.659)***	-0.014	(-0.443)
Intermediate Momentum	0.005	(4.334)***	0.002	(0.447)
Put volatility minus call volatility	-0.039	(-9.843)***	-0.017	(-0.45)
EPS forecast revision	0.001	(2.87)***	0.002	(0.458)
Total assets to market	0.001	(2.032)**	0.000	(0.471)
Change in capex (three years)	0.001	(-3.886)***	0.000	(-0.485)
Patents to RD expenses	0.001	(2.596)***	0.002	(0.493)
Return seasonality years 16 to 20	0.010	(2.644)***	-0.017	(-0.503)
Sales growth over inventory growth	0.001	(2.538)**	0.001	(0.507)
Investment to revenue	-0.001	(-5.838)***	0.001	(0.508)
Up Forecast	0.002	(4.201)***	0.003	(0.527)
Change in net financial assets	0.006	(5.069)***	-0.005	(-0.53)
Junk Stock Momentum	0.012	(3.566)***	-0.012	(-0.531)
Abnormal Accruals	-0.011	(-7.233)***	0.009	(0.54)
Operating leverage	0.001	(3.842)***	0.001	(0.543)
Change in financial liabilities	-0.010	(-6.438)***	0.006	(0.547)
Days with zero trades	0.001	(1.906)*	0.000	(0.548)

Table VI:
All Anomalies Continued...

Anomaly Description	Without PD Interaction		With PD Interaction	
	β	t-stat	β	t-stat
	(1)	(2)	(3)	(4)
Momentum without the seasonal part	0.089	(6.711)***	0.024	(0.57)
Asset growth	-0.005	(-8.427)***	-0.002	(-0.572)
Sales-to-price	0.001	(3.173)***	0.000	(-0.593)
Market leverage	0.001	(1.777)*	0.001	(0.596)
Return seasonality years 11 to 15	0.011	(3.343)***	0.016	(0.609)
Real estate holdings	0.002	(1.943)*	0.007	(0.615)
Book-to-market and accruals	0.008	(3.125)***	0.009	(0.621)
Revenue Surprise	0.001	(5.167)***	0.000	(-0.635)
IPO and no R&D spending	-0.004	(-2.495)**	0.027	(0.642)
Momentum in high volume stocks	0.001	(3.28)***	0.000	(-0.643)
Intangible return using CFtoP	-0.003	(-1.849)*	-0.007	(-0.646)
Spinoffs	0.005	(3.763)***	0.099	(0.653)
Momentum (6 month)	0.010	(5.27)***	0.004	(0.662)
Organizational capital	0.001	(5.389)***	0.002	(0.676)
Revenue Growth Rank	0.001	(1.736)*	0.000	(-0.691)
Return seasonality last year	0.008	(3.87)***	0.009	(0.694)
R&D over market cap	0.028	(4.015)***	0.033	(0.711)
Momentum (12 month)	0.007	(5.655)***	0.003	(0.714)
Consensus Recommendation	-0.008	(-5.143)***	0.012	(0.718)
Employment growth	-0.002	(-2.37)**	-0.004	(-0.734)
Efficient frontier index	0.002	(2.865)***	0.003	(0.739)
Customers momentum	0.001	(2.92)***	0.001	(0.77)
Volume Variance	-0.003	(-2.436)**	0.004	(0.773)
Inst Own and Idio Vol	0.003	(5.887)***	-0.002	(-0.793)
Tail risk beta	0.002	(1.802)*	0.004	(0.808)
Inst Own and Market to Book	0.003	(7.04)***	-0.002	(-0.813)
Breadth of ownership	0.002	(2.924)***	-0.002	(-0.834)
Change in capex (two years)	0.001	(-3.121)***	0.000	(0.851)
Change in put vol	-0.007	(-1.952)*	-0.025	(-0.857)
Accruals	-0.011	(-5.13)***	0.013	(0.871)

Table VI:
All Anomalies Continued...

Anomaly Description	Without PD Interaction β (1)	Without PD Interaction t-stat (2)	With PD Interaction β (3)	With PD Interaction t-stat (4)
Mohanram G-score	0.001	(4.361)***	-0.003	(-0.875)
Momentum and LT Reversal	0.013	(6.337)***	0.011	(0.888)
Exchange Switch	-0.005	(-3.401)***	0.018	(0.912)
Momentum based on FF3 residuals	0.009	(8.153)***	0.003	(0.975)
Inventory Growth	-0.016	(-4.473)***	0.025	(0.985)
Earnings surprise streak	0.07	(3.504)***	-0.181	(-1.005)
Tangibility	0.007	(3.937)***	-0.012	(-1.02)
EPS Forecast Dispersion	-0.001	(-2.07)**	-0.006	(-1.039)
Down forecast EPS	-0.002	(-4.552)***	-0.006	(-1.042)
Short Interest	0.001	(-3.786)***	0.000	(1.131)
Dividend Omission	-0.004	(-2.343)**	0.048	(1.147)
Volatility smirk near the money	-0.020	(-3.585)***	-0.06	(-1.151)
Bid-ask spread	-0.224	(-3.231)***	-0.269	(-1.153)
Industry concentration (sales)	-0.002	(-2.382)**	0.005	(1.159)
Volume Trend	-0.064	(-4.186)***	-0.085	(-1.186)
Off season long-term reversal	-0.119	(-7.729)***	-0.091	(-1.205)
Change in equity to assets	-0.008	(-3.75)***	-0.017	(-1.272)
Net Payout Yield	0.006	(1.733)*	0.046	(1.275)
Change in call vol	0.009	(2.828)***	-0.035	(-1.287)
Composite debt issuance	0.001	(-2.085)**	0.001	(1.311)
Change in Net Working Capital	-0.004	(-2.116)**	0.026	(1.342)
Earnings Surprise	0.001	(7.458)***	0.001	(1.355)
Change in recommendation	0.001	(5.409)***	0.003	(1.362)
Net equity financing	-0.006	(-2.208)**	-0.024	(-1.368)
Long-vs-short EPS forecasts	0.001	(-1.926)*	0.000	(-1.378)
Suppliers momentum	0.001	(2.547)**	0.001	(1.383)
Intangible return using BM	-0.002	(-2.577)***	-0.004	(-1.397)
Industry concentration (assets)	-0.002	(-2.394)**	0.006	(1.439)
Taxable income to income	0.001	(2.214)**	0.001	(1.45)
Cash-based operating profitability	0.011	(6.977)***	0.017	(1.491)

Table VI:
All Anomalies Continued...

Anomaly Description	Without PD Interaction β (1)	Without PD Interaction t-stat (2)	With PD Interaction β (3)	With PD Interaction t-stat (4)
Idiosyncratic risk (AHT)	-0.196	(-3.458)***	-0.231	(-1.512)
Off season reversal years 6 to 10	-0.043	(-3.447)***	-0.133	(-1.516)
Net external financing	-0.006	(-4.232)***	-0.017	(-1.527)
Equity Duration	0.001	(-5.407)***	-0.001	(-1.544)
Realized (Total) Volatility	-0.221	(-6.197)***	-0.181	(-1.561)
Analyst earnings per share	0.001	(3.58)***	0.001	(1.607)
Book to market (Stattman 1980)	0.005	(10.493)***	0.002	(1.612)
Return seasonality years 6 to 10	0.015	(5.48)***	0.036	(1.623)
Volume to market equity	-0.024	(-3.572)***	-0.053	(-1.635)
Unexpected R&D increase	0.001	(2.811)***	-0.010	(-2.076)**
52 week high	0.005	(1.808)*	-0.024	(-2.991)***
Industry return of big firms	0.125	(11.546)***	0.129	(2.354)**
Dividend seasonality	0.003	(11.356)***	0.005	(2.182)**
Change in Taxes	0.120	(10.396)***	0.193	(2.164)**
Predicted div yield next month	0.002	(10.936)***	0.003	(2.833)***
Maximum return over month	-0.069	(-8.567)***	-0.092	(-2.524)**
Conglomerate return	0.064	(7.003)***	0.106	(1.755)*
Idiosyncratic risk (3 factor)	-0.249	(-7.062)***	-0.244	(-1.904)*
Earnings forecast revisions	0.03	(5.578)***	0.073	(1.658)*
Return on assets (qtrly)	0.086	(5.217)***	0.265	(2.12)**
Return skewness	-0.001	(-4.116)***	-0.003	(-2.231)**
gross profits / total assets	0.003	(2.442)**	0.010	(1.901)*
Trend Factor	0.474	(11.058)***	1.094	(5.077)***
Option to stock volume	0.001	(-2.051)**	0.000	(-3.341)***
Return seasonality years 2 to 5	0.012	(4.199)***	0.063	(3.021)***
Coskewness	-0.003	(-3.472)***	-0.013	(-2.593)***
Share turnover volatility	-0.029	(-2.596)***	-0.215	(-2.591)***

Table VII:
All Anomalies Put Together, Announcement Returns, and PD

This table shows the results of Fama-MacBeth cross-sectional regressions of next three months' average announcement returns on the anomaly ranking variable after controlling for well-known empirical regularities, the price inefficiency measure of Hou and Moskowitz (2005), and PD and its interactions with the anomaly ranking variable among sub-samples divided using PD value from the previous month. Using the data from Chen and Zimmermann (2022), each month, each firm, based on firm's the anomaly variable value for the month and the sign of return predictability of the anomaly variable, I assign each firm in to three terciles - high, medium, and low. The ALRank (Anomaly Long Ranking) is the firm's average tercile ranking for the month across all two hundred plus anomalies. PD is the price inefficiency of firm-specific information as defined by equation 2, and D3_HM is the semi-strong form price inefficiency measure of Hou and Moskowitz (2005) as defined by equation 3. The sample period runs from January 1967 through December 2020, and the price filter used is $5. All variables are defined in Appendix A. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively. Standard errors are Newey adjusted with three lags.

Dep Var: Next Three Month Announcement Returns (Chan et al. (1996))				
	Low PD		High PD	
	(1)	(2)	(3)	(4)
$ALRank_{-1}$	2.388***	-2.120	2.917***	5.004**
	(13.814)	(-1.514)	(14.238)	(2.507)
MCAP_−1	-0.004	-0.005	0.023*	0.023*
	(-0.303)	(-0.339)	(1.694)	(1.682)
BM_{-12}	0.022	0.021	-0.075**	-0.074**
	(0.668)	(0.656)	(-2.214)	(-2.203)
$AsstGrowth_{-12}$	0.252***	0.243***	0.378***	0.381***
	(2.674)	(2.638)	(4.464)	(4.479)
ROA_{-12}	-0.559**	-0.548*	-0.884***	-0.890***
	(-1.999)	(-1.956)	(-3.191)	(-3.202)
PD_{-1}		-5.165***		2.410
		(-3.299)		(1.204)
PD_{-1} x $ALRank_{-1}$		2.731***		-1.090
		(3.317)		(-1.035)
Constant	-4.220***	4.315	-5.495***	-10.104***
	(-10.901)	(1.557)	(-11.608)	(-2.646)
Observations	908,067	908,067	904,962	904,962
Months	648	648	648	648

Table VIII:
PD and Key Corporate Developments

This table shows the results of Fama-MacBeth cross-sectional regressions of PD on the key corporate developments relate to a firm. The dependent variable, PD, is the price inefficiency regarding firm-specific information as defined by equation 2. Each Key Development variable is natural logarithm of number of key developments in the relevant area at the month $t-1$. Investments & Financing includes items such as M&A transaction announcements and private placements. Earnings & and Guidance include items such as expected earning release date and new corporate guidance. Investors & Clients includes items such as investor conference and client announcements. Board & Governance includes items such as annual general meetings, and executive changes. And, Miscellaneous Other includes items such as index constituent adds, and index constituent drops. Due to the availability of Key Developments Data, the sample period runs from January 1985 through December 2020, and the price filter used is $5. 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.

	PD	PD	PD	PD	PD	PD
Investments & Financing$_{-1}$	0.008**					0.005*
	(2.404)					(1.780)
Earnings & Guidance$_{-1}$		0.002***				0.001**
		(3.701)				(2.582)
Investors & Clients$_{-1}$			0.004***			0.003***
			(4.887)			(4.455)
Board & Governance$_{-1}$				0.005***		0.003***
				(3.489)		(2.655)
Miscellaneous Other$_{-1}$					0.004	0.002
					(1.612)	(1.087)
Constant	1.783***	1.783***	1.782***	1.783***	1.783***	1.778***
	(1248.556)	(1254.234)	(1244.757)	(1227.636)	(1230.322)	(721.831)
Months	432	432	432	432	432	432
Observations	974,105	974,105	974,105	974,105	974,105	974,105

Table IX:
PD and Level and Variance of Profitability

This table shows the results of Fama-MacBeth cross-sectional regressions of PD on various measures of level and variance of profitability. Cross-sectional regression takes the form $PD_t = \alpha + \beta \ Variable_t \ + \epsilon$, where the variable can be any of the twelve variables presented in the table. PD is the price inefficiency concerning firm-specific information as defined by equation 2. The results show that high PD firms have relatively lower profitability but higher uncertainty around profitability. The higher PD firms have a very low payout ratio, and dividends make up a smaller percentage of returns. Results are consistent with Pástor and Veronesi (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 $5. All variables are defined in Appendix A. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively.

Panel A: Profitability & Payouts

	Profitability			Payouts	
	O_MARGIN (1)	NI_MARGIN (2)	EBITA_MARGIN (3)	PAYOUT_RATIO (4)	DIV_RET
β	-0.028***	-0.026***	-0.006***	-0.015***	-1.22***
T Stat	(-13.912)	(-12.702)	(-6.9308)	(-17.428)	(-28.414)

Panel B: Variance of Profitability

	SD_OM (1)	SD_NIM (2)	SD_EBITAM (3)	SD_SALES (4)
β	0.009***	0.009***	0.004***	0.012***
T Stat	(8.935)	(8.182)	(6.748)	(20.643)

Table X:
PD, Information Uncertainty, Limits of Arbitrage, and Opaqueness

This table shows the results of Fama-MacBeth cross-sectional regressions of PD on various firm characteristics measures of information uncertainty, limits of arbitrage, and firm opaqueness variables. Cross-sectional regression takes the form $PD_t = \alpha + \beta \ Variable_t \ + \epsilon$, where the variable can be any of the sixteen variables presented in the tables. PD is the price inefficiency concerning firm-specific information as defined by equation 2. The results show that high PD 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 PD firms have lower limits of arbitrag and they are more opaque. Results show that high-PD 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 $5. 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	14.960***	1.000***	0.033***	0.027***	0.004***	0.002***	0.087	0.448***
T Stat	(4.352)	(35.197)	(2.918)	(13.704)	(21.645)	(4.747)	(31.396)	(31.535)

Panel D: Limits of Arbitrage & Opaqueness

	Limits of Arbitrage			Opaqueness		
	AILLIQ (1)	DOLLAR_VOL (2)	BA_SPREAD (3)	MB (4)	INTAN_AT (5)	RND_AT (6)
β	-0.796***	0.001	-0.444***	0.003***	0.025***	0.068***
T Stat	(-8.773)	(12.759)	(-9.048)	(26.469)	(11.589)	(14.070)

Table XI: Economic Determinants of Aggregate Economy-Wide PD

This table shows the results of univariate and multivariate pooled OLS regressions of APD_EQ on potential economy-wide determinants of price inefficiency concerning firm-specific Information such as business cycle variables. The dependent variable APD_EQ is the economy-wide aggregate equally-weighted average PD of all firms in the cross-section whose closing price for the month was at least $5. 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. 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 $5. 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)
DIVIDEND_YIELD	-0.820***							0.0661
	(-19.133)							(0.653)
TERM_SPREAD		0.256***						0.210***
		(6.722)						(4.988)
PRICE-To-EARNIGNS			0.0470***					-0.00126
			(7.292)					(-0.381)
DEFAULT_RSPREAD				0.165***				0.101***
				(11.179)				(5.482)
STOCK_VARIANCE					0.174			-1.582**
					(0.914)			(-2.374)
EPU						0.0346***		-0.0171
						(3.512)		(-1.568)
REALIZED_VARIANCE							0.015	0.206***
							(0.989)	(2.607)
Constant	1.799***	1.770***	1.766***	1.784***	1.774***	1.778***	1.786***	1.787***
	(1369.923)	(2214.632)	(1274.536)	(1744.397)	(2391.136)	(1169.822)	(2695.909)	(696.335)
Observations	732	732	732	732	732	432	372	372
R^2 Adjusted	0.281	0.0440	0.0994	0.130	0.00115	0.0132	0.00172	0.130

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

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.

PD: The price inefficiency regarding firm-specific information as defined by equation 2.

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: Additional Robustness & Tables

Appendix B.1. Additional Tables

Table IA1:
Return Predictability Price Inefficiency of Firm-Specific Information (PD) among Winner and Loser Groups

This table shows the results of Fama-MacBeth cross-sectional regressions of month t returns on PD after controlling for well-known empirical regularities within five quintiles divided using past six months' cumulative returns. PD is the price inefficiency of firm-specific information as defined by equation 2. Table shows that PD predicts returns negatively among losers and at the same time predicts returns positively among winners. 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.

	Dependent Variable: Month t Returns				
	High	Quintile 2	Quintile 2	Quintile 2	Low
PD_{-1}	-0.004*	-0.001	-0.002*	-0.001	0.004**
	(-1.869)	(-0.427)	(-1.864)	(-0.533)	(2.360)
$D3\_HM_{-1}$ x $BHR6M_{-1,-6}$	-0.024	-0.016	-0.028	-0.015	-0.018**
	(-1.395)	(-0.936)	(-1.140)	(-0.863)	(-2.382)
$D3\_HM_{-1}$	0.025*	0.020	0.026	0.019	0.019**
	(1.919)	(1.297)	(1.073)	(1.014)	(2.119)
$BHR6M_{-1,-6}$	-0.006	0.004	0.029**	-0.003	0.008***
	(-0.411)	(0.414)	(2.002)	(-0.324)	(2.765)
$LnMCAP_{-1}$	-0.002***	-0.001*	-0.000	-0.001**	-0.001***
	(-3.857)	(-1.665)	(-1.344)	(-2.507)	(-3.622)
$LnBM_{-1}$	-0.000	0.001	0.002**	0.000	0.000
	(-0.092)	(0.768)	(2.472)	(0.685)	(0.125)
$AsstGrowth_{-1}$	-0.021***	-0.011***	-0.007***	-0.003	0.002
	(-7.277)	(-7.321)	(-4.585)	(-1.521)	(0.692)
ROA_{-1}	0.014***	0.021***	0.012	0.023***	0.025***
	(2.632)	(3.327)	(1.366)	(3.298)	(2.788)
Constant	0.032***	0.016	-0.010	0.026**	0.014*
	(2.872)	(1.593)	(-0.668)	(2.147)	(1.714)
Observations	433,570	490,647	445,341	485,358	541,466
Number of Groups	744	744	744	744	744

Table IA2:
List of Anomalies Examined in this Paper

This table lists the 209 financial market 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 the anomaly variables; The author shows the authors of the the original paper that discovered the anomaly; the year shows the year the paper was published; and 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 PD 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
ShareIss1Y	Share issuance (1 year)	Pontiff and Woodgate	2008	JF	Yes
ConvDebt	Convertible debt indicator	Valta	2016	JFQA	Yes
dCPVolSpread	Change in put and call vol	An, Ang, Bali, Cakici	2014	JF	Yes
IntanSP	Intangible return using Sale2P	Daniel and Titman	2006	JF	Yes
DolVol	Past trading volume	Brennan, Chordia, Subra	1998	JFE	Yes
ChForecastAccrual	Change in Forecast and Accrual	Barth and Hutton	2004	RAS	Yes
CPVolSpread	Call minus Put Vol	Bali and Hovakimian	2009	MS	Yes
ShareIss5Y	Share issuance (5 year)	Daniel and Titman	2006	JF	Yes
ChNNCOA	Change in Net Noncurrent Op Assets	Soliman	2008	AR	Yes
PS	Piotroski F-score	Piotroski	2000	JAR	Yes
RIO_Turnover	Inst Own and Turnover	Nagel	2005	JFE	Yes
GrLTNOA	Growth in long term operating assets	Fairfield, Whisenant and Yohn	2003	AR	Yes
Recomm_ShortInterest	Analyst Recom. and Short-Interest	Drake, Rees and Swanson	2011	AR	Yes
DelCOA	Change in current operating assets	Richardson et al.	2005	JAE	Yes
NOA	Net Operating Assets	Hirshleifer et al.	2004	JAE	Yes
LRreversal	Long-run reversal	De Bondt and Thaler	1985	JF	Yes
CoskewACX	Coskewness using daily returns	Ang, Chen and Xing	2006	RFS	Yes
DebtIssuance	Debt Issuance	Spiess and Affleck-Graves	1999	JFE	Yes
RIO_Disp	Inst Own and Forecast Dispersion	Nagel	2005	JFE	Yes
Cash	Cash to assets	Palazzo	2012	JFE	Yes
ChInvIA	Change in capital inv (ind adj)	Abarbanell and Bushee	1998	AR	Yes
NetDebtFinance	Net debt financing	Bradshaw, Richardson, Sloan	2006	JAE	Yes
CF	Cash flow to market	Lakonishok, Shleifer, Vishny	1994	JF	Yes
NumEarnIncrease	Earnings streak length	Loh and Warachka	2012	MS	Yes
ShareRepurchase	Share repurchases	Ikenberry, Lakonishok, Vermaelen	1995	JFE	Yes
InvestPPEInv	change in ppe and inv/assets	Lyandres, Sun and Zhang	2008	RFS	Yes
cfp	Operating Cash flows to price	Desai, Rajgopal, Venkatachalam	2004	AR	Yes
dNoa	change in net operating assets	Hirshleifer, Hou, Teoh, Zhang	2004	JAE	Yes
IndMom	Industry Momentum	Grinblatt and Moskowitz	1999	JF	Yes
TotalAccruals	Total accruals	Richardson et al.	2005	JAE	Yes
CustomerMomentum	Customer momentum	Cohen and Frazzini	2008	JF	Yes
AnnouncementReturn	Earnings announcement return	Chan, Jegadeesh and Lakonishok	1996	JF	Yes
MRreversal	Medium-run reversal	De Bondt and Thaler	1985	JF	Yes
InvGrowth	Inventory Growth	Belo and Lin	2012	RFS	Yes
EarnSupBig	Earnings surprise of big firms	Hou	2007	RFS	Yes
zerotrade12M	Days with zero trades	Liu	2006	JFE	Yes
FirmAgeMom	Firm Age - Momentum	Zhang	2006	JF	Yes
IntMom	Intermediate Momentum	Novy-Marx	2012	JFE	Yes
SmileSlope	Put volatility minus call volatility	Yan	2011	JFE	Yes
AnalystRevision	EPS forecast revision	Hawkins, Chamberlin, Daniel	1984	FAJ	Yes
AM	Total assets to market	Fama and French	1992	JF	Yes
grcapx3y	Change in capex (three years)	Anderson and Garcia-Feijoo	2006	JF	Yes
PatentsRD	Patents to RD expenses	Hirschleifer, Hsu and Li	2013	JFE	Yes
MomSeason16YrPlus	Return seasonality years 16 to 20	Heston and Sadka	2008	JFE	Yes
GrSaleToGrInv	Sales growth over inventory growth	Abarbanell and Bushee	1998	AR	Yes
Investment	Investment to revenue	Titman, Wei and Xie	2004	JFQA	Yes
UpRecomm	Up Forecast	Barber et al.	2001	JF	Yes
DelNetFin	Change in net financial assets	Richardson et al.	2005	JAE	Yes
Mom6mJunk	Junk Stock Momentum	Avramov et al	2007	JF	Yes
AbnormalAccruals	Abnormal Accruals	Xie	2001	AR	Yes
OPLeverage	Operating leverage	Novy-Marx	2011	ROF	Yes
DelFINL	Change in financial liabilities	Richardson et al.	2005	JAE	Yes
zerotrade6M	Days with zero trades	Liu	2006	JFE	Yes
Mom12mOffSeason	Momentum without the seasonal part	Heston and Sadka	2008	JFE	Yes
AssetGrowth	Asset growth	Cooper, Gulen and Schill	2008	JF	Yes
SP	Sales-to-price	Barbee, Mukherji and Raines	1996	FAJ	Yes
Leverage	Market leverage	Bhandari	1988	JF	Yes
MomSeason11YrPlus	Return seasonality years 11 to 15	Heston and Sadka	2008	JFE	Yes
realestate	Real estate holdings	Tuzel	2010	RFS	Yes
AccrualsBM	Book-to-market and accruals	Bartov and Kim	2004	RFQA	Yes
RevenueSurprise	Revenue Surprise	Jegadeesh and Livnat	2006	JAE	Yes

Table IA2:
List of Anomalies Examined in this Paper Continued...

Acronym	Long Description	Author	Year	Journal	Subsumed?
RDIPO	IPO and no R&D spending	Gou, Lev and Shi	2006	JBFA	Yes
MomVol	Momentum in high volume stocks	Lee and Swaminathan	2000	JF	Yes
IntanCFP	Intangible return using CFtoP	Daniel and Titman	2006	JF	Yes
Spinoff	Spinoffs	Cusatis, Miles and Woolridge	1993	JFE	Yes
Mom6m	Momentum (6 month)	Jegadeesh and Titman	1993	JF	Yes
OrgCap	Organizational capital	Eisfeldt and Papanikolaou	2013	JF	Yes
MeanRankRevGrowth	Revenue Growth Rank	Lakonishok, Shleifer, Vishny	1994	JF	Yes
MomSeasonShort	Return seasonality last year	Heston and Sadka	2008	JFE	Yes
RD	R&D over market cap	Chan, Lakonishok and Sougiannis	2001	JF	Yes
Mom12m	Momentum (12 month)	Jegadeesh and Titman	1993	JF	Yes
ConsRecomm	Consensus Recommendation	Barber et al.	2001	JF	Yes
hire	Employment growth	Bazdresch, Belo and Lin	2014	JPE	Yes
Frontier	Efficient frontier index	Nguyen and Swanson	2009	JFQA	Yes
iomom_cust	Customers momentum	Menzly and Ozbas	2010	JF	Yes
VolSD	Volume Variance	Chordia, Subra, Anshuman	2001	JFE	Yes
RIO_Volatility	Inst Own and Idio Vol	Nagel	2005	JFE	Yes
BetaTailRisk	Tail risk beta	Kelly and Jiang	2014	RFS	Yes
RIO_MB	Inst Own and Market to Book	Nagel	2005	JFE	Yes
DelBreadth	Breadth of ownership	Chen, Hong and Stein	2002	JFE	Yes
grcapx	Change in capex (two years)	Anderson and Garcia-Feijoo	2006	JF	Yes
dVolPut	Change in put vol	An, Ang, Bali, Cakici	2014	JF	Yes
Accruals	Accruals	Sloan	1996	AR	Yes
MS	Mohanram G-score	Mohanram	2005	RAS	Yes
MomRev	Momentum and LT Reversal	Chan and Ko	2006	JOIM	Yes
ExchSwitch	Exchange Switch	Dharan and Ikenberry	1995	JF	Yes
ResidualMomentum	Momentum based on FF3 residuals	Blitz, Huij and Martens	2011	JEmpFin	Yes
ChInv	Inventory Growth	Thomas and Zhang	2002	RAS	Yes
EarningsStreak	Earnings surprise streak	Loh and Warachka	2012	MS	Yes
tang	Tangibility	Hahn and Lee	2009	JF	Yes
ForecastDispersion	EPS Forecast Dispersion	Diether, Malloy and Scherbina	2002	JF	Yes
DownRecomm	Down forecast EPS	Barber et al.	2001	JF	Yes
ShortInterest	Short Interest	Dechow et al.	2001	JFE	Yes
DivOmit	Dividend Omission	Michaely, Thaler and Womack	1995	JF	Yes
skew1	Volatility smirk near the money	Xing, Zhang and Zhao	2010	JFQA	Yes
BidAskSpread	Bid-ask spread	Amihud and Mendelson	1986	JFE	Yes
Herf	Industry concentration (sales)	Hou and Robinson	2006	JF	Yes
VolumeTrend	Volume Trend	Haugen and Baker	1996	JFE	Yes
MomOffSeason	Off season long-term reversal	Heston and Sadka	2008	JFE	Yes
DelEqu	Change in equity to assets	Richardson et al.	2005	JAE	Yes
NetPayoutYield	Net Payout Yield	Boudoukh et al.	2007	JF	Yes
dVolCall	Change in call vol	An, Ang, Bali, Cakici	2014	JF	Yes
CompositeDebtIssuance	Composite debt issuance	Lyandres, Sun and Zhang	2008	RFS	Yes
ChNWC	Change in Net Working Capital	Soliman	2008	AR	Yes
EarningsSurprise	Earnings Surprise	Foster, Olsen and Shevlin	1984	AR	Yes
ChangeInRecommendation	Change in recommendation	Jegadeesh et al.	2004	JF	Yes
NetEquityFinance	Net equity financing	Bradshaw, Richardson, Sloan	2006	JAE	Yes
EarningsForecastDisparity	Long-vs-short EPS forecasts	Da and Warachka	2011	JFE	Yes
iomom_supp	Suppliers momentum	Menzly and Ozbas	2010	JF	Yes
IntanBM	Intangible return using BM	Daniel and Titman	2006	JF	Yes
HerfAsset	Industry concentration (assets)	Hou and Robinson	2006	JF	Yes
Tax	Taxable income to income	Lev and Nissim	2004	AR	Yes
CBOperProf	Cash-based operating profitability	Ball et al.	2016	JFE	Yes
IdioVolAHT	Idiosyncratic risk (AHT)	Ali, Hwang, and Trombley	2003	JFE	Yes
MomOffSeason06YrPlus	Off season reversal years 6 to 10	Heston and Sadka	2008	JFE	Yes
XFIN	Net external financing	Bradshaw, Richardson, Sloan	2006	JAE	Yes
EquityDuration	Equity Duration	Dechow, Sloan and Soliman	2004	RAS	Yes
RealizedVol	Realized (Total) Volatility	Ang et al.	2006	JF	Yes
FEPS	Analyst earnings per share	Cen, Wei, and Zhang	2006	WP	Yes
BM	Book to market (Stattman 1980)	Stattman	1980	Other	Yes
MomSeason06YrPlus	Return seasonality years 6 to 10	Heston and Sadka	2008	JFE	Yes
VolMkt	Volume to market equity	Haugen and Baker	1996	JFE	Yes
SurpriseRD	Unexpected R&D increase	Eberhart, Maxwell and Siddique	2004	JF	Yes
High52	52 week high	George and Hwang	2004	JF	Yes
IndRetBig	Industry return of big firms	Hou	2007	RFS	Weakens
DivSeason	Dividend seasonality	Hartzmark and Salomon	2013	JFE	Weakens
ChTax	Change in Taxes	Thomas and Zhang	2011	JAR	Weakens
DivYieldST	Predicted div yield next month	Litzenberger and Ramaswamy	1979	JFE	Weakens
MaxRet	Maximum return over month	Bali, Cakici, and Whitelaw	2011	JFE	Weakens
retConglomerate	Conglomerate return	Cohen and Lou	2012	JFE	Weakens
IdioVol3F	Idiosyncratic risk (3 factor)	Ang et al.	2006	JF	Weakens
REV6	Earnings forecast revisions	Chan, Jegadeesh and Lakonishok	1996	JF	Weakens
roaq	Return on assets (qtrly)	Balakrishnan, Bartov and Faurel	2010	JAE	Weakens
ReturnSkew	Return skewness	Bali, Engle and Murray	2015	Book	Weakens
GP	gross profits / total assets	Novy-Marx	2013	JFE	Weakens
TrendFactor	Trend Factor	Han, Zhou, Zhu	2016	JFE	Weakens
OptionVolume1	Option to stock volume	Johnson and So	2012	JFE	NO
MomSeason	Return seasonality years 2 to 5	Heston and Sadka	2008	JFE	NO
Coskewness	Coskewness	Harvey and Siddique	2000	JF	NO
std_turn	Share turnover volatility	Chordia, Subra, Anshuman	2001	JFE	NO