Frog in the Pan: Continuous Information and Momentum*

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Abstract

We develop and test a *frog-in-the-pan* (FIP) hypothesis that predicts investors are less attentive to information arriving continuously in small amounts than to information with the same cumulative stock price implications arriving in large amounts at discrete timepoints. Intuitively, we hypothesize that a series of gradual frequent changes attracts less attention than infrequent dramatic changes. Consistent with our FIP hypothesis, we find strong evidence that continuous information induces stronger and more persistent return continuation. Over a six-month holding period, momentum decreases monotonically from 8.86% for stocks with continuous information during their formation period to 2.91% for stocks with discrete information but similar cumulative formation-period returns. Analysts forecast errors are also consistent with the FIP hypothesis. Finally, higher media coverage and higher analyst coverage are associated with discrete and continuous information, respectively, while management press releases coincide with continuous good information.

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1 Introduction

Limited cognitive resources can prevent investors from immediately processing all available information. Sims (2003), Peng and Xiong (2006), as well as DellaVigna and Pollet (2007) provide theoretical foundations that allow limited attention to influence asset prices. Motivated by the notion that a series of gradual changes attracts less attention than a sudden dramatic change, we develop and test a frog-in-the-pan (FIP) hypothesis. This hypothesis predicts that investors are less attentive to information arriving continuously in small amounts than to information with the same cumulative stock price implications arriving in large amounts at discrete timepoints.

According to the frog-in-the-pan anecdote, a frog will jump out of a pan containing boiling water since the dramatic temperature change induces an immediate reaction. Conversely, if the water in the pan is slowly raised to a boil, the frog will underreact and perish. In the psychology literature, Gino and Bazerman (2009) demonstrate that a series of small gradual changes induce less critical evaluation than large dramatic changes. This psychological property appears in the consumer behavior literature on *just noticeable differences* as the marketing profession endeavors to have small continuous price increases that are not discernible to consumers and large dramatic price decreases that are apparent to consumers (Lamb, Hair, and McDaniel, 2008). In a similar finance context, Daniel, Hirshleifer, and Teoh (2002) argue that the large inflows into mutual funds with extraordinarily high recent returns are consistent with limited attention.

Nonetheless, with the exception of Hou, Peng, and Xiong (2008), limited attention's role in momentum (Jegadeesh and Titman, 1993) has not been explored. Limited attention offers a middle ground between rational explanations (Johnson, 2002; Sagi and Seasholes, 2007 among others) and behavioral explanations (Daniel, Hirshleifer, and Subrahmanyam, 1998, among others) for momentum. The cost of processing information, as in Merton (1987), also links our FIP hypothesis with limited attention. For example, the cost of carefully reading an analyst research report is higher than the cost of reading its less informative heading or recommendation. Provided the amount of information in these reports can be ascertained from their headings, research reports that are initially categorized as having small amounts of information receive less attention even if they arrive frequently and have important cumulative implications for stock prices.

The existing limited attention literature implicitly assumes the existence of an upper attention threshold that constrains the maximum amount of information on *all* firms that investors can process in a single period. For example, Hirshleifer, Lim, and Teoh (2009) find greater post-earnings announcement drift following days with a large number of earnings announcements. They conclude that investors are overwhelmed by the large amounts of information released on these days. In contrast, we posit the existence of a lower attention threshold for firm-specific information. Specifically, by failing to attract investor attention, the FIP hypothesis predicts an underreaction to information that arrives continuously in small amounts. Therefore, while the prior literature has focused on an upper bound for attention, information discreteness is motivated by the existence of a lower attention bound.

Appendix A contains an illustrative framework that formalizes the economic structure underlying our FIP hypothesis. This two-period framework involves two types of investors, each with CARA utility. Information received during the first period is divided into subsignals. Subsignals whose magnitude is below a minimum threshold are processed with a delay by FIP investors while rational investors process all subsignals immediately. Thus, the presence of FIP investors in the economy is responsible for momentum.

To empirically test our FIP hypothesis, we introduce a measure of information discreteness that describes the flow of information within the formation period of momentum strategies. We then examine the impact of information discreteness on holding-period returns. Our first measure of information discreteness is derived from signed daily returns during the formation period.[1] Specifically, information discreteness identifies time series variation in the daily returns that culminate in equivalent formation-period returns. Intuitively, a high percentage of positive daily returns relative to negative daily returns implies that a high formation-period return is attributable to a large number of small positive returns. As the high formation-period return accumulated gradually over many days, the flow of information is continuous. However, if the high formation-period return accumulated over a few days, then the flow of information is discrete. Empirical evidence confirms that discrete information is associated with jumps in daily returns. Figure 1 provides a visual illustration of continuous versus discrete information.

Information intermediaries such as the financial media and analysts partially determine infor-

[1] Although daily stocks returns measure information with error because of market frictions and behavioral biases, this error is small relative to the amount of information underlying extreme formation-period returns.

mation discreteness. Higher media coverage, measured by the number of news articles appearing on the Dow Jones newswire, is associated with more discrete information. This finding is consistent with the financial media accumulating information before releasing their salient conclusions as well as the media's focus on major corporate events. Indeed, media coverage and press releases capture an array of newsworthy corporate events such as mergers and acquisitions. In contrast, after controlling for media coverage, greater analyst coverage is associated with more continuous information. Finally, management-issued press releases are correlated with continuous good information, consistent with the notion that managers immediately release good news while withholding bad news.

We first investigate whether information discreteness influences return continuation using sequential double-sorted portfolios that condition on formation-period returns and information discreteness. Consistent with our FIP hypothesis, continuous information induces stronger and more persistent return continuation than discrete information after conditioning on the magnitude of formation-period returns. Over a six-month holding period, price momentum increases monotonically from 2.91% in the discrete information portfolio to 8.86% in the continuous information portfolio during our 1976 to 2007 sample period. Independent double-sorts reveal a similar monotonic increase in return continuation that remains significant after risk-adjustment. The stronger return continuation following continuous information is also present in an extended sample period that begins in 1927 during which return continuation following discrete information is negligible. In conjunction with the relationship between media coverage and discrete information, our study refines the channel through which media coverage produces discrete information and therefore weaker return continuation. Furthermore, lower analyst coverage, which is associated with continuous information, does not necessarily imply stronger momentum provided a firm attracts sufficient media coverage.

The interaction between institutional holdings and information discreteness also suggests that limited attention is responsible for the stronger momentum following continuous information. In particular, information discreteness identifies stronger return continuation among stocks with less concentrated institutional ownership. Following Hartzell and Starks (2003), the concentration of institutional ownership is defined as the proportion of institutional ownership accounted for by the five largest institutional investors in a firm. As less concentrated institutional ownership is associated with less attentive investors, the ability of information discreteness to better explain cross-sectional differences in momentum among firms with less concentrated institutional ownership is consistent with limited attention.

Furthermore, the momentum profit following continuous information persists for eight months while the momentum profit following discrete information is insignificant after two months. Nonetheless, the eight-month horizon corresponding to continuous information's return predictability is easier to reconcile with limited attention than risk. Moreover, the return predictability associated with continuous information does not reverse. The lack of long-term return reversal following continuous information is consistent with investors underreacting to continuous information, and provides support for the limited attention motivation underlying our FIP hypothesis.[2] An additional empirical test indicates that investor conservatism towards disconfirming information is not responsible for the stronger momentum following continuous information.

Our return-based information discreteness measure is related to the return consistency measure of Grinblatt and Moskowitz (2004). However, information discreteness is a much stronger predictor of price momentum than return consistency. Within the subsample of stocks with consistent returns (return consistency dummy variable equals one), portfolio double-sorts confirm that continuous information results in stronger momentum than discrete information. Moreover, information discreteness explains the return continuation of both past winners and past losers while the return predictability of return consistency is limited to past winners. The ability of an analyst forecast-based information discreteness measure to explain momentum also provides greater empirical support for our FIP hypothesis than the disposition effect that motivates return consistency. Thus, FIP and the disposition effect are distinct forces that both contribute to price momentum.

In addition, analyst forecast errors are larger following continuous information. This finding suggests that continuous information fails to attract analyst attention. Therefore, we identify a specific channel through which FIP affects asset prices. Furthermore, a modified information discreteness measure defined by signed monthly analyst forecast revisions instead of daily returns also demonstrates that continuous information induces stronger momentum than discrete information.

Discrete information is associated with high idiosyncratic volatility on average. Although Zhang

[2]We find evidence of long-term return reversals following discrete information. Thus, return predictability over different horizons may arise from distinct forces with information discreteness identifying this variation among past winners and past losers.

(2006) reports that momentum is stronger in stocks with high idiosyncratic volatility, past winners and past losers have high idiosyncratic volatility as a consequence of their extreme formation-period returns. After accounting for the influence of formation-period returns on idiosyncratic volatility, we report that momentum is not stronger for stocks with higher idiosyncratic volatility.

In addition to return consistency and idiosyncratic volatility, a large literature identifies additional firm characteristics that are related to the strength of momentum. These characteristics include turnover (Lee and Swaminathan, 2000), size and analyst coverage (Hong, Lim, and Stein, 2000), book-to-market ratios (Daniel and Titman, 1999) as well as institutional ownership (Hou and Moskowitz, 2005). To account for the correlations between these characteristics and information discreteness, we compute *residual* information discreteness by regressing information discreteness on them. Over a six-month holding period, price momentum continues to increase monotonically from 3.19% to 8.57% as residual information discreteness in the formation period varies from discrete to continuous. Consequently, the return predictability of continuous information is distinct from firm characteristics in the existing momentum literature.

Fama-MacBeth regressions confirm that the stronger return predictability of continuous information is not caused by a delayed reaction to information. Unlike Hou and Moskowitz (2005)'s price delay measure, which is a persistent firm characteristic that cannot explain momentum, the average first-order autocorrelation coefficient is near zero (0.019) when information discreteness is computed over non-overlapping annual calendar-time horizons. This lack of autocorrelation is compatible with the need to frequently rebalance momentum portfolios. Our Fama-MacBeth regressions also control for firm-level unrealized capital gains (Grinblatt and Han, 2005). Although Shumway and Wu (2005) find evidence that the disposition effect is responsible for momentum, the inclusion of unrealized capital gains does not weaken the ability of information discreteness to explain cross-sectional differences in either price momentum or earnings momentum. Ben-David and Hirshleifer (2011) also cast doubt on the reluctance of investors to realize large losses (in past losers). Furthermore, these authors find evidence of a reverse disposition effect for share purchases that undermines the propensity of investors to sell past winners.

To clarify, we examine the flow of information over time rather than its diffusion across investors (Hong and Stein, 1999). As detailed in Hong and Stein (2007), limited attention is able to affect prices provided investors fail to understand that their trades are based on a subset of relevant information. This assumption highlights a potentially important role for information intermediaries in asset pricing that leads us to investigate the roles of the financial media, management-issued press releases, and analyst coverage in determining information discreteness to better understand its economic origins. Therefore, besides contributing to the literatures on momentum and limited investor attention, our paper also links information discreteness with the recent literature that documents the influence of the media on asset prices.[3] This literature includes contributions by Tetlock (2007, 2010, and 2011), Tetlock, Saar-Tsechansky, and Macskassy (2008), Fang and Peress (2009).

The remainder of this paper is organized as follows. Section 2 describes our measure of information discreteness whose economic motivations are examined in Section 3. Section 4 then presents our results on the importance of information discreteness to momentum while Section 5 tests our FIP hypothesis using analyst forecasts. Section 6 then concludes and offers suggestions for future research.

2 Definition of Information Discreteness

Return data is obtained from CRSP after adjusting for delistings. Shares splits are also accounted for using the split factor in CRSP. Firm-level accounting data is obtained from COMPUSTAT. Negative book values are eliminated from our sample period that begins in 1976 and ends in 2007. A total of 2,301,912 firm-month observations are available in this sample.

Our benchmark information discreteness measure is determined by the sign of daily returns and ignores their magnitude by equally-weighting each observed return. The percentage of days during the formation period with positive and negative returns are denoted $\%pos$ and $\%neg$, respectively.[4] Information discreteness, which is abbreviated ID, is defined as

$$\text{ID} \;=\; \text{sgn}(\text{PRET}) \cdot [\%neg - \%pos] \;, \tag{1}$$

[3] The growing limited attention literature includes important contributions by Cohen and Frazzini (2008) on supplier-customer linkages, Corwin and Coughenour (2008) on liquidity provision, Da, Engelberg, and Gao (2011) on the popularity of information, as well as Bae and Wang (2011) on the stock ticker name. This literature has recognized the need for information to attract investor attention with Barber and Odean (2008) reporting that small investors buy attention-grabbing stocks. However, the prior literature has not distinguished between continuous and discrete information.

[4] We obtain similar results if $\%pos$ and $\%neg$ are defined using market-adjusted daily returns.

where the cumulative return during the formation period is denoted PRET. Specifically, PRET is defined as a firm's cumulative return over the past twelve months after skipping the most recent month. The sign of PRET is denoted sgn(PRET) and equals: +1 when PRET $>$ 0, -1 when PRET $<$ 0, and 0 when PRET = 0. The difference $\%neg - \%pos$ is implicitly normalized by $\%pos + \%neg + \%zero$, which sums to one.[5] Although PRET is determined by the magnitude of daily returns, ID does not differentiate between small and large daily returns. By ignoring the magnitude of daily returns, ID is distinct from return skewness and volatility. Instead, through its dependence on the sign of daily returns, ID reflects an imbalance in the time series of daily returns underlying PRET.

A large ID measure signifies discrete information while a small ID measure signifies continuous information.[6] For emphasis, ID is interpreted after conditioning on the magnitude of formation-period returns, PRET. For past winners with a high PRET, a high percentage of positive returns ($\%pos > \%neg$) implies that PRET is comprised of a large number of small positive returns. According to equation (1), a high percentage of positive returns culminating in a positive PRET yields a low value for ID and corresponds to continuous information. Indeed, if the series of daily returns are all positive, then ID equals its minimum value of -1. In contrast, if a few large positive returns are responsible for the positive PRET while the remaining daily returns are frequently negative, then ID is closer to +1 and information is discrete. The same intuition applies to past losers with a low PRET. Appendix A contains an illustrative framework that supports our ID definition. For emphasis, lower bound on investor attention that motivates our FIP hypothesis applies to continuous information. Therefore, our empirical study predicts stronger momentum profits in firms with low (negative) ID measures.

Figure 1 provides a visual illustration of information discreteness. Both stocks in this figure have the same PRET over 250 "daily" periods. The stock with continuous information achieves this cumulative return with small positive daily returns that arrive frequently while the stock with

[5] The frequency of zero daily returns has been interpreted as a measure of illiquidity by Lesmond, Ogden, and Trzcinka (1999). A high percentage of zero daily returns biases ID toward zero. Therefore, illiquidity does not lead to continuous or discrete information. In unreported results, the positive correlation of 0.10 between ID and $\%zero$ suggests that a higher frequency of zero returns is associated with discrete information. Consequently, illiquidity is unlikely to be responsible for the stronger return predictability of continuous information. Incorporating the usual one-month interval between the formation period and holding period also mitigates the impact of short-term return reversals attributable to illiquidity.

[6] Morck, Yeung, and Yu (2000) estimate a similar measure to capture cross-sectional commonality in the returns within individual countries. In contrast, ID is estimated from a time series of returns for individual firms.

discrete information has a few large positive daily returns arriving infrequently. The ID measures for the two stocks are -0.136 and 0.072, respectively.

The noise in daily returns implies that ID reflects the flow of information with error. However, this measurement error is small relative to the extreme formation-period returns of winners and losers. Indeed, PRET provides a general measure of both the aggregate quantity and quality of information released during the formation period. Nonetheless, we acknowledge that our ID measure does not perfectly capture information discreteness. Instead, equation (1) provides a simple proxy for information discreteness that is robust to whether PRET is near zero or large in absolute value. To the extent that this noisy proxy exerts a significant impact on return continuation, our results underestimate the true impact of information discreteness on asset prices.

Our later empirical tests of the FIP hypothesis are careful to distinguish between ID and idiosyncratic volatility denoted IVOL. As in Fu (2009), IVOL is estimated using the residuals from a four-factor model applied to daily returns during the formation period. The relationship between ID and jumps is also examined using the following jump5 variable

$$\text{jump5} \;=\; [\text{5 largest positive} + \text{5 largest negative daily returns}] \cdot \text{sgn(PRET)}\,, \tag{2}$$

and the following jump10 variable

$$\text{jump10} \;=\; [\text{10 largest positive} + \text{10 largest negative daily returns}] \cdot \text{sgn(PRET)}\,. \tag{3}$$

Intuitively, these jump variables measure the extent to which the formation-period return is determined by a few daily returns. The inclusion of sgn(PRET) enables the jump variables to be larger if negative jumps in the formation period are larger in absolute value than positive jumps. Thus, large values of jump5 and jump10 capture return skewness. However, these jump variables are near zero if the positive and negative jumps cancel each other since they are not intended to capture kurtosis. Indeed, despite increasing return volatility, jumps of the opposite sign are not relevant to momentum provided PRET is near zero.

To examine whether ID is a firm characteristic, we estimate the price delay measure in Hou and Moskowitz (2005) that regresses firm-level weekly stock returns on contemporaneous market returns and lagged market returns over the prior four weeks. Using weekly returns over the prior year, the R-squared is denoted R_L^2 when lagged returns are included in this time series regression while the contemporaneous R-squared without lagged market returns is denoted R_C^2. The price delay measure is then defined as

$$\text{DELAY} \;=\; 1 - \frac{R_C^2}{R_L^2}\,. \tag{4}$$

Intuitively, if prices rapidly incorporate market-level information, then lagged market returns are unimportant and R_C^2 is near R_L^2, with the DELAY metric being closer to zero as a consequence. However, if prices slowly incorporate market-level information, then R_C^2 is far below R_L^2 and DELAY is closer to one. Thus, firms whose prices experience slower price reactions to market-level information have larger DELAY metrics. Hou and Moskowitz (2005) report that DELAY is a firm characteristic related to analyst coverage and institutional ownership that explains several return anomalies but not momentum. In contrast, ID describes the flow of information to investors and varies over time for individual firms. Specifically, in December of every year, we compute ID over the prior calendar year for each firm in our sample. For the 2,500 firms with at least twenty observations, we regress each firm's ID measure on its prior calendar year's ID measure to compute first order autocorrelation coefficients. In unreported results, the cross-sectional average of these firm-level autocorrelation coefficients is 0.019. Therefore, unlike size or analyst coverage, ID is not a persistent firm characteristic.

Finally, to control for the disposition effect, we investigate the return consistency dummy variable (RC) in Grinblatt and Moskowitz (2004) as well as an unrealized capital gains variable (UCG). As in Grinblatt and Han (2005), UCG is defined relative to a reference price computed using prior stock prices and trading volume.

Table 1 summarizes the main variables in our study and reports on their correlations. The summary statistics in Panel A indicate that ID has a mean near zero. Furthermore, daily returns are positively skewed while jump5 and jump10 are also positive on average. According to Panel B, ID is not highly correlated with IVOL. While IVOL has a positive correlation with the absolute value of formation-period returns, ID is negatively correlated with |PRET|.

Furthermore, Panel B of Table 1 confirms that discrete information is associated with jumps. In particular, ID is positively correlated with skewness and the jump variables.[7] ID is also positively correlated with the price delay measure of Hou in Moskowitz (2005) in equation (4). Thus, continuous information does not correspond to the slow incorporation of information into stock prices. Moreover, the negative correlation between RC and ID indicates that continuous information coincides with a greater likelihood that monthly returns have the same sign as PRET. Therefore, our portfolio double-sorts and Fama-MacBeth regressions in the next section control for return consistency. Finally, although ID and UCG are not highly correlated, UCG and PRET have a high positive correlation since past returns are a major determinant of unrealized capital gains (losses).

3 Information Discreteness and Information Intermediaries

Our next analysis explores the economic determinants of information discreteness. In particular, we demonstrate that information discreteness is partially determined by information intermediaries such as the financial press and analysts.

Management press releases and media coverage are important internal and external sources of information, respectively. However, not all press releases receive media coverage. To mitigate their confounding effects, we examine press releases that do not receive media coverage within seven days (PR) and articles in the financial press (MEDIA) that do not occur within seven days of a press release. The PR and MEDIA variables refer to the number of press releases and news articles in the prior year for an individual firm, respectively.

Corporate press releases are typically issued via newswire services. After firms distribute their press releases to newswire companies, press releases are disseminated to news distribution channels that include local newspapers, national newspapers, TV networks, and financial news services such as Bloomberg, Dow Jones/Factiva, and Thomson Reuters. News distribution channels may distribute these press releases depending on the newsworthiness of the press release and their news processing capacity. Our press release dataset contains all corporate press releases disseminated by PR Newswire from over 4,700 public companies which are traded on NASDAQ, NYSE, and AMEX from January 2000 to December 2007. Firms typically engage one newswire company at a given point in time. Neuhierl, Scherbina, and Schlusche (2010) report that nearly 60% of

[7] Unreported results confirm that jumps occur uniformly during the formation period. In particular, large daily returns are not concentrated at the beginning (or end) of this twelve month interval.

all publicly traded firms use PR Newswire. However, as our sample is not comprehensive, we restrict our analysis to firms that have at least one recorded press release in PR Newswire. In unreported results, firms using PR Newswire versus other alternatives do not differ in terms of firm characteristics such as firm size, growth, and industry affiliations. We match press releases to firm identifiers (CRSP permno) using the source identifier provided by PR Newswire, which includes the website URL of the issuing company as well as its name and address. We match these source identifiers to the company information in COMPUSTAT. To further improve the match quality, we use the soundex algorithm in SAS to match the firm names reported in the press releases with the firms names in COMPUSTAT. Our final sample contains over 220,000 press releases for 4,702 firms.

Our media data is obtained from Factiva, which contains media reports from several sources including newswires as well as local and national newspapers. From these sources, we focus on the most comprehensive financial news service, Dow Jones Newswire. Dow Jones Newswire obtains data from several sources including press releases, firm disclosures, and reports produced by financial journalists. As our sample begins in 2000, it does not suffer from the backfill bias reported in Tetlock (2010). To match news stories with financial databases, we use the ticker symbols, firm names, and name variants from the CRSP database as the search strings in Factiva using procedures outlined in Gurun and Butler (2010). Specifically, using a web crawler, we search name variants by singular and plural versions of the following abbreviations from the company names: ADR, CO, CORP, HLDG, INC, IND, LTD, and MFG. Our final sample includes over 420,000 firm-day media reports for 5,330 firms between 2000 and 2007.

Analysts represent another external information intermediary between firms and investors. Therefore, we include analyst coverage denoted COVER in our analysis, which is defined as one plus the log number of analysts issuing forecasts for a particular firm.[8] The prior literature (Bushee and Noe, 2000) reports that higher institutional ownership coincides with better disclosure while information may also be in greater demand for large firms. Thus, our next analysis controls for institutional ownership (IO) as a proxy for corporate disclosure along with SIZE. Quarterly data on institutional ownership is obtained from the portfolio holdings reported in 13f filings with the

[8] Information intermediaries such as analysts and financial journalists can alter the discreteness of information by releasing salient information gradually or aggregating small amounts of information.

SEC. These holdings are normalized by the total number of shares outstanding to compute the percentage of shares held by institutions. Institutional ownership is then computed as one plus the log percentage of shares owned by institutions. SIZE is defined as the log of a firm's market capitalization.

In addition, firm fixed effects are included in the following Fama-MacBeth regression:

$$\begin{aligned} \mathrm{ID}_{i,t} &= \beta_0 + \beta_1\,\mathrm{PR}_{i,t} + \beta_2\,\mathrm{MEDIA}_{i,t} + \beta_3\,\mathrm{COVER}_{i,t} + \beta_4\,\mathrm{SIZE}_{i,t} \\ &\quad + \beta_5\,\mathrm{IO}_{i,t} + \beta_6\,|\mathrm{PRET}|_{i,t} + \epsilon_{i,t}\,. \end{aligned} \tag{5}$$

This regression is conducted separately for stocks with high and low formation-period returns since ID is an interaction variable whose interpretation requires us to condition on PRET. In particular, equation (5) is estimated for stocks whose formation-period returns are above and below the cross-sectional median, while |PRET| is also included as an additional control variable.

The correlations between the variables in equation (5) are reported in Panel A of Table 2. PR and MEDIA are negatively correlated although both are positively correlated with COVER and SIZE. Thus, large firms have more analyst coverage, attract more media coverage, and issue more press releases than small firms.

Panel B reports on the beta estimates for past winners. These coefficients are multiplied by 100 for ease of interpretation. The negative β_1 coefficient for PR indicates that management press releases (without media coverage) yield continuous good information, consistent with the notion that management releases good information whenever it is available. The positive β_2 coefficient in Panel B implies that media coverage (unrelated to management press releases) produces discrete information. Intuitively, news articles appearing in the financial press are required to be sufficiently salient in order to be published. Indeed, media outlets follow a large number of firms, while management is only responsible for releasing information regarding their firm. Furthermore, major corporate events such as mergers and acquisitions that coincide with the discrete release of information are likely to attract media attention. Greater analyst coverage results in more continuous information since β_3 is negative. This property may arise from the regular issuance of earnings forecasts and stock recommendations by analysts. For past winners, larger firms and those with higher institutional ownership also have more continuous information as the β_4 and β_5 coefficients are both negative.

Panel C reports on the beta estimates from equation (5) for past losers. Once again, these coefficients are multiplied by 100 for ease of interpretation. In contrast to past winners, the β_1 coefficient for PR is insignificant. The β_2 coefficient for MEDIA remains positive but is less significant, implying that news articles on past losers have a marginal impact on ID. PR exerts an insignificant impact on ID for past losers, consistent with the notion that managers are reluctant to release bad news. Analyst coverage continues to lower ID as the β_3 coefficient remains negative. Interestingly, the β_4 coefficient for SIZE is positive for past losers. Thus, large firms that have done poorly in the formation period have more discrete information.

In summary, articles in the financial press are associated with discrete information while greater analyst coverage is associated with continuous information. In particular, after controlling for media coverage, greater analyst coverage leads to more continuous information. Management press releases produce continuous information but this finding is limited to good information. Conversely, greater analyst coverage is associated with continuous good and bad information.

The next section explores the relationship between information discreteness and momentum, hence the link between momentum and information intermediaries such as the financial press and analysts.

4 Information Discreteness and Momentum

To examine the importance of information discreteness to momentum, we form double-sorted portfolios sequentially that first condition on formation-period returns, then information discreteness. Specifically, after imposing a $5 price filter, we sort stocks into quintiles according to their PRET and then subdivide these quintiles into ID subportfolios. Post-formation returns over the next six-months and three-years are then computed. These holding-period returns are risk-adjusted according to the three-factor model of Fama and French (1993) that includes market, book-to-market, and size factors.

Panel A of Table 3 reports that momentum, the six-month return from buying winners and selling losers, decreases monotonically from 8.86% in the low ID quintile containing stocks with continuous information to 2.91% in the high ID quintile containing stocks with discrete information.

This 5.95% difference is highly significant with a t-statistic of 5.13. Risk-adjusting the momentum returns increases the disparity between the six-month holding-period returns to 6.89% (t-statistic of 7.01).

Figure 2 plots the momentum profits for the continuous and discrete information portfolios from one to ten months after portfolio formation. These momentum profits are not cumulative but represent "marginal" momentum profits within a particular month after portfolio formation. This figure indicates that momentum profits following continuous information persist for eight months. In particular, the momentum profit of 50bp (t-statistic of 2.27) in the eighth month after portfolio formation decreases to an insignificant 21bp (t-statistic of 0.98) by month nine. In contrast, for stocks in the discrete information portfolio, the momentum profit of 32bp is insignificant by the third month after portfolio formation (t-statistic of 1.34). Therefore, momentum is stronger and more persistent following continuous information than discrete information. Nonetheless, the relatively short horizon associated with the return continuation of continuous information is compatible with limited attention. Indeed, while the return predictability of continuous information can be exploited without incurring high transaction costs arising from frequent re-balancings, its lack of persistence is difficult to reconcile with risk.

The 2.70% increase in return continuation across the ID quintiles for past winners, from 8.38% up to 11.08%, parallels the 3.25% decrease for past losers, from 5.47% down to 2.22%. Thus, our FIP hypothesis applies to past winners as well as past losers. However, the returns across the five ID quintiles are monotonic for past losers but not past winners. Intuitively, this asymmetry may arise from investors expending more effort processing information when screening potential purchases than sales (short-sales). In the context of Appendix A, k can be lower for positive subsignals than negative subsignals. This property is a natural consequence of short-sell constraints that implicitly raise the threshold for processing bad information since trading based on small negative subsignals is not profitable.

Recall from Table 2 that large firms with poor returns have more discrete information during the formation period. In conjunction with discrete information resulting in weaker momentum, this finding indicates that return continuation is stronger for small stocks that are past losers (Hong, Lim, and Stein, 2000). Moreover, consistent with the results in Peress (2009), greater media coverage weakens return continuation. Indeed, our study refines the channel through which greater media coverage produces more discrete information and consequently weaker return continuation. Intuitively, lower analyst coverage does not necessarily imply stronger return continuation provided a firm attracts media coverage.

Recall that ID is defined by unadjusted returns since momentum strategies condition on the unadjusted formation-period returns of individual firms. However, Cooper, Gutierrez, and Hameed (2004) find evidence that momentum profits depend on market returns. Therefore, we also construct information discreteness using market-adjusted daily returns that subtract daily value-weighted market returns from the daily returns of individual stocks in our original definition. This market-adjusted information discreteness measure produces similar empirical results as those in Panel A of Table 3. In unreported results, the three-factor alpha increases from 3.65% over a six-month holding period to 7.98% as market-adjusted information discreteness ranges from discrete to continuous. This 4.33% difference in return continuation is significant (t-statistic of 3.16). Furthermore, the returns of past winners are monotonically increasing across the information discreteness quintiles, unlike those in Panel A of Table 3.

The average ID, PRET, SIZE, book-to-market ratio (BM), analyst forecast dispersion (DISP), and IVOL corresponding to past winners and past losers in each of the ID quintiles are reported in Panel B of Table 3. DISP is computed as one plus the log standard deviation of analyst forecasts. These averages indicate that stocks with continuous information have similar characteristics as stocks with discrete information. Indeed, the variation in momentum profits identified by ID does not appear to be associated with cross-sectional differences in BM characteristics or earnings uncertainty. Furthermore, continuous information is not limited to small stocks with high IVOL, nor is continuous information concentrated in past losers.[9]

Panel C reports the momentum profits from independent double-sorts derived from conditioning first on PRET, then ID. The results in Panel C parallel those in Panel A, with momentum increasing monotonically from an insignificant 1.63% to a highly significant 8.33% over the six-month holding period as information during the formation period becomes more continuous. Thus, the impact of ID on return continuation is insensitive to whether the double-sorted portfolios are formed sequentially or independently.

[9]In unreported results, we confirm that our results are nearly identical if NASDAQ-listed firms are removed from our sample.

Overall, the momentum profits in Table 3 provide empirical evidence that investors underreact to continuous information in a manner that is consistent with our FIP hypothesis. To clarify, the lack of short-term return continuation following discrete information does not contradict the concept of an upper threshold for investor attention. The maximum amount of information that investors can process in one day is determined by the aggregate amount of information regarding all firms released each day, as in Hirshleifer, Lim, and Teoh (2009)'s study. In contrast, our empirical tests focus on time series variation in daily returns during the twelve month formation-period. The flow of industry and macroeconomic information as well as information regarding individual firms and their peers are manifested in these daily returns.

An underreaction to information does not predict post-formation return reversals over the long term. George and Hwang (2004) cast doubt on the link between short-term return continuation and long-term return reversals. The three-year holding-period returns in Table 3 are inconsistent with long-term return reversals for stocks with continuous information, despite their significant short-term return continuation. Indeed, stocks with continuous information in the formation period have higher long-term risk-adjusted returns than stocks with discrete information in the formation period. Furthermore, there is evidence that investors overreact to discrete information. Specifically, discrete information during the formation period leads to negative (albeit insignificant) risk-adjusted returns in the three years after portfolio formation. Figure 2 also indicates that momentum profits following discrete information are negative within seven months of portfolio formation.

The weaker return predictability following discrete information cannot be attributed to recent losers in the past winner portfolio nor recent winners in the past loser portfolio. Although large buy (sell) order flow imbalances can induce upward (downward) price pressures whose subsequent reversals dampen momentum, a month between the formation and holding periods is skipped to guard against the influence of temporary price pressures.[10] In unreported results, including the liquidity factor of Pástor and Stambaugh (2003) in the risk-adjustment procedure does not alter the empirical results in Table 3.

[10] Order flow imbalances over short horizons are not appropriate for measuring the flow of information. Liquidity shocks can induce large order flow imbalances but exert a small influence on returns. Conversely, important information can exert a large influence on returns but induce a relatively small order flow imbalance if investors agree on its implications.

Additional evidence in Panel D based on sequential double-sorts starting in 1927 confirm the robustness of our prior empirical support for the FIP hypothesis. Although firm characteristics based on accounting data and analyst forecasts are not available in the earlier subperiod, the return predictability of continuous information continues to be stronger relative to discrete information in an extended sample period.[11] Moreover, in this extended sample period, momentum is negative following discrete information.

Finally, a 6-1-6 momentum strategy whose formation period and holding period are both six months produces similar momentum profits as the 12-1-6 strategy whose profits are reported in Table 3. In unreported results, profits from the 6-1-6 momentum strategy are monotonic across the ID portfolios, providing a highly significant 10.34% unadjusted holding-period return following continuous information.

In the remainder of this section, we contrast information discreteness with return consistency and idiosyncratic volatility in the existing momentum literature. Cross-sectional regressions also demonstrate that information discreteness is distinct from firm characteristics that have previously been found to explain cross-sectional differences in momentum.

4.1 Information Discreteness and Limited Attention

This subsection provides corroborating evidence that the empirical support for our FIP hypothesis in Table 3 is attributable to limited attention.

As recent information is more likely to be unprocessed by investors with limited attention, we assign declining weights to the daily returns underlying the ID measure based on the particular month of the formation period in which they occur. Specifically, daily returns in the most recent month of the formation period receive a weight of 12, daily returns in the second most recent month receive a weight of 11, and so forth until the daily returns in the first month of the formation period receive a weight of 1. These declining weights are applied to the numerator and denominator of the ID measure to produce a declining time-weighted ID measure that is denoted DWID.

Panel A of Table 4 reports insignificant momentum of 1.23% following discrete information (high DWID) and highly significant momentum of 10.59% following continuous information (low

[11] Stronger return continuation following continuous information is also found in a more recent subperiod beginning in 1997 during which, unconditionally, momentum is not significant.

DWID). The 9.36% return disparity is higher than in previous double-sorts, indicating a stronger underreaction to recent continuous information. This finding provides additional support for the limited attention motivation underlying our FIP hypothesis. Furthermore, the disparity in the return predictability of continuous and discrete information is not driven by returns early in the formation period (Novy-Marx, 2010).

Information discreteness also identifies stronger return variation among stocks with less concentrated institutional ownership. Following Hartzell and Starks (2003), we define the concentration of institutional ownership as the proportion of institutional ownership accounted for by the five largest institutional investors in a firm. In our context, less concentrated institutional ownership is associated with less attentive investors.

Consistent with the limited attention motivation of our FIP hypothesis, the results in Panel B of Table 4 indicate that our ID measure is better able to explain cross-sectional differences in momentum among firms with less attentive investors. In particular, the disparity in momentum profits following continuous versus discrete information is 11.23% in stocks with less concentrated institutional ownership. This difference in momentum is more than double the 5.44% disparity in stocks with more concentrated institutional ownership.

4.2 Return Consistency and Alternative Hypotheses

This subsection first distinguishes between information discreteness and return consistency by providing two important findings regarding their relative importance. First, information discreteness explains cross-sectional differences in return continuation better than return consistency. Second, as predicted by limited attention, information discreteness has a symmetric impact on past winners and past losers. In contrast, the implications of return consistency are limited to past winners.

As defined in Grinblatt and Moskowitz (2004), the return consistency dummy variable RC equals one if a stock's monthly returns are positive (negative) for at least eight months of the twelve-month formation period and PRET is also positive (negative). Besides the need to specify a threshold (such as eight out of the past twelve months), this dummy variable is based on monthly returns while ID is a continuous variable based on daily returns.

The subsample of stocks for which RC equals one comprises 17.24% of the firm-month observations in our original dataset. The results in Panel A of Table 5 arise from a sorting procedure that first conditions on stocks with consistent returns (RC equals one) before conditioning on ID. Post-formation momentum returns are defined as the returns from buying winners and selling losers. Both unadjusted returns and risk-adjusted returns relative to the three-factor model of Fama and French (1993) are presented over six-month and three-year post-formation horizons. As in Panel A of Table 3, momentum profits are monotonically increasing over the ID quintiles, from 5.19% to 10.14%. This 4.95% return difference is significant (t-statistic of 3.55). This return difference increases to 7.27% after risk-adjustment. Thus, the marginal return predictability of continuous information is significant after controlling for return consistency. As expected, unreported results indicate that ID explains an even greater portion of cross-sectional differences in momentum among stocks with inconsistent returns (RC equals zero).

The following Fama-MacBeth regression examines the return predictability of return consistency

$$
\begin{aligned}
r_{i,t+h} \quad = \quad & \beta_0 + \beta_1 \,\mathrm{PRET}_{i,t} + \beta_2 \,\mathrm{NegPRET}_{i,t} + \beta_3 \,\mathrm{PosRC}_{i,t} + \beta_4 \,\mathrm{NegRC}_{i,t} + \beta_5 \,\mathrm{PosID}_{i,t} + \beta_6 \,\mathrm{NegID}_{i,t} \\
& + \beta_7 \,\mathrm{SIZE}_{i,t} + \beta_8 \,\mathrm{BM}_{i,t} + \beta_9 \,\mathrm{TURN}_{i,t} + \beta_{10} \,\mathrm{SUE} + \beta_{11} \,\mathrm{AMIHUD}_{i,t} + \beta_{12} \,\mathrm{DELAY}_{i,t} \\
& + \alpha \, X_{i,t} + \epsilon_{i,t+h} \,, \qquad (6)
\end{aligned}
$$

where NegPRET is defined as $\min\{0, \mathrm{PRET}\}$. PosRC and NegRC refer to positive and negative RC dummy variables, respectively. As in Grinblatt and Moskowitz (2004), both PosRC and NegRC are defined using monthly returns with PosRC (NegRC) requiring eight of the twelve monthly returns during the formation period to have the same positive (negative) sign as PRET. Signed versions of ID denoted PosID and NegID, respectively are defined using daily returns as follows

$$
\mathrm{PosID} = \begin{cases} \%pos - \%neg & \text{if PRET} > 0 \\ 0 & \text{otherwise} \end{cases}
$$

and

$$
\mathrm{NegID} = \begin{cases} \%neg - \%pos & \text{if PRET} < 0 \\ 0 & \text{otherwise.} \end{cases}
$$

Recall that $\%pos$ and $\%neg$ denote the percentage of days during the formation period with positive and negative returns, respectively. Additional independent variables include turnover during the formation period (TURN), the most recent quarterly earnings surprises (SUE), and Amihud (2002)'s illiquidity measure (AMIHUD). A firm's SUE is computed by comparing its realized earnings in the most recent quarter with its realized earnings in the same quarter of the prior year. This difference is then normalized by the standard deviation of the firm's earnings over the prior eight quarters.

Jegadeesh, Kim, Krische, and Lee (2004) identify several additional firm characteristics that predict returns. As defined in their Appendix A, these characteristics include price-earnings ratios, total assets, capital expenditures to total assets (CAPEX), previous sales growth, and analyst coverage. Total assets is defined using a firm's current assets.[12] CAPEX sums a firm's capital expenditures over the prior four quarters, on a rolling basis. Both total assets and CAPEX are quarterly variables normalized by a firm's total assets. Sales growth is a ratio whose numerator equals quarterly sales over the prior four quarters and whose denominator equals quarterly sales over a non-overlapping horizon consisting of the prior four to eight quarters. For completeness, we also include skewness and kurtosis in our subsequent cross-sectional regressions to account for the possibility that ID is capturing these statistical properties of daily returns. These characteristics form a vector X of control variables whose individual coefficients are not reported for brevity.

The results in Panel B of Table 5 are generally consistent with those in Grinblatt and Moskowitz (2004) since the β_3 coefficient for PosRC is positive while the β_4 coefficient for NegRC is insignificant (and positive rather than negative). Thus, return consistency cannot explain the return continuation of past losers. Grinblatt and Moskowitz (2004) attribute this failure to tax-loss selling in December, which leads to purchases in January that offset the return continuation of past losers. In contrast, the β coefficients for PosID and NegID are both significant. Indeed, the positive β_5 coefficient and negative β_6 coefficient corroborate the holding-period returns in Panel A since ID is capable of explaining the return continuation of past winners as well as past losers.

In unreported results, both PosID and NegID continue to predict returns in the extended sample period that begins in 1927, suggesting that limited attention provides a better explanation for the return predictability of continuous information than the disposition effect.[13] Computing ID using monthly instead of daily returns yields similar results. Specifically, return continuation equals

[12] Depreciation along with changes in cash, current liabilities, current long-term debt, and deferred taxes are then subtracted from current assets.

[13] The t-statistics for PosRC and NegRC are both insignificant (0.25 and 0.28, respectively), while the t-statistics for PosID and NegID are significantly positive and negative (1.98 and -5.98), respectively.

7.90% following continuous information versus 3.50% following discrete information when ID is defined using monthly returns during the formation period. This 4.40% difference is significant but smaller than the 5.95% reported in Panel A of Table 3. Consequently, higher frequency returns appear to increase the return predictability of information discreteness.

There are several other distinctions between information discreteness and return consistency. One motivation for Grinblatt and Moskowitz (2004)'s study of return consistency is the disposition effect that posits investors are less inclined to sell a stock whose price has decreased below its purchase price than a stock whose price has increased above this reference price. However, in later cross-sectional regressions, neither return consistency nor unrealized capital gains explain the return predictability of continuous information. Moreover, limited attention is applicable to analysts as well as investors while the disposition effect that motivates return consistency does not apply to analysts. Evidence presented in Table 7 indicates that ID predicts analyst forecast errors. Indeed, our finding that continuous information leads to larger forecast errors is consistent with the FIP hypothesis but not the disposition effect. Therefore, FIP and the disposition effect appear to be distinct forces that both contribute to price momentum.

Besides return consistency, the prior literature has also claimed to have found that momentum profits are larger in stocks with high idiosyncratic volatility. To address the possibility that information discreteness is higher (more discrete) when idiosyncratic volatility is higher, we re-visit Zhang (2006)'s finding that momentum is stronger in stocks with higher idiosyncratic volatility.[14] The belief that continuous information corresponds to low idiosyncratic volatility suggests a contradiction between our finding that stronger momentum corresponds to continuous information and Zhang's finding that stronger momentum corresponds to higher idiosyncratic volatility.

Zhang (2006) first conditions on idiosyncratic volatility before conditioning on formation-period returns. In unreported results, we also find evidence of stronger momentum in high IVOL stocks using this double-sort procedure.[15] From the low IVOL to high IVOL quintiles, momentum increases from 3.31% to 8.90% over a six-month holding period, a difference of 5.59%. However, this result may be mechanical if the extreme returns that define past winners and past losers also induce

[14]Besides the disposition effect, Grinblatt and Moskowitz (2004)'s study is also motivated by the possibility that return consistency impacts return volatility.

[15]Nonetheless, there are several differences between our respective methodologies. For example, Zhang (2006) examines a shorter sample period and a shorter holding period.

high idiosyncratic volatility. Specifically, provided high IVOL stocks are more likely to be extreme past winners or losers, momentum profits will appear to be higher among high IVOL stocks even if IVOL itself is not important to return continuation.

To address the possibility of such a mechanical relationship, we reverse the order of double-sort and first condition on PRET, then IVOL. This reverse double-sort examines the marginal return predictability of IVOL after controlling for PRET. The results in Panel C indicate a far weaker increase in momentum across the IVOL quintiles from 4.34% to 7.02%, a difference of only 2.68%. Thus, reversing the order of the double-sort reduces the amount of momentum attributable to IVOL by over a half.

Moreover, we compute residual IVOL (Res IVOL) that is orthogonal to the absolute value of formation-period returns. Res IVOL is computed by the following cross-sectional regression

$$\mathrm{IVOL}_{i,t} \quad = \quad \gamma_{0,t} + \gamma_{1,t}\ |\mathrm{PRET}|_{i,t} + \epsilon_{i,t}^{IVOL}\,. \tag{7}$$

The $\epsilon_{i,t}^{IVOL}$ residual for firm i defines its Res IVOL in month t. The next double-sort we conduct first conditions on Res IVOL, then PRET. This double-sort parallels the procedure in Zhang (2006) except that IVOL is replaced with Res IVOL to remove the confounding influence of formation-period returns.

According to Panel D, stocks with high Res IVOL produce a six-month momentum return of 6.87% while those with low Res IVOL produce a momentum return of 6.62%. This 0.25% difference is insignificant. Indeed, the t-statistic of 0.37 indicates that momentum is not stronger in stocks with higher idiosyncratic volatility after accounting for the influence of formation-period returns. In summary, after controlling for the influence of formation-period returns, higher idiosyncratic volatility is not associated with stronger momentum.

Finally, we examine whether the conservatism bias is responsible for the return predictability of information discreteness. Conservatism can cause investors to ignore continuous information that does not support their prior beliefs until discrete information forces a reevaluation of these beliefs. Therefore, we assign a higher weight of 10 to daily returns of the same sign as the firm's cumulative return during the previous ten days as a proxy for confirming information.[16] The confirmation

[16] Our results are robust to using smaller weights for confirming information such as 5 or 2.

bias predicts that this modification of information discreteness denoted CID will explain a greater portion of momentum than the original ID measure.

However, the evidence in Panel E indicates that emphasizing days with confirming information at the expense of those with disconfirming information does not lead to a better explanation of momentum profits. Indeed, the 6.12% difference in momentum following continuous versus discrete information is comparable to the 5.95% in Panel A of Table 3. Therefore, the conservatism bias does not appear to be responsible for the ability of information discreteness to explain cross-sectional differences in momentum.

4.3 Residual Information Discreteness and Fama-MacBeth Regressions

In addition to return consistency and idiosyncratic volatility, the momentum literature identifies several firm characteristics that are related to the strength of momentum. Hou, Peng, and Xiong (2009) interpret low turnover as evidence of investor inattention while Lee and Swaminathan (2000) interpret high turnover as a sign of investor sentiment in their study of price momentum. Zhang (2006) also finds that momentum is stronger in small firms and firms with less analyst coverage. Furthermore, Daniel and Titman (1999) document a negative relationship between the value premium and momentum. Hou and Moskowitz (2005) find that investor recognition characteristics such as institutional ownership and analyst coverage explain price delays while Hong, Lim, and Stein (2000) report that stocks with lower analyst coverage have stronger momentum.

To ensure that our findings regarding ID are distinct from the existing momentum literature, we compute *residual* information discreteness (Res ID) from a cross-sectional regression of ID on the absolute value of PRET along with firm characteristics that the existing literature has identified as being associated with cross-sectional differences in momentum profits

$$\begin{aligned} \mathrm{ID}_{i,t} &= \delta_{0,t} + \delta_{1,t}\,|\mathrm{PRET}|_{i,t} + \delta_{2,t}\,\mathrm{TURN}_{i,t} + \delta_{3,t}\,\mathrm{SIZE}_{i,t} + \delta_{4,t}\,\mathrm{BM}_{i,t} + \delta_{5,t}\,\mathrm{COVER}_{i,t} \\ &\quad + \delta_{6,t}\,\mathrm{IVOL}_{i,t} + \delta_{7,t}\,\mathrm{IO}_{i,t} + \delta_{8,t}\,\mathrm{RC}_{i,t} + \epsilon^{ID}_{i,t}\,. \end{aligned} \tag{8}$$

Res ID is defined as $\epsilon^{ID}_{i,t}$ for firm i in month t.

Panel A of Table 6 reports coefficients from equation (8) that are estimated using a Fama-MacBeth methodology that parallels the monthly cross-sectional regressions performed each month.

According to Panel A, ID is unrelated to size and book-to-market characteristics, although information is more continuous for firms with higher turnover and lower institutional ownership. Overall, the adjusted R^2 of 0.141 indicates that the firm characteristics in the existing momentum literature do not exert a major influence on ID. This result supports our earlier finding that ID captures a time-varying characteristic of information rather than a persistent firm characteristic

According to Panel B, momentum profits are monotonically increasing across the Res ID portfolios from 3.19% to 8.57%. This 5.38% difference is highly significant (t-statistic of 3.83). This evidence confirms that information discreteness explains cross-sectional differences in momentum after controlling for existing variables in the momentum literature.

We also estimate Fama-MacBeth regressions to determine whether continuous information is responsible for momentum after controlling for firm characteristics that the prior literature has shown to predict returns. We examine both price momentum and earnings momentum. The dependent variable in these regressions are individual stock returns over a six-month horizon. To examine price momentum and earnings momentum, our cross-sectional regressions involve PRET and SUE, respectively.

SIZE and BM are also included in the cross-sectional regression since these characteristics are the basis for the Fama-French factors. Gervais, Kaniel, and Mingelgrin (2001) also document that turnover predicts returns and attribute this finding to the ability of high volume to overcome investor inattention. Besides TURN, IVOL is also included to ensure that the return predictability attributable to ID is not a manifestation of idiosyncratic volatility's return predictability (Ang, Hodrick, Xing, and Zhang, 2006). In addition, Sadka (2006) reports that liquidity has a systematic component that affects asset prices. Therefore, we include AMIHUD to control for illiquidity. Including the percentage of days with zero return (%zero) as an additional proxy for illiquidity does not alter any of our results and this variable is therefore omitted for brevity. DELAY controls for the speed at which investors incorporate information into stock prices. In addition, to examine the influence of the disposition effect on our results, we control for the return predictability of firm-level unrealized capital gains. A separate interaction between UCG and PRET is included since UCG is positive for gains and negative for losses.

Observe that several of the independent variables in equation (9) below are also independent variables in the computation of Res ID in equation (8). This commonality arises from the prior literature's use of firm characteristics such as size to predict returns and to explain cross-sectional differences in momentum profits.

We estimate several Fama-MacBeth (1973) regression specifications to evaluate the impact of Res ID on return continuation. The first specification examines the influence of Res ID on price momentum

$$\begin{aligned} r_{i,t+h} \;=\;& \beta_0 + \beta_1 \,\mathrm{PRET}_{i,t} + \beta_2 \,\mathrm{Res\ ID}_{i,t} + \beta_3 \,(\mathrm{Res\ ID} \cdot \mathrm{PRET})_{i,t} + \beta_4 \,\mathrm{SUE}_{i,t} \\ & + \beta_5 \,\mathrm{SIZE}_{i,t} + \beta_6 \,\mathrm{BM}_{i,t} + \beta_7 \,\mathrm{TURN}_{i,t} + \beta_8 \,\mathrm{IVOL}_{i,t} + \beta_9 \,\mathrm{AMIHUD}_{i,t} \\ & + \beta_{10} \,\mathrm{DELAY}_{i,t} + \beta_{11} \,\mathrm{UCG}_{i,t} + \beta_{12} \,(\mathrm{UCG} \cdot \mathrm{PRET})_{i,t} + \alpha \, X_{i,t} + \epsilon_{i,t+h} \,. \end{aligned} \tag{9}$$

The price momentum literature implies a positive β_1 coefficient. More importantly, a negative β_3 coefficient for the interaction variable Res ID $\cdot$ PRET indicates that continuous information results in stronger price momentum than discrete information. In particular, discrete information (high Res ID) corresponds with weaker return continuation if β_3 is negative.

Panel C confirms the influence of Res ID on price momentum. The positive β_1 coefficient for PRET is consistent with price momentum. Most importantly, the negative β_3 coefficient indicates that price momentum is stronger when information during the formation period is continuous, supporting our FIP hypothesis.

The coefficients of the other variables are broadly consistent with the prior literature. Although the β_{11} coefficient is insignificant, the interaction between UCG and PRET results in a positive β_{12} coefficient. Hence, unrealized capital gains and losses correspond to higher and lower future returns, respectively. This evidence is consistent with Grinblatt and Han (2005). Nonetheless, after controlling for UCG, Res ID continues to explain cross-sectional differences in momentum. Res ID also explains price momentum after controlling for IVOL. For emphasis, IVOL is computed during the formation period. Therefore, it is not directly comparable to the idiosyncratic volatility in Ang, Hodrick, Xing, and Zhang (2006) based on returns in the most recent month, which is omitted from the formation period.[17] However, in unreported results, computing IVOL using daily returns in the month prior to portfolio formation does not alter the return predictability of Res ID.

[17]Bali, Scherbina, and Tang (2010) find short-term return reversals follow increases in idiosyncratic volatility that arise from firm-level news. In contrast, return continuation following continuous information does not reverse.

Using cumulative prospect theory, Barberis and Huang (2008) demonstrate that the positive skewness of initial public offerings and distressed firms can result in negative excess returns. Besides controlling for return skewness in our Fama-MacBeth regressions, unreported results demonstrate that removing initial public offerings (IPOs) and distressed firms from our sample does not alter our holding-period returns. IPOs are defined as firms whose initial appearance in CRSP occurs twelve months before portfolio formation. Firms are distressed if their KMV default scores are in the top decile.[18] The imposition of a \$5 price filter also eliminates the potential for low-priced lottery stocks to influence our results. Consequently, while discrete information coincides with positive skewness (according to Panel B of Table 1), skewness is not responsible for the return predictability of continuous information.[19] Indeed, replacing the Res ID measure in equation (9) with |SKEW| does not result in a significant β_3 coefficient. Furthermore, replacing Res ID with the jump variables also does not result in significant return predictability. Therefore, although skewness and jumps are correlated with discrete information according to Table 1, Res ID is not captured by conventional moments of the return distribution.

In unreported results, the addition of interaction variables involving PRET, such as TURN $\cdot$ PRET, and interaction variables involving ID, such as SIZE $\cdot$ ID, as well as triple interaction variables involving both PRET and ID, such as SIZE $\cdot$ PRET $\cdot$ ID, does not diminish the significance of the β_3 coefficient. Therefore, it is unlikely that the ability of continuous information to identify cross-sectional variability in momentum profits is attributable to an omitted variable.

Finally, we incorporate the probability of informed trading (PIN) to control for the possibility that continuous information corresponds to the diffusion of private information across investors. This data is obtained from the website of Soeren Hvidkjaer for a restricted sample of NYSE stocks from 1983 until 2001. In unreported results, the addition of this informed trading proxy does not diminish the significance of the β_3 coefficient.

To analyze the impact of Res ID on earnings momentum, specifically the post-earnings announcement drift identified by Bernard and Thomas (1990), the following Fama-MacBeth regression

[18] A description of these default scores is available on http://www.moodyskmv.com/research/index.html.

[19] The negative coefficient for skewness indicates that stocks with positive skewness may have lower expected returns but function as a "lottery" by having a low probability of a high return. Bali, Cakici, and Whitelaw (2011) report that extremely large positive returns in the prior month, which are not included in formation-period returns, are associated with negative subsequent returns.

is estimated

$$
\begin{aligned}
r_{i,t+h} \;=\;& \beta_0 + \beta_1 \,\mathrm{SUE}_{i,t} + \beta_2 \,\mathrm{Res\ ID}_{i,t} + \beta_3 \,(\mathrm{Res\ ID} \,\cdot\, \mathrm{SUE})_{i,t} + \beta_4 \,\mathrm{PRET}_{i,t} \\
& + \beta_5 \,\mathrm{SIZE}_{i,t} + \beta_6 \,\mathrm{BM}_{i,t} + \beta_7 \,\mathrm{TURN}_{i,t} + \beta_8 \,\mathrm{IVOL}_{i,t} + \beta_9 \,\mathrm{AMIHUD}_{i,t} \\
& + \beta_{10} \,\mathrm{DELAY}_{i,t} + \beta_{11} \,\mathrm{UCG}_{i,t} + \beta_{12} \,(\mathrm{UCG} \,\cdot\, \mathrm{PRET})_{i,t} + \alpha \, X_{i,t} + \epsilon_{i,t+h} \,. \qquad (10)
\end{aligned}
$$

In this specification, the β_1 coefficient corresponds to the most recent SUE instead of formation-period returns, while the interaction variable underlying the β_3 coefficient involves the most recent earnings surprise, Res ID $\cdot$ SUE.

Panel D of Table 6 demonstrates the influence of Res ID on earnings momentum. The positive β_1 coefficient is consistent with earnings momentum while the negative β_3 coefficient indicates that earnings momentum is stronger for stocks with continuous information during the formation period. Thus, continuous information generates stronger earnings momentum as well as stronger price momentum. The positive β_4 coefficient for PRET accounts for price momentum while the remaining beta coefficients have similar interpretations as their counterparts in Panel C. Overall, the empirical results in Table 3 through Table 6 provide strong support for our FIP hypothesis.

5 Analysts and Information Discreteness

Besides investors, the FIP hypothesis can also cause analysts to underreact to continuous information. In contrast, the disposition effect is not directly applicable to analysts since their forecasts are not compared with reference thresholds to determine gains or losses. Furthermore, analyst forecasts are important sources of information for investors. If the FIP hypothesis applies to analysts, then we have identified a channel through which our concept of limited attention can affect asset prices. Indeed, our earlier analysis has shown that analyst coverage influences ID.

To examine whether continuous information leads to larger earnings surprises, we begin by obtaining annual earnings per share forecasts from the Institutional Brokers Estimate System (IBES) Summary unadjusted file between 1985 and 2007. Unadjusted IBES forecasts are not adjusted by share splits after their issuance date. Following Livnat and Mendenhall (2006), analyst-based earnings surprises denoted SURP are defined as the difference between a firm's actual earnings per share and the analyst consensus forecast. This difference is then normalized by the firm's share price on its earnings announcement date. Considering only the most recent forecast issued by each analyst, the analyst consensus forecast is defined as the median of forecasts issued within 90 days prior to the earnings announcement.

To test whether continuous information yields larger analyst forecast errors, we regress analyst forecast errors on ID along with its interaction with PRET and other variables that can affect the accuracy of consensus forecasts such as DISP that captures the uncertainty surrounding a firm's earnings. Analysts may expend more effort on their earnings forecasts for stocks with high past returns and high turnover as well as growth stocks and large stocks if information on their future earnings is in greater demand by investors, including institutional investors (O'Brien and Bhushan, 1990), and can generate larger trading commissions. Therefore, to test the FIP hypothesis using analyst forecast errors, we estimate the following regression

$$\begin{aligned} \mathrm{SURP}_{i,t} &= \beta_0 + \beta_1\,\mathrm{ID}_{i,t} + \beta_2\,\mathrm{PRET}_{i,t} + \beta_3\,(\mathrm{ID}\cdot\mathrm{PRET})_{i,t} + \beta_4\,\mathrm{DISP}_{i,t} + \beta_5\,\mathrm{COVER}_{i,t} \\ &\quad + \beta_6\,\mathrm{BM}_{i,t} + \beta_7\,\mathrm{SIZE}_{i,t} + \beta_8\,\mathrm{TURN}_{i,t} + \beta_9\,\mathrm{IO}_{i,t} + \epsilon_{i,t}\,. \end{aligned} \tag{11}$$

Once again, a negative β_3 coefficient for the interaction between ID and PRET provides support for the FIP hypothesis. In particular, the negative β_3 coefficient implies that continuous information leads to larger analyst forecast errors.

Panel A of Table 7 contains the coefficient estimates from equation (11). Consistent with our FIP hypothesis, the β_3 coefficient is negative with a t-statistic of -2.19. This finding indicates that analysts are indeed slower to incorporate continuous information into their forecasts than discrete information.

An alternative proxy for information discreteness is constructed using signed monthly analyst forecast revisions where *%upward* and *%downward* are defined by the percentage of upward and downward revisions, respectively, for the current fiscal year's forecasted earnings. Besides being derived from earnings forecast revisions instead of returns, this alternative proxy is defined using monthly rather than daily information flows.

The analyst forecast-based information discreteness is denoted ID_f and equals

$$\mathrm{ID}_f \quad = \quad \mathrm{sgn(CUMREV)} \cdot [\%downward - \%upward] \; . \tag{12}$$

The cumulative revision during the formation period is denoted CUMREV. The sign of CUMREV denoted sgn(CUMREV) equals +1 when CUMREV > 0 (upward revision), -1 when CUMREV < 0 (downward revision), and 0 when CUMREV = 0. For every firm-fiscal year, we define CUMREV as the difference between the last consensus forecast before an annual earnings announcement and the first forecast. As with our original ID measure, ID_f in equation (12) is lower when information arrives continuously.

The correlation between ID and ID_f equals 0.13. According to Panel B of Table 7, sequential double-sorts that condition on PRET, then ID_f, reveal that momentum increases as ID_f ranges from discrete to continuous. In particular, the difference of 10.93% over a six-month holding period is highly significant (t-statistic of 11.02) and significantly greater than the 5.95% difference in Panel A of Table 3. Furthermore, momentum following discrete information is insignificant.

We also repeat the cross-sectional regressions in equation (9) and equation (10) with ID_f replacing ID in the independent variables corresponding to the β_2 and β_3 coefficients. For price momentum, the Fama-MacBeth regression specification is

$$\begin{aligned} r_{i,t+h} \quad = \quad & \beta_0 + \beta_1 \, \mathrm{PRET}_{i,t} + \beta_2 \, \mathrm{ID}_{f\,i,t} + \beta_3 \, (\mathrm{ID}_f \cdot \mathrm{PRET})_{i,t} + \beta_4 \, \mathrm{SUE}_{i,t} \\ & + \beta_5 \, \mathrm{SIZE}_{i,t} + \beta_6 \, \mathrm{BM}_{i,t} + \beta_7 \, \mathrm{TURN}_{i,t} + \beta_8 \, \mathrm{IVOL}_{i,t} + \beta_9 \, \mathrm{AMIHUD}_{i,t} \\ & + \beta_{10} \, \mathrm{DELAY}_{i,t} + \beta_{11} \, \mathrm{UCG}_{i,t} + \beta_{12} \, (\mathrm{UCG} \cdot \mathrm{PRET})_{i,t} + \alpha \, X_{i,t} + \epsilon_{i,t+h} \, , \end{aligned} \tag{13}$$

and for earnings momentum the Fama-MacBeth regression specification is

$$\begin{aligned} r_{i,t+h} \quad = \quad & \beta_0 + \beta_1 \, \mathrm{SUE}_{i,t} + \beta_2 \, \mathrm{ID}_{f\,i,t} + \beta_3 \, (\mathrm{ID}_f \cdot \mathrm{SUE})_{i,t} + \beta_4 \, \mathrm{PRET}_{i,t} \\ & + \beta_5 \, \mathrm{SIZE}_{i,t} + \beta_6 \, \mathrm{BM}_{i,t} + \beta_7 \, \mathrm{TURN}_{i,t} + \beta_8 \, \mathrm{IVOL}_{i,t} + \beta_9 \, \mathrm{AMIHUD}_{i,t} \\ & + \beta_{10} \, \mathrm{DELAY}_{i,t} + \beta_{11} \, \mathrm{UCG}_{i,t} + \beta_{12} \, (\mathrm{UCG} \cdot \mathrm{PRET})_{i,t} + \alpha \, X_{i,t} + \epsilon_{i,t+h} \, . \end{aligned} \tag{14}$$

The results from these regressions are reported in Panel C and Panel D of Table 7, respectively.

The β_3 coefficients for the interaction variables involving ID_f along with either PRET or SUE are both negative. Consequently, continuous information defined by analyst forecast revisions results in greater price momentum and earnings momentum than discrete information. Thus, Table 7 provides additional empirical support for the FIP hypothesis, and demonstrates the robustness of our original ID measure based on daily returns.

6 Conclusions

We test a frog-in-the-pan hypothesis that predicts investors underreact to small amounts of information that arrive continuously. This hypothesis is motivated by the limited attention literature in asset pricing. After controlling for the cumulative amount of information within the formation period, we find strong evidence that small amounts of information that arrive continuously predict returns and explain cross-sectional differences in momentum. Thus, consistent with our hypothesis, investors appear to underreact to small amounts of information that arrive continuously, despite their important cumulative implications for stock prices.

Information discreteness is first defined using signed daily returns to distinguish between small amounts of information that arrive continuously versus information that arrives in large amounts at discrete points in time. Therefore, information discreteness identifies time series variation in the daily returns that comprise the formation-period returns of momentum strategies. The interpretation of information discreteness is conditional on a formation-period return. Indeed, only after conditioning on formation-period returns is it possible to distinguish between the return implications of continuous versus discrete information. Greater media coverage by the financial press is associated with more discrete information, and weaker momentum as a consequence. In contrast, for past winners, a larger number of management press releases is associated with more continuous information. After controlling for media coverage and management press releases, greater analyst coverage corresponds to more continuous information for all firms.

Information discreteness is not influenced by extreme returns and differs from idiosyncratic volatility. Moreover, after accounting for the impact of extreme formation-period returns, higher idiosyncratic volatility is not associated with stronger momentum. Instead, information discreteness exerts a greater impact on momentum than idiosyncratic volatility. Furthermore, information discreteness is distinct from the return consistency examined by Grinblatt and Moskowitz (2004). Unlike return consistency, information discreteness also explains cross-sectional differences in the return continuation of past losers as well as past winners. Moreover, the return predictability of continuous information remains significant after controlling for return consistency and unrealized capital gains. Information discreteness also identifies stronger return variation among stocks with less concentrated institutional ownership. As less concentrated institutional ownership is associated with less attentive investors, this finding provides additional support for our frog-in-the-pan hypothesis. A modified information discreteness measure fails to find evidence that the conservatism bias is responsible for our results. Overall, our results are more likely the result of limited attention than the disposition effect or conservatism.

Analyst forecast errors are also larger following continuous information. Thus, besides investors, analysts also appear to underreact to continuous information. Moreover, an alternative measure of information discreteness defined using signed analyst forecast revisions instead of signed daily returns confirms that momentum is stronger following continuous information. Thus, our conclusions are dependent on the use of daily returns to measure information discreteness.

References

Amihud, Y., 2002, Illiquidity and stock returns: Cross-section and time series effects. Journal of Financial Markets 5, 31-56.

Ang, A., R. Hodrick, Y. Xing, and X. Zhang, 2006, The cross-section of volatility and expected returns. Journal of Finance 61, 259-299.

Bae, K. and W. Wang, 2011, What's in a "China" name? A test of investor attention hypothesis. Forthcoming in Financial Management.

Bali, T., N. Cakici, and R. Whitelaw, 2011, Maxing out: Stocks as lotteries and the cross-sectional of expected returns. Journal of Financial Economics 99, 427-446.

Bali, T. G., A. Scherbina, and Y. Tang, 2010, Unusual events and the cross-section of stock returns. Working Paper.

Barber, B., and T. Odean, 2008, All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. Review of Financial Studies 21, 785-818.

Barberis, N., and M. Huang, 2008, Stocks as lotteries: The implications of probability weighting for security prices. American Economic Review 98, 2066-2100.

Ben-David, I., and D. Hirshleifer, 2011, Beyond the disposition effect: Do investors really like realizing gains more than losses? Working Paper.

Bernard, V., and J. Thomas, 1990, Evidence that stock prices do not fully reflect the implications of current earnings for future earnings. Journal of Accounting and Economics 13, 305-340.

Bushee, B., and C. Noe, 2000, Corporate disclosure practices, institutional investors, and stock return volatility. Journal of Accounting Research 38, 171-202.

Cohen, L., and A. Frazzini, 2008, Economic links and predictable returns. Journal of Finance 63, 1977-2011.

Cooper, M., R. Gutierrez, and A. Hameed, 2004, Market states and momentum. Journal of Finance 59, 1345-1365.

Corwin, S., and J. Coughenour, 2008, Limited attention and the allocation of effort in securities trading. Journal of Finance 63, 3031-3067.

Da, Z., J. Engelberg, and P. Gao, 2011, In search of attention. Journal of Finance 66, 1461-1499.

Daniel, K., D. Hirshleifer, and A. Subrahmanyam, 1998, Investor psychology and security market under- and overreactions. Journal of Finance 53, 1839-1885.

Daniel, K., D. Hirshleifer, and S. Teoh, 2002, Investor psychology in capital markets: Evidence and policy implications. Journal of Monetary Economics 49, 139-209.

Daniel, K., and S. Titman, 1999, Market efficiency in an irrational world. Financial Analyst Journal 55, 28-40.

DellaVigna, S., and J. Pollet, 2007, Demographics and industry returns. American Economic Review 97, 1667-1702.

Fama, E., and K. French, 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33, 3-56.

Fama, E., and J. MacBeth, 1973, Risk, return, and equilibrium: Empirical tests. Journal of Political Economy 81, 607-636.

Fang, L., and J. Peress, 2009, Media coverage and the cross-section of stock return. Journal of Finance 64, 2023-2052.

Fu, F., 2009, Idiosyncratic risk and the cross-section of expected stock returns. Journal of Financial Economics 91, 24-37.

George, T., and C. Y. Hwang, 2004, The 52-week high and momentum investing. Journal of Finance 59, 2145-2176.

Gervais, S., R. Kaniel, and D. Mingelgrin, 2001, The high-volume return premium. Journal of Finance 61, 877-919.

Gino, F., and M. Bazerman, 2009, When misconduct goes unnoticed: The acceptability of gradual erosion in others' unethical behavior. Journal of Experimental Social Psychology 45, 708-719.

Grinblatt, M., and B. Han, 2005, Prospect theory, mental accounting, and momentum. Journal of Financial Economics 78, 311-339.

Grinblatt, M., and T. Moskowitz, 2004, Predicting stock price movements from past returns: The role of consistency and tax-loss selling. Journal of Financial Economics 71, 541-579.

Gurun, U. G., and A. Butler, 2010, Don't believe the hype: Local media slant, local advertising, and firm value. Forthcoming in Journal of Finance.

Hartzell, J., and L. Starks, 2003, Institutional investors and executive compensation. Journal of Finance 58, 2351-2374.

Hirshleifer, D., S. Lim, and S. Teoh, 2009, Driven to distraction: Extraneous events and underreaction to earnings news. Journal of Finance 64, 2289-2325.

Hong, H., T. Lim, and J. Stein, 2000, Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies. Journal of Finance 55, 265-295.

Hong, H., and J. Stein, 2007, Disagreement and the stock market. Journal of Economic Perspectives 21, 109-128.

Hong, H., and J. Stein, 1999, A unified theory of underreaction, momentum trading, and overreaction in asset markets. Journal of Finance 54, 2143-2184.

Hou, K., L. Peng, and W. Xiong, 2009, A tale of two anomalies: The implication of investor attention for price and earnings momentum. Working Paper.

Hou, K., and T. Moskowitz, 2005, Market frictions, price delay, and the cross-section of expected returns. Review of Financial Studies 18, 981-1020.

Jegadeesh, N., J. Kim, S. Krische, and C. Lee, 2004, Analyzing the analysts: When do recommendations add value? Journal of Finance 59, 1083-1124.

Jegadeesh, N., and S. Titman, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency. Journal of Finance 48, 65-91.

Johnson, T., 2002, Rational momentum effects. Journal of Finance 57, 585-608.

Lamb, C., J. Hair, and C. McDaniel, 2008, Marketing. Thompson South-Western.

Lee, C., and B. Swaminathan, 2000, Price momentum and trading volume. Journal of Finance 55, 2017-2069.

Lesmond, D., J. Ogden, and C. Trzcinka, 1999, A new estimate of transaction costs. Review of Financial Studies 12, 1113-1141.

Livnat, J., and R. Mendenhall, 2006, Comparing the post-earnings announcement drift for surprises calculated from analyst and time series forecasts. Journal of Accounting Research 44, 177-205.

Merton, R., 1987, A simple model of capital market equilibrium with incomplete information. Journal of Finance 42, 483-510.

Morck, R., B. Yeung, and W. Yu, 2000, The information content of stock markets: Why do emerging markets have synchronous stock price movements. Journal of Financial Economics 58, 215-260.

Neuhierl, A., Scherbina, A., and B. Schlusche, 2010, Market reaction to corporate news and the influence of the financial crisis. Working Paper.

Novy-Marx, R., 2010, Is momentum really momentum? Forthcoming in the Journal of Financial Economics.

O'Brien, P., and R. Bhushan, 1990, Analyst following and institutional ownership. Journal of Accounting Research 28 (Supplement), 55-76.

Pástor, L., and R. Stambaugh, 2003, Liquidity risk and stock returns. Journal of Political Economy 111, 642-685.

Peng, L., and W. Xiong, 2006, Limited attention, overconfidence and category learning. Journal of Financial Economics 80, 563-602.

Peress, J., 2009, Media coverage and investors' attention to earnings announcements. Working Paper.

Sadka, R., 2006, Momentum and post-earnings announcement drift anomalies: The role of liquidity risk. Journal of Financial Economics 80, 309-349.

Sagi, J., and M. Seasholes, 2007, Firm-specific attributes and the cross-section of momentum. Journal of Financial Economics 84, 389-434.

Shumway, T., and G. Wu, 2005, Does disposition drive momentum? Working Paper.

Sims, C., 2003, Implications of rational inattention. Journal of Monetary Economics 50, 665-690.

Tetlock, P., 2007, Giving content to investor sentiment: The role of media in the stock market. Journal of Finance 62, 1139-1168.

Tetlock, P., 2010, Does public financial news resolve asymmetric information? Review of Financial Studies 23, 3520-3557.

Tetlock, P., 2011, All the news that's fit to reprint: Do investors react to stale information? Review of Financial Studies 24, 1481-1512.

Tetlock, P., M. Saar-Tsechansky, and S. Macskassy, 2008, More than words: Quantifying language to measure firms' fundamentals. Journal of Finance 63, 1437-1467.

Zhang, F., 2006, Information uncertainty and stock returns. Journal of Finance 61, 105-137.

Appendix A: Illustrative Framework

Consider a two-period model with two types of agents that parallels Tetlock (2011). The first type of agents are rational while the second type are influenced by the FIP hypothesis. Their proportions are $1-m$ and m, respectively. The stock price at the end of the second period equals the dividend paid upon the firm's liquidation. This dividend equals the sum of two mean-zero independent signals s_1 and s_2 received at time 1 and time 2, respectively. As the expectations of s_1 and s_2 are both zero at time 0, the stock price P_0 equals 0.

The s_1 signal, distributed $\mathcal{N}\left(0,\sigma^2\right)$, is divided into N subsignals denoted s_1^i for $i=1,\ldots,N$. Rational investors process all N subsignals. Thus, from their perspective, the stock's value is s_1 at time 1. However, under the FIP hypothesis, subsignals that are small (in absolute value) are not processed. In particular, if their magnitude $\left|s_1^i\right|$ is below a threshold k, they are not processed until time 2 for FIP investors. Thus, based on the s_1 realization, rational investors and FIP investors value the stock differently with their respective demands determining the time 1 stock price P_1. Nonetheless, both investors agree on the stock price $P_2 = s_1 + s_2$ at time 2.

To compute P_1, we make several simplifying assumptions. First, we assume that both investors have CARA utility over next period's wealth with an identical absolute risk-aversion parameter. Second, we assume that FIP investors are unaware of their own attention constraints. Third, the stock is assumed to be in zero net supply and the interest rate is normalized to zero. Let $s_1^{FIP} = f \cdot s_1$ denote the expected value of the stock at time 1 from the perspective of FIP investors, with $0 < f \leq 1$ capturing the property that small subsignals are not processed at time 1.

Under these assumptions, one can compute the optimal demand for the stock from each type of investor, and then set the aggregate demand to zero to obtain

$$P_1 = (1-m) \cdot s_1 + m \cdot s_1^{FIP} = s_1 \cdot \left[1 - m \cdot (1-f)\right] , \tag{15}$$

which equals the correct price s_1 when $m=0$ and all investors are rational. The covariance in the price changes between the first and second periods equals

$$\begin{aligned} Cov\left(P_2 - P_1, P_1 - P_0\right) &= Cov\left(s_2 + m \cdot (1-f) \cdot s_1 \, , \, s_1 - m \cdot (1-f) \cdot s_1\right) \\ &= m \cdot (1-f) \cdot \left[1 - m \cdot (1-f)\right] \cdot Var(s_1). \end{aligned} \tag{16}$$

Consequently, when $m = 0$, this covariance equals zero and there is no momentum. Conversely, when $m > 0$ and $f < 1$, the covariance is positive and momentum is attributable to FIP investors. Provided the economy is not dominated by FIP investors ($m < \frac{1}{2}$ for example), the covariance is increasing in m and stronger momentum arises from having more FIP investors in the economy.[20]

To formalize f, consider the following information structure where each row represents the expectations of subsignals s_1^i for $i = 1, \cdots, N-1$. Without loss of generality, the subsignals are ordered from largest to smallest in terms of their expectations.

discrete	$\frac{1}{2}s_1$	$\frac{1}{2}s_1$	0	0	0	0	0	...	0
	$\frac{1}{2}s_1$	$\frac{1}{4}s_1$	$\frac{1}{4}s_1$	0	0	0	0	...	0
	$\frac{1}{2}s_1$	$\frac{1}{4}s_1$	$\frac{1}{8}s_1$	$\frac{1}{8}s_1$	0	0	0	...	0
	$\frac{1}{2}s_1$	$\frac{1}{4}s_1$	$\frac{1}{8}s_1$	$\frac{1}{16}s_1$	$\frac{1}{16}s_1$	0	0	...	0
	$\frac{1}{2}s_1$	$\frac{1}{4}s_1$	$\frac{1}{8}s_1$	$\frac{1}{16}s_1$	$\frac{1}{32}s_1$	$\frac{1}{32}s_1$	0	...	0
continuous	...								

Each subsignal has a uniform distribution around its respective expectation with a variance ϵ that is less than k, $U\left(E\left[s_1^i\right] - \epsilon, E\left[s_1^i\right] + \epsilon\right)$. In addition, a final "absorbing" signal that equals the difference between s_1 and the sum of these subsignals s_1^i is assumed to always be processed by both types of investors at time 1.

Moving from the top to bottom row, information changes from discrete to continuous. Provided $\left|E\left[s_1^i\right] \pm \epsilon\right| > k$, the i^{th} subsignal is processed. However, as information becomes more continuous, realizations of the subsignals eventually fall within the $(-k, k)$ band and are unprocessed until time 2, resulting in $f < 1$ and price momentum. This "truncation" is more likely to occur when k is large. Intuitively, more information is unprocessed at time 1 when attention constraints are more severe.

Our ID measure in equation (1) is consistent with this illustrative framework. For a positive s_1, which proxies for PRET, interpret each subsignal s_1^i as a daily return. As information becomes continuous, more subsignals have positive expectations, and therefore are more likely to be positive although these subsignals are less likely to be processed. Consequently, the ID measure in equation (1) becomes more negative. Thus, ID is motivated by the above framework with random subsignals.

[20]Intuitively, as m increases for a fixed f, the covariance can eventually become smaller due to lower return volatility during the first period.

Table 1: Summary Statistics

Panel A of this table reports summary statistics for information discreteness (ID) defined as sgn(PRET) $\cdot$ [$\%neg - \%pos$] in equation (1) where $\%pos$ and $\%neg$ denote the respective percentage of positive and negative daily returns during the formation period. Summary statistics are also reported for formation-period returns (PRET) and their absolute value, idiosyncratic volatility (IVOL), skewness, kurtosis, two jump variables, the price delay measure (DELAY) of Hou and Moskowitz (2005), the return consistency dummy variable (RC) defined in Grinblatt and Moskowitz (2004), and unrealized capital gains (UCG) defined in Grinblatt and Han (2005). Summary statistics include the mean and standard deviation (Std. Dev.) along with the 25th, 50th, and 75th percentiles. ID captures the distribution of daily returns across the formation period. Continuous information arrives frequently in small amounts while discrete information arrives infrequently in large amounts. PRET corresponds to a firm's formation-period return in the prior twelve months after skipping the most recent month, while IVOL is estimated according to Fu (2009) within the same formation period. Skewness and kurtosis apply to daily firm-level returns during the formation period. The jump5 variable is defined in equation (2) using the sum of the five largest daily positive and negative returns underlying PRET. Similarly, jump10 is defined in equation (3) using the ten largest daily positive and negative returns underlying PRET. DELAY is defined in equation (4) while RC equals one if a stock's monthly returns are positive (negative) for at least eight months of the twelve-month formation period and PRET is also positive (negative). Panel B contains the correlations between the variables in Panel A.

Panel A: Summary statistics

		Percentiles			
	Mean	25th	50th	75th	Std. Dev.
ID	-0.034	-0.065	-0.031	0.000	0.053
PRET	0.177	-0.189	0.078	0.367	0.904
|PRET|	0.430	0.125	0.279	0.528	0.815
IVOL	0.517	0.053	0.139	0.385	4.321
skewness	0.212	-0.166	0.186	0.611	1.392
kurtosis	7.337	1.468	3.109	7.184	14.021
jump5	0.058	-0.022	0.036	0.120	0.189
jump10	0.087	-0.019	0.059	0.172	0.238
DELAY	0.562	0.293	0.568	0.849	0.303
RC	0.180	0.000	0.000	0.000	0.384
UCG	-0.160	-0.173	0.068	0.206	0.885

Panel B: Correlations

	ID	PRET	|PRET|	IVOL	skewness	kurtosis	jump5	jump10	DELAY	RC	UCG
ID	1										
PRET	0.163	1									
|PRET|	-0.304	0.366	1								
IVOL	0.081	-0.181	0.339	1							
skewness	0.133	0.304	0.156	0.098	1						
kurtosis	-0.008	-0.086	0.099	0.148	0.095	1					
jump5	0.242	0.245	0.266	0.127	0.147	0.208	1				
jump10	0.264	0.300	0.319	0.141	0.162	0.203	0.953	1			
DELAY	0.047	-0.063	0.041	0.253	0.093	0.107	0.064	0.069	1		
RC	-0.299	0.115	0.337	-0.056	0.005	-0.030	0.002	0.023	0.005	1	
UCG	0.056	0.685	0.100	-0.442	0.149	-0.129	0.133	0.163	-0.109	0.105	1

Table 2: Information Discreteness and Information Intermediaries

This table addresses the economic determinants of information discreteness (ID), which is defined in equation (1) as sgn(PRET) $\cdot$ [$\%neg - \%pos$] where $\%pos$ and $\%neg$ denote the respective percentage of positive and negative daily returns during the formation period. PRET corresponds to a firm's formation-period return in the prior twelve months after skipping the most recent month. ID captures the distribution of daily returns across this formation period. Continuous information, which corresponds to low ID, arrives frequently in small amounts while discrete information, which corresponds to high ID, arrives infrequently in large amounts. The results below are from the Fama-MacBeth regression in equation (5), $\mathrm{ID}_{i,t} = \beta_0 + \beta_1\,\mathrm{PR}_{i,t} + \beta_2\,\mathrm{MEDIA}_{i,t} + \beta_3\,\mathrm{COVER}_{i,t} + \beta_4\,\mathrm{SIZE}_{i,t} + \beta_5\,\mathrm{IO}_{i,t} + \beta_6\,|\mathrm{PRET}|_{i,t} + \epsilon_{i,t}$ whose independent variables are press releases by management that are not covered by the media within seven days (PR), news articles in the media (MEDIA) that are not attributable to press releases within the prior seven days, analyst coverage (COVER), the log of market capitalization (SIZE), institutional ownership (IO), and the absolute value of formation-period returns (|PRET|). PR and MEDIA refer to the number of press releases without media coverage and the number of news articles that are not attributable to press releases in the prior year, respectively. This regression is conducted separately for stocks whose formation-period returns are above and below the cross-sectional median since ID is an interaction variable whose interpretation is conditional on PRET. The correlations between the independent variables are recorded in Panel A. Panel B reports the coefficients of the cross-sectional regression for winner stocks whose formation-period returns are above the median, which have been multiplied by 100 for ease of interpretation. Panel C reports these coefficients for loser stocks whose formation-period returns are below the median. The t-statistics are Newey-West adjusted with six lags and reported in italics.

Panel A: Correlations between independent variables

	ID	PR	MEDIA	COVER	SIZE	IO	|PRET|
ID	1						
PR	0.014	1					
MEDIA	-0.020	-0.134	1				
COVER	0.011	0.139	0.297	1			
SIZE	0.012	0.185	0.332	0.648	1		
IO	0.043	0.162	0.180	0.425	0.535	1	
|PRET|	-0.149	0.005	0.001	-0.073	0.011	-0.066	1

Panel B: Information discreteness and firm characteristics for firms with above-median PRET

	intercept	PR	MEDIA	COVER	SIZE	IO	|PRET|	adj. R^2
coefficient	0.0892	-0.0015	0.0048	-0.0030	-0.0078	-0.0049	-0.0273	0.383
t-stat	*16.45*	*-4.40*	*9.63*	*-2.62*	*-18.67*	*-4.38*	*-19.17*	

Panel C: Information discreteness and firm characteristics for firms with below-median PRET

	intercept	PR	MEDIA	COVER	SIZE	IO	|PRET|	adj. R^2
coefficient	-0.0624	0.0003	0.0008	-0.0029	0.0042	0.0006	-0.1399	0.454
t-stat	*-12.35*	*0.96*	*1.68*	*-3.00*	*12.30*	*0.54*	*-104.34*	

Table 3: Information Discreteness and Momentum

This table reports post-formation returns from sequentially double-sorted portfolios involving formation-period returns (PRET) and information discreteness (ID). ID is defined in equation (1) as sgn(PRET) $\cdot$ $[\%neg - \%pos]$ where $\%pos$ and $\%neg$ denote the respective percentage of positive and negative daily returns during the formation period. PRET corresponds to a firm's formation-period return in the prior twelve months after skipping the most recent month. ID captures the distribution of daily returns across this formation period. Continuous information arrives frequently in small amounts while discrete information arrives infrequently in large amounts. Both unadjusted returns and risk-adjusted returns relative to the three-factor model of Fama and French (1993) are presented over six-month and three-year post-formation horizons. The results in Panel A are from sequential double-sorts involving PRET quintiles, then ID quintiles. Post-formation momentum returns, defined as the return from buying winners and selling losers, are reported for each ID quintile. Panel B records the average ID, PRET, log of market capitalization (SIZE), book-to-market ratio (BM), log of analyst forecast dispersion (DISP), and idiosyncratic volatility (IVOL) for past winners and past losers across the ID quintiles. Panel C reports on the returns from independent double-sorts (rather than the sequential double-sorts in Panel A) that condition on PRET, then ID. The results in Panel A through Panel C pertain to our 1976 to 2007 sample period. Panel D replicates the sequential double-sorts in Panel A during an extended sample period that begins in 1927. All t-statistics are Newey-West adjusted with six lags and reported in italics.

Panel A: Sequential double-sorts involving formation-period returns and information discreteness

ID	Winner 1	2	3	4	Loser 5	Average ID	unadjusted six-month return	unadjusted six-month *t*-stat	three-factor six-month alpha	three-factor six-month *t*-stat	unadjusted three-year return	unadjusted three-year *t*-stat	three-factor three-year alpha	three-factor three-year *t*-stat
discrete	8.38	7.83	7.42	6.83	5.47	0.03	2.91	*2.10*	4.84	*5.19*	-4.63	*-0.90*	-4.37	*-0.88*
2	10.06	9.46	8.26	7.40	5.39	-0.01	4.67	*3.89*	6.46	*7.21*	1.64	*0.36*	1.95	*0.44*
3	11.52	9.80	8.63	7.44	4.80	-0.03	6.72	*5.75*	8.88	*9.30*	5.89	*1.26*	6.25	*1.37*
4	11.31	9.49	8.46	7.24	3.89	-0.06	7.42	*6.27*	9.70	*9.60*	3.52	*0.71*	5.28	*1.20*
continuous	11.08	9.12	8.38	7.15	2.22	-0.10	8.86	*6.82*	11.72	*9.70*	8.07	*1.47*	11.77	*2.49*
continuous - discrete						-0.13	5.95	*5.13*	6.89	*7.01*	12.69	*2.45*	16.20	*3.55*

Panel B: Firm characteristics of sequentially double-sorted portfolios

	ID		PRET		SIZE		BM		DISP		IVOL	
ID	Winner	Loser	Winner	Loser	Winner	Loser	Winner	Loser	Winner	Loser	Winner	Loser
discrete	0.03	0.01	97.82	-20.76	11.34	10.71	0.52	0.71	0.04	0.08	0.54	0.29
2	-0.02	-0.03	101.51	-23.53	11.26	10.61	0.56	0.72	0.06	0.08	0.38	0.33
3	-0.04	-0.05	108.08	-25.92	11.37	10.79	0.55	0.73	0.05	0.10	0.32	0.33
4	-0.07	-0.08	113.3	-28.98	11.64	10.97	0.52	0.72	0.06	0.08	0.26	0.30
continuous	-0.11	-0.12	129.85	-35.15	12.16	11.13	0.49	0.70	0.05	0.07	0.18	0.30

Panel C: Independent double-sorts involving formation-period returns and information discreteness

ID	Winner 1	2	3	4	Loser 5	Average ID	unadjusted six-month return	unadjusted six-month *t*-stat	three-factor six-month alpha	three-factor six-month *t*-stat	unadjusted three-year return	unadjusted three-year *t*-stat	three-factor three-year alpha	three-factor three-year *t*-stat
discrete	7.95	7.79	7.58	7.16	6.32	0.04	1.63	*1.03*	3.48	*3.93*	-0.40	*-0.07*	-1.59	*-0.29*
2	9.72	9.19	8.48	7.32	5.56	-0.01	4.16	*3.37*	6.11	*5.48*	-1.93	*-0.41*	-0.98	*-0.22*
3	10.58	9.45	8.38	7.55	4.95	-0.03	5.63	*4.87*	7.54	*8.82*	-0.23	*-0.05*	1.72	*0.38*
4	11.16	9.77	8.47	6.97	4.59	-0.06	6.57	*5.72*	8.96	*10.08*	4.45	*0.94*	5.63	*1.23*
continuous	11.13	9.01	8.13	6.86	2.80	-0.10	8.33	*6.66*	10.94	*9.73*	6.77	*1.25*	8.98	*1.88*
continuous - discrete						-0.14	6.70	*4.65*	7.46	*5.42*	7.16	*1.31*	10.57	*2.08*

Panel D: Sequential double-sorts involving formation-period returns and information discreteness since 1927

ID	Winner 1	2	3	4	Loser 5	Average ID	unadjusted six-month return	unadjusted six-month *t*-stat	three-factor six-month alpha	three-factor six-month *t*-stat	unadjusted three-year return	unadjusted three-year *t*-stat	three-factor three-year alpha	three-factor three-year *t*-stat
discrete	7.53	7.77	7.35	7.40	9.60	0.03	-2.07	*-2.01*	*-2.01*	*0.03*	-21.54	*-5.68*	-18.70	*-5.93*
2	9.48	8.67	8.25	7.84	8.84	-0.01	0.64	*0.58*	3.53	*4.13*	-14.27	-3.87	-10.30	*-3.30*
3	10.01	8.60	8.35	7.60	6.89	-0.03	3.12	*3.11*	5.05	*6.52*	-7.97	*-2.32*	-5.62	*-1.75*
4	9.98	8.38	7.84	6.86	5.62	-0.06	4.36	*4.14*	6.71	*7.89*	-6.13	*-1.74*	-3.84	*-1.18*
continuous	9.56	7.70	6.90	5.64	3.62	-0.10	5.94	*4.63*	8.77	*8.76*	-1.08	*-0.30*	2.16	*0.64*
continuous - discrete						-0.13	8.01	*8.54*	10.78	*10.55*	20.46	*5.83*	20.86	*6.41*

Table 4: Information Discreteness and Limited Attention

This table reports the results from several modifications of the original information discreteness (ID) measure in equation (1), which is defined as sgn(PRET) $\cdot$ [$\%neg - \%pos$] where $\%pos$ and $\%neg$ denote the respective percentage of positive and negative daily returns during the formation period. PRET corresponds to a firm's formation-period return in the prior twelve months after skipping the most recent month. ID captures the distribution of daily returns across this formation period. Continuous information arrives frequently in small amounts while discrete information arrives infrequently in large amounts. The results in Panel A correspond to a declining time-weighted information discreteness measure denoted DWID that assigns declining weights to the daily returns underlying the ID measure. Specifically, daily returns in the most recent month of the formation period receive a weight of 12, daily returns in the second most recent month receive a weight of 11, and so forth until the daily returns in the first month of the formation period receive a weight of 1. Panel B replicates the sequential double-sorts based on PRET, then ID, in Panel A of Table 3 among stocks with low and high concentrated institutional ownership. The concentration of institutional ownership equals the proportion of institutional ownership accounted for by the five largest institutional investors in a firm.

Panel A: Sequential double-sorts involving formation-period returns and declining time-weighted information discreteness

DWID	Winner 1	2	3	4	Loser 5	Average DWID	unadjusted six-month return	*t*-stat	three-factor six-month alpha	*t*-stat	unadjusted three-year return	*t*-stat	three-factor three-year alpha	*t*-stat
discrete	7.34	7.25	7.02	6.87	6.11	0.04	1.23	*0.88*	3.25	*3.65*	1.38	*0.93*	3.23	*3.48*
2	10.24	9.37	8.32	7.49	5.86	-0.01	4.38	*3.63*	6.58	*7.57*	3.95	*3.12*	5.93	*6.62*
3	10.93	9.70	8.70	7.53	4.79	-0.03	6.14	*5.18*	8.12	*8.07*	6.21	*4.81*	8.26	*8.02*
4	11.78	9.72	8.51	7.63	3.52	-0.06	8.26	*6.77*	10.52	*9.84*	7.33	*5.76*	9.49	*8.70*
continuous	12.10	9.69	8.60	6.55	1.51	-0.11	10.59	*8.68*	13.16	*11.25*	10.02	*7.67*	12.64	*10.94*
continuous - discrete						-0.15	9.36	*7.69*	9.91	7.60	8.65	*7.15*	9.41	*9.43*

Panel B: Sequential double-sorts involving formation-period returns and information discreteness across high and low institutional ownership concentrations

Concentration of institutional ownership	ID	Winner 1	2	3	4	Loser 5	Average ID	unadjusted six-month return	*t*-stat	three-factor six-month alpha	*t*-stat	unadjusted three-year return	*t*-stat	three-factor three-year alpha	*t*-stat
high	discrete	7.88	7.01	6.28	5.94	4.55	0.14	3.33	*2.27*	6.42	*4.08*	0.97	*0.22*	-0.76	-0.22
	2	9.04	7.67	6.99	6.47	4.96	0.00	4.08	*4.18*	6.80	*6.51*	6.13	1.15	4.48	*0.96*
	3	9.68	7.74	7.38	6.50	4.33	-0.01	5.35	*4.46*	8.25	*7.42*	15.24	*2.64*	16.39	*3.67*
	4	9.90	7.67	7.43	6.33	3.61	-0.04	6.29	4.53	8.99	*7.11*	9.39	1.04	11.14	1.85
	continuous	10.52	7.69	7.29	6.19	1.75	-0.24	8.77	*5.59*	12.14	*7.59*	20.02	*2.50*	22.05	*2.95*
	continuous - discrete						-0.38	5.44	*4.88*	5.72	*5.61*	19.05	*2.52*	22.81	*2.94*
low	discrete	3.49	5.93	5.92	5.39	4.29	0.03	-0.80	*-0.42*	0.07	*0.05*	-19.79	*-2.96*	-19.91	-2.58
	2	8.45	8.10	8.02	6.54	2.92	-0.01	5.53	*2.64*	9.31	*4.99*	-4.75	-0.44	-8.06	*-0.72*
	3	9.78	9.51	8.41	7.23	1.90	-0.03	7.88	5.09	9.85	*7.30*	-1.29	*-0.10*	-3.62	*-0.35*
	4	10.08	9.10	9.23	7.93	1.25	-0.05	8.83	5.08	11.30	*6.59*	4.39	0.39	-5.99	-0.51
	continuous	9.43	10.35	10.32	7.04	-1.00	-0.09	10.43	*5.75*	11.74	*6.62*	18.30	*1.41*	8.44	*0.72*
	continuous - discrete						-0.13	11.23	*4.57*	11.66	*5.59*	38.09	*2.62*	28.35	*2.02*

Table 5: Return Consistency and Alternative Explanations

This table first reports on the return continuation from conditioning on formation-period returns (PRET), information discreteness (ID), and return consistency (RC). ID is defined in equation (1) as sgn(PRET) $\cdot$ [$\%neg - \%pos$] where $\%pos$ and $\%neg$ denote the respective percentage of positive and negative daily returns during the formation period. PRET corresponds to a firm's formation-period return in the prior twelve months after skipping the most recent month. ID captures the distribution of daily returns across this formation period. Continuous information arrives frequently in small amounts while discrete information arrives infrequently in large amounts. As defined in Grinblatt and Moskowitz (2004), the RC dummy variable equals one if a stock's monthly returns are positive (negative) for at least eight months of the twelve-month formation period and PRET is also positive (negative). Sequential double-sorts involving PRET quintiles, then ID quintiles are computed. In Panel A, the initial sorting procedure conditions ex-ante on stocks with consistent returns (RC equals one). The post-formation momentum returns are defined as the return from buying winners and selling losers. Both unadjusted momentum returns and risk-adjusted returns relative to the three-factor model of Fama and French (1993) are presented over six-month and three-year post-formation horizons for each ID quintile. Panel B contains the results from the Fama-MacBeth regression in equation (6), $r_{i,t+h} = \beta_0 + \beta_1\,\mathrm{PRET}_{i,t} + \beta_2\,\mathrm{NegPRET}_{i,t} + \beta_3\,\mathrm{PosRC}_{i,t} + \beta_4\,\mathrm{NegRC}_{i,t} + \beta_5\,\mathrm{PosID}_{i,t} + \beta_6\,\mathrm{NegID}_{i,t} + \beta_7\,\mathrm{SIZE}_{i,t} + \beta_8\,\mathrm{BM}_{i,t} + \beta_9\,\mathrm{TURN}_{i,t} + \beta_{10}\,\mathrm{SUE} + \beta_{11}\,\mathrm{AMIHUD}_{i,t} + \beta_{12}\,\mathrm{DELAY}_{i,t} + \alpha\,X_{i,t} + \epsilon_{i,t+h}$. NegPRET is defined as $\min\{0, \mathrm{PRET}\}$. PosRC and NegRC refer to positive and negative RC dummy variables, respectively. As in Grinblatt and Moskowitz (2004), PosRC (NegRC) requires eight of the twelve monthly returns during the formation period to have the same positive (negative) sign as PRET. PosID equals $\%pos - \%neg$ if PRET is positive and zero otherwise while NegID equals $\%neg - \%pos$ if PRET is negative and zero otherwise. The regression specification also includes control variables for the log of market capitalization (SIZE), book-to-market ratios (BM), turnover (TURN), standardized earnings surprises (SUE), Amihud's liquidity measure (AMIHUD), and the price delay measure (DELAY) in equation (4). A firm's SUE is computed by comparing its realized earnings in the most recent quarter with its realized earnings in the same quarter of the prior year. This difference is then normalized by the standard deviation of its earnings over the prior eight quarters. The firm characteristics in X include price-earnings ratios, total assets, capital expenditures to total assets, previous sales growth, unrealized capital gains, analyst coverage as well as the skewness and kurtosis of firm-level daily returns. All t-statistics are Newey-West adjusted with six lags and reported in italics. Panels C and D are based on idiosyncratic volatility (IVOL), which is estimated during the formation period using the procedure in Fu (2009). In Panel C, a sequential double-sort that first conditions on PRET, then IVOL examines the marginal influence of IVOL on momentum after controlling for formation-period returns. Unadjusted returns and risk-adjusted returns relative to the three-factor model of Fama and French (1993) over a six-month holding period are then presented. In Panel D, the double-sorts first condition on residual IVOL (Res IVOL), then PRET. Res IVOL is defined using the residuals of the following cross-sectional regression $\mathrm{IVOL}_{i,t} = \gamma_{0,t} + \gamma_{1,t}\,|\mathrm{PRET}|_{i,t} + \epsilon_{i,t}^{IVOL}$ in equation (7) to control for the influence of formation-period returns on IVOL. In Panel E, weights of 10 are assigned to daily returns of the same sign as the firm's cumulative return during the previous ten days as a proxy for confirming information. The resulting CID measure therefore accentuates the importance of confirming information at the expense of disconfirming information.

Panel A: Double-sorts that condition on consistent past returns and information discreteness

ID	Winner 1	2	3	4	Loser 5	Average ID	unadjusted six-month return	unadjusted six-month t-stat	three-factor six-month alpha	three-factor six-month t-stat	unadjusted three-year return	unadjusted three-year t-stat	three-factor three-year alpha	three-factor three-year t-stat
discrete	9.24	8.39	6.02	6.36	4.05	0.02	5.19	*3.25*	6.15	*4.68*	-3.64	-0.42	-2.24	*-0.36*
2	10.24	9.27	8.42	7.22	4.12	-0.02	6.12	*4.49*	8.45	*7.70*	-0.81	*-0.17*	1.12	*0.16*
3	11.71	9.68	8.51	6.31	3.42	-0.04	8.29	*6.12*	10.93	*9.16*	4.28	*1.21*	9.62	*1.51*
4	11.76	9.44	8.18	6.59	2.54	-0.06	9.22	*7.26*	12.00	*10.80*	3.66	*0.69*	6.64	*1.10*
continuous	11.34	8.86	8.08	6.22	1.20	-0.11	10.14	*7.01*	13.42	*9.35*	2.24	*1.13*	11.28	*1.87*
continuous - discrete						-0.14	4.95	*3.55*	7.27	*4.86*	5.88	*1.51*	13.52	*2.16*

Panel B: Cross-sectional regressions of price momentum on signed return consistency and signed information discreteness

	intercept	PRET	NegPRET	PosRC	NegRC	PosID	NegID	SIZE	BM	TURN	SUE	AMIHUD	DELAY	X	adj. R^2
coefficient	0.0541	0.0130	0.0047	0.0089	0.0034	0.1212	-0.1359	0.0013	0.0163	-0.0027	0.0022	-0.0002	0.0060	Yes	0.145
t-stat	*2.46*	*3.82*	*0.43*	*4.01*	*1.19*	*6.71*	*-6.75*	*0.73*	*6.33*	*-0.34*	*1.24*	*-0.04*	*1.53*		

Panel C: Double-sorts involving formation-period returns, then idiosyncratic volatility

IVOL	Winner 1	2	3	4	Loser 5	Average IVOL	unadjusted six-month return	unadjusted six-month t-stat	three-factor six-month alpha	three-factor six-month t-stat
high	7.11	8.29	8.07	6.54	0.09	0.75	7.02	*4.14*	8.87	*6.80*
2	10.90	9.66	8.92	7.38	3.48	0.29	7.42	*5.30*	9.93	*8.62*
3	11.35	9.80	8.38	7.66	4.93	0.14	6.42	*4.73*	8.92	*8.32*
4	10.95	9.24	8.07	7.45	5.94	0.08	5.01	*4.13*	7.08	*6.90*
low	10.33	8.72	7.78	7.07	5.99	0.03	4.34	*4.26*	6.13	*7.28*
high-low						0.72	2.68	*2.07*	2.75	*2.44*

Panel D: Double-sorts involving residual idiosyncratic volatility, then formation-period returns

Res IVOL	Winner 1	2	3	4	Loser 5	Average Res IVOL	unadjusted six-month return	unadjusted six-month t-stat	three-factor six-month alpha	three-factor six-month t-stat
high	7.31	8.30	8.01	6.50	0.44	0.31	6.87	*4.17*	9.60	*6.42*
2	9.62	9.42	8.74	7.47	3.86	-0.19	5.76	*5.77*	7.97	*7.33*
3	10.83	9.60	8.39	7.56	5.08	-0.33	5.75	*4.64*	8.25	*8.09*
4	10.68	9.19	7.98	7.46	5.58	-0.40	5.10	*4.61*	7.05	*7.51*
low	12.37	9.22	8.06	7.11	5.75	-0.49	6.62	*4.78*	8.36	*8.37*
high-low						0.80	0.25	*0.37*	1.24	*1.04*

Panel E: Double-sorts involving formation-period returns and conservatism-weighted information discreteness

CID	Winner 1	2	3	4	Loser 5	Average CID	unadjusted six-month return	unadjusted six-month t-stat	three-factor six-month alpha	three-factor six-month t-stat	unadjusted three-year return	unadjusted three-year t-stat	three-factor three-year alpha	three-factor three-year t-stat
discrete	8.65	8.09	7.55	6.92	5.58	0.02	3.07	*2.43*	4.85	*5.28*	-1.17	*-0.26*	-1.04	-0.24
2	10.61	9.72	8.57	7.38	5.36	-0.04	5.25	4.54	7.05	*8.38*	3.01	0.66	3.96	0.95
3	10.94	9.65	8.48	7.50	5.03	-0.07	5.91	5.39	7.75	*8.61*	3.03	0.65	3.02	0.70
4	11.01	9.48	8.38	7.50	3.90	-0.12	7.11	5.98	9.33	*9.41*	1.63	0.33	4.00	0.83
continuous	11.09	8.78	8.16	6.77	1.90	-0.19	9.19	*6.22*	12.59	*9.27*	7.72	*1.29*	10.75	*1.96*
continuous - discrete						-0.21	6.12	*6.70*	7.74	*9.94*	8.89	*6.70*	11.79	*9.94*

Table 6: Residual Information Discreteness and Cross-sectional Regressions

This table reports on the return implications of residual information discreteness (Res ID). Information discreteness (ID) is defined in equation (1) as sgn(PRET) $\cdot$ [$\%neg - \%pos$] where $\%pos$ and $\%neg$ denote the respective percentage of positive and negative daily returns during the formation period. PRET corresponds to a firm's formation-period return in the prior twelve months after skipping the most recent month. Res ID is estimated from equation (8) as the $\epsilon^{ID}_{i,t}$ residual from the following cross-sectional regression, $\text{ID}_{i,t} = \delta_{0,t} + \delta_{1,t}\,|\text{PRET}|_{i,t} + \delta_{2,t}\,\text{TURN}_{i,t} + \delta_{3,t}\,\text{SIZE}_{i,t} + \delta_{4,t}\,\text{BM}_{i,t} + \delta_{5,t}\,\text{COVER}_{i,t} + \delta_{6,t}\,\text{IVOL}_{i,t} + \delta_{7,t}\,\text{IO}_{i,t} + \delta_{8,t}\,\text{RC}_{i,t} + \epsilon^{ID}_{i,t}$, using firm characteristics that include turnover (TURN), the log of market capitalization (SIZE), book-to-market ratios (BM), analyst coverage (COVER), idiosyncratic volatility (IVOL), institutional ownership (IO), and a dummy variable for return consistency (RC). As defined in Grinblatt and Moskowitz (2004), RC equals one if a stock's monthly returns are positive (negative) for at least eight months of the twelve-month formation period and PRET is also positive (negative). Panel A contains the coefficients from the above cross-sectional regression. The returns reported in Panel B are from sequential double-sorts involving PRET quintiles, then Res ID quintiles. Post-formation momentum returns are defined as the return from buying winners and selling losers. Both unadjusted momentum returns and risk-adjusted returns relative to the three-factor model of Fama and French (1993) are presented over six-month and three-year post-formation horizons. Panel C and Panel D contain the results from Fama-MacBeth regressions in equation (9) and equation (10), respectively, that examine the ability of Res ID to explain cross-sectional variation in price momentum based on PRET and earnings momentum based on SUE. A firm's SUE is computed by comparing its realized earnings in the most recent quarter with its realized earnings in the same quarter of the prior year. This difference is then normalized by the standard deviation of its earnings over the prior eight quarters. The dependent variables in these regressions are the six-month post-formation returns of individual stocks while the additional independent variables are Amihud's liquidity measure (AMIHUD), the price delay measure (DELAY) in equation (4), and the unrealized capital gains (UCG) computed in Grinblatt and Han (2005). The X vector contains price-earnings ratios, total assets, capital expenditures to total assets, previous sales growth, analyst coverage as well as the skewness and kurtosis of firm-level daily returns. All t-statistics are Newey-West adjusted with six lags and reported in italics.

Panel A: Fama-MacBeth coefficients for residual information discreteness

	intercept	|PRET|	TURN	SIZE	BM	COVER	IVOL	IO	RC	adj. R^2
coefficient	-0.0248	-0.0234	-0.0043	0.0001	0.0001	-0.0010	0.0184	0.0019	-0.0336	0.141
t-stat	*-27.81*	*-16.47*	*-4.47*	*1.06*	*0.59*	*-1.67*	*14.01*	*3.08*	*-78.50*	

Panel B: Sequential double-sorts involving formation-period returns and residual information discreteness

Res ID	Winner 1	2	3	4	Loser 5	Average Res ID	unadjusted six-month return	unadjusted six-month t-stat	three-factor six-month alpha	three-factor six-month t-stat	unadjusted three-year return	unadjusted three-year t-stat	three-factor three-year alpha	three-factor three-year t-stat
discrete	8.50	7.89	7.46	6.82	5.31	0.06	3.19	*2.13*	5.07	*4.98*	-6.65	*-1.28*	-6.52	*-1.26*
2	10.45	9.43	8.24	7.41	5.31	0.02	5.14	*4.21*	6.58	*7.10*	2.37	*0.47*	2.47	*0.49*
3	11.12	9.77	8.62	7.46	4.79	0.00	6.33	*5.31*	8.36	*8.54*	4.62	*1.01*	5.61	*1.31*
4	11.31	9.49	8.45	7.26	3.98	-0.02	7.33	*6.01*	9.82	*8.87*	5.39	*1.10*	7.17	*1.64*
continuous	10.98	9.12	8.38	7.11	2.41	-0.07	8.57	*6.62*	11.53	*9.40*	8.80	*1.62*	12.18	*2.63*
continuous - discrete						-0.13	5.38	*3.83*	6.46	*5.70*	15.45	*2.85*	18.70	*3.87*

Panel C: Cross-sectional regressions of price momentum on residual information discreteness

	intercept	PRET	Res ID	Res ID · PRET	SUE	SIZE	BM	TURN	IVOL	AMIHUD	DELAY	UCG	UCG ·PRET	X	adj. R^2
coefficient	0.0800	0.0249	0.0884	-0.2893	0.0087	0.0008	0.0074	-0.0188	0.0241	0.0036	0.0018	0.0024	0.0279	Yes	0.159
t-stat	*3.70*	*7.05*	*6.57*	*-9.67*	*3.56*	*0.46*	*3.50*	*-2.72*	*1.92*	*4.19*	*0.43*	*0.69*	*6.29*		

Panel D: Cross-sectional regressions of earnings momentum on residual information discreteness

	intercept	SUE	Res ID	Res ID ·SUE	PRET	SIZE	BM	TURN	IVOL	AMIHUD	DELAY	UCG	UCG ·PRET	X	adj. R^2
coefficient	0.0810	0.0095	0.0706	-0.0246	0.0162	0.0010	0.0073	-0.0217	0.0189	0.0037	0.0016	0.0034	0.0282	Yes	0.156
t-stat	*3.74*	*3.87*	*5.30*	*-3.51*	*5.59*	*0.53*	*3.47*	*-3.10*	*1.49*	*4.37*	*0.38*	*0.98*	*6.26*		

Table 7: Analyst Forecasts and Information Discreteness

This table reports on the relationship between earnings surprises, defined relative to the consensus forecast of analysts, and information discreteness (ID). ID is defined in equation (1) as $\text{sgn}(\text{PRET}) \cdot [\%neg - \%pos]$ where $\%pos$ and $\%neg$ denote the respective percentage of positive and negative daily returns during the formation period. PRET corresponds to a firm's formation-period return in the prior twelve months after skipping the most recent month. ID captures the distribution of daily returns across this formation period. Continuous information arrives frequently in small amounts while discrete information arrives infrequently in large amounts. Low values of ID are generated by continuous information while high values of ID are generated by discrete information. The relationship between analyst forecast errors (SURP) and ID is examined by the following regression, $\text{SURP}_{i,t} = \beta_0 + \beta_1\,\text{ID}_{i,t} + \beta_2\,\text{PRET}_{i,t} + \beta_3\,(\text{ID} \cdot \text{PRET})_{i,t} + \beta_4\,\text{DISP}_{i,t} + \beta_5\,\text{COVER}_{i,t} + \beta_6\,\text{BM}_{i,t} + \beta_7\,\text{SIZE}_{i,t} + \beta_8\,\text{TURN}_{i,t} + \beta_9\,\text{IO}_{i,t} + \epsilon_{i,t}$. Besides ID, PRET, and their interaction, the independent variables are analyst forecast dispersion (DISP), analyst coverage (COVER), book-to-market ratios (BM), the log of market capitalization (SIZE), turnover (TURN), and institutional ownership (IO). Panel A reports on their respective β coefficients. Panel B contains the results from sequential double-sorts that condition on PRET, then information discreteness defined by analyst forecasts. This alternative measure of information discreteness is denoted ID_f and defined in equation (12) as $\text{sgn}(\text{CUMREV}) \cdot [\%downward - \%upward]$ based on signed analyst forecast revisions. The cumulative revision during the formation period is denoted CUMREV, and its sign is +1 when CUMREV > 0 and -1 when CUMREV < 0. For every firm-fiscal year, we define CUMREV as the difference between the last consensus forecast before an annual earnings announcement and the first forecast. The results in Panel C and Panel D also involve ID_f. Panel C reports on the relationship between price momentum and ID_f using the Fama-MacBeth regression in equation (13), $r_{i,t+h} = \beta_0 + \beta_1\,\text{PRET}_{i,t} + \beta_2\,\text{ID}_{f\,i,t} + \beta_3\,(\text{ID}_f \cdot \text{PRET})_{i,t} + \beta_4\,\text{SUE}_{i,t} + \beta_5\,\text{SIZE}_{i,t} + \beta_6\,\text{BM}_{i,t} + \beta_7\,\text{TURN}_{i,t} + \beta_8\,\text{IVOL}_{i,t} + \beta_9\,\text{AMIHUD}_{i,t} + \beta_{10}\,\text{DELAY}_{i,t} + \beta_{11}\,\text{UCG}_{i,t} + \beta_{12}\,(\text{UCG} \cdot \text{PRET})_{i,t} + \alpha\,X_{i,t} + \epsilon_{i,t+h}$. Earnings momentum is examined by replacing PRET with SUE, where a firm's SUE is computed by comparing its realized earnings in the most recent quarter with its realized earnings in the same quarter of the prior year. This difference is then normalized by the standard deviation of its earnings over the prior eight quarters. Panel D reports on the relationship between earnings momentum and ID_f using the Fama-MacBeth regression in equation (14), $r_{i,t+h} = \beta_0 + \beta_1\,\text{SUE}_{i,t} + \beta_2\,\text{ID}_{f\,i,t} + \beta_3\,(\text{ID}_f \cdot \text{SUE})_{i,t} + \beta_4\,\text{PRET}_{i,t} + \beta_5\,\text{SIZE}_{i,t} + \beta_6\,\text{BM}_{i,t} + \beta_7\,\text{TURN}_{i,t} + \beta_8\,\text{IVOL}_{i,t} + \beta_9\,\text{AMIHUD}_{i,t} + \beta_{10}\,\text{DELAY}_{i,t} + \beta_{11}\,\text{UCG}_{i,t} + \beta_{12}\,(\text{UCG} \cdot \text{PRET})_{i,t} + \alpha\,X_{i,t} + \epsilon_{i,t+h}$. The dependent variable $r_{i,t+h}$ is the six-month return of stock i following month t. The additional independent variables in this regression include idiosyncratic volatility (IVOL), Amihud's illiquidity measure (AMIHUD), the price delay measure (DELAY) in equation (4), and unrealized capital gains (UCG) computed according to Grinblatt and Han (2005). The X vector contains price-earnings ratios, total assets, capital expenditures to total assets, previous sales growth, analyst coverage as well as the skewness and kurtosis of firm-level daily returns. The t-statistics are Newey-West adjusted with six lags and reported in italics.

Panel A: Cross-sectional regressions of analyst forecast errors on information discreteness defined by returns

	intercept	ID	PRET	ID·PRET	DISP	COVER	BM	SIZE	TURN	IO	adj. R^2
coefficient	-0.0026	0.0008	0.0020	-0.0028	-0.0011	0.0000	-0.0011	0.0003	-0.0013	0.0001	0.087
t-stat	*-3.95*	*1.22*	*7.44*	*-2.19*	*-2.64*	*-0.13*	*-3.42*	*5.32*	*-5.54*	*0.58*	

Panel B: Sequential double-sort involving past returns and information discreteness defined by analyst forecasts

ID_f	Winner 1	2	3	4	Loser 5	Average ID_f	unadjusted six-month return	unadjusted six-month t-stat	three-factor six-month alpha	three-factor six-month t-stat	unadjusted three-year return	unadjusted three-year t-stat	three-factor three-year alpha	three-factor three-year t-stat
discrete	6.10	6.96	7.29	7.73	5.83	0.07	0.27	*0.31*	3.53	*1.91*	-12.91	*-1.99*	-17.00	*-2.83*
middle	7.41	4.32	3.59	3.13	1.45	-0.01	5.96	*3.23*	8.33	*5.11*	3.65	*0.54*	2.33	*0.36*
continuous	14.70	11.73	9.98	7.34	3.50	-0.18	11.20	*7.52*	13.66	*9.85*	2.18	*0.38*	7.04	*1.10*
continuous - discrete						-0.25	10.93	*11.02*	10.13	*6.73*	15.09	*2.89*	24.04	*6.13*

Panel C: Cross-sectional regressions of price momentum on information discreteness defined by analyst forecasts

	intercept	PRET	ID_f	$ID_f \cdot$PRET	SUE	SIZE	BM	TURN	IVOL	AMIHUD	DELAY	UCG	UCG·PRET	X	adj. R^2
coefficient	0.0790	0.0273	0.1025	-0.1752	0.0008	-0.0012	0.0199	-0.0001	0.0121	-0.0277	0.0003	0.0395	0.0617	Yes	0.132
t-stat	3.88	*4.74*	*5.85*	*-2.79*	*1.26*	*-0.87*	*4.32*	*-0.01*	*0.47*	*-0.86*	*0.06*	*4.26*	*5.53*		

Panel D: Cross-sectional regressions of earnings momentum on information discreteness defined by analyst forecasts

	intercept	SUE	ID_f	$ID_f \cdot$ SUE	PRET	SIZE	BM	TURN	IVOL	AMIHUD	DELAY	UCG	UCG·PRET	X	adj. R^2
coefficient	0.0783	0.0004	0.0590	-0.0479	0.0230	-0.0011	0.0207	0.0006	0.0133	-0.0174	-0.0011	0.0414	0.0709	Yes	0.130
t-stat	*3.83*	*0.64*	*5.63*	*-6.74*	*4.11*	*-0.84*	*4.76*	*0.08*	*0.54*	*-0.53*	*-0.17*	*4.41*	5.91		

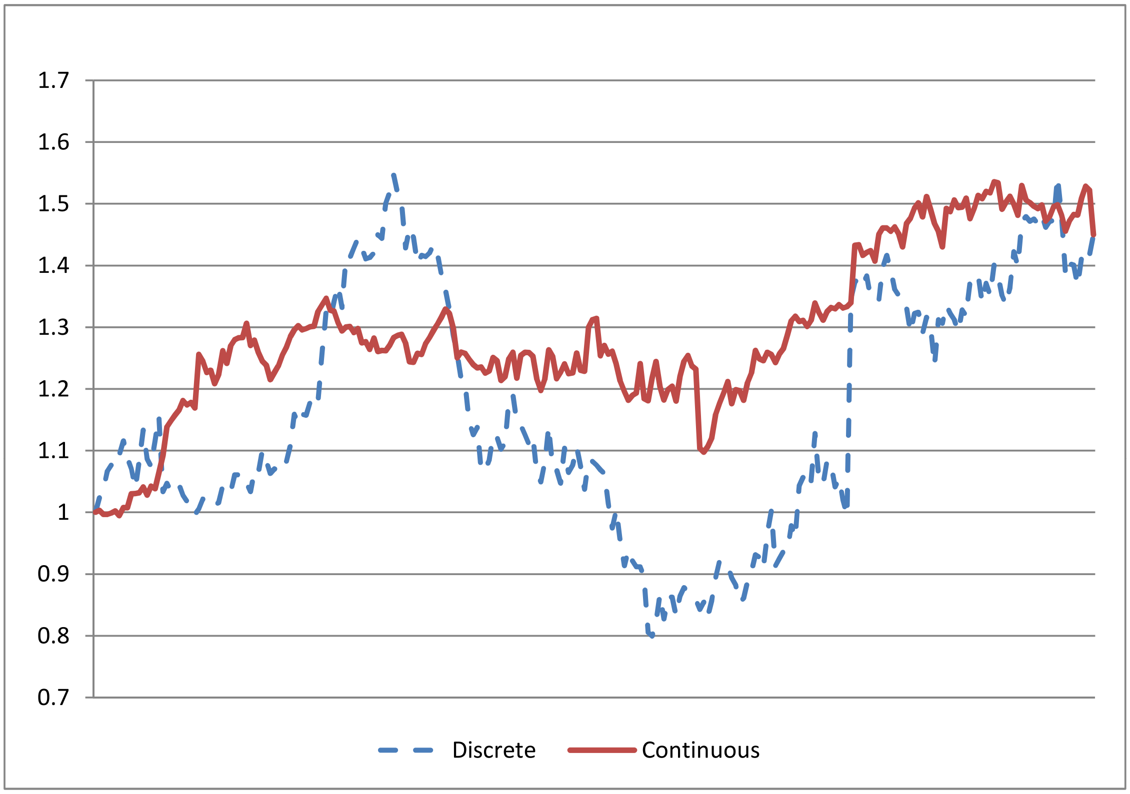
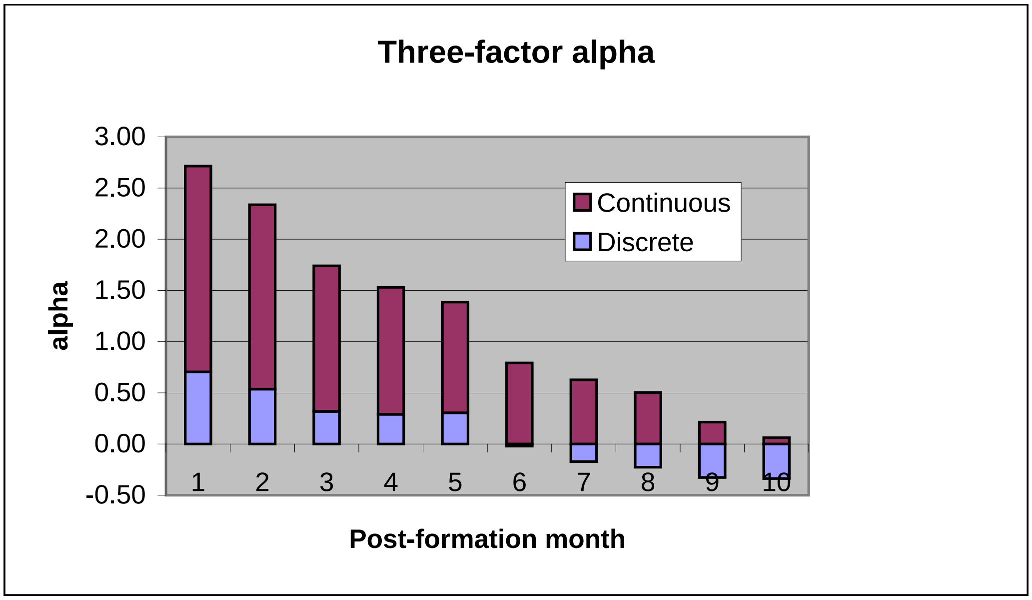


Figure 1 This figure provides a visual illustration of the difference between continuous information versus discrete information. Both firms have the same starting and ending stocks prices but with different intermediate returns over the 250 "daily" periods. Information discreteness (ID) is defined in equation (1) to capture the distribution of daily returns across the formation period. Continuous information arrives frequently in small amounts while discrete information arrives infrequently in large amounts. In this figure, the ID measure equals -0.136 for the stock with continuous information and 0.072 for the stock with discrete information.



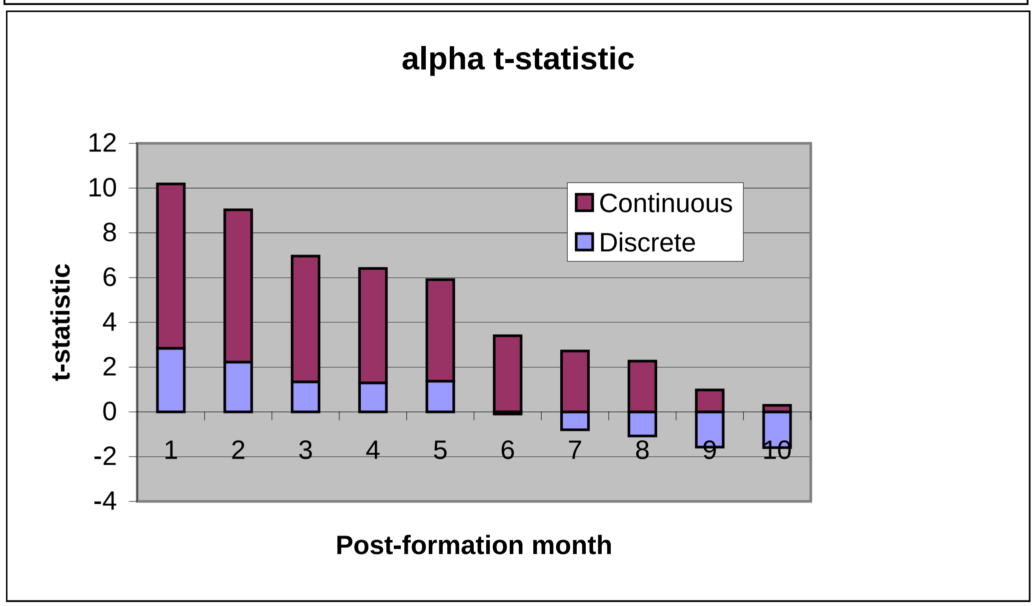


Figure 2 This figure plots risk-adjusted momentum profits in the continuous and discrete information portfolios from one to ten months after portfolio formation. Information discreteness is defined in equation (1) to capture the distribution of daily returns across the formation period. Continuous information arrives frequently in small amounts while discrete information arrives infrequently in large amounts. Momentum profits in month $t+x$, where x ranges from 1 to 10, based on double-sorted portfolios formed in month t according to formation-period returns and information discreteness. These momentum profits are not cumulative. Instead, they are time series averages of holding-period returns in a single month after portfolio formation, with the month of portfolio formation varying across the sample period.