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 frequent gradual changes attracts less attention than infrequent dramatic changes and construct an information discreteness measure to capture the intensity of firm-level information flows. In contrast to most firm characteristics that explain return continuation, information discreteness is not persistent. Consistent with our FIP hypothesis, we find that continuous information induces strong persistent return continuation that does not reverse in the long run. 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. Moreover, the ability of continuous information to explain return continuation increases when investor attention constraints are more likely to bind and is not attributable to the disposition effect.

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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 sudden dramatic changes, 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 that arrives 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 since firms endeavor 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 can be explained by limited attention.

With the exception of Hou, Peng, and Xiong (2008), the role of limited attention in generating momentum (Jegadeesh and Titman, 1993) has not been explored. However, 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 provides a link between our FIP hypothesis and 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 analyst reports can be ascertained from their headings, research reports that are initially categorized as containing 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 by multiple firms. 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 over a long horizon.

Appendix A provides an illustrative model that formalizes our FIP hypothesis. This two-period model involves two types of investors. Signals whose magnitudes are below a lower threshold k are processed with a delay by FIP investors while rational investors process all signals immediately. Momentum is stronger when the k threshold is higher since more signals and larger signals are temporarily "truncated" by FIP investors and incorporated into the stock price with a delay. A simulation exercise in Appendix A confirms that our model produces momentum patterns that parallel our subsequent empirical findings.

Our model demonstrates that momentum originates from the truncation of small signals whose signs are the same as the formation-period return. Conditional on a specific formation-period return, momentum strengthens with the frequency of these small signals. Therefore, to test our FIP hypothesis, we construct an information discreteness measure that proxies for the frequency of small signals without imposing any distributional assumptions on daily returns. Intuitively, information discreteness identifies time series variation in the daily returns that culminate in formation-period returns.[1] For example, a high percentage of positive daily returns relative to negative daily returns implies that a past winner's formation-period return is attributable to a large number of small positive returns. As the formation-period return accumulated gradually over many days, the flow of information is continuous. In contrast, if the formation-period return accumulated over a few days, then the flow of information is discrete. Figure 1 provides a visual illustration of continuous versus discrete information.

For emphasis, the FIP hypothesis predicts that information discreteness has a conditional re-

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

lationship with momentum. Therefore, only after conditioning on formation-period returns is the influence of information discreteness on momentum examined. We first investigate whether information discreteness influences holding-period returns using sequential double-sorted portfolios that condition on formation-period returns, then 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, 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. This monotonic increase is also present in an extended sample period beginning in 1927.

Momentum following continuous information persists for eight months while the momentum profit following discrete information becomes 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 is consistent with investors underreacting to continuous information, and therefore supports the FIP hypothesis.

The investor attention constraint, which is represented by the k parameter in our model, is responsible for the FIP effect. Our illustrative model predicts that the FIP effect strengthens when the investor attention constraint is more likely to bind (a higher k). We examine this novel prediction using cross-sectional as well as time series regressions. Intuitively, disperse institutional ownership and low media coverage are associated with less attentive investors and a higher k threshold. In support of the FIP hypothesis, information discreteness explains more cross-sectional variation in momentum among stocks with disperse rather than concentrated institutional ownership and among stocks that receive low rather than high media coverage. We also examine the returns from an enhanced momentum strategy that purchases past winners and sells past winners following continuous information. The k threshold is higher when more stocks are available for investment as the amount of investor attention allocated to an individual stock is lower, on average. In support of the FIP hypothesis, the enhanced momentum strategy produces higher returns when more stocks are available for investment. Furthermore, as predicted by limited attention, increased media coverage of past winners and past losers coincides with weaker momentum (Peress, 2009).

Despite similarities in their construction, the economic motivation for information discreteness differs considerably from the return consistency measure of Grinblatt and Moskowitz (2004). Return consistency is a dummy variable equaling one if a stock's monthly returns are positive (negative) for at least eight months of the twelve-month formation period and its formation-period return is also positive (negative). Thus, while information discreteness is a continuous variable based on daily returns, return consistency is a discrete variable based on monthly returns and contingent on the eight-month threshold. More importantly, instead of of limited attention, return consistency is motivated by the disposition effect that predicts investors are more likely to sell stocks in their portfolio that have unrealized capital gains than those with unrealized capital losses. Intuitively, the disposition effect is caused by the reluctance of investors to realize losses. When evaluating the disposition effect, unrealized capital gains (losses) are computed relative to reference prices that are usually unobservable at the investor level. Return consistency supplements the unrealized capital gains variable in Grinblatt and Han (2005) that estimates firm-level reference prices using prior returns and turnover. With consistent returns, these firm-level estimates are more representative of the true but heterogeneous investor-specific reference prices.

Is the disposition effect responsible for the FIP effect? A battery of empirical tests suggest that the answer is no. First, neither unrealized capital gains nor return consistency explain the returns from our enhanced momentum strategy that conditions on continuous information. Second, the ability of return consistency to predict returns is limited to past winners. In contrast, information discreteness explains the return continuation of both past winners and past losers, even during an extended sample period beginning in 1927.[2] Third, post-formation order flow imbalances are inconsistent with the disposition effect's prediction that investors are more likely to sell past winners than past losers. Instead, following continuous information, past winners have positive order flow imbalances while past losers have negative order flow imbalances. These order flow imbalances support our FIP hypothesis as investors appear to delay the processing of continuous information. Fourth, we examine equity analysts since their earnings forecasts affect prices although analysts are not influenced by the disposition effect when issuing these forecasts. We

[2]Information discreteness is also a stronger predictor of 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 continues to induce stronger momentum than discrete information.

find larger analyst forecast errors following continuous information. Consistent with the FIP effect, this finding suggests that continuous information fails to attract analyst attention. However, this finding is inconsistent with the disposition effect that predicts biased investor trading decisions, not biased earnings forecasts. Fifth, besides return consistency and unrealized capital gains, the prior literature on momentum identifies several firm characteristics that are related to its strength such as turnover (Lee and Swaminathan, 2000), firm size and analyst coverage (Hong, Lim, and Stein, 2000; Brennan, Jegadeesh, and Swaminathan, 1993), idiosyncratic return volatility (Zhang, 2006) and book-to-market ratios (Daniel and Titman, 1999). Fama-MacBeth regressions confirm that the return predictability of continuous information interacted with formation-period returns is not attributable to these firm characteristics nor proxies for the disposition effect. Moreover, the economic significance of the Fama-MacBeth regression coefficients illustrates the greater return predictability of information discreteness relative to return consistency and unrealized capital gains.

In aggregate, a myriad of firm characteristics (size, book-to-market ratios, turnover, idiosyncratic volatility, analyst coverage, institutional ownership, absolute formation-period returns) including return consistency only explain about 14% of the time series variation in information discreteness. This property is consistent with the lack of persistence in information discreteness and justifies its use as a proxy for time-varying information flows at the firm-level. Indeed, this lack of persistence distinguishes our FIP hypothesis from momentum explanations that are based on persistent firm characteristics.

For emphasis, the FIP hypothesis depends on the cumulative importance of a sequence of small signals. Provided a signal is sufficiently large to attract investor attention, its exact magnitude is irrelevant. This jump independence distinguishes information discreteness from skewness and kurtosis. Empirically, assigning more weight to larger daily returns (in absolute value) does not improve upon the ability of information discreteness to explain cross-sectional variation in momentum.

Finally, to examine the robustness of our return-based information discreteness measure, we construct a modified information discreteness measure by replacing daily returns with signed monthly analyst forecast revisions. This analyst-forecast based measure of information discreteness confirms that continuous information induces stronger momentum than discrete information. Thus, the economic implications of information discreteness are robust to the noise in daily returns.

To clarify, we focus on the flow of information over time rather than its diffusion across investors

(Hong and Stein, 1999). 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.

The remainder of this paper is organized as follows. Section 2 describes our measure of information discreteness. Section 3 then presents our results on the importance of information discreteness to momentum while Section 4 examines their robustness using analyst forecasts. Section 5 then concludes and offers suggestions for future research.

2 Definition of Information Discreteness

Return data is obtained from CRSP after adjusting for delistings. 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.[3] Information discreteness, which is abbreviated ID, is defined as

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

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 and -1 when PRET $<$ 0. Although PRET is determined by the magnitude of daily returns, ID does not differentiate between small and large daily returns. Ignoring the magnitude of daily returns dif-

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

ferentiates ID from return volatility as well as skewness and kurtosis. Instead, ID refers to a time series property of PRET that is defined by the sign of daily returns underlying this cumulative formation-period return. However, as a robustness test, we examine a modified ID measure that incorporates the magnitude of daily returns.

As emphasized in Appendix A, ID enables us to examine conditional momentum where the conditioning is conducted on PRET. In particular, our model demonstrates that momentum originates from the initial truncation of signals below the k threshold. Conditional on PRET, momentum becomes stronger when more signals (and larger signals) with the same sign as PRET are truncated. Our ID definition in equation (1) captures this initial truncation without imposing any distributional assumptions on daily returns.

A large ID measure signifies discrete information while a small ID measure signifies continuous information.[4] 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 formed by 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 PRET being positive while the remaining daily returns are negative, then ID is closer to +1 and information is discrete. The same intuition applies to past losers with a low PRET.

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 discrete information has a few large positive daily returns arriving infrequently.

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. While ID measure does not perfectly capture

[4]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.

information discreteness, equation (1) provides a simple proxy that is robust to whether PRET is near zero or large in absolute value.

Although ID is derived exclusively from the sign of daily returns, the following modification of ID, which is motivated by the Herfindahl index, also accounts for their magnitude

$$\mathrm{ID}_{HERF} \;=\; -N \cdot \mathrm{sgn}(\mathrm{PRET}) \cdot \sum_{i=1}^{N} \mathrm{sgn}\left(\mathrm{Ret}_i\right) \cdot \left(\frac{\mathrm{Ret}_i}{\sum_{i=1}^{N} |\mathrm{Ret}_i|}\right)^2 , \tag{2}$$

where N denotes the number of days in the formation period. Observe that large absolute returns exert more influence on ID_{HERF} than small returns. If daily returns had the same absolute magnitude, then ID_{HERF} would reduce to our original ID measure.

Furthermore, the $\%neg - \%pos$ difference that defines ID is implicitly normalized by one since $\%pos + \%neg + \%zero = 1$, where $\%zero$ denotes the percentage of zero return days. Although the frequency of zero daily returns has been interpreted as a measure of illiquidity by Lesmond, Ogden, and Trzcinka (1999), incorporating a one-month interval between the formation period and holding period mitigates the impact of short-term return reversals due to illiquidity. Nonetheless, we investigate the impact of zero return days using the following modification of information discreteness

$$\mathrm{ID}_Z \;=\; \mathrm{sgn}(\mathrm{PRET}) \cdot \frac{[\%neg - \%pos]}{[\%neg + \%pos]} , \tag{3}$$

that is identical ID whenever $\%zero = 0$.

Our later empirical tests carefully distinguish between ID and idiosyncratic return 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. IVOL often proxies for the incorporation of firm-level information into stock prices. Hou and Moskowitz (2005) estimate a distinct price delay measure for the incorporation of market-level information in stock prices by regressing firm-level weekly stock returns on contemporaneous market returns and lagged market returns over the prior four weeks. The R-squared is denoted R_L^2 when lagged returns are included in this time series regression while the 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 a firm's stock price rapidly incorporates market-level information, then lagged market returns are unimportant and R_C^2 is near R_L^2, with DELAY being closer to zero as a consequence. However, if the firm's stock price slowly incorporates market-level information, then DELAY is closer to one. Hou and Moskowitz (2005) report that DELAY is a persistent firm characteristic that identifies "neglected" stocks.

Finally, to control for the disposition effect, we investigate return consistency (RC) and unrealized capital gains (UCG). Recall that Grinblatt and Moskowitz (2004) define RC as a dummy variable equaling one if a stock's monthly returns are positive (negative) for at least eight months of the twelve-month formation period and its formation-period return is also positive (negative). Grinblatt and Han (2005) estimate reference prices from prior returns, turnover, and market capitalizations and then use these estimates to define UCG.

Table 1 summarizes the main variables in our study. To examine the autocorrelation of each characteristic, we compute the firm variables over calendar year horizons every June. We then compute first-order autocorrelation coefficients using a pooled regression of each characteristic on its lagged value from the previous year. The summary statistics in Panel A indicate that ID has a mean near zero. Unlike DELAY, IVOL and other firm characteristics, information discreteness is not persistent since its autocorrelation coefficient is 0.034. The lack of persistence is consistent with the notion that ID reflects time-varying firm-level information flows rather than a persistent firm characteristic. UCG is also more persistent than ID with an autocorrelation of 0.660. Intuitively, information discreteness varies over time for individual firms while the disposition effect is determined by persistent unrealized capital gains.

According to Panel B of Table 1, UCG and PRET have a 0.685 correlation since past returns are a major determinant of unrealized capital gains. This high correlation complicates empirical tests that attempt to link the disposition effect with momentum. In contrast, ID is not highly correlated with PRET or UCG. The positive correlation between ID and DELAY suggests that continuous information does not result from the slow incorporation of market information into stock prices.

Instead, information discreteness is determined by the flow of firm-specific information.

3 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 at the beginning of each month, 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 2 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. The weaker return predictability following discrete information cannot be attributed to illiquidity. Although large order flow imbalances can induce 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. Furthermore, in unreported results, the inclusion of the Pástor and Stambaugh (2003) liquidity factor does not alter our empirical results.

Figure 2 plots the momentum profits following continuous and discrete information from one to ten months after portfolio formation. These momentum profits are not cumulative but represent "marginal" momentum profits within each month. The 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 32bp momentum profit 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 eight-month horizon associated with the return continuation of continuous information is more compatible with limited attention than risk since the return predictability of continuous information does not require high transaction costs to be incurred as a result of frequent portfolio re-balancings.

According to Panel A of Table 2, 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. This property is confirmed by later regressions in Table 5.

An underreaction to information does not predict return reversals over the long term. The three-year holding-period returns in Panel A do not indicate that long-term return reversals follow short-term return continuation. In particular, stocks with continuous information in the formation period have higher long-term risk-adjusted returns than stocks following discrete information. Therefore, consistent with an underreaction to continuous information, stocks in the low ID portfolio have stronger short-term return continuation that does not precede long-term return reversal. Overall, ID appears to identify variation in return predictability over different horizons.[5]

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 an information discreteness measure using market-adjusted daily returns that subtract daily value-weighted market returns from the daily returns of individual stocks. However, this market-adjusted information discreteness measure produces similar empirical results. 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 has a t-statistic of 3.16.

Panel B reports the momentum profits from independent double-sorts derived from conditioning first on PRET, then ID. These results display the same pattern as 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-sorts are formed sequentially or independently.

[5] George and Hwang (2004) also cast doubt on the link between short-term return continuation and long-term return reversals.

The results in Panel C are based on ID_{HERF} in equation (2) and provide evidence that the return predictability of information discreteness is not attributable to the magnitude of daily returns. In particular, the difference in momentum between continuous information and discrete information is smaller at 4.77% in Panel C than the 5.95% momentum difference in Panel A although the difference is insignificant. This comparison supports the FIP hypothesis that posits the exact magnitude of signals are irrelevant to return continuation provided they are sufficiently salient to attract investor attention.

Panel D contains the results for ID_Z in equation (3) that accounts for the percentage of zero daily returns since a higher percentage is associated with lower liquidity. The results for ID_Z parallel those based on our original ID measure. Specifically, the difference in momentum between continuous and discrete information in Panel D is 6.12%. After a three-factor adjustment, the difference of 6.83% using ID_Z is slightly smaller than the 6.89% difference using the original ID measure. Consequently, illiquidity does not appear to be responsible for the stronger return continuation following continuous information.

Panel E replicates the earlier sequential double-sorts starting in 1927 to confirm the robustness of our FIP hypothesis. In this extended sample period, ID continues to explain cross-sectional variation in momentum. 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. Indeed, in unreported results, profits from the 6-1-6 momentum strategy increase monotonically across the ID portfolios as information during the formation period becomes more continuous.

In the remainder of this section, we differentiate between ID, which is motivated by limited attention, and return consistency whose motivation lies with the disposition effect. We also examine the ability of ID to explain cross-sectional variance in momentum using Fama-MacBeth regressions that control for an array of firm characteristics in the existing momentum literature.

3.1 The Role of Investor Limited Attention

The lower bound on investor attention is responsible for the FIP effect and is represented by the k parameter in our illustrative model. Specifically, our model predicts that the FIP effect strengthens when this investor attention constraint is higher. We first test this prediction in the cross-section using institutional ownership concentration and media coverage as firm-level proxies for the k

parameter.

Intuitively, institutional investors with large positions in a firm are more attentive to information regarding its fundamentals while disperse institutional ownership is associated with less attentive investors and a higher k threshold. Similarly, high media coverage for a firm focuses investor attention on its fundamentals while low media coverage is associated with less attentive investors and a higher k threshold.

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. This data is obtained from the portfolio holdings reported in 13f filings with the SEC. These holdings are normalized by the total number of shares outstanding to compute the percentage of shares held by institutions (IO).

High media coverage for a firm is defined by the number of news articles in a quarter being four or above since four is the cross-sectional median for quarterly firm-level media coverage. Consequently, low media coverage is defined by the number of news articles in a quarter being three or less. Peress (2009) finds evidence that media coverage of quarterly earnings announcements mitigates post-earnings announcement drift. This finding is compatible with a lower attention bound provided earnings announcements that fail to attract media coverage also fail to attract investor attention.

Data on media coverage is obtained from Factiva, which contains media reports from several sources including newswires as well as local and national newspapers. We focus on the most comprehensive financial news service, the Dow Jones Newswire. Dow Jones Newswire obtains data from several sources including press releases, firm disclosures, and reports produced by financial journalists. To match news stories with firms, we use the ticker symbols, firm names, and name variants from the CRSP database using procedures outlined in Gurun and Butler (2010). Specifically, a web crawler is used to search name variants by singular and plural versions for the following abbreviations from the company names: ADR, CO, CORP, HLDG, INC, IND, LTD, and MFG. Our final sample includes over 1,200,000 firm-day media reports for 9,500 firms between January 1991 and December 2007.

Consistent with the limited attention motivation of our FIP hypothesis, the results in Panel A of Table 3 indicate that our ID measure is better at explaining cross-sectional differences in momentum among firms with disperse institutional ownership. In particular, the disparity in six-month momentum profits following continuous versus discrete information is 11.23% in stocks with disperse institutional ownership. This difference in momentum is more than double the 5.44% difference for stocks with concentrated institutional ownership. Therefore, our FIP hypothesis is most relevant to firms having disperse institutional ownership (high k parameters).

The results in Panel B for media coverage parallel those in Panel A as our ID measure is better at explaining cross-sectional differences in momentum among firms that receive less media coverage. In particular, the disparity in momentum between continuous and discrete information is 5.89% for firms with low media coverage, which is nearly 60% greater than the 3.75% difference for stocks with high media coverage. After applying the three-factor model, this difference increases dramatically from 1.96% to 5.94%. Therefore, our FIP hypothesis is most relevant to firms that receive low media coverage (high k parameters). This result is consistent with the evidence in Peress (2009) that media coverage mitigates earnings momentum.

However, the results in Panel B may appear to contradict those in Chan (2003). Chan (2003) reports that media coverage leads to return continuation for past winners and past losers. Conversely, in the absence of media coverage, Chan (2003) finds evidence of short-term reversals for past winners and past losers. However, our empirical methodology differs from Chan (2003) in several important aspects. First, Chan (2003) examines returns and media coverage over a relatively short formation period of one month. Second, Chan (2003) does not insert a one-month interval between the formation and holding periods. Third, Chan (2003) focuses on unconditional momentum. For completeness, we investigated the importance of these methodological differences by sorting stocks according to their returns, then ID measures in each month. Specifically, ID was computed using daily returns during the one-month formation period. This double-sort procedure was performed separately for stocks with and without media coverage during the one-month formation period. For each ID quintile, momentum profits were computed from one to seven months after portfolio formation without the usual one-month interval separating the formation and holding periods. Consistent with the results in Panel B of Table 3, unreported results indicate that the FIP effect is stronger in stocks without media coverage. Moreover, starting from the second month after portfolio formation, the FIP effect is present in both subsets. Overall, we are able to replicate Chan (2003)'s unconditional results and verify that the FIP effect is present, after the first post-formation month, in stocks with and without media coverage.

Overall, the results in Table 3 support the prediction of our model based on limited attention. Specifically, empirical support for our FIP hypothesis is stronger among firms with higher k parameters. These firms have disperse institutional ownership and receive less media coverage.

3.2 Disposition Effect

One concern regarding our ID measure is its similarity with the RC variable in Grinblatt and Moskowitz (2004). However, their economic motivations are distinct since ID is based on limited attention while RC is based on the disposition effect. Therefore, this subsection investigates whether the ability of ID to explain cross-section differences in momentum can be attributed to the disposition effect.

To distinguish between the economic implications of ID and RC, our first empirical test examines their respective impacts on past winners and past losers separately. Limited attention predicts that ID explains the return continuation of past winners as well as past losers. Therefore, signed versions of ID denoted PosID and NegID are defined using daily returns as follows

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

and

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

Recall that $\%pos$ and $\%neg$ denote the percentage of days during the formation period with positive and negative returns, respectively. 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.

Using six-month returns, the following Fama-MacBeth regression examines the return predictability of signed information discreteness and signed return consistency

$$
\begin{aligned}
r_{i,t+1,t+6} \;=\;& \beta_0 + \beta_1\,\mathrm{PRET}_{i,t} + \beta_2\,\mathrm{NegPRET}_{i,t} + \beta_3\,\mathrm{PosRC}_{i,t} + \beta_4\,\mathrm{NegRC}_{i,t} \\
& + \beta_5\,\mathrm{PosID}_{i,t} + \beta_6\,\mathrm{NegID}_{i,t} + \beta_7\,\mathrm{SIZE}_{i,t} + \beta_8\,\mathrm{BM}_{i,t} + \epsilon_{i,t}\,,
\end{aligned} \tag{5}
$$

where NegPRET is defined as $\min\{0, \mathrm{PRET}\}$. For ease of comparison with Grinblatt and Moskowitz (2004), we include SIZE and BM characteristics as control variables in the post 1976 period. BM ratios are computed in July using firm-level book equity and market capitalization for the fiscal year ending in the preceding calendar year. SIZE is defined as the log of a firm's market capitalization.

The results in Panel A of Table 4 indicate that both signed ID measures predict returns. Specifically, the positive β_5 coefficient and negative β_6 coefficient for PosID and NegID, respectively, indicate that limited attention explains the return continuation of both past winners and past losers. This finding applies to the extended sample period starting in 1927 as well as the post 1976 period. The significance of the signed ID coefficients are not dependent on the inclusion of BM and SIZE controls. Overall, the significance of the PosID and NegID coefficients across the regression specifications confirms the robustness of our FIP hypothesis.

As with their signed ID counterparts, PosRC and NegRC are predicted to have a positive β_3 coefficient and negative β_4 coefficient, respectively. However, the β_3 coefficient for PosRC is insignificant in the post 1927 period. Moreover, with controls for BM and SIZE, the β_4 coefficient for NegRC is insignificant (t-statistic of 1.54) in the post 1976 period but positive (t-statistic of 2.24) in the absence of these controls. Overall, return consistency cannot explain the return continuation of past losers in the post 1976 period. 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.

Gutierrez and Kelley (2008) also report that return consistency cannot predict returns when this measure is constructed using weekly instead of monthly returns. In contrast, the next section provides evidence that an alternative measure of information discreteness based on monthly information flows continues to explain cross-sectional variation in momentum. Consequently, the relationship between RC and momentum appears to be less robust than the relationship between

ID and momentum.[6] However, since RC is only an indirect proxy for the disposition effect, we implement additional tests to differentiate our FIP hypothesis from the disposition effect.

Our second test is a time-series "horse-race" between the disposition and FIP effects to determine which explanation is better at accounting for time series variation in the momentum profits following continuous information. We denote the three-factor adjusted six-month holding-period returns from a momentum strategy that conditions on continuous information as $\text{FIPRet}_{t+1,t+6}$ and estimate the following time series regression

$$\begin{aligned} FIPRet_{t+1,t+6} &= \beta_0 + \beta_1 \,\text{Trend} + \beta_2 \,\text{AGG MKT}_{t-1} + \beta_3 \,\text{AGG UCG}_{t-1} + \beta_4 \,\text{AGG RC}_{t-1} \\ &\quad + \beta_5 \,\text{Log(NUMST)}_{t-1} + \beta_6 \,\Delta\text{Log(MEDIA)}_{t-1} + \epsilon_t \,. \end{aligned} \tag{6}$$

The independent variables include the aggregate market return (AGG MKT), aggregate unrealized capital gains (AGG UCG), and aggregate return consistency (AGG RC) during the formation period ending in month $t-1$. Unrealized capital gains and return consistency are included to account for the disposition effect. AGG UCG is constructed by equally-weighting the difference between the unrealized capital gains of past winners and past losers following continuous information during the formation period. AGG RC is the equally-weighted sum of RC for past winners and past losers following continuous information. The disposition effect predicts that AGG RC and AGG RC have positive β_3 and β_4 coefficients, respectively.

In contrast, the FIP hypothesis predicts higher FIPRet following periods when the lower bound on investor attention is more likely to bind. The log number of listed stocks during the formation period denoted Log(NUMST) is our first proxy for limited attention. Indeed, the allocation of investor attention to each stock is lower, on average, when the number of stocks available for investment is greater. This time series regression also controls for changes in the formation-period media coverage of stocks involved in the enhanced momentum strategy through the ΔLog(MEDIA) variable. Changes in media coverage provide another proxy for limited attention. As this regression

[6] In unreported results, the subsample of stocks for which RC equals one comprises 17.24% of the firm-month observations in our original dataset. Within this subsample of stocks with consistent returns, momentum continues to increase monotonically over the ID quintiles, from 5.19% following discrete information to 10.14% following continuous information. This 4.95% return difference is significant (t-statistic of 3.55) and increases to 7.27% after being risk-adjusted by the three-factor model. Thus, the marginal return predictability of continuous information is significant after controlling for return consistency.

specification involves media coverage, the sample period begins in 1991 with the time TREND variable being 1 in January of 1992.

The use of ΔLog(MEDIA) and Log(NUMST) as proxies for investor attention can be attributed to Barber and Odean (2008). These authors implicitly distinguish between passive and active investor attention. Active attention originates from investor decisions to analyze firm-level fundamentals. Passive attention originates from an external source such as the media leading investors to analyze a firm. Greater media coverage increases passive investor attention for a firm while having fewer stocks available for investment increases the amount of active investor attention per firm.[7] Although investors may be confronted by more firm-specific information when the number of stocks available for investment increases, the FIP hypothesis is distinct from the "driven-to-distraction" hypothesis in Hirshleifer, Lim, and Teoh (2009). Specifically, the FIP hypothesis conditions firm-level information flows over the entire formation period, while the investor distraction hypothesis conditions on the release of information by multiple firms in a single day.

Panel B contains the results of the above time series regression. The β_5 coefficient for Log(NUMST) equals 22.5052 (t-statistic of 3.86). Therefore, as predicted by the FIP hypothesis, this positive coefficient indicates that during periods when more stocks are available for investment, our enhanced momentum strategy that conditions on continuous information produces higher risk-adjusted returns. Conversely, the negative β_6 coefficient suggests that these returns are lower in periods where past winners and past losers receive increased media coverage. Therefore, consistent with Peress (2009), the negative β_6 coefficient provides empirical support for the ability of media coverage to mitigate the limited attention of investors.

In contrast, unrealized capital gains and return consistency cannot explain time series variation in momentum following continuous information since both β_3 and β_4 are insignificant. Consequently, the disposition effect is less relevant to our FIP hypothesis than limited attention. Furthermore, the insignificant β_2 coefficient indicates that momentum profits following continuous information are independent of market returns while the insignificant β_1 coefficient indicates that the profits from our enhanced momentum strategy have not declined during the past two decades.

Our third test uses order flow imbalances to differentiate between the predictions of our FIP

[7] The proxies for active and passive attention are not necessarily orthogonal. For example, the amount of media coverage per stock may decrease when the number of stocks increases.

hypothesis and the disposition effect. Chordia, Goyal, and Jegadeesh (2011) utilize order flow imbalances to investigate the disposition effect. Specifically, when studying the disposition effect, they examine whether investors are more likely to initiate sell trades for past winners than for past losers. In contrast to the disposition effect, the FIP hypothesis predicts that investors are more willing to initiate buy trades for past winners than for past losers. In particular, positive and negative order flow imbalances, respectively, for past winners and past losers are consistent with the FIP hypothesis since positive and negative signals below the k threshold are processed with a delay according to our model. Therefore, our FIP hypothesis and the disposition effect have distinct empirical predictions regarding order flow imbalances.

Post-formation order flow imbalances (OIB) in month t to month $t+2$ are investigated where t denotes the one-month interval between the formation and holding periods. We use tick-by-tick transactions from 1983 to 1992 in the Institute for the Study of Security Markets (ISSM) database and from 1993 to 2004 in the Trades and Quotes (TAQ) database. The data ends in 2004 since the Lee and Ready (1991) algorithm is required to sign trades and create firm-level order flow imbalances

$$\text{OIB} \quad = \quad \frac{\text{\# of Share Purchases - \# of Share Sales}}{\text{Total Volume}} \times 100 \tag{7}$$

that are aggregated within each month. These OIB figures are then adjusted by subtracting the average OIB imbalance across firms in each month.

The OIB plots in Figure 3 are consistent with the FIP hypothesis but not the disposition effect. Specifically, for past winners following continuous information, OIB is positive instead of negative. Furthermore, for past losers following continuous information, OIB is negative instead of zero. In contrast to the disposition effect, investors are unlikely to sell past winners and hold past losers if they anticipate further gains and losses, respectively. Instead, according to Ben-David and Hirshleifer (2011), unrealized capital gains predict returns by focusing investor attention.

Overall, the evidence in Table 4 and Figure 3 indicates that limited attention instead of the disposition effect is responsible for the return continuation in low ID stocks. Later evidence derived from cross-sectional regressions and analyst forecasts provides additional empirical support for limited attention. Indeed, Fama-MacBeth regression coefficients for RC and UCG are found to be inconclusive while the return predictability of ID interacted with PRET is robust. Moreover, while analysts are not subject to the disposition effect, limited attention can bias their forecasts. We report larger analyst forecast errors following continuous information. This finding suggests that the slow updating of analyst forecasts due to limited attention may be responsible for the underreaction of investors to continuous information.

3.3 Alternative Explanations

Besides the disposition effect, we also examine whether investor conservatism is responsible for the return predictability of information discreteness. The conservatism bias can cause investors to ignore disconfirming continuous information until discrete information forces them to re-evaluate their prior beliefs. We proxy for the prior beliefs of investors using long-term analyst earnings growth forecasts denoted LTG.

Confirming information corresponds to past winners with high LTG and past losers with low LTG. Conversely, disconfirming information corresponds to past winners and past losers with low LTG and high LTG, respectively. High and low LTG correspond to above-median and below-median LTG, respectively, before the formation period (months $t-25$ to $t-13$). We then implement our enhanced momentum strategy that conditions on continuous information but separate stocks into confirming and disconfirming portfolios before computing holding-period returns.

The conservatism bias predicts that disconfirming information leads to stronger momentum than confirming information since conservatism predicts that investors underreact to disconfirming information. However, the returns in Panel A of Table 5 indicate that momentum following disconfirming continuous information is lower at 5.14% than the momentum following continuous confirming information at 8.02%. This evidence is inconsistent with the conservatism bias being responsible for the return continuation following continuous information.

Brav and Heaton (2002) argue that the appearance of return anomalies can arise from investors rationally updating their prior beliefs. For example, conservatism can appear when investors have strong prior beliefs about firm-level fundamentals while representativeness, which describes the tendency to condition on uninformative past trends, can appear when the prior beliefs of investors are less informative. Low analyst forecast dispersion provides a proxy for strong prior beliefs while high analyst forecast dispersion coincides with disperse prior beliefs. Therefore, we examine the momentum spread between stocks with continuous and discrete information in their formation periods separately for stocks with high and low analyst forecast dispersion.

The results in Panel B of Table 5 indicate that Bayesian updating is not responsible for the ability of ID to explain cross-sectional variation in momentum. The momentum spread following continuous and discrete information is 5.66% among high dispersion stocks and 5.12% among low dispersion stocks. The difference between these momentum spreads is statistically insignificant. Therefore, the ability of information discreteness to explain cross-sectional differences in momentum is difficult to attribute to Bayesian updating.

Zhang (2006) concludes that momentum is stronger in stocks with higher idiosyncratic return volatility. However, the positive correlation between ID and IVOL in Panel B of Table 1 suggests that continuous information corresponds to low idiosyncratic volatility. Therefore, our finding that momentum is stronger following continuous information may appear to contradict Zhang (2006)'s conclusion. Although Zhang (2006) examines a shorter sample period and a shorter holding period, unreported results confirm that return continuation is stronger in high IVOL stocks using a portfolio double-sort that first conditions on idiosyncratic volatility, then formation-period returns. Specifically, across the low IVOL to high IVOL quintiles, momentum increases from 3.31% to 8.90% over a six-month holding period. However, this increase in momentum may be mechanical if the extreme returns that define past winners and past losers also induce high idiosyncratic volatility. Indeed, provided high IVOL stocks are more likely to be extreme past winners or losers, momentum profits will be stronger among high IVOL stocks even if IVOL is irrelevant to return continuation.

To address the influence of formation-period returns on idiosyncratic return volatility, we compute residual idiosyncratic volatility (RES IVOL) that is orthogonal to the absolute value of formation-period returns using the following cross-sectional regression

$$\mathrm{IVOL}_{i,t} \;=\; \gamma_{0,t} + \gamma_{1,t}\,|\mathrm{PRET}|_{i,t} + \epsilon_{i,t}^{IVOL}\,. \tag{8}$$

The $\epsilon_{i,t}^{IVOL}$ residual for firm i defines its RES IVOL in month t. A double-sort that conditions on RES IVOL, then PRET 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 C of Table 5, 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 on idiosyncratic volatility, higher idiosyncratic volatility is not associated with stronger momentum.

3.4 Fama-MacBeth Regressions

The momentum literature identifies many firm characteristics that explain cross-sectional differences in momentum. Therefore, we estimate several Fama-MacBeth (1973) regression specifications to evaluate the impact of ID on return continuation

$$\begin{aligned} r_{i,t+1,t+6} &= \beta_0 + \beta_1\, \mathrm{PRET}_{i,t} + \beta_2\, \mathrm{ID}_{i,t} + \beta_3\, (\mathrm{PRET} \cdot \mathrm{ID})_{i,t} \\ &\quad + \alpha\, X_{i,t} + \alpha_I\, (\mathrm{PRET} \cdot X)_{i,t} + \epsilon_{i,t}\,. \end{aligned} \tag{9}$$

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

The X vector contains an array of control variables. Besides controlling for UCG and RC to account for the influence of the disposition effect, the most recent quarterly earnings surprises (SUE) is examined to control for post-earnings announcement drift (Bernard and Thomas, 1990). 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. BM and SIZE are included in the cross-sectional regression since these characteristics are the basis for the Fama-French factors. Zhang (2006) also finds that momentum is stronger in small firms while Daniel and Titman (1999) document a negative relationship between the value premium and momentum. We also include turnover (TURN) during the formation-period in the Fama-MacBeth regression since Hou, Peng, and Xiong (2009) interpret low turnover as evidence of investor inattention while Lee and

Swaminathan (2000) interpret high turnover as an indication of investor sentiment. The inclusion of IVOL is motivate by Zhang (2006), which reports stronger momentum in stocks with high IVOL as well as the results in Hong, Lim, and Stein (2000) and Brennan, Jegadeesh, and Swaminathan (1993) that document stronger momentum in stocks with low analyst coverage (COVER). Analyst coverage is defined as one plus the log number of analysts issuing forecasts for a particular firm. Amihud's measure (AMIHUD) controls for cross-sectional differences in liquidity. Finally, DELAY controls for the possibility that continuous information is more common in neglected stocks. In summary, the X vector is defined as

$$[\text{RC, UCG, SUE, BM, SIZE, TURN, IVOL, COVER, AMIHUD, DELAY}]$$

with all of these characterisics computed before month t.

Panel A of Table 6 contains the coefficient estimates from the Fama-MacBeth regression in equation (9). Most importantly, the β_3 coefficient is negative in every specification. Indeed, the addition of interaction variables involving PRET does not diminish the significance of the β_3 coefficient. In contrast, the sign of the coefficients for RC and UCG are unstable across the various regression specifications. This property also holds for their respective interactions with PRET. Thus, ID appears to be a more robust predictor of firm-level returns than either return consistency or unrealized capital gains. The positive β_2 coefficient indicates the presence of a return premium for jump risk or skewness.

The positive coefficients for SUE and BM are consistent with post-earnings announcement drift and the value premium while the negative coefficient for SIZE is consistent with the size premium. As in Gervais, Kaniel, and Mingelgrin (2001), high turnover predicts lower returns as the coefficient for TURN is negative. Less liquid stocks with higher Amihud measures also have higher average returns. Similarly, stocks with high DELAY metrics, which are slower at incorporating market-level information, have higher returns even after controlling for analyst coverage. For emphasis, IVOL is computed during the formation period. Therefore, it is not directly comparable to the idiosyncratic volatility computed by Ang, Hodrick, Xing, and Zhang (2006) based on returns in the most recent month that are omitted from the formation period. However, in unreported results, computing IVOL using daily returns in the month prior to portfolio formation does not alter the β_3 coefficient.

The economic significance of the estimates in Panel A are reported in Panel B. Using one standard deviation fluctuations in the other firm characteristics from their average within these portfolios, we compute the return implications of these fluctuations in conjunction with the coefficients from equation (9). In particular, Panel B records the return implications for fluctuations in these characteristics within both the portfolio of past winners as well as losers. As an example, for ID, denote one standard deviations above and below the mean as ID_{+1} and ID_{-1}, respectively, with their difference being ID_{+1} - ID_{-1}. Conditional on the β_2 coefficient for ID and the β_3 coefficient for its PRET interaction, the resulting return difference attributable to variation in ID equals

$$\beta_2 \cdot (\text{ID}_{+1} - \text{ID}_{-1}) + \beta_3 \cdot \bar{\text{PRET}} \cdot (\text{ID}_{+1} - \text{ID}_{-1}) \ ,$$

where $\bar{\text{PRET}}$ averages 1.122 for past winners and -0.276 for past losers. Past winners and past losers are examined separately given the large difference in their average PRET. The β coefficients used in this analysis are reported in the bottom row of Panel A for each firm characteristic as well as their respective interactions with PRET.

The above procedure is then applied to standard deviations for other firm characteristics in conjunction with their respective beta coefficients. The absolute return difference relative to ID normalizes the amount of return variation that can be attributed to fluctuations in each characteristic by the return variation of ID. This normalization assesses the economic importance of each characteristic relative to the FIP effect.

Relative to RC and UCG, fluctuations in ID exert a far greater influence on returns. For past winners, RC and UCG explain 31.52% and 50.76%, respectively, of the return variation attributable to ID. For past losers, these percentages are lower at 0.31% and 15.89%, respectively. Earlier results in Table 4 also indicated that return consistency cannot explain the return predictability of past losers. Similarly, the return implications of idiosyncratic volatility and analyst coverage are weaker than ID. Only for past winners does turnover exert a greater influence on returns than ID. Although BM explains more return variation than ID for past winners as well as past losers, the FIP hypothesis is not intended to explain the value premium.

3.5 Residual Information Discreteness

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 have been associated with cross-sectional differences in momentum

$$\begin{aligned} \mathrm{ID}_{i,t} &= \delta_{0,t} + \delta_{1,t}\,|\mathrm{PRET}|_{i,t} + \delta_{2,t}\,\mathrm{RC}_{i,t} + \delta_{3,t}\,\mathrm{BM}_{i,t} + \delta_{4,t}\,\mathrm{SIZE}_{i,t} + \delta_{5,t}\,\mathrm{TURN}_{i,t} \\ &\quad + \delta_{6,t}\,\mathrm{IVOL}_{i,t} + \delta_{7,t}\,\mathrm{COVER}_{i,t} + \delta_{8,t}\,\mathrm{IO}_{i,t} + \epsilon_{i,t}^{ID}\,. \end{aligned} \tag{10}$$

In unreported results, the adjusted R^2 of the above regression is 0.141, indicating that ID is distinct from other predictors of momentum. This low adjusted R^2 measure is not unexpected since ID is designed to capture the nature of time-varying information flows at the firm level rather than persistent firm characteristics.

RES ID is defined as $\epsilon_{i,t}^{ID}$ for firm i in month t. As RES ID is orthogonal to the absolute value of PRET, low RES ID (continuous residual information discreteness) is not associated with more extreme formation-period returns. Observe that several of the control variables in the X vector of equation (9) are independent variables in the computation of RES ID in equation (10) since firm characteristics such as SIZE have been documented to predict returns as well as explain cross-sectional variation in momentum.

According to Panel A of Table 7, 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 replace ID with RES ID in the Fama-MacBeth regressions specified in equation (9). Panel B of Table 7 confirms the ability of RES ID to explain cross-sectional variation in momentum. Once again, the negative β_3 coefficient indicates that momentum is stronger when information during the formation period is continuous, even after controlling for turnover, idiosyncratic volatility, and analyst coverage. The other coefficients are broadly consistent with the results in Table 6. In particular, the coefficients for RC and UCG are inconclusive as they vary across the different specifications. Overall, the ability of continuous information to predict returns is not driven by the disposition effect nor other firm characteristics in the existing momentum literature.

4 Analyst Forecasts and Information Discreteness

The FIP hypothesis is applicable to analysts as well as investors due to its limited attention origin. In contrast, the disposition effect does not affect analysts since their forecasts are not conditioned on reference prices. Therefore, we examine whether continuous information induces larger analyst forecast errors than discrete information as a final test to differentiate between limited attention and the disposition effect.

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. 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. The consensus forecast is defined as the median of analyst forecasts issued within 90 days before an earnings announcement.

To test whether continuous information yields larger SURPs, we regress analyst forecast errors on ID and its interaction with PRET. This regression includes other variables that may affect the accuracy of analyst forecasts such as their dispersion (DISP). Furthermore, 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 this information is in greater demand by institutional investors (O'Brien and Bhushan, 1990) and consequently can generate larger trading commissions. Consequently, 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 8 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 slower to incorporate continuous information into their forecasts than discrete information. Therefore, analyst forecast biases can be partially attributed to limited attention. The underreaction of analysts to continuous information identifies a specific channel through which continuous information can induce a corresponding investor underreaction. For emphasis, this channel cannot be attributed to the disposition effect whose predictions are limited to the trading decisions of investors.

To guard against the possibility that our return-based ID results are driven by noise in daily returns, we construct an alternative proxy for information discreteness using signed monthly analyst forecast revisions. Although the evidence in Panel A indicates that analyst forecasts are biased due to an apparent underreaction by analysts to continuous information, their forecast revisions are more informative for stock prices than the level of their forecasts.

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

$$\text{ID}_f = \text{sgn}(\text{CUMREV}) \cdot [\%downward - \%upward] , \tag{12}$$

where $\%upward$ and $\%downward$ are defined by the percentage of upward and downward revisions, respectively, for the current fiscal year's forecasted earnings. 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.

According to Panel B of Table 8, 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).

Furthermore, momentum following discrete information is insignificant.

We also repeat the cross-sectional regression in equation (9) with ID_f replacing ID. The results from this regression is reported in Panel C of Table 8. The β_3 coefficients for the interaction variable involving ID_f and PRET is negative. Consequently, continuous information defined by analyst forecast revisions results in greater momentum than discrete information. Overall, the implications of our orignal ID measure are robust to the noise in daily returns.

5 Conclusions

We test a frog-in-the-pan (FIP) hypothesis that predicts investors underreact to small amounts of information that arrive continuously. This hypothesis is motivated by limited attention. To formalize the role of limited attention, we provide a two-period illustrative model with two types of investors. Signals whose magnitudes are below a lower attention threshold are processed with a delay by FIP investors while rational investors process all signals immediately. Momentum is stronger when this lower threshold is larger. In particular, the FIP hypothesis predicts stronger momentum after continuous information that is defined by the frequent arrival of small signals.

Our model motivates the construction of our information discreteness measure that is defined using signed daily returns. Intuitively, information discreteness identifies time series variation in the daily returns that comprise the cumulative formation-period returns of momentum strategies. Consistent with the FIP hypothesis, investors appear to underreact to continuous information. Moreover, despite inducing stronger short-term return continuation, continuous information is not associated with long-term return reversals. This lack of return reversal is consistent with limited attention causing investors to underreact to continuous information. Furthermore, we find empirical support for both the cross-sectional as well as time series predictions of our model. In particular, information discreteness is better at explaining cross-sectional variation in momentum among stocks with disperse institutional ownership and among stocks that receive low media coverage. From a time series perspective, the returns from an enhanced momentum trading strategy that conditions on continuous information are stronger when more stocks are available for investment but lower when past winners and past losers receive greater media coverage. This evidence provides additional support for the FIP hypothesis since investor attention per stock is lower on average when more stocks are available for investment but higher if a stock receives media coverage.

While information discreteness is based on limited attention, the return consistency measure in Grinblatt and Moskowitz (2004) originates from the disposition effect. Return consistency supplements unrealized capital gains, which is the primary proxy for the disposition effect, since the reference prices required to compute unrealized capital gains are more representative of investor-specific reference prices when returns are consistent. However, unlike unrealized capital gains, which is the primary proxy for the disposition effect, information discreteness is not persistent at the firm-level. Moreover, unrealized capital gains and return consistency fail to explain the returns from conditioning momentum on continuous information. Furthermore, unlike information discreteness, return consistently cannot explain the return continuation of past losers. Order flow imbalances are also inconsistent with the disposition effect. Instead of investors being more likely to sell past winners than past losers, we find positive and negative post-formation order flow imbalances for past winners and past losers, respectively, following continuous information. These imbalances support our FIP hypothesis. Fama-MacBeth regressions confirm that the return predictability of information discreteness interacted with formation-period returns is robust across different sample periods and specifications. In contrast, proxies for the disposition effect have unstable regression coefficients. The economic significance of the information discreteness interaction coefficients is also greater than disposition effect proxies and firm characteristics such as analyst coverage and idiosyncratic volatility.

Analyst forecast errors are also larger following continuous information. Thus, analysts 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, the return implications of continuous information are robust to the noise in daily returns.

In summary, our paper contributes to the limited attention and momentum literatures by examining firm-level information flows. Motivated by our model, we propose a measure of information discreteness and predict that return continuation is greater following continuous information that corresponds to low information discreteness. Continuous information is defined by the frequent arrival of small amounts of information that, despite their initial failure at attracting investor attention, can nonetheless have important cumulative stock price implications. We then provide empirical tests that verify the predictions of our model and confirm the unique contribution of information discreteness to momentum.

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.

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.

Ben-David, I., and D. Hirshleifer, 2011, Beyond the disposition effect: Do investors really like realizing gains more than losses? Forthcoming in the Review of Financial Studies.

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.

Brav, A., and J. B. Heaton, 2002, Competing theories of financial anomalies. Review of Financial Studies 15, 575-606.

Brennan, M., N. Jegadeesh, and B. Swaminathan, 1993, Investment analysis and the adjustment of stock prices to common information. Review of Financial Studies 6, 799-824.

Chan, W., 2003, Stock price reaction to news and no-news: Drift and reversal after headlines. Journal of Financial Economics 70, 223-260.

Chordia, T., A. Goyal, and N. Jegadeesh, 2011, Buyers versus sellers: Who initiates trades and when? Working Paper.

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.

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.

Gutierrez, R, and E. Kelley, 2008, The long-lasting momentum in weekly returns. Journal of Finance 63, 415-447.

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

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

Hirshleifer, D., and S. H. Teoh, 2003, Limited attention, information disclosure, and financial reporting. Journal of Accounting and Economics 36, 337-386.

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, 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., 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 M. Ready, 1991, Inferring trade direction from intradaily data. Journal of Finance 46, 733-746.

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.

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.

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

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

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

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

Appendix A: Illustrative Model

A1: Economy

Our two-period illustrative model parallels Hirshleifer and Teoh (2003) as well as Tetlock (2011). Consider a stock that pays a liquidating dividend at the end of the second period. This dividend equals the sum of N independent signals (s^i for $i = 1, \ldots, N$) received during the first period and another independent signal denoted s_2 at time 2. All the signals are assumed to have zero mean. Therefore, the stock price at time 0, P_0, equals 0. Let s_1 equal the sum of all N signals during the first period, $s_1 = \sum_{i=1}^{N} s^i$. The stock price at time 2, P_2, equals $s_1 + s_2$.

There are two types of agents. The first type (rational investors) do not have an attention constraint and process all N signals during the first period. The second type (FIP investors) are influenced by the FIP hypothesis. Specifically, any signals during the first period whose absolute values are below a lower threshold k are not processed by FIP investors until time 2 when the dividend is realized. FIP investors account for a fraction m of the economy while rational investors account for the remaining $1 - m$. Based on s^i realizations, they value the stock differently at time 1 with their respective demands determining the stock price P_1.

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, the stock is assumed to be in zero net supply and the interest rate is normalized to zero. Third, the N signals during the first period are drawn from an *i.i.d.* uniform distributions over $[-L, L]$ with $L > k$.

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

$$P_1 \quad = \quad s_1 - m \sum_{i=1}^{N} s^i \, 1_{\{|s^i| < k\}} \, . \tag{13}$$

Intuitively, small signals are only partially incorporated into P_1 because of FIP investors.

A2: Unconditional Momentum

According to equation (13), the covariance for price changes between the first and second periods equals

$$\begin{aligned} Cov\,(P_1 - P_0, P_2 - P_1) &= Cov\,(P_1 - 0\,,\, s_2 + s_1 - P_1) \\ &= Cov\,(P_1\,,\, s_1 - P_1) \\ &= Cov\left(s_1 - m \sum_{i=1}^{N} s^i\, 1_{\{|s^i|<k\}}\,,\, m \sum_{i=1}^{N} s^i 1_{\{|s^i|<k\}}\right) \\ &= Cov\left((1-m) \sum_{i=1}^{N} s^i 1_{\{|s^i|<k\}}\,,\, m \sum_{i=1}^{N} s^i\, 1_{\{|s^i|<k\}}\right) \\ &= m\,(1-m)\, Var\left(\sum_{i=1}^{N} s^i\, 1_{\{|s^i|<k\}}\right) \\ &= m\,(1-m)\, N\, Var\left(s^i\, 1_{\{|s^i|<k\}}\right)\,. \end{aligned} \tag{14}$$

Define x as the truncated signal $s^i\, 1_{\{|s^i|<k\}}$. Although the probability density function of s^i is $\frac{1}{2\,L}$, the x variable is zero over the $[-L, -k]$ and $[k, L]$ intervals. Thus, the variance in equation (14) equals

$$\begin{aligned} Var\left(s^i\, 1_{\{|s^i|<k\}}\right) &= \int_{-k}^{k} \frac{1}{2\,L}\, x^2\, dx \\ &= \frac{1}{2\,L}\, \frac{2\,k^3}{3}\,. \end{aligned} \tag{15}$$

Substituting the above variance in equation (15) into equation (14) yields the following expression for the covariance

$$Cov\,(P_1 - P_0\,,\, P_2 - P_1) = m\,(1-m)\, N\, \frac{k^3}{3\,L}\,. \tag{16}$$

The covariance in equation (16) is positive for $0 < m < 1$. Intuitively, provided FIP investors do not dominate the economy, their failure to process small signals induces price changes in both the first and second periods that are positively correlated, which results in price momentum. Indeed, signals whose absolute values are below k are processed by rational investors in the first period and then by FIP investors in the second period. In addition, an increase in k leads to stronger momentum since more signals and larger signals (in absolute value) are truncated. Finally, the momentum effect is decreasing in L since signal truncations are less likely when L is higher.

A3: Conditional Momentum: Frog-in-the-Pan Effect

Having demonstrated the ability of FIP investors to generate price momentum unconditionally, we also explore the intuition behind our ID measure's ability to affect price momentum conditional on past returns (PRET=P_1). In our illustrative model, the expected price change in the second period at time 1 is simply the net truncation during the first period defined as:

$$E_1[P_2 - P_1] = m \sum_{i=1}^{N} s^i \, 1_{\{|s^i|<k\}} \, . \tag{17}$$

Consider two past winners with an identical PRET > 0 but different ID measures. The first stock has a negative ID near -1 that implies more positive than negative signals were realized during the first period with the positive signals likely to be small on average. Consequently, the net truncation is also likely to be positive when PRET is positive and ID is negative. Conversely, if the second stock has a positive ID near 1 but the same PRET, then more negative than positive signals are realized during the first period. For the second stock to have the same positive PRET, the positive signals are required to be large on average while the negative signals are small in absolute value. Therefore, the net truncation is likely to be negative for the second stock with a positive ID. Consequently, although PRET is equivalent for both stocks, stronger return continuation is predicted for the first stock with a negative ID. The same intuition applies to past losers.

Overall, a negative ID yields a high percentage of small signals whose sign is the same as PRET. In other words, conditional on PRET, ID provides a simple non-parametric proxy for the net truncation. As such, ID predicts future price changes and explains cross-sectional differences in momentum.

The above implications are confirmed in simulations. We use the following parameter values: m=0.5, k=0.02, L=0.05, and N=250 to simulate 10,000 paths of daily signals simulated using draws from the Uniform distribution. We then compute price changes in the first period (PRET) based on P_1 in equation (13) and expected price changes in the second period (FRET) based on $s_1 - P_1$ in equation (17).

ID is also computed based on the signs of the N draws. We then sequentially double-sort the price paths into PRET and ID quintiles. This double-sort procedure parallels the procedure underlying Panel A of Table 2. The corresponding FRET for each of the 25 "PRET by ID" double-sorts is recorded in the following table

		PRET = P_1					FRET = $s_1 - P_1$					
ID of	Average	Winner				Loser	Winner				Loser	
N signals	ID	1	2	3	4	5	1	2	3	4	5	momentum
discrete	0.013	51.19	22.20	0.84	-21.57	-50.74	-5.01	-5.70	-0.62	5.73	4.08	-9.09
2	-0.020	56.08	24.06	-0.69	-22.39	-55.15	-1.10	-2.14	0.57	1.92	0.62	-1.72
3	-0.041	59.67	23.99	-0.14	-24.71	-58.24	1.41	0.46	0.35	-0.44	-1.45	2.86
4	-0.063	70.71	23.97	-1.52	-26.10	-68.73	2.85	3.11	-0.06	-2.76	-2.89	5.74
continuous	-0.098	80.50	26.06	-0.75	-27.44	-82.20	6.88	6.28	-0.44	-6.45	-6.27	13.15
average	-0.042	63.63	24.06	-0.39	-24.44	-63.01	1.01	0.40	-0.04	-0.40	-1.18	2.19

The simulation results confirm our model's ability to generate an unconditional momentum profit, which equals 2.19%. Moreover, momentum increases monotonically as ID becomes more continuous. Following continuous information, the momentum profit is 13.15% relative to the -9.09% reversal following discrete information.[8]

A4: The Lower Bound on Investor Attention

The lower bound on investor attention is responsible for the FIP effect in our illustrative model and is represented by the k parameter. A higher k parameter implies that FIP investors are more likely to truncate signals and delay their incorporation in the stock price.

Equation (16) predicts that a higher k parameter increases momentum unconditionally. Conditionally, holding PRET constant, a higher k also predicts a stronger FIP effect since more signals are temporarily truncated, especially when information is continuous and small signals arrive frequently. Unreported simulation results confirm these unconditional and conditional predictions. Furthermore, as the lower bound on investor attention varies over time and across stocks, we empirically test these predictions using proxies for k that also vary over time and across stocks.

[8]The simulation exercise is not intended to match the empirical results in Panel A of Table 2 exactly due to the simplistic assumptions underlying our illustrative model.

Table 1: Summary Statistics

Panel A of this table reports summary statistics for information discreteness (ID), formation-period returns (PRET) and their absolute value (|PRET|), idiosyncratic volatility (IVOL), 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, standard deviation, and autocorrelation along with the 25th, 50th, and 75th percentiles. The first-order autocorrelations are computed over non-overlapping calendar-time horizons starting and ending in June using a pooled regression involving lagged values for each firm-level characteristic. ID is 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. 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 formation period. 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). Grinblatt and Han (2005) estimate the UCG variable at the firm-level using reference prices defined by prior returns and turnover. Panel B contains the cross-sectional correlations between the variables in Panel A.

Panel A: Summary statistics

		Percentiles			Standard	Auto-
	Mean	25th	50th	75th	deviation	correlation
ID	-0.034	-0.065	-0.031	0.000	0.053	0.034
PRET	0.177	-0.189	0.078	0.367	0.904	-0.040
|PRET|	0.430	0.125	0.279	0.528	0.815	0.062
IVOL	0.517	0.053	0.139	0.385	4.321	0.833
DELAY	0.562	0.293	0.568	0.849	0.303	0.333
RC	0.180	0.000	0.000	0.000	0.384	0.046
UCG	-0.160	-0.173	0.068	0.206	0.885	0.660

Panel B: Correlations

	ID	PRET	|PRET|	IVOL	DELAY	RC	UCG
ID	1						
PRET	0.163	1					
|PRET|	-0.304	0.366	1				
IVOL	0.081	-0.181	0.339	1			
DELAY	0.047	-0.063	0.041	0.253	1		
RC	-0.299	0.115	0.337	-0.056	0.005	1	
UCG	0.056	0.685	0.100	-0.442	-0.109	0.105	1

Table 2: 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 pertain to 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 reports the holding-period returns from independent double-sorts (rather than sequential double-sorts) that condition on PRET, then ID. Panel C contains the results from a modification of ID denoted ID_{HERF} in equation (2) that incorporates the magnitude of daily returns. Panel D reports on another modification of information discreteness denoted ID_Z in equation (3) to account for zero return days that coincide with low liquidity. The results in Panel A through Panel D pertain to the 1976 to 2007 sample period. Panel E 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 ID

ID	Winner				Loser	Average	unadjusted six-month		three-factor six-month		unadjusted three-year		three-factor three-year	
	1	2	3	4	5	ID	return	t-stat	alpha	t-stat	return	t-stat	alpha	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: Independent double-sorts involving formation-period returns and ID

ID	Winner				Loser	Average	unadjusted six-month		three-factor six-month		unadjusted three-year		three-factor three-year	
	1	2	3	4	5	ID	return	t-stat	alpha	t-stat	return	t-stat	alpha	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 C: Sequential double-sorts involving formation-period returns and ID_{HERF}

ID_{HERF}	Winner				Loser	Average	unadjusted six-month		three-factor six-month		unadjusted three-year		three-factor three-year	
	1	2	3	4	5	ID_{HERF}	return	t-stat	alpha	t-stat	return	t-stat	alpha	t-stat
discrete	8.95	8.72	8.94	8.63	7.04	0.04	1.91	*1.36*	3.85	*3.22*	-8.59	*-1.57*	-5.16	*-0.96*
2	9.25	8.56	8.43	8.13	5.95	0.02	3.30	*2.45*	6.00	*4.89*	-1.83	*-0.36*	0.59	*0.12*
3	9.11	8.22	7.76	7.23	5.46	0.00	3.65	*2.55*	6.91	*4.61*	*1.89*	*0.40*	5.12	*1.15*
4	9.13	8.52	7.87	7.41	4.81	-0.01	4.32	*3.12*	7.81	*5.63*	4.04	*0.85*	6.73	*1.44*
continuous	10.14	9.43	7.78	6.42	3.46	-0.05	6.68	*5.29*	9.84	*6.40*	4.77	*0.87*	7.20	*1.32*
continuous - discrete							4.77	*4.19*	5.99	*4.08*	13.36	*2.76*	12.36	*2.80*

Panel D: Sequential double-sorts involving formation-period returns and ID_Z

ID_Z	Winner				Loser	Average	unadjusted six-month		three-factor six-month		unadjusted three-year		three-factor three-year	
	1	2	3	4	5	ID_Z	return	t-stat	alpha	t-stat	return	t-stat	alpha	t-stat
discrete	8.40	7.92	7.54	7.03	5.41	0.04	2.99	*2.14*	4.92	*5.37*	-3.96	*-0.77*	-4.00	*-0.80*
2	9.83	9.08	8.14	7.33	5.04	-0.01	4.79	*3.99*	6.61	*7.54*	1.99	*0.40*	1.44	*0.30*
3	11.21	9.60	8.36	7.12	4.54	-0.04	6.67	*5.48*	9.01	*8.87*	3.70	*0.79*	4.77	*1.04*
4	11.11	9.67	8.41	7.08	3.95	-0.07	7.16	*6.03*	9.24	*8.85*	2.41	*0.50*	4.62	*1.04*
continuous	11.79	9.45	8.63	7.51	2.68	-0.15	9.11	*7.31*	11.75	*10.39*	9.90	*1.86*	13.72	*3.06*
continuous - discrete							6.12	*5.03*	6.83	*6.45*	13.86	*2.68*	17.72	*3.76*

Panel E: Sequential double-sorts involving formation-period returns and ID since 1927

ID	Winner				Loser	Average	unadjusted six-month		three-factor six-month		unadjusted three-year		three-factor three-year	
	1	2	3	4	5	ID	return	t-stat	alpha	t-stat	return	t-stat	alpha	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 3: Model Predictions

This table reports on the results from two cross-sectional tests based on proxies for the k parameter in our model. The k parameter defines the lower bound on investor attention, as detailed in Appendix A. Institutional ownership concentration and media coverage provide two firm-level proxies for this parameter. Firms with disperse institutional ownership and those receiving low media coverage have less attentive investors (higher k parameters) than firms with concentrated institutional ownership and those receiving high media coverage. The information discreteness (ID) measure in equation (1) is defined as $\text{sgn(PRET)} \cdot [\%neg - \%pos]$ 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. Panel A and Panel B replicate the sequential double-sorts in Panel A of Table 2 based on PRET, then ID among stocks with concentrated / disperse institutional ownership and high / low media coverage, respectively. Returns over six-month holding periods are then reported. The concentration of institutional ownership equals the proportion of institutional ownership accounted for by the five largest institutional investors in a firm. High media coverage occurs when firms receive four or more news articles in a quarter since four is the cross-sectional median for the number of quarterly firm-level news articles. In Panel B, our final sample includes over 1,200,000 firm-day media reports for 9,500 firms between 1991 and 2007. All t-statistics are Newey-West adjusted with six lags and reported in italics.

Panel A: Double-sorts involving PRET and ID across disperse and concentrated institutional ownership

Institutional ownership	ID	Winner 1	2	3	4	Loser 5	Average ID	unadjusted return	unadjusted *t*-stat	three-factor alpha	three-factor *t*-stat
concentrated	discrete	7.88	7.01	6.28	5.94	4.55	0.14	3.33	*2.27*	6.42	*4.08*
	2	9.04	7.67	6.99	6.47	4.96	0.00	4.08	*4.18*	6.80	*6.51*
	3	9.68	7.74	7.38	6.50	4.33	-0.01	5.35	*4.46*	8.25	*7.42*
	4	9.90	7.67	7.43	6.33	3.61	-0.04	6.29	*4.53*	8.99	*7.11*
	continuous	10.52	7.69	7.29	6.19	1.75	-0.24	8.77	*5.59*	12.14	*7.59*
	continuous - discrete						-0.38	5.44	*4.88*	5.72	*5.61*
disperse	discrete	3.49	5.93	5.92	5.39	4.29	0.03	-0.80	*-0.42*	0.07	*0.05*
	2	8.45	8.10	8.02	6.54	2.92	-0.01	5.53	*2.64*	9.31	*4.99*
	3	9.78	9.51	8.41	7.23	1.90	-0.03	7.88	*5.09*	9.85	*7.30*
	4	10.08	9.10	9.23	7.93	1.25	-0.05	8.83	*5.08*	11.30	*6.59*
	continuous	9.43	10.35	10.32	7.04	-1.00	-0.09	10.43	*5.75*	11.74	*6.62*
	continuous - discrete						-0.13	11.23	*4.57*	11.66	*5.59*

Panel B: Double-sorts involving PRET and ID across high and low media coverage

Media		Winner				Loser	Average	unadjusted		three-factor	
coverage	ID	1	2	3	4	5	ID	return	*t*-stat	alpha	*t*-stat
high	discrete	7.15	6.04	5.31	5.47	3.18	0.03	3.97	*0.70*	9.12	*3.52*
	2	9.82	7.69	6.54	5.80	5.43	-0.01	4.39	*1.32*	8.56	*3.11*
	3	11.15	7.58	5.78	6.95	4.47	-0.01	6.68	*1.49*	9.25	*2.90*
	4	9.46	8.12	7.94	5.78	3.36	-0.06	6.10	*1.53*	10.03	*3.38*
	continuous	11.14	6.94	7.14	6.47	3.42	-0.10	7.72	*1.87*	11.07	*3.89*
	continuous - discrete						-0.14	3.75	*1.05*	1.96	*1.01*
low	discrete	7.41	6.63	5.78	5.90	5.73	0.03	1.68	*0.50*	4.81	*2.62*
	2	8.92	8.30	7.17	6.71	4.52	-0.01	4.40	*1.82*	7.39	*3.78*
	3	10.52	8.31	7.32	6.57	4.17	-0.04	6.35	*2.11*	7.91	*3.59*
	4	9.44	8.14	7.63	6.52	4.31	-0.06	5.13	*1.82*	8.79	*4.40*
	continuous	9.23	7.54	7.55	6.88	1.66	-0.10	7.57	*7.01*	10.74	4.16
	continuous - discrete						-0.14	5.89	*1.87*	5.94	*2.30*

Table 4: Disposition effect

This table provides evidence that limited attention instead of the disposition effect is responsible for the ability of information discreteness (ID) to explain cross-section differences in momentum. 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. Panel A contains the results from the Fama-MacBeth regression in equation (5), $r_{i,t+1,t+6} = \beta_0 + \beta_1 \,\mathrm{PRET}_{i,t} + \beta_2 \,\mathrm{NegPRET}_{i,t} + \beta_3 \,\mathrm{PosRC}_{i,t} + \beta_4 \,\mathrm{NegRC}_{i,t} + \beta_5 \,\mathrm{PosID}_{i,t} + \beta_6 \,\mathrm{NegID}_{i,t} + \beta_7 \,\mathrm{SIZE}_{i,t} + \beta_8 \,\mathrm{BM}_{i,t} + \epsilon_{i,t}$. 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. For ease of comparison with Grinblatt and Moskowitz (2004), firm size (SIZE) and book-to-market ratios (BM) are included as control variables to match their specification. Panel B contains the results from the time series regression in equation (6), $FIPRet_{t+1,t+6} = \beta_0 + \beta_1 \,\mathrm{Trend} + \beta_2 \,\mathrm{AGG\ MKT}_{t-1} + \beta_3 \,\mathrm{AGG\ UCG}_{t-1} + \beta_4 \,\mathrm{AGG\ RC}_{t-1} + \beta_5 \,\mathrm{Log(NUMST)}_{t-1} + \beta_6 \,\Delta\mathrm{Log(Media)}_{t-1} + \epsilon_t$, which examines the six-month holding-period return from an enhanced momentum strategy that conditions on continuous information. This enhanced momentum strategy buys past winners and sells past losers following continuous information in the formation period. The independent variables are the aggregate market return (AGG MKT), aggregate unrealized capital gains (AGG UCG), and aggregate return consistency (AGG RC) during the formation period. These aggregate characteristics equally-weight the firm-specific characteristics of stocks in the long and short portfolios. The log number of all stocks available for investment, which is denoted Log(NUMST), proxies for limited attention along with ΔLog(Media) that is defined by changes in the media coverage of stocks included in the enhanced momentum strategy. The Trend index starts in January of 1992 while the MEDIA variable is based on over 1,200,000 firm-day news reports for 9,500 firms between 1991 and 2007. All t-statistics are Newey-West adjusted with six lags and reported in italics.

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

		intercept	PRET	NegPRET	PosRC	NegRC	PosID	NegID	SIZE	BM	adj. R^2
Post 1927	coefficient	0.0659	0.0366	-0.0220	-0.0018	-0.0103	0.0628	-0.1295			0.040
	t-stat	*12.24*	*9.79*	*-1.58*	*-0.57*	*-4.39*	*2.01*	*-9.60*			
Post 1976	coefficient	0.0806	0.0206	0.1319	0.0040	0.0052	0.1180	-0.0943			0.033
	t-stat	*14.19*	*4.94*	*9.45*	*2.42*	*2.24*	*4.38*	*-4.95*			
	coefficient	0.1024	0.0167	0.1146	0.0040	0.0039	0.1925	-0.1346	-0.0033	0.0209	0.048
	t-stat	*10.05*	*3.84*	*8.66*	*2.04*	*1.54*	*6.59*	*-6.53*	*-5.20*	*7.33*	

Panel B: Time series variation in momentum following continuous information

	Trend	AGG MKT	AGG UCG	AGG RC	Log(NUMST)	ΔLog(MEDIA)	adj. R^2
coefficient	-0.0007	-5.3253	13.2547	-5.7681	22.5052	-5.1734	0.163
t-stat	*-0.04*	*-0.95*	*1.60*	*-0.79*	*3.86*	*-2.66*	

Table 5: Alternative explanations

This table examines alternative explanations to limited attention for the stronger momentum following continuous information. Panel A contains the results for an enhanced momentum strategy that conditions on stocks with continuous information during their formation period but distinguishes between formation-period returns (PRET) that were confirming or disconfirming relative to long-term analyst forecasts (LTG). For past winners, confirming information is defined by high LTG forecasts before the formation period while disconfirming information is defined by low LTG forecasts. Conversely, for past losers, confirming information is defined by low LTG forecasts before the formation period while disconfirming information is defined by high LTG forecasts. Unadjusted momentum returns and risk-adjusted returns relative to the three-factor model of Fama and French (1993) are presented over six-month horizons. The empirical methodology underlying Panel B parallels Table 3 with institutional ownership concentration (media coverage) replaced with analyst forecast dispersion. Analyst forecast dispersion proxies for the strength of investor prior beliefs with higher forecast dispersion associated with less informative priors. In Panel C, unadjusted returns and risk-adjusted returns relative to the three-factor model of Fama and French (1993) over a six-month holding period are presented for sequential double-sorts that first condition on residual idiosyncratic volatility (RES IVOL), then PRET. RES IVOL is defined using the $\epsilon_{i,t}^{IVOL}$ residuals of the following cross-sectional regression $\text{IVOL}_{i,t} = \gamma_{0,t} + \gamma_{1,t} \, |\text{PRET}|_{i,t} + \epsilon_{i,t}^{IVOL}$ in equation (8) to control for the influence of formation-period returns on IVOL. Idiosyncratic volatility (IVOL) is estimated during the formation period using the procedure in Fu (2009). All t-statistics are Newey-West adjusted with six lags and reported in italics.

Panel A: Momentum following confirming or disconfirming continuous information

					disconfirming - confirming			
			unadjusted		unadjusted		three-factor	
LTG vs PRET	Winner	Loser	return	t-stat	return	t-stat	return	t-stat
confirming	11.03	3.02	8.02	*4.13*	-2.87	*-1.20*	-3.89	*-1.59*
disconfirming	10.37	5.23	5.14	*2.00*				

Panel B: Double-sorts involving PRET and ID across high and low analyst forecast dispersion

Forecast dispersion	ID	Winner 1	2	3	4	Loser 5	Average ID	unadjusted return	unadjusted *t*-stat	three-factor alpha	three-factor *t*-stat
high	discrete	7.58	7.00	5.91	5.83	4.73	0.03	2.85	*1.32*	4.88	*3.62*
	2	9.13	8.35	7.01	6.16	4.22	-0.01	4.91	*2.66*	7.10	*5.75*
	3	10.56	8.33	7.26	6.32	4.02	-0.03	6.54	*3.76*	9.08	*6.81*
	4	9.70	7.95	7.21	6.08	3.07	-0.06	6.63	*3.91*	9.25	*6.19*
	continuous	9.88	7.58	6.84	5.69	1.37	-0.10	8.51	*4.51*	11.01	*6.44*
	continuous - discrete						-0.13	5.66	*3.10*	6.13	*5.48*
low	discrete	7.10	6.70	5.52	6.17	5.38	0.03	1.72	*0.72*	4.10	*2.42*
	2	6.74	7.09	6.30	6.81	4.31	-0.01	2.43	*1.07*	5.48	*2.97*
	3	7.52	8.38	6.19	6.77	4.80	-0.04	2.72	*1.42*	5.90	*3.27*
	4	8.06	7.70	7.46	6.15	4.11	-0.06	3.95	*2.04*	6.78	*3.10*
	continuous	9.97	7.70	7.65	7.57	3.13	-0.10	6.84	*2.47*	9.97	*4.01*
	continuous - discrete						-0.13	5.12	*2.47*	5.87	*3.56*

Panel C: Double-sorts involving residual IVOL, then formation-period returns

RES IVOL	Winner 1	2	3	4	Loser 5	Average RES IVOL	unadjusted return	unadjusted *t*-stat	three-factor alpha	three-factor *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*

Table 6: Fama-MacBeth Regressions

This table reports on the ability of information of information discreteness to explain cross-sectional variation in momentum after controlling for an array of firm characteristics. 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. Panel A contains the results from Fama-MacBeth regressions based on the specification in equation (9), $r_{i,t+1,t+6} = \beta_0 + \beta_1\,\mathrm{PRET}_{i,t} + \beta_2\,\mathrm{ID}_{i,t} + \beta_3\,(\mathrm{PRET}\cdot\mathrm{ID})_{i,t} + \alpha\,X_{i,t} + \alpha_I\,(\mathrm{PRET}\cdot X)_{i,t} + \epsilon_{i,t}$. The X vector consists of return consistency (RC), unrealized capital gains (UCG), earnings surprises (SUE), book-to-market ratios (BM), firm size (SIZE), turnover during the formation period (TURN), idiosyncratic volatility (IVOL), analyst coverage (COVER), Amihud's liquidity ratio (AMIHUD), and the price delay metric (DELAY) of Hou and Moskowitz (2005). The dependent variable in these regressions is the six-month return of individual stocks. As defined in Grinblatt and Moskowitz (2004), RC is a dummy variable that 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). Grinblatt and Han (2005) estimate UCG using reference prices defined by prior returns and turnover. 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. BM ratios are computed in July using firm-level book equity and market capitalization for the fiscal year ending in the preceding calendar year while SIZE is defined as the log of a firm's market capitalization in July. IVOL is estimated during the formation period using the procedure in Fu (2009) while analyst coverage is defined as one plus the log number of analysts issuing forecasts for a particular firm. All t-statistics are Newey-West adjusted with six lags and reported in italics. Panel B examines the economic significance of the Fama-MacBeth coefficients. This analysis uses one standard deviation fluctuations in firm characteristics from their averages within the portfolios of past winners and past losers. We then compute the return implications of these fluctuations using the coefficient estimates from the bottom row of Panel A that accounts for all firm characteristics as well as their interactions with PRET.

Panel A: Fama-MacBeth regressions involving information discreteness

Specification		intercept	PRET	ID	PRET · ID	RC	UCG	SUE	BM	SIZE	TURN	IVOL	COVER	AMIHUD	DELAY	adj. R^2
Post 1927	coefficient	0.0642	0.0109	0.0323	-0.0634											0.035
	t-stat	*11.61*	*2.65*	*7.06*	*-3.17*											
Post 1976	coefficient	0.0873	0.0096	0.1254	-0.2177											0.013
	t-stat	*12.05*	*2.83*	*8.08*	*-5.39*											
disposition effect	coefficient	0.0858	0.0159	0.1405	-0.2831	0.0040	-0.0078									0.026
	t-stat	*12.97*	*3.86*	*10.12*	*-7.14*	*2.81*	*-1.94*									
all characteristics	coefficient	0.1344	0.0083	0.0826	-0.2748	0.0033	-0.0038	0.0069	0.0091	-0.0044	-0.0236	0.0060	0.0066	0.0025	-0.0108	0.067
	t-stat	*11.79*	*3.10*	*6.78*	*-10.39*	*2.29*	*-1.35*	*14.04*	*5.07*	*-5.82*	*-3.76*	*0.41*	*3.42*	*3.88*	*-2.77*	
disposition effect	coefficient	0.0850	0.0145	0.1515	-0.2878	0.0027	0.0004									0.031
with interactions	t-stat	*12.89*	*3.62*	*10.81*	*-6.66*	*1.57*	*0.10*									
all characteristics	coefficient	0.1274	0.0234	0.0805	-0.2817	-0.0017	0.0107	0.0074	0.0121	-0.0044	-0.0191	0.0131	0.0064	0.0035	-0.0125	0.081
with interactions	t-stat	*11.66*	*2.42*	*6.61*	*-8.54*	*-0.96*	*2.65*	*14.31*	*7.07*	*-6.17*	*-3.14*	*0.85*	*2.95*	*3.34*	*-3.12*	

Continuation of Panel A: Interaction terms from above Fama-MacBeth regressions

Specification		PRET · RC	PRET · UCG	PRET · SUE	PRET · BM	PRET · SIZE	PRET · TURN	PRET · IVOL	PRET · COVER	PRET · AMIHUD	PRET · DELAY
disposition effect	coefficient	0.0169	-0.0037								
with interactions	t-stat	*4.30*	*-1.28*								
all characteristics	coefficient	-0.0059	0.0215	-0.0012	0.0102	0.0013	-0.0264	-0.0148	-0.0050	-0.0008	-0.0099
with interactions	t-stat	*-2.11*	*4.06*	*-1.08*	*5.63*	*1.29*	*-3.75*	*-1.48*	*-1.49*	*-0.34*	*-1.71*

Panel B: Economic significance of the β coefficients within past winners and past losers

		PRET	ID	RC	UCG	BM	SIZE	TURN	IVOL	COVER
Past	mean	1.122	-0.043	0.353	0.230	0.500	11.875	0.618	0.248	0.377
winners	std. dev.		0.054	0.478	0.184	0.695	2.496	0.291	0.238	0.790
	beta for characteristic		0.0805	-0.0017	0.0107	0.0121	-0.0044	-0.0191	0.0131	0.0064
	interaction beta with PRET		-0.2817	-0.0059	0.0215	0.0102	0.0013	-0.0264	-0.0148	-0.0050
	return: above mean		-0.002	-0.007	0.014	0.028	-0.043	-0.044	-0.002	0.001
	return: below mean		0.023	0.001	0.002	-0.005	-0.028	-0.016	0.000	0.000
	return difference		-0.025	-0.008	0.013	0.033	-0.015	-0.028	-0.002	0.001
	absolute return difference relative to ID			31.52%	50.76%	130.07%	59.55%	112.55%	6.56%	4.52%
Past	mean	-0.276	-0.054	0.150	-0.190	0.680	11.082	0.564	0.228	0.452
losers	std. dev.		0.052	0.357	0.278	2.612	2.535	0.290	0.232	0.865
	beta for characteristic		0.0805	-0.0017	0.0107	0.0121	-0.0044	-0.0191	0.0131	0.0064
	interaction beta with PRET		-0.2817	-0.0059	0.0215	0.0102	0.0013	-0.0264	-0.0148	-0.0050
	return: above mean		0.000	0.000	0.000	0.031	-0.065	-0.010	0.008	0.010
	return: below mean		-0.017	0.000	-0.002	-0.018	-0.041	-0.003	0.000	-0.003
	return difference		0.017	0.000	0.003	0.049	-0.024	-0.007	0.008	0.013
	absolute return difference relative to ID			0.31%	15.89%	292.29%	146.11%	41.16%	47.98%	80.73%

Table 7: Residual Information Discreteness

This table reports on the ability of information discreteness (ID) to explain cross-sectional variation in momentum after orthogonalizing ID against an array of firm characteristics. 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. Residual information discreteness (RES ID) is estimated from equation (10) as the $\epsilon_{i,t}^{ID}$ residuals from regressing ID on the absolute value of PRET, return consistency (RC), book-to-market ratios (BM), firm size (SIZE), turnover during the formation period (TURN), idiosyncratic volatility (IVOL), analyst coverage (COVER), and institutional ownership. As defined in Grinblatt and Moskowitz (2004), return consistency (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). BM ratios are computed in July using firm-level book equity and market capitalization for the fiscal year ending in the preceding calendar year while SIZE is defined as the log of a firm's market capitalization in July. IVOL is estimated during the formation period using the procedure in Fu (2009) while analyst coverage is defined as one plus the log number of analysts issuing forecasts for a particular firm. IO is defined using quarterly data on institutional ownership reported in 13f filings with the SEC. The holding-period returns reported in Panel A 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 B contains the results from several Fama-MacBeth regression specifications based on equation (9). All t-statistics are Newey-West adjusted with six lags and reported in italics.

Panel A: Double-sorts involving PRET and residual ID

							unadjusted six-month		three-factor six-month		unadjusted three-year		three-factor three-year	
RES ID	Winner 1	2	3	4	Loser 5	Average RES ID	return	t-stat	alpha	t-stat	return	t-stat	alpha	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 B: Fama-MacBeth regressions of momentum on residual ID

Specification		intercept	PRET	RES ID	PRET · RES ID	RC	UCG	SUE	BM	SIZE	TURN	IVOL	COVER	AMIHUD	DELAY	adj. R^2
Post 1976	coefficient	0.0836	0.0204	0.1297	-0.3394											0.014
	t-stat	*11.09*	*4.13*	*9.09*	*-8.39*											
disposition effect	coefficient	0.0789	0.0310	0.1002	-0.3816	0.0024	-0.0067									0.027
	t-stat	*10.69*	*7.59*	*7.48*	*-10.82*	*1.35*	*-1.48*									
all characteristics	coefficient	0.1240	0.0306	0.0847	-0.3890	0.0013	-0.0033	0.0059	0.0098	-0.0041	-0.0258	0.0098	0.0071	0.0029	-0.0079	0.066
	t-stat	*10.99*	*8.88*	*7.57*	*-12.46*	*0.88*	*-1.13*	*12.14*	*5.44*	*-5.49*	*-4.11*	*0.65*	*3.67*	*4.51*	*-2.02*	
disposition effect	coefficient	0.0788	0.0257	0.1088	-0.3824	-0.0023	0.0047									0.031
with interactions	t-stat	*10.68*	*6.05*	*8.15*	*-10.35*	*-1.27*	*0.91*									
all characteristics	coefficient	0.1207	0.0224	0.0782	-0.3618	-0.0055	0.0088	0.0069	0.0125	-0.0043	-0.0214	0.0148	0.0071	0.0039	-0.0105	0.079
with interactions	t-stat	*11.01*	*2.43*	*6.88*	*-9.68*	*-3.26*	*2.21*	*13.17*	*7.27*	*-5.92*	*-3.48*	*0.92*	*3.22*	*3.73*	*-2.60*	

Continuation of Panel B: Interaction terms from above Fama-MacBeth regressions

Specification		PRET · RC	PRET · UCG	PRET · SUE	PRET · BM	PRET · SIZE	PRET · TURN	PRET · IVOL	PRET · COVER	PRET · AMIHUD	PRET · DELAY
disposition effect	coefficient	0.0176	0.0055								
with interactions	t-stat	*3.60*	*1.85*								
all characteristics	coefficient	0.0069	0.0193	-0.0006	0.0115	0.0020	-0.0229	0.0029	-0.0063	-0.0001	-0.0067
with interactions	t-stat	*2.58*	*4.06*	*-0.53*	*6.58*	*2.06*	*-3.38*	*0.29*	*-1.82*	*-0.05*	*-1.21*

Table 8: 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 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. 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, $\mathrm{SURP}_{i,t} = \beta_0 + \beta_1\,\mathrm{ID}_{i,t} + \beta_2\,\mathrm{PRET}_{i,t} + \beta_3\,(\mathrm{ID}\cdot\mathrm{PRET})_{i,t} + \beta_4\,\mathrm{DISP}_{i,t} + \beta_5\,\mathrm{COVER}_{i,t} + \beta_6\,\mathrm{BM}_{i,t} + \beta_7\,\mathrm{SIZE}_{i,t} + \beta_8\,\mathrm{TURN}_{i,t} + \beta_9\,\mathrm{IO}_{i,t} + \epsilon_{i,t}$. 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 sgn(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. Panel C reports on the relationship between momentum and ID_f using the Fama-MacBeth regression specifications based on equation (9) that replace ID with ID_f. The t-statistics are Newey-West adjusted with six lags and reported in italics.

Panel A: Cross-sectional regressions of analyst forecast errors on ID

	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: Double-sort involving PRET and ID_f

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: Fama-MacBeth regressions involving ID_f

Specification		intercept	PRET	ID_f	PRET · ID_f	RC	UCG	SUE	BM	SIZE	TURN	IVOL	COVER	AMIHUD	DELAY	adj. R^2
Post 1976	coefficient	0.0711	0.0214	0.0398	-0.1283											0.037
	t-stat	*10.33*	*3.32*	*4.92*	*-6.94*											
disposition effect	coefficient	0.0665	0.0072	0.0479	-0.1285	0.0125	0.0306									0.060
	t-stat	*9.29*	*0.90*	*5.88*	*-6.66*	*3.62*	*3.23*									
all characteristics	coefficient	0.0954	0.0141	0.0519	-0.1439	0.0164	0.0285	0.0019	0.0218	-0.0025	-0.0141	0.0101	0.0049	-0.6977	-0.0099	0.118
	t-stat	*3.48*	*2.88*	*5.44*	*-6.76*	*2.91*	*3.96*	*3.87*	*4.97*	*-1.43*	*-2.19*	*0.41*	*2.76*	*-0.95*	*-1.61*	
disposition effect	coefficient	0.0640	0.0048	0.0482	-0.1245	0.0090	0.0457	0.0331	-0.0022							0.069
with interactions	t-stat	*8.96*	*0.56*	*5.62*	*-6.36*	*2.00*	*4.83*	*2.27*	*-0.48*							
all characteristics	coefficient	0.1160	0.0550	0.0721	-0.1710	0.0067	0.0141	0.0013	0.0100	-0.0028	-0.0149	-0.0186	0.0007	-2.3048	-0.0151	0.146
with interactions	t-stat	*2.31*	*2.05*	*4.73*	*-5.61*	*1.13*	*0.65*	*1.38*	*0.83*	*-1.33*	*-1.88*	*-0.36*	*0.26*	*-1.04*	*-1.02*	

Continuation of Panel C: Interaction terms from above Fama-MacBeth regressions

Specification		PRET · RC	PRET · UCG	PRET · SUE	PRET · BM	PRET · SIZE	PRET · TURN	PRET · IVOL	PRET · COVER	PRET · AMIHUD	PRET · DELAY
disposition effect	coefficient	-0.0022	0.0331								
with interactions	t-stat	*-0.48*	*2.27*								
all characteristics	coefficient	0.0023	0.1226	-0.0017	0.0243	-0.0023	-0.0375	-0.0709	0.0027	3.4302	-0.0370
with interactions	t-stat	*0.44*	*1.41*	*-1.04*	*1.17*	*-1.33*	*-0.78*	*-1.59*	*0.49*	*1.09*	*-1.79*

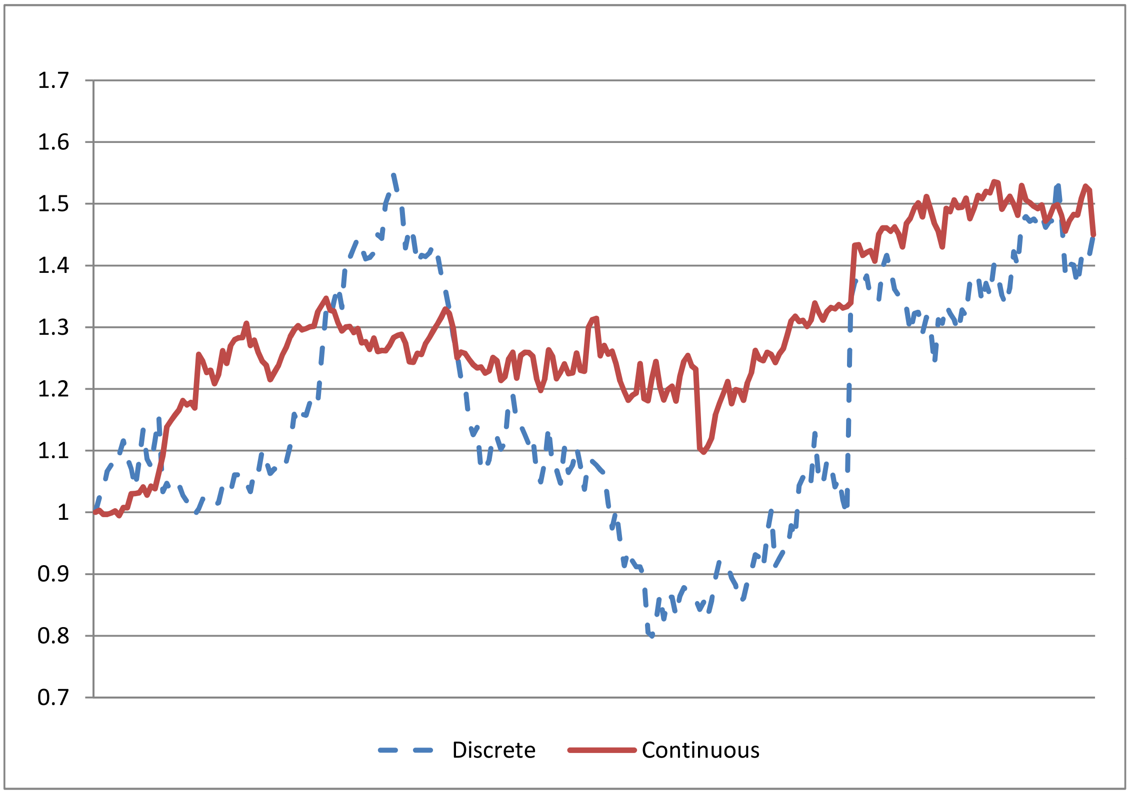

Figure 1 This figure provides a visual illustration of the difference between continuous information versus discrete information. Both firms have the same starting and ending stocks prices but with different intermediate returns over the 250 "daily" periods. Information discreteness (ID) is defined in 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.

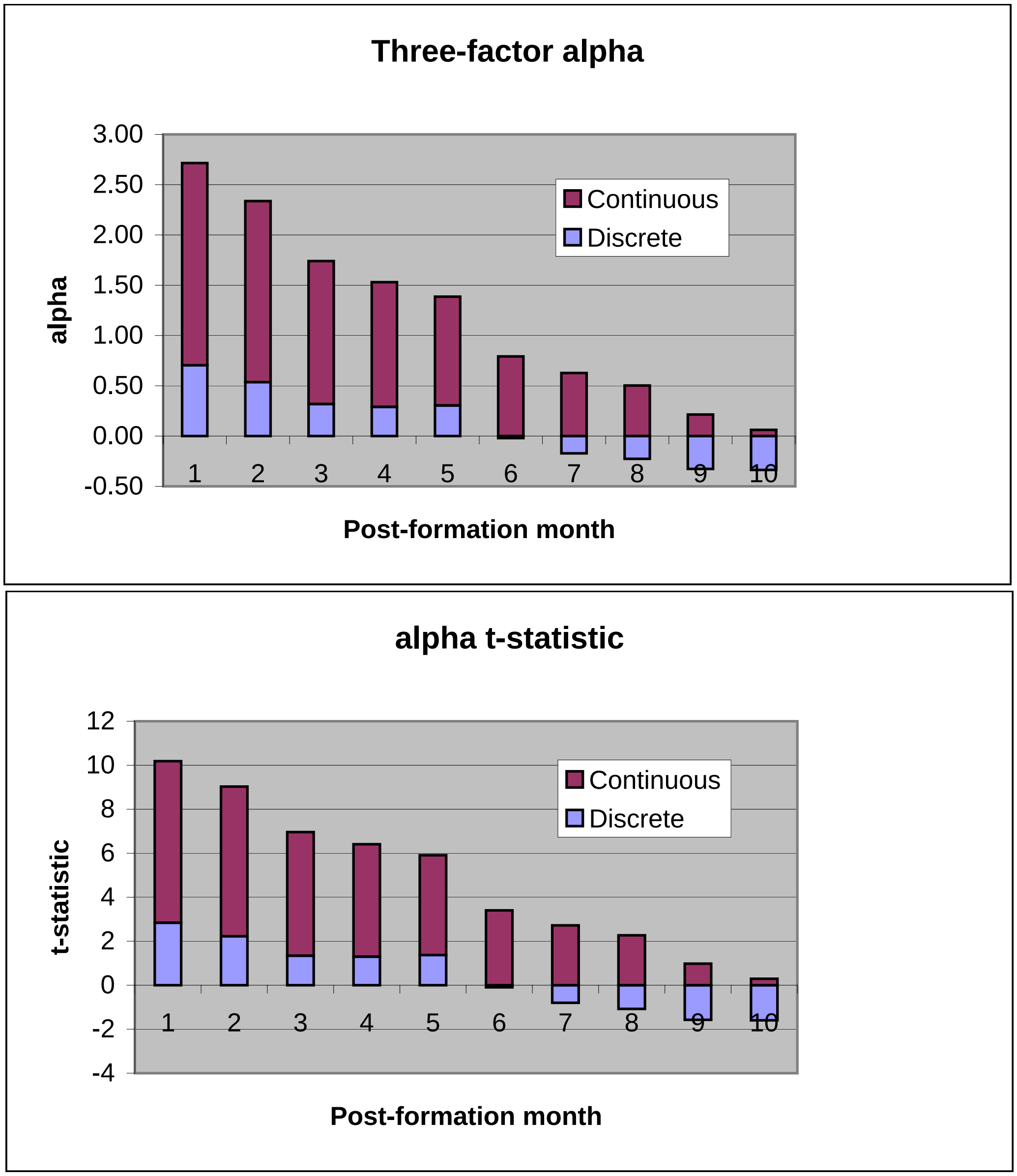

Figure 2 This figure plots risk-adjusted momentum profits in the continuous and discrete information portfolios from one to ten months after portfolio formation. Information discreteness is defined in equation (1) to capture the distribution of daily returns across the formation period. Continuous information 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.

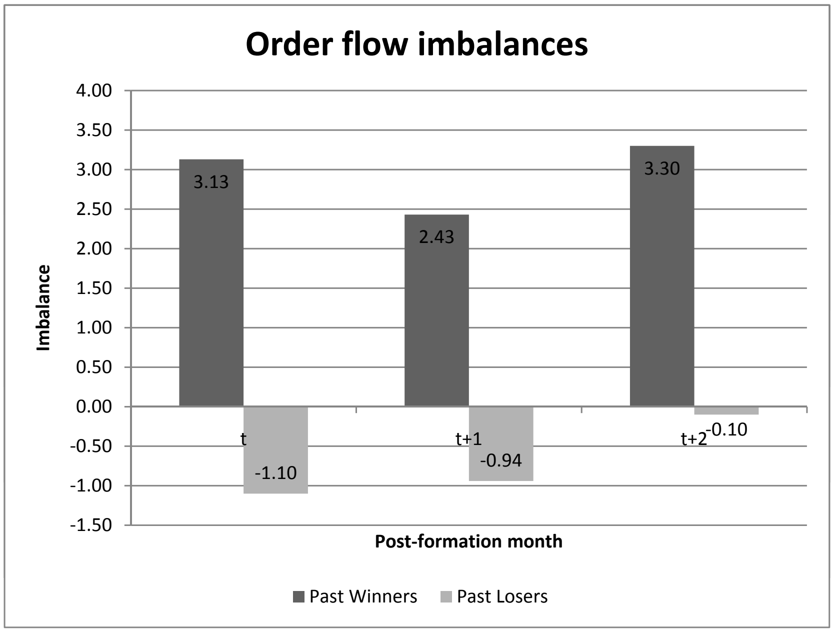

Figure 3 This figure plots post-formation order flow imbalances for past winners and past losers following continuous information. Continuous information arrives frequently in small amounts and is defined by a low firm-level information discreteness measure. Information discreteness is defined in equation (1) to capture the distribution of daily returns across the formation period of a momentum strategy. A twelve-month formation period is examined that ends in month $t-1$. The three post-formation months in which firm-level order flow imbalances are computed are denoted month t, $t+1$, and $t+2$. These imbalances are adjusted to account for the cross-sectional average of the order flow imbalances each month. Order flow imbalances are computed using the Lee and Ready (1991) algorithm.