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Frog in the Pan: Continuous Information and Momentum[*]

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Abstract

We test a *frog-in-the-pan* (FIP) hypothesis that predicts investors are inattentive to information arriving continuously in small amounts. Intuitively, we hypothesize that a series of frequent gradual changes attracts less attention than infrequent dramatic changes. Consistent with the FIP hypothesis, we find that continuous information induces strong persistent return continuation that does not reverse in the long run. Momentum decreases monotonically from 5.94% for stocks with continuous information during their formation period to -2.07% for stocks with discrete information but similar cumulative formation-period returns. Higher media coverage coincides with discrete information and mitigates the stronger momentum following continuous information.

Limited cognitive resources can prevent investors from immediately processing all available information.[1] 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 that originates from limited investor attention. 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) conclude that small gradual changes induce less critical evaluation than large dramatic changes. Their study found a greater acceptance of unethical behavior, defined as instances of cheating, when behavior gradually erodes compared to abrupt shifts in behavior. The authors interpret this finding as evidence of a *slippery slope*.

With the exception of Hou, Peng, and Xiong (2008), the role of limited attention in generating momentum has not been explored.[2] 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 during a short horizon. 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 large amounts of information. We posit the existence of a lower attention threshold, with the FIP hypothesis predicting an underreaction to information that arrives continuously in small amounts over a long horizon. Intuitively, this continuous information is beneath the radar screens of investors. Specifically, the FIP hypothesis predicts that investors process continuous information with a delay.

Appendix A provides an illustrative model that formalizes the FIP hypothesis. Signals whose magnitudes are below a lower threshold k are processed with a delay by FIP investors. 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.

[1] Hirshleifer and Teoh (2003), Sims (2003), Peng and Xiong (2006), as well as DellaVigna and Pollet (2007) provide theoretical foundations that allow limited attention to influence asset prices.

[2] Rational explanations for momentum are offered by Johnson (2002) and Sagi and Seasholes (2007) while behavioral explanations include Daniel, Hirshleifer, and Subrahmanyam (1998) among others.

The model illustrates 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 the FIP hypothesis, we construct a proxy for information discreteness denoted ID that captures the relative frequency of small signals (below k). ID identifies time series variation in the daily returns that culminate in formation-period returns.[3] Specifically, ID is defined exclusively by the sign of daily returns underlying this cumulative formation-period return. For example, a high percentage of positive daily returns relative to negative daily returns implies that a past winner's high formation-period return is attributable to many small positive returns. Intuitively, as the formation-period return accumulated gradually over many days, the flow of information is continuous. In contrast, if the majority of 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. Empirically, discrete information coincides with increased turnover as well as higher media coverage, more management press releases, and larger earnings surprises. These relationships suggest that discrete information attracts attention.

The FIP hypothesis predicts that ID has a conditional relationship with momentum. Therefore, only after conditioning on formation-period returns is the influence of ID on momentum relevant. We first investigate whether ID influences holding-period returns using sequential double-sorted portfolios that condition on formation-period returns, then ID. Consistent with the 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 -2.07% in the discrete information portfolio to 5.94% in the continuous information portfolio. Independent double-sorts reveal a similar monotonic increase in return continuation that remains significant after adjusting for risk using the three-factor model.

Momentum following continuous information persists for eight months while the momentum profit following discrete information becomes insignificant after two months. Nonetheless, the eight-

[3] 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. In addition, a modified version of ID based on analyst forecast revisions instead of returns yields similar results.

month horizon corresponding to continuous information's return predictability is easier to reconcile with limited attention than risk. Moreover, the return predictability associated with continuous information does not reverse. The lack of long-term return reversal following continuous information is consistent with an investor underreaction, and therefore supports the FIP hypothesis.

The investor attention constraint, which is represented by the k parameter in the model, is responsible for return continuation under the FIP hypothesis. Therefore, the FIP hypothesis predicts that momentum strengthens when the investor attention constraint is more likely to bind (higher k parameter). We examine this novel prediction using cross-sectional as well as time series regressions. Intuitively, stocks with low institutional ownership, disperse institutional ownership, small market capitalizations, low analyst coverage, and low media coverage are associated with less attentive investors and a higher k threshold. In support of the FIP hypothesis, ID explains more cross-sectional variation in momentum among stocks in these subsets. We also examine the returns from an enhanced momentum strategy that buys past winners and sells past losers following continuous information. The k threshold is higher when more stocks are available for investment since 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).[4]

As with any empirical proxy, ID is not a perfect measure for information discreteness. In particular, since ID does not depend on the magnitude of daily returns, counterexamples can be constructed where discrete and continuous information flows have the same value of ID. However, such counterexamples occur less frequently as the number of daily returns increases. A simulation of the illustrative model in the appendix demonstrates ID's ability to capture the FIP effect and explain cross-sectional differences in momentum. In addition, we explicitly examine a modification of ID that does depend on the magnitude of daily returns. Additional simulation and empirical evidence both suggest that overweighing small daily returns better captures the truncation of signals below the k threshold. However, these truncations are small in magnitude and consequently

[4]We utilize media coverage throughout the paper as a proxy for investor attention but acknowledge that media coverage is not exogenous. For example, large firms are more likely to appear in the financial press. In unreported tests, we address this endogeneity concern by orthogonalizing media coverage with respect to several stock characteristics. The residual media coverage resulting from this regression was found to provide similar results.

contribute less to return continuation. Therefore, ID provides a parsimonious proxy for information discreteness that is sufficiently accurate for testing the FIP hypothesis.

Despite similarities in their construction, the economic motivation underlying ID 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). Return consistency is motivated by the disposition effect's prediction that investors are more likely to sell stocks in their portfolio that have unrealized capital gains than those with unrealized capital losses.

A battery of empirical tests indicate that the disposition effect is not responsible for the return predictability of continuous information. First, although the disposition effect does not apply to analysts, their forecast errors are larger following continuous information. Consequently, continuous information fails to attract analyst attention. This failure cannot be attributed to the disposition effect. Instead, consistent with the FIP hypothesis, it provides a channel through which analyst inattention causes investors to process continuous information with a delay.

Second, post-formation order flow imbalances contradict 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 imbalances support the FIP hypothesis since investors appear to delay the processing of continuous information.

Third, in time series tests, neither unrealized capital gains nor return consistency explain the returns from an enhanced momentum strategy that conditions on continuous information. Instead, momentum is weaker among stocks with higher media coverage. Hence, media coverage appears to mitigate investor inattention, although this finding is subject to the critique that media coverage is endogenous. Conversely, in cross-sectional tests, the ability of return consistency to predict returns is limited to past winners, while ID explains the return continuation of both past winners and past losers.[5] In addition, the interaction between ID and formation-period returns remains a significant predictor of price momentum in every Fama-MacBeth regression specification, even after controlling

[5]ID is also a stronger predictor of momentum than return consistency. Within the subset of stocks with consistent returns (return consistency dummy variable equals one), portfolio double-sorts confirm that continuous information induces stronger momentum than discrete information.

for unrealized capital gains, return consistency, and the capital gains overhang variable in Frazzini (2006) that is derived from mutual fund holdings.

Besides proxies for the disposition effect, the prior literature has identified several firm characteristics that are related to the strength of price momentum 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. Moreover, the economic significance of the Fama-MacBeth regression coefficients illustrates the greater return predictability of ID relative to characteristics in the existing momentum literature.

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 cross-sectional variation in ID. This property is consistent with the lack of persistence in ID at the firm-level, which justifies its ability to proxy for time-varying information flows at the firm-level. Indeed, this lack of persistence distinguishes the FIP hypothesis from theories of momentum that predict its strength is related to persistent firm characteristics such as firm size.

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 property distinguishes ID from skewness and proxies for extreme returns (Bali, Cakici, and Whitelaw, 2011) measured over the same formation period.

As a final robustness test, we construct ID using signed monthly analyst forecast revisions instead of daily returns. This analyst-forecast based ID proxy confirms that continuous information induces stronger momentum than discrete information. Thus, the momentum implications of the original return-based ID proxy are robust to the noise in daily returns.

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 web-search-based attention, as well as Bae and Wang (2012) 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 the continuous and discrete arrival of information, which is the focus of our paper. This focus involves the flow of information over time rather than its diffusion across investors (Hong and Stein, 1999). Our paper also complements the emerging literature that studies the media's role in asset pricing (Tetlock (2007), Engelberg and Parsons (2011), and Gurun and Butler (2012) among others) since our findings suggest that media coverage alleviates the underreaction of investors to information.

1 Proxy for Information Discreteness

We obtain return data from CRSP after adjusting for delistings and firm-level accounting data from COMPUSTAT. We then eliminate negative book values from the sample, which ends in 2007. The starting dates for the sample period range from 1927 to 1992 depending on the availability of certain firm characteristics. The exact starting dates are listed above each panel when our empirical results are reported.

Our benchmark ID proxy 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.[6] ID is defined as

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

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.

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 minimum attention threshold k. Conditional on PRET, momentum becomes stronger when more signals (and larger signals) with the same sign as PRET are truncated. The ID definition in equation (1) captures this initial truncation.

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

A large ID measure signifies discrete information while a small ID measure signifies continuous information.[7] 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 ID. Both stocks in this figure have the same PRET over 250 "daily" periods in a year. The stock with continuous information during the formation period achieves this cumulative return with many small positive daily returns while the stock with discrete information has a few large positive daily returns.

As ID does not depend on the magnitude of daily returns, counterexamples can be formulated. For example, sequence A=$\{2, 2, 2, 2, 2, 2\}$ and sequence B=$\{1, 1, 1, 1, 1, 7\}$ both have an ID of -1 and PRET of 12, although sequence B may be considered more "discrete" than sequence A due to its last element, which also results in sequence B having more volatility. However, counterexamples of this nature are less likely to occur as N increases. Furthermore, the implications of ID for return continuation are robust to controlling for return volatility in the empirical analyses.

While ID is not a perfect measure for information discreteness, equation (1) is simple, parsimonious, and motivated by the illustrative model in the appendix. Furthermore, ID is robust to whether PRET is near zero or large in absolute value. ID also does not contain any apparent biases capable of inducing a spurious inverse relationship with momentum that is predicted by the FIP hypothesis.

A simulation exercise with N=250 in the appendix verifies that ID explains cross-sectional differences in momentum. This simulation demonstrates that for stocks with a large absolute PRET (past winners and past losers), ID is negatively correlated with momentum. Specifically, the

[7] 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.

correlation between ID and return continuation is -0.65 for past winners and -0.67 for past losers. Therefore, as predicted by the FIP hypothesis, more continuous information (low ID) is associated with greater return continuation. In contrast, when PRET is near zero, the correlation between ID and return continuation is negligible. Overall, ID is a robust proxy for information discreteness that captures the economic motivation underlying the FIP hypothesis in subsequent empirical tests.

We also construct a modified ID measure denoted ID_{MAG} that depends on the magnitude of daily returns. Specifically, ID_{MAG} is formed by sorting daily returns into firm-specific quintiles based on their absolute value. The first quintile contains the smallest daily returns while the fifth quintile contains the largest returns. The decision to define "small" and "large" returns using quintiles rather than fixed thresholds allows for heterogeneity across firms and over time. We then assign monotonically declining weights w_i of 5/15, 4/15, 3/15, 2/15, and 1/15 to the respective $|\text{Return}_i|$ quintiles. These weights, which sum to one, ensure that small daily returns are assigned more weight than large daily returns in the following definition

$$\text{ID}_{MAG} \;=\; -\frac{1}{N}\,\text{sgn}(\text{PRET}) \cdot \sum_{i=1}^{N} \text{sgn}\left(\text{Return}_i\right) \cdot w_i\,, \tag{2}$$

where N denotes the number of days in the formation period. While the linear declining weighting scheme is somewhat arbitrary, other monotonically declining weighting schemes yield similar results. Observe that if daily returns have the same absolute magnitude, then ID_{MAG} reduces to the original ID measure.

We consider another alternative ID measure to account for the occurrence of zero return days. Recall that 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. While 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 ID

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

which is identical to 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

$$\mathrm{D} \ = \ 1 - \frac{R_C^2}{R_L^2} \, . \tag{4}$$

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 D being closer to zero as a consequence. However, if the firm's stock price slowly incorporates market-level information, then D is closer to one. Hou and Moskowitz (2005) report that this delay measure 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. We also examine the capital gains overhang variable (CGO) in Frazzini (2006) that is derived from mutual fund holdings. This proxy for the disposition effect computes reference prices by calculating the amount of previously purchased shares that are held by a fund under the first-in / first-out assumption. The difference between the current stock price and the reference price is normalized by the current price to produce CGO.

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 the delay measure, IVOL and other firm characteristics, ID is not persistent since the average firm-level autocorrelation coefficient is 0.033. The lack of persistence is consistent with the notion that ID reflects time-varying flows of firm-specific information. In contrast, UCG and CGO are more persistent than ID with autocorrelations of 0.668 and 0.681, respectively. Intuitively, ID 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 0.747 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. UCG also has a 0.659 correlation with CGO. In contrast, ID is not highly correlated with PRET, UCG, or CGO. The non-negative correlation between ID and D suggests that continuous information does not result from the slow incorporation of market information into stock prices. Instead, ID is determined by the flow of firm-specific information.

According to the FIP hypothesis, discrete information attracts attention. To examine this notion, we estimate the following Fama-MacBeth regression

$$ID_{i,t} = \beta_0 + \beta_1\,\Delta\text{TURN}_{i,t} + \beta_2\,\Delta\text{MEDIA}_{i,t} + \beta_3\,\Delta\text{PR}_{i,t} + \beta_4\,\Delta\text{COV}_{i,t} + \beta_5\,|\text{S}\bar{\text{U}}\text{E}|_{i,t} + \epsilon_{i,t}\,, \quad (5)$$

using firm-month observations for several attention proxies. ΔTURN denotes the change in turnover. This change is defined as average turnover from month t to month $t-11$, which corresponds to the period in which a firm's ID is computed, minus the average turnover in month $t-12$ to month $t-23$. This definition is in spirit similar to the abnormal turnover computed in Barber and Odean (2008) as well as Gervais, Kaniel, and Mingelgrin (2001). ΔMEDIA and ΔPR refer to changes in the number of articles in the financial press and the number of press releases regarding a firm, respectively. These changes are defined using the same procedure as ΔTURN. Similarly, ΔCOV corresponds to firm-level changes in analyst coverage. 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. $|\bar{\text{SUE}}|$ corresponds to the absolute value of the average SUE during month t to $t-11$. Due to the correlations between media coverage, press releases, and analyst coverage, the above specification is estimated separately for each of these variables as well as jointly.

Data on media coverage is obtained from Factiva, which contains media reports from several sources. We focus on the most comprehensive financial news service, the Dow Jones Newswire. To match news articles with firms, we use ticker symbols and firm names in CRSP using procedures outlined in Gurun and Butler (2012). Specifically, a web crawler is used to search name variants by singular and plural versions for the following abbreviations of company names: ADR, CO, CORP, HLDG, INC, IND, LTD, and MFG. Press release data is obtained from PR Newswire. The source identifier provided by PR Newswire includes the name and address of the firm, which is matched with the company information in COMPUSTAT. To further improve the match quality, we use the soundex algorithm in SAS to match the firm names in the press releases with those in COMPUSTAT. Due to the availability of the press release data, the sample period for this test ranges from 2000 to 2007.

The positive β_1 through β_3 coefficients in Panel C of Table 1 indicate that discrete information is associated with increased turnover as well as higher media coverage and more press releases. Intuitively, the β_1 coefficient indicates that discrete information initiates trades by market participants. Discrete information regarding a firm also coincides with more articles about the firm appearing in the financial press and more press releases being issued by its management. While the financial press appears to increase their coverage of a firm in response to discrete information, analyst coverage does not increase significantly. Instead, larger earnings surprises (in absolute value) are associated with discrete information as the β_5 coefficient is positive. Overall, these results support the key assumption underlying the FIP hypothesis that discrete information attracts attention.

More comprehensive analyses involving media coverage are reported in Table 3 and Table 4. These later results test cross-sectional and time series predictions from the illustrative model. Consequently, the endogeneity surrounding media coverage and firm characteristics such as size is mitigated by these later tests, which nonetheless provide suggestive evidence that continuous information attracts less investor attention.

2 Information Discreteness and Momentum

To examine the importance of ID to momentum (Jegadeesh and Titman, 1993), we form double-sorted portfolios sequentially that first condition on formation-period returns, then ID during the 1927 to 2007 sample period. 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. In unreported results, the inclusion of the Pástor and Stambaugh (2003) liquidity factor does not alter our empirical results.

Panel A of Table 2 reports that momentum, the six-month return from buying winners and selling losers, decreases monotonically from 5.94% in the low ID quintile containing stocks with continuous information to -2.07% in the high ID quintile containing stocks with discrete information. This 8.01% difference in momentum has a t-statistic of 8.54 during the post-1927 sample period. Similar results are obtained during the post-1980 sample period. We examine this more recent subperiod since later empirical tests, involving residual ID for example, often use variables that are only available after 1980.

Figure 2 plots the momentum profits following continuous and discrete information from one to ten months after portfolio formation during the post-1927 sample period. 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 46bp (t-statistic of 2.08) in the eighth month after portfolio formation decreases to an insignificant 21bp (t-statistic of 0.97) by month nine. In contrast, for stocks in the discrete information portfolio, the 31bp momentum profit is insignificant by the third month after portfolio formation (t-statistic of 1.30). 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-balancing.

Recall that ID is defined by raw daily returns since momentum strategies condition on the raw 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 ID using market-adjusted daily returns that subtract daily value-weighted market returns from the daily returns of individual stocks. This market-adjusted ID measure produces similar empirical results.

The sequential double-sorts in Panel A examine the marginal impact of ID on momentum after conditioning on the most extreme formation-period returns (PRET). Since ID and PRET are positively correlated, the second sort on ID may generate further variation in PRET that explains the difference in momentum following continuous versus discrete information. Therefore, as a robustness test, Panel B reports the momentum profits from independent double-sorts on PRET and ID. The results in Panel B display the same pattern as those in Panel A, with momentum increasing monotonically from an insignificant -0.63% to a highly significant 5.72% over the six-month holding period as information during the formation period becomes more continuous during the post-1927 period. A similar pattern is observed during the post-1980 period. Thus, the impact of ID on return continuation is insensitive to whether the double-sorts are formed sequentially or independently.

Panel C 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 from the original ID measure. Specifically, the difference in momentum between continuous and discrete information is 4.75% (t-statistic of 4.11) during the post-1927 sample period. After a three-factor adjustment, this difference widens to 5.66% (t-statistic of 5.85). Consequently, illiquidity does not appear to be responsible for the stronger return continuation following continuous information.

Panel D investigates the performance of modified ID measure that depends on the magnitude of the daily returns. In particular, by overweighting small daily returns, the difference in momentum between continuous information and discrete information is 9.62% (t-statistic of 6.02) using ID_{MAG} in equation (2) during the post-1927 period. This difference is significantly larger than the 8.01% difference in Panel A, although the marginal increase in momentum attributable to weighting daily returns by their magnitude is limited. Observe that the risk-adjusted momentum spreads increase monotonically as information during the formation period becomes more continuous during both the post-1927 and post-1980 sample periods.

More complicated proxies for information discreteness that assign larger weights to smaller daily returns are unable to dramatically improve upon the economic implications of ID for momentum. In unreported results, we examined three alternative weighting schemes for ID_{MAG} and replicated the double-sort in Panel D of Table 2 for each alternative during the post-1927 period.

The first alternative assigned more weight to smaller returns using the following weighting scheme; 25/55, 16/55, 9/55, 4/55, 1/55. As predicted by the FIP hypothesis, exerting more emphasis on the smallest daily returns induced a greater difference in momentum; 11.05% versus 9.62%.

The second alternative weighting scheme examined daily return deciles (10/55, 9/55, ..., 2/55, 1/55) while the third alternative assigned weights to daily return terciles (5/9, 3/9, 1/9). However, these alternative weights for daily returns produced similar results as those reported in Panel D of Table 2. Overall, the additional complexity associated with weighting daily returns by their magnitude is of limited economic value. The appendix provides additional justification and intuition for using ID as the primary proxy for information discreteness.

An underreaction to information does not predict long-term return reversals. The three-year holding-period returns in Panel E indicate that long-term return reversals are not associated with continuous information in the formation period. In particular, stocks with continuous information in the formation period have higher long-term returns than stocks following discrete information. Therefore, consistent with an underreaction to continuous information, strong short-term return continuation does not precede long-term return reversal. Overall, ID appears to identify variation in return predictability over different horizons.[8]

The remainder of this section tests novel predictions of the FIP hypothesis that links investor attention to momentum. It also differentiates between ID, which is motivated by limited attention, and return consistency whose motivation lies with the disposition effect. Finally, we examine alternative explanations and 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.

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

2.1 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 the illustrative model. Specifically, the 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, firm size, analyst coverage, and media coverage as firm-level proxies for the k parameter.

Intuitively, more investor attention is received by firms that have high levels of institutional ownership than low levels of institutional ownership. Besides having greater incentives to monitor, institutional investors with concentrated portfolio positions in a firm are considered to be more attentive to its fundamentals than institutional investors with disperse portfolio positions. To define institutional ownership concentration, we follow Hartzell and Starks (2003) by examining the proportion of institutional ownership accounted for by the five largest institutional investors in a firm. Institutional ownership 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). Large firms are also associated with more attentive investors than small firms. High media coverage and high analyst coverage of a firm are associated with more attentive investors, while low media coverage and low analyst coverage are associated with less attentive investors and a higher k threshold. Analyst coverage is defined as one plus the log number of analysts issuing forecasts for a particular firm.

The thresholds that determine high versus low institutional ownership as well as concentrated versus disperse institutional ownership are the top 30% and bottom 30% of these characteristics at the beginning of the formation period, hence one year before portfolio formation. Similarly, the thresholds that define large and small firms are the top 30% and bottom 30% of market capitalizations at the beginning of the formation period. As many firms do not have analyst coverage, median analyst coverage during the formation period serves as the threshold between high and low. Indeed, using the cross-sectional median for analyst coverage instead of top 30% and bottom 30% thresholds ensures that a similar number of stocks are available in each subset. 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.

Consistent with the limited attention motivation of the FIP hypothesis, the results in Panel A of Table 3 indicate that ID is better at explaining cross-sectional differences in momentum among firms with low institutional ownership than high institutional ownership. In particular, the disparity in six-month momentum profits following continuous versus discrete information is 8.79% among stocks with low institutional ownership while this disparity is 5.48% among stocks with high institutional ownership. The 3.31% different is significant with a t-statistic of 2.41.

Furthermore, the results in Panel B indicate that ID 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% among stocks with disperse institutional ownership. This difference is more than double the 5.44% disparity among stocks with concentrated institutional ownership. The 5.79% difference between these subsets is significant with a t-statistic of 2.41. Therefore, the FIP hypothesis is most relevant to firms having disperse institutional ownership (high k parameters).

Panel C and Panel D provide confirming evidence since ID is better able to explain cross-sectional variation in momentum among small firms and firms with low analyst coverage in comparison to large firms and those with high analyst coverage, respectively. In particular, with small stocks, the return disparity between having continuous versus discrete information during the formation period is 7.17%, which decreases to 4.92% among large stocks. Similarly, within the subset of stocks with low analyst coverage, the return disparity of 6.83% exceeds the 3.41% disparity among stocks with high analyst coverage. The differences in these disparities, which equal 2.25% and 3.42%, are both significant with t-statistics of 2.18 and 2.24, respectively.

The results in Panel E for media coverage indicate that the 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, the disparity in momentum following continuous and discrete information increases from 1.96% to 5.94%, with this difference of 3.98% being significant (t-statistic of 2.09). Therefore, the FIP hypothesis is most relevant to firms that receive low media coverage (high k parameters). This finding is consistent with the evidence in Peress (2009) that media coverage mitigates earnings momentum.

The results in Panel E 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 E, 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.

Unreported results confirm that the disparity in six-month momentum following continuous and discrete information for the "middle" 40% of firms in Panel A through Panel C lies between the reported subsets. Thus, the disparity in momentum profits increases monotonically from high to low levels of institutional ownership, from concentrated to disperse institutional ownership, and from small to large firms. Recall that the firm subsets with analyst coverage and media coverage are divided by their respective medians rather than their 30^{th} and 70^{th} percentiles.

Overall, empirical support for the FIP hypothesis is stronger among firms that are associated with less attentive investors that have higher k parameters.

2.2 Disposition Effect

While ID is a continuous variable based on daily returns, return consistency in Grinblatt and Moskowitz (2004) is a discrete variable based on monthly returns and contingent on the eight-month threshold. When evaluating the disposition effect, unrealized capital gains (losses) are usually computed relative to reference prices that are unobservable at the investor level. Return consistency is intended to supplement 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.

Furthermore, the respective economic motivations underlying ID and return consistency are distinct since ID is based on limited attention while return consistency 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 return consistency, 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.[9]

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

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

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 1980 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 both the sample period starting in 1927 as well as 1980 and is not dependent on the inclusion of BM and SIZE controls. Overall, the significance of the PosID and NegID coefficients across the three regression specifications highlights the robustness of the 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 not positive in the post 1927 period. Moreover, with controls for BM and SIZE, the β_4 coefficient for NegRC is not negative in the post 1980 period and positive (t-statistic of 2.05) in the absence of these controls. Overall, return consistency does not explain the return continuation of past losers. Grinblatt and Moskowitz (2004) attribute this failure to tax-loss selling in December, which leads to purchases in January that offset the return continuation of past losers.

In unreported results, the subsample of stocks for which RC equals one comprises 17.24% of the firm-month observations in the original dataset. Within this subset of stocks with consistent returns, momentum continues to increase monotonically as information during the formation period becomes

[9] Gutierrez and Kelley (2008) report that return consistency cannot predict returns when this measure is constructed using weekly instead of monthly returns.

more continuous, resulting in a significant disparity between discrete and continuous. Thus, the marginal return predictability of continuous information is significant after controlling for return consistency. However, since RC is only an indirect proxy for the disposition effect, we implement additional tests to differentiate the FIP hypothesis from the disposition effect.

The next test implements 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

$$\begin{aligned} FIPRet_{t+1,t+6} &= \beta_0 + \beta_1 \,\text{Trend} + \beta_2 \,\text{AGG MKT}_{t-1} + \beta_3 \,\text{AGG UCG}_{t-1} + \beta_4 \,\text{AGG RC}_{t-1} \\ &\quad + \beta_5 \,\text{Log(NUMST)}_{t-1} + \beta_6 \,\Delta\text{Log(MEDIA)}_{t-1} + \epsilon_t \,. \end{aligned} \tag{7}$$

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 UCG 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 the 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 examines changes in the formation-period media coverage of stocks involved in the enhanced momentum strategy through the ΔLog(MEDIA) variable. Lower media coverage provides another proxy for limited attention. As this regression specification involves media coverage, the sample period begins in 1992 with the TREND variable starting at 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.[10] Investors are confronted by more firm-specific information, such as the release of earnings, when the number of stocks available for investment increases. Consequently, the amount of attention devoted to an individual stock decreases. Therefore, the FIP hypothesis complements the "driven-to-distraction" hypothesis in Hirshleifer, Lim, and Teoh (2009) since k increases, and the FIP effect strengths, with the number of stocks available for investment .

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, the 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, subject to the critique that media coverage is endogenous, the negative β_6 coefficient provides empirical support for the ability of media coverage to mitigate the limited attention of investors (Peress, 2009).

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 the 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 the enhanced momentum strategy have not declined during the past two decades.

The third test uses order flow imbalances to differentiate between the predictions of the FIP 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,

[10]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.

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 the model. Therefore, the 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

$$\text{OIB} \quad = \quad \frac{\text{\# of Share Purchases - \# of Share Sales}}{\text{Total Volume}} \times 100 \tag{8}$$

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 (2012), unrealized capital gains predict returns by focusing investor attention. Figure 3 also supports Birru (2012)'s findings based on trade-level data. The empirical results in Birru (2012) indicate that the disposition effect around share splits, when inattentive investors may confuse the winner versus loser status of their holdings by failing to properly adjust their reference prices, is insufficient to explain momentum.

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.

2.3 Alternative Explanations

Besides the disposition effect, we also examine whether investor conservatism is responsible for the return predictability of ID. 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 the 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.

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. 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

$$\mathrm{IVOL}_{i,t} \quad = \quad \gamma_{0,t} + \gamma_{1,t} \, |\mathrm{PRET}|_{i,t} + \epsilon_{i,t}^{IVOL} \,. \tag{9}$$

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 B of Table 5, stocks with high RES IVOL produce a six-month momentum return of 6.30% while those with low RES IVOL produce a momentum return of 6.28%. This 0.02% difference is insignificant. Indeed, the t-statistic of 0.25 indicates that momentum is not stronger in high idiosyncratic volatility stocks. In summary, after controlling for the influence of formation-period returns on idiosyncratic volatility, higher idiosyncratic volatility is not associated with stronger momentum.

2.4 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

$$\begin{aligned} r_{i,t+1,t+6} \quad = \quad & \beta_0 + \beta_1 \, \mathrm{PRET}_{i,t} + \beta_2 \, \mathrm{ID}_{i,t} + \beta_3 \, (\mathrm{PRET} \, \cdot \, \mathrm{ID})_{i,t} \\ & + \alpha \, X_{i,t} + \alpha_I \, (\mathrm{PRET} \, \cdot \, X)_{i,t} + \epsilon_{i,t} \,. \end{aligned} \tag{10}$$

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 capital gain overhang (CGO) variable in Frazzini (2006) based on reference prices derived from mutual fund holdings provides an additional control for the disposition effect. As noted in Table 1, CGO is highly correlated with UCG.

The most recent quarterly earnings surprises (SUE) is included to control for post-earnings announcement drift (Bernard and Thomas, 1990). 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 motivated by Zhang (2006) that reports stronger momentum in stocks with high IVOL. Analyst coverage is also included since Hong, Lim, and Stein (2000) as well as Brennan, Jegadeesh, and Swaminathan (1993) document stronger momentum in stocks with low analyst coverage (COV).

Amihud's measure (AMI) controls for cross-sectional differences in liquidity, while the delay measure D controls for the possibility that continuous information is more common in neglected stocks.

To account for extreme returns, we include the maximum daily return over the prior month (MAX), as in Bali, Cakici, and Whitelaw (2011), as well as the conditional skewness variable (CSKEW) in Harvey and Siddique (2000). Conditional skewness is computed over a five-year horizon each month.

In summary, the X vector is defined as

$$[\text{RC, UCG, CGO, SUE, BM, SIZE, TURN, IVOL, COV, AMI, D, MAX, CSKEW}]$$

with all of these characteristics computed before month t.

Panel A of Table 6 contains the coefficient estimates from the Fama-MacBeth regression in equation (10). 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 interacted with PRET differ across the last two regression specifications. Similarly, the coefficient for the interaction between PRET and CGO is not significant (t-statistic of 1.29) when proxies for the disposition effect are examined in conjunction with ID. Overall, ID appears to be a more robust predictor of momentum than proxies for the disposition effect.

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. High turnover is not associated with lower returns as the coefficient for TURN is negative. Less liquid stocks with higher Amihud measures also have higher average returns. According to the D metric, stocks that are slower at incorporating market-level information have higher returns even after controlling for analyst coverage. Finally, large returns in the prior month are associated with short-term return reversals as the coefficient for MAX is negative. High conditional skewness is also associated with a lower return, albeit insignificant.

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 for a subset of the interaction coefficients in Panel A are reported in Panel B for past winners as well as past losers. As an example, for ID, denote one standard deviations above and below the mean as ID_{+1} and ID_{-1}, respectively. Conditional on the β_3 coefficient for the interaction with ID, the resulting return difference attributable to variation in ID equals

$$\beta_3 \cdot \mathrm{PR\bar{E}T} \cdot (\text{ID}_{+1} - \text{ID}_{-1}) \ ,$$

where $\mathrm{PR\bar{E}T}$ 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 from the bottom row of Panel A for each variable's interaction with PRET.

The absolute return difference relative to ID normalizes the amount of return variation that can be attributed to fluctuations in each variable by the absolute return difference of ID. This normalization assesses the economic importance of each variable relative to the FIP effect.

Relative to RC and UCG, fluctuations in ID exert a far greater influence on returns. For past winners, the economic significance of RC and UCG are 17.59% and 41.02%, respectively, of ID. For past losers, these percentages are lower at 13.41% and 63.21%, respectively. Similarly, the return implications of size, turnover, idiosyncratic volatility, and analyst coverage are weaker than ID. Although BM explains more return variation than ID for past losers, the FIP hypothesis is not intended to explain the value premium.

Finally, ID in equation (10) is replaced with ID_{MAG} to determine whether small returns exert a greater influence on return continuation, as predicted by the FIP hypothesis. In unreported results, the β_3 coefficient for the interaction between $\text{ID}_{MAG} \cdot \text{PRET}$ is -0.1121 (t-statistic of -7.27) in the post-1927 period and -0.2653 (t-statistic of -5.94) in the post-1980 period. These coefficients are larger than their respective counterparts, -0.0634 and -0.2118, reported in Panel A of Table 6.

2.5 Residual Information Discreteness

To ensure that our findings regarding ID are distinct from the existing momentum literature, we compute *residual* ID denoted 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

$$\begin{aligned}\text{ID}_{i,t} \quad = \quad & \delta_{0,t} + \delta_{1,t}\,|\text{PRET}|_{i,t} + \delta_{2,t}\,\text{RC}_{i,t} + \delta_{3,t}\,\text{BM}_{i,t} + \delta_{4,t}\,\text{SIZE}_{i,t} + \delta_{5,t}\,\text{TURN}_{i,t} \\ & + \delta_{6,t}\,\text{IVOL}_{i,t} + \delta_{7,t}\,\text{COV}_{i,t} + \delta_{8,t}\,\text{IO}_{i,t} + \epsilon^{ID}_{i,t}\,. \end{aligned} \tag{11}$$

In unreported results, the adjusted R^2 of this regression is 0.141, indicating that ID is distinct from other predictors of momentum. The low adjusted R^2 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 $\epsilon^{ID}_{i,t}$ for firm i in month t. As RES ID is orthogonal to the absolute value of PRET, low RES ID is not associated with more extreme formation-period returns. Observe that several of the control variables in the X vector of equation (10) are independent variables in the computation of RES ID in equation (11) 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 0.98% to 6.73%. This 5.75% difference is highly significant (t-statistic of 4.86). This evidence confirms that ID 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 (10). 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, analyst coverage, and proxies for the disposition effect. The other coefficients are broadly consistent with the results in Table 6. Overall, the ability of continuous information to predict returns is not driven by firm characteristics in the existing momentum literature.

3 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 influence 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

$$\begin{aligned} \mathrm{SURP}_{i,t} &= \beta_0 + \beta_1\,\mathrm{ID}_{i,t} + \beta_2\,\mathrm{PRET}_{i,t} + \beta_3\,(\mathrm{ID}\cdot\mathrm{PRET})_{i,t} + \beta_4\,\mathrm{DISP}_{i,t} + \beta_5\,\mathrm{COV}_{i,t} \\ &\quad + \beta_6\,\mathrm{BM}_{i,t} + \beta_7\,\mathrm{SIZE}_{i,t} + \beta_8\,\mathrm{TURN}_{i,t} + \beta_9\,\mathrm{IO}_{i,t} + \epsilon_{i,t}\,. \end{aligned} \tag{12}$$

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. As an example, large positive earnings surprises are expected for past winners. However, a negative β_3 coefficient indicates that discrete information is associated with smaller positive forecast errors provided analysts underreact less to discrete information. In contrast, continuous (good) information is associated with larger positive forecast errors.

Panel A of Table 8 contains the coefficient estimates from equation (12). Consistent with the 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 the return-based ID results are driven by noise in daily returns, we construct an alternative ID measure 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.

The analyst forecast-based ID measure is denoted ID_f and equals

$$\text{ID}_f \quad = \quad \text{sgn(CUMREV)} \cdot [\%downward - \%upward] \ , \tag{13}$$

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 the original ID measure, ID_f in equation (13) 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 (10) with ID_f replacing ID. The results from this regression is reported in Panel C of Table 8. Once again, 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 the original ID measure are robust to the noise in daily returns.

4 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. The FIP hypothesis predicts stronger momentum after continuous information that is defined by the frequent arrival of small signals that are beneath investors' radar screens.

An illustrative model motivates the construction of a proxy for information discreteness, and 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. 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.

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.

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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

$$P_1 = s_1 - m \sum_{i=1}^{N} s^i \, 1_{\{|s^i| < k\}} \, . \tag{14}$$

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

A2: Unconditional Momentum

According to equation (14), the covariance for price changes between the first and second periods equals

$$
\begin{aligned}
Cov\,(P_1 - P_0, P_2 - P_1) &= Cov\,(P_1 - 0\,,\, s_2 + s_1 - P_1) \\
&= Cov\,(P_1\,,\, s_1 - P_1) \\
&= Cov\left(s_1 - m\sum_{i=1}^{N} s^i\,1_{\{|s^i|<k\}}\,,\, m\sum_{i=1}^{N} s^i 1_{\{|s^i|<k\}}\right) \\
&= Cov\left((1-m)\sum_{i=1}^{N} s^i 1_{\{|s^i|<k\}}\,,\, m\sum_{i=1}^{N} s^i\,1_{\{|s^i|<k\}}\right) \\
&= m\,(1-m)\,Var\left(\sum_{i=1}^{N} s^i\,1_{\{|s^i|<k\}}\right) \\
&= m\,(1-m)\,N\,Var\left(s^i\,1_{\{|s^i|<k\}}\right)\,. \qquad (15)
\end{aligned}
$$

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 (15) equals

$$
\begin{aligned}
Var\left(s^i\,1_{\{|s^i|<k\}}\right) &= \int_{-k}^{k} \frac{1}{2\,L}\,x^2\,dx \\
&= \frac{1}{2\,L}\,\frac{2\,k^3}{3}\,. \qquad (16)
\end{aligned}
$$

Substituting the above variance in equation (16) into equation (15) yields the following expression for the covariance

$$
Cov\,(P_1 - P_0\,,\, P_2 - P_1) = m\,(1-m)\,N\,\frac{k^3}{3\,L}\,. \qquad (17)
$$

The covariance in equation (17) 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 ID's ability to influence price momentum conditional on past returns (PRET=P_1). In the illustrative model, the expected price change in the second period at time 1 is simply the net truncation during the first period defined as:

$$E_1[P_2 - P_1] = m \sum_{i=1}^{N} s^i \, 1_{\{|s^i|<k\}} \,. \tag{18}$$

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 (14) and expected price changes in the second period (FRET) based on $s_1 - P_1$ in equation (18).

ID is also computed based on the sign 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	winner	2	3	4	loser	winner	2	3	4	loser	momentum
discrete	51.19	22.20	0.84	-21.57	-50.74	-5.01	-5.70	-0.62	5.73	4.08	-9.09
	56.08	24.06	-0.69	-22.39	-55.15	-1.10	-2.14	0.57	1.92	0.62	-1.72
	59.67	23.99	-0.14	-24.71	-58.24	1.41	0.46	0.35	-0.44	-1.45	2.86
	70.71	23.97	-1.52	-26.10	-68.73	2.85	3.11	-0.06	-2.76	-2.89	5.74
continuous	80.50	26.06	-0.75	-27.44	-82.20	6.88	6.28	-0.44	-6.45	-6.27	13.15
average	63.63	24.06	-0.45	-24.44	-63.01	1.01	0.40	-0.04	-0.40	-1.18	2.19
	correlation between ID and FRET					-0.65	-0.75	-0.02	-0.75	-0.67	

The simulation results confirm the model's ability to generate unconditional momentum, 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.[11]

The above simulation justifies using ID as a proxy for information discreteness in later empirical tests. In particular, the correlations between ID and FRET are -0.65 and -0.67 for past winners and past losers, respectively. These inverse relationships demonstrate that, despite its simple specification, ID captures the truncation of small signals provided formation-period returns are large in absolute value. Conversely, when PRET is near zero (third quintile), the correlation is a negligible -0.02. In this case, small positive and small negative signals are equally likely to be truncated, which results in the stock price P_1 being near its true value, s_1.

A4: The Lower Bound on Investor Attention

The lower bound on investor attention yields the FIP effect 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 into the stock price.

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

Equation (17) 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.

A5: Magnitude of Daily Returns

The above simulation exercise is extended by replacing ID with ID_{MAG} in equation (2) where monotonically declining weights w_i of 5/15, 4/15, 3/15, 2/15, and 1/15 to the respective $|\text{Return}_i|$ quintiles of daily returns. Therefore, the ID_{MAG} modification emphasizes smaller daily returns at the expense of larger daily returns. Although this emphasis is consistent with the FIP effect, the simulation results below indicate that this modification offers a limited improvement over ID.

	PRET = P_1					FRET = $s_1 - P_1$					
ID_{MAG}	winner	2	3	4	loser	winner	2	3	4	loser	momentum
discrete	56.14	23.29	-0.01	-23.13	-57.14	-5.10	-5.47	-0.19	5.55	4.29	-9.39
	59.38	24.40	-0.27	-24.09	-61.12	-1.33	-2.04	0.30	2.05	1.16	-2.49
	64.69	23.39	-0.63	-24.22	-62.57	0.98	0.58	0.09	-0.66	-0.99	1.98
	66.55	24.07	-0.31	-25.11	-63.69	3.11	2.83	0.12	-2.73	-3.35	6.46
continuous	71.39	25.15	-0.75	-25.65	-70.53	7.37	6.12	-0.52	-6.21	-7.02	14.39
average	63.63	24.06	-0.39	-24.44	-63.01	1.01	0.40	-0.04	-0.40	-1.18	2.19
correlation between ID_{MAG} and FRET						-0.71	-0.72	-0.02	-0.73	-0.72	

Observe that the correlation between ID_{MAG} and momentum is -0.71 for past winners and -0.72 for past losers. These correlations are only slightly larger in absolute value than the respective -0.65 and -0.67 correlations with ID. The increase in the resulting momentum profit is also marginal. For stocks with continuous information during the formation period, the momentum profit is 14.39% with ID_{MAG} compared to 13.15% with ID. The intuition for this limited improvement is apparent from the model: while certain weighting schemes emphasize small signals that are truncated (below the unknown k parameter), these truncations are small in magnitude and contribute less to return continuation.

Table 1: Summary Statistics

Panel A of this table reports summary statistics for the information discreteness proxy (ID), formation-period returns (PRET) and their absolute value (|PRET|), idiosyncratic volatility (IVOL), the price delay measure (D) of Hou and Moskowitz (2005), the return consistency dummy variable (RC) defined in Grinblatt and Moskowitz (2004), the unrealized capital gains variable (UCG) defined in Grinblatt and Han (2005), and the capital gains overhang variable (CGO) in Frazzini (2006). 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. D 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. CGO is defined in Frazzini (2006) using mutual funds holdings. The sample period ranges from 1980 to 2007. Panel B contains the cross-sectional correlations between the variables in Panel A. Panel C reports on the results from the Fama-MacBeth regression in equation (5), $ID_{i,t} = \beta_0 + \beta_1 \, \Delta\mathrm{TURN}_{i,t} + \beta_2 \, \Delta\mathrm{MEDIA}_{i,t} + \beta_3 \, \Delta\mathrm{PR}_{i,t} + \beta_4 \, \Delta\mathrm{COV}_{i,t} + \beta_5 \, |\bar{\mathrm{SUE}}|_{i,t} + \epsilon_{i,t}$, which examines the firm-level determinants of ID. ΔTURN denotes the change in turnover from month t to month $t-11$, the period in which ID is computed, minus the average turnover in month $t-12$ to month $t-23$. ΔMEDIA and ΔPR refer to changes in the number of articles in the financial press and the number of press releases, respectively, using the same procedure. Similarly, ΔCOV corresponds to firm-level changes in analyst coverage. 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. $\left|\bar{\mathrm{SUE}}\right|$ corresponds to the absolute value of the average SUE during month t to $t-11$. The sample period is 2000-2007 for the tests in Panel C due to the availability of the press release data.

Panel A: Summary statistics

	Mean	Percentiles 25th	50th	75th	Standard deviation	Auto-correlation
ID	-0.035	-0.067	-0.032	0.000	0.054	0.033
PRET	0.165	-0.211	0.065	0.354	0.932	-0.045
|PRET|	0.434	0.125	0.282	0.531	0.841	0.078
IVOL	0.552	0.056	0.147	0.412	4.554	0.843
D	0.565	0.297	0.573	0.851	0.303	0.381
RC	0.180	0.000	0.000	0.000	0.329	0.047
UCG	-0.158	-0.185	0.062	0.200	0.782	0.668
CGO	0.262	0.043	0.083	0.216	0.480	0.681

Panel B: Correlations

	ID	PRET	|PRET|	IVOL	D	RC	UCG	CGO
ID	1.000							
PRET	0.167	1.000						
|PRET|	-0.332	0.387	1.000					
IVOL	0.085	-0.182	0.347	1.000				
D	0.048	-0.065	0.045	0.261	1.000			
RC	-0.307	0.121	0.339	-0.057	0.005	1.000		
UCG	0.061	0.747	0.109	-0.455	-0.113	0.108	1.000	
CGO	-0.022	0.671	0.041	-0.210	0.245	0.066	0.659	1.000

Panel C: ID and investor attention

	intercept	ΔTURN	ΔMEDIA	ΔPR	ΔCOV	$\tilde{\lvert SUE \rvert}$	Adj. R^2
coefficient	-0.0413	0.3137	0.0033			0.1034	0.005
t-stat	*-41.19*	*4.77*	*2.87*			*8.54*	
coefficient	-0.0415	0.3103		0.0510		0.1038	0.006
t-stat	*-41.03*	*4.73*		*3.05*		*8.59*	
coefficient	-0.0414	0.3307			0.1274	0.1036	0.005
t-stat	*-41.47*	*5.07*			*1.10*	*8.57*	
coefficient	-0.0414	0.2882	0.0035	0.0576	0.1215	0.1035	0.008
t-stat	*-40.80*	*4.35*	*3.05*	*3.05*	*1.05*	*8.55*	

Table 2: Information Discreteness and Momentum

This table reports post-formation returns from sequentially double-sorted portfolios involving formation-period returns (PRET) and the proxy for 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 post-formation holding periods. The results in Panel A pertain to sequential double-sorts involving PRET quintiles, then ID quintiles. Post-formation momentum returns over six months, defined as the return from buying winners and selling losers, are reported for each ID quintile after skipping one intermediate month. Panel B reports the holding-period returns from independent (rather than sequential) double-sorts that condition on PRET, then ID. Panel C contains the results from a modification of ID denoted ID_Z in equation (3) that accounts for zero return days. Panel D contains the results from a modification of ID denoted ID_{MAG} that incorporates the magnitude of daily returns. This modification sorts daily returns into five quintiles based on their absolute value. The first quintile contains the smallest daily returns while the fifth quintile contains the largest returns. Monotonically declining weights of 5/15, 4/15, 3/15, 2/15, and 1/15 are then assigned to the respective quintile-based ID portfolios. This modification assigns smaller returns more weight than larger returns. Panel E reports long-term post-formation returns over a three-year holding period based on the sequential double-sorts in Panel A. All t-statistics are Newey-West adjusted with six lags and reported in italics.

Panel A: Sequential double-sorts involving PRET and ID

ID	1927							1980						
			average	unadjusted		three-factor				average	unadjusted		three-factor	
	winner	loser	ID	return	t-stat	alpha	t-stat	winner	loser	ID	return	t-stat	alpha	t-stat
discrete	7.53	9.60	0.03	-2.07	*-2.01*	-2.01	*0.03*	7.60	5.24	0.03	2.36	*1.53*	4.85	*4.54*
2	9.48	8.84	-0.01	0.64	*0.58*	3.53	*4.13*	9.53	4.82	-0.01	4.71	*3.57*	7.08	*7.15*
3	10.01	6.89	-0.03	3.12	*3.11*	5.05	*6.52*	10.86	4.33	-0.03	6.53	*4.94*	9.20	*8.02*
4	9.98	5.62	-0.06	4.36	*4.14*	6.71	*7.89*	10.57	3.55	-0.06	7.02	*5.38*	9.40	*7.75*
continuous	9.56	3.62	-0.10	5.94	*4.63*	8.77	*8.76*	10.54	1.44	-0.10	9.10	*6.35*	11.75	*8.55*
continuous - discrete			0.13	8.01	*8.54*	10.78	*10.55*			-0.13	6.74	*5.41*	6.90	*5.85*

Panel B: Independent double-sorts involving PRET and ID

ID	1927							1980						
			average	unadjusted		three-factor				average	unadjusted		three-factor	
	winner	loser	ID	return	t-stat	alpha	t-stat	winner	loser	ID	return	t-stat	alpha	t-stat
discrete	7.12	7.75	0.03	-0.63	*-0.52*	-0.19	*-0.02*	6.89	6.22	0.04	0.67	*0.41*	3.35	*3.18*
2	9.46	9.88	-0.01	-0.42	*-0.40*	1.64	*2.04*	9.34	5.09	-0.01	4.25	*3.05*	6.59	*5.17*
3	9.87	8.86	-0.02	1.01	*0.87*	3.19	*4.00*	9.87	4.52	-0.03	5.35	*4.19*	7.74	*7.62*
4	9.85	6.64	-0.05	3.21	*2.82*	5.76	*7.19*	10.50	4.15	-0.06	6.35	*5.00*	8.98	*8.90*
continuous	9.77	4.05	-0.12	5.72	*4.82*	8.31	*9.25*	10.54	2.31	-0.11	8.23	*5.93*	10.89	*8.14*
continuous - discrete			-0.15	6.35	*4.48*	8.50	*6.86*			-0.15	7.56	*5.32*	7.54	*5.98*

Panel C: Sequential double-sorts involving PRET and ID_Z

ID_Z	1927							1980						
			average	unadjusted		three-factor				average	unadjusted		three-factor	
	winner	loser	ID_Z	return	*t*-stat	alpha	*t*-stat	winner	loser	ID_Z	return	*t*-stat	alpha	*t*-stat
discrete	7.58	8.22	0.06	-0.64	*-0.65*	0.73	*0.97*	7.59	5.09	0.04	2.50	*1.59*	5.04	*4.45*
2	9.28	7.52	-0.02	1.76	*1.57*	4.32	*5.23*	9.33	4.72	-0.01	4.61	*3.48*	6.96	*6.91*
3	9.86	6.32	-0.05	3.54	*3.34*	5.65	*7.20*	10.62	4.08	-0.04	6.54	*4.85*	9.25	*7.94*
4	10.09	5.45	-0.08	4.64	*4.36*	6.84	*8.39*	10.52	3.58	-0.07	6.94	*5.31*	9.18	*7.61*
continuous	9.91	5.80	-0.19	4.11	*3.27*	6.39	*6.90*	11.05	1.84	-0.14	9.21	*6.66*	11.96	*8.96*
continuous - discrete			0.25	4.75	*4.11*	5.66	*5.85*			0.18	6.71	*5.85*	6.93	*5.92*

Panel D: Sequential double-sorts involving PRET and ID_{MAG}

ID_{MAG}	1927							1980						
			average	unadjusted		three-factor				average	unadjusted		three-factor	
	winner	loser	ID_{MAG}	return	*t*-stat	alpha	*t*-stat	winner	loser	ID_{MAG}	return	*t*-stat	alpha	*t*-stat
discrete	7.19	8.96	0.02	-1.77	*-2.31*	-1.57	*-0.64*	8.00	8.58	0.02	-0.58	*-0.37*	0.38	*1.11*
2	8.61	9.28	0.00	-0.67	*-0.60*	2.01	*2.58*	9.86	9.10	0.00	0.76	*0.46*	2.60	*2.10*
3	9.83	6.93	-0.01	2.90	*2.77*	5.07	*6.68*	11.31	8.73	-0.02	2.58	*1.66*	4.65	*3.05*
4	10.48	4.55	-0.02	5.93	*5.69*	7.66	*8.81*	12.81	7.86	-0.03	4.95	*3.01*	6.69	*3.77*
continuous	10.70	2.85	-0.04	7.85	*6.69*	9.60	*9.83*	12.94	5.23	-0.05	7.71	*3.79*	7.94	*4.00*
continuous - discrete			0.06	9.62	*6.02*	11.17	*6.61*			0.06	8.29	*2.89*	7.57	*3.07*

Panel E: Long-term returns following sequential double-sorts

ID	1927				1980			
	unadjusted		three-factor		unadjusted		three-factor	
	return	*t*-stat	alpha	*t*-stat	return	*t*-stat	alpha	*t*-stat
discrete	-8.48	*-2.08*	-8.79	*-2.04*	-11.03	*-2.38*	-11.32	*-2.68*
2	-3.65	*-0.67*	-2.93	*-0.65*	-4.19	*-0.90*	-4.05	*-0.89*
3	0.65	*0.16*	1.40	*0.30*	0.86	*0.18*	1.73	*0.35*
4	0.49	*0.09*	1.79	*0.45*	0.68	*0.12*	2.35	*0.49*
continuous	5.39	*2.23*	9.56	*2.14*	6.57	*1.06*	10.40	*1.90*
continuous - discrete	13.88	*2.49*	18.34	*3.08*	17.60	*2.40*	16.20	*3.88*

Table 3: Model Predictions

This table reports on the results from two cross-sectional tests based on proxies for the k parameter in the model. The k parameter defines the lower bound on investor attention, as detailed in Appendix A. Institutional ownership concentration, size, analyst coverage, and media coverage provide firm-level proxies for this parameter. Firms with disperse institutional ownership, small market capitalizations, low analyst coverage, and those receiving low media coverage are predicted to have the least attentive investors (highest k parameters). ID in equation (1) is defined as sgn(PRET) $\cdot$ $[\%neg - \%pos]$ where $\%pos$ and $\%neg$ denote the respective percentage of positive and negative daily returns during the formation period. PRET corresponds to a firm's formation-period return in the prior twelve months after skipping the most recent month. ID captures the distribution of daily returns across this formation period. Continuous information arrives frequently in small amounts while discrete information arrives infrequently in large amounts. The sequential double-sorts in Panel A of Table 2 based on PRET, then ID are replicated among stocks with high / low levels of institutional ownership, concentrated / disperse institutional ownership, large / small market capitalizations, high / low analyst coverage, and high / low media coverage, respectively. Returns over six-month holding periods are reported. High and low levels of institutional ownership are above the 70^{th} percentile and below the 30^{th} percentile, respectively. The proportion of institutional ownership accounted for by the five largest institutional investors is examined in Panel B. This proportion is above the 70^{th} percentile for concentrated institutional ownership and below the 30^{th} percentile for disperse institutional ownership. In Panel C, large firms are those above the 70^{th} percentile in terms of market capitalization while small firms are those below the 30^{th} percentile. In Panel D, high and low analyst coverage are separated by the cross-sectional median. In Panel E, high media coverage is defined by four or more news articles in a quarter since four is the cross-sectional median for the number of quarterly firm-level news articles. All t-statistics are Newey-West adjusted with six lags and reported in italics.

Panel A: Double-sorts involving PRET and ID across high and low levels of institutional ownership from 1980

institutional		winner				loser	average	unadjusted		three-factor	
ownership	ID	1	2	3	4	5	ID	return	t-stat	alpha	t-stat
high	discrete	7.36	6.88	6.42	6.42	5.53	0.03	1.83	*1.34*	4.34	*4.12*
	2	8.48	8.1	7.26	7.29	5.54	-0.01	2.94	*2.05*	6.18	*4.78*
	3	9.37	8.07	8.23	7.28	5.51	-0.03	3.86	*2.74*	6.80	*4.77*
	4	9.65	8.79	8.33	7.49	4.98	-0.06	4.67	*3.26*	7.79	*6.40*
	continuous	10.08	9.11	8.71	7.37	2.77	-0.10	7.31	*4.48*	10.73	*6.55*
	continuous - discrete						-0.13	5.48	*4.85*	6.39	*5.73*
low	discrete	6.29	6.78	6.34	7.41	4.85	0.03	1.44	*0.75*	4.45	*3.14*
	2	8.94	7.1	8.47	7.23	4.41	-0.01	4.53	*1.95*	8.40	*4.94*
	3	9.22	9.26	8.86	7.25	3.01	-0.03	6.21	*2.82*	11.21	*6.36*
	4	9.85	8.78	8.18	7.02	1.46	-0.05	8.39	*3.68*	11.30	*6.18*
	continuous	9.92	8.57	8.21	6.2	-0.31	-0.09	10.23	*4.48*	14.64	*6.48*
	continuous - discrete						-0.13	8.79	*4.57*	10.19	*5.59*
low - high								3.31	*2.41*	3.80	*2.88*

Panel B: Double-sorts involving PRET and ID across disperse and concentrated institutional ownership from 1980

institutional		winner				loser	average	unadjusted		three-factor	
ownership	ID	1	2	3	4	5	ID	return	*t*-stat	alpha	*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*
disperse - concentrated								5.79	*2.41*	5.94	*3.88*

Panel C: Double-sorts involving PRET and ID across small and large stocks from 1980

		winner				loser	average	unadjusted		three-factor	
size	ID	1	2	3	4	5	ID	return	*t*-stat	alpha	*t*-stat
large	discrete	10.39	8.91	8.34	7.77	6.41	0.03	3.98	*3.89*	5.32	*4.77*
	2	11.67	10.04	9.59	8.30	5.56	-0.01	6.11	*6.99*	7.19	*8.19*
	3	11.98	10.57	9.62	8.73	5.52	-0.03	6.46	*7.02*	7.39	*8.31*
	4	12.94	10.79	9.81	8.22	3.86	-0.05	9.08	*9.42*	10.32	*10.80*
	continuous	12.35	10.80	9.13	7.49	3.45	-0.08	8.90	*6.94*	11.04	*8.40*
	continuous - discrete						-0.11	4.92	*3.11*	5.72	*3.64*
small	discrete	7.16	6.58	6.64	6.48	5.28	0.03	1.88	*1.11*	4.26	*3.98*
	2	9.55	8.69	7.62	7.12	4.97	-0.01	4.58	*3.17*	7.24	*6.42*
	3	10.27	8.91	8.18	7.17	4.41	-0.03	5.86	*4.01*	8.58	*6.58*
	4	10.62	9.04	8.25	7.10	3.68	-0.06	6.94	*4.93*	9.73	*7.43*
	continuous	10.71	9.09	8.70	7.04	1.66	-0.10	9.05	*6.03*	12.15	*8.50*
	continuous - discrete						-0.14	7.17	*6.19*	7.89	*7.89*
small - large								2.25	*2.18*	2.17	*1.98*

Panel D: Double-sorts involving PRET and ID across low and high analyst coverage from 1982

analyst coverage	ID	winner 1	2	3	4	loser 5	average ID	unadjusted return	unadjusted *t*-stat	three-factor alpha	three-factor *t*-stat
high	discrete	7.53	6.73	5.41	6.21	5.33	0.03	2.20	*0.97*	4.65	*3.11*
	2	6.28	6.91	6.51	6.80	4.53	-0.01	1.75	*0.76*	4.57	*2.18*
	3	7.53	8.34	6.17	6.51	4.52	-0.04	3.01	*1.57*	6.18	*3.45*
	4	8.11	7.72	7.28	6.22	4.28	-0.06	3.83	*1.96*	6.88	*3.18*
	continuous	9.75	7.75	7.87	7.46	4.14	-0.10	5.61	*2.45*	8.83	*4.04*
	continuous - discrete						-0.13	3.41	*2.26*	4.19	*3.31*
low	discrete	7.55	7.06	5.95	5.87	5.81	0.03	1.74	*1.32*	4.21	*3.63*
	2	9.09	8.26	6.92	6.18	4.16	-0.01	4.93	*2.70*	7.16	*5.76*
	3	10.59	8.42	7.35	6.34	4.19	-0.03	6.40	*3.73*	8.97	*6.73*
	4	9.75	7.87	7.14	6.05	3.03	-0.06	6.72	*3.85*	9.12	*6.09*
	continuous	9.89	7.61	6.86	5.70	1.32	-0.10	8.57	*4.55*	11.46	*6.53*
	continuous - discrete						-0.14	6.83	*1.87*	7.25	*2.30*
low - high								3.42	*2.24*	3.06	*2.69*

Panel E: Double-sorts involving PRET and ID across low and high media coverage from 1992

media coverage	ID	winner 1	2	3	4	loser 5	average ID	unadjusted return	unadjusted *t*-stat	three-factor alpha	three-factor *t*-stat
high	discrete	7.15	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*
low - high								2.14	*1.59*	3.98	*2.09*

Table 4: Disposition effect

This table provides evidence that limited attention instead of the disposition effect is responsible for the ability of the information discreteness proxy (ID) to explain cross-sectional differences in momentum. ID is defined in equation (1) as $\text{sgn}(\text{PRET}) \cdot [\%neg - \%pos]$ where $\%pos$ and $\%neg$ denote the respective percentage of positive and negative daily returns during the formation period. PRET corresponds to a firm's formation-period return in the prior twelve months after skipping the most recent month. ID captures the distribution of daily returns across this formation period. Continuous information arrives frequently in small amounts while discrete information arrives infrequently in large amounts. Panel A contains the results from the Fama-MacBeth regression in equation (6), $r_{i,t+1,t+6} = \beta_0 + \beta_1\,\text{PRET}_{i,t} + \beta_2\,\text{NegPRET}_{i,t} + \beta_3\,\text{PosRC}_{i,t} + \beta_4\,\text{NegRC}_{i,t} + \beta_5\,\text{PosID}_{i,t} + \beta_6\,\text{NegID}_{i,t} + \beta_7\,\text{SIZE}_{i,t} + \beta_8\,\text{BM}_{i,t} + \epsilon_{i,t}$. NegPRET is defined as $\min\{0, \text{PRET}\}$. 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 (7), $FIPRet_{t+1,t+6} = \beta_0 + \beta_1\,\text{Trend} + \beta_2\,\text{AGG MKT}_{t-1} + \beta_3\,\text{AGG UCG}_{t-1} + \beta_4\,\text{AGG RC}_{t-1} + \beta_5\,\text{Log(NUMST)}_{t-1} + \beta_6\,\Delta\text{Log(Media)}_{t-1} + \epsilon_t$, 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 when the MEDIA variable becomes available. 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 ID

		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 1980	coefficient	0.0731	0.0156	0.1327	0.0043	0.0052	0.1497	-0.1137			0.035
	t-stat	*11.74*	*3.42*	*8.36*	*2.32*	*2.05*	*4.94*	*-5.63*			
	coefficient	0.0922	0.0148	0.1120	0.0046	0.0040	0.1881	-0.1438	-0.0028	0.0224	0.047
	t-stat	*9.36*	*3.46*	*8.45*	*2.36*	*1.61*	*6.25*	*-7.07*	*-4.50*	*7.84*	

Panel B: Time series variation in momentum following continuous information from 1992

	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 from 1982. In Panel B, 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 (9) 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: Confirming and disconfirming continuous information from 1982

					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 residual IVOL, then formation-period returns from 1980

	winner				loser	average	unadjusted		three-factor	
RES IVOL	1	2	3	4	5	RES IVOL	return	t-stat	alpha	t-stat
high	6.71	7.63	7.34	5.89	0.41	0.31	6.30	*3.97*	8.27	*5.59*
2	8.89	8.80	8.07	6.86	3.50	-0.19	5.39	*4.25*	6.76	*6.16*
3	9.82	8.85	7.84	7.10	4.76	-0.33	5.06	*4.74*	7.12	*6.79*
4	9.74	8.43	7.27	6.82	5.22	-0.40	4.52	*4.12*	5.84	*6.42*
low	11.55	8.32	7.45	6.52	5.27	-0.49	6.28	*3.10*	7.09	*7.00*
high-low						0.80	0.02	*0.25*	1.05	*0.87*

Table 6: Fama-MacBeth Regressions

This table reports on the ability of information of the information discreteness proxy (ID) to explain cross-sectional variation in momentum after controlling for an array of firm characteristics. 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 (10), $r_{i,t+1,t+6} = \beta_0 + \beta_1 \,\text{PRET}_{i,t} + \beta_2 \,\text{ID}_{i,t} + \beta_3 \,(\text{PRET} \cdot \text{ID})_{i,t} + \alpha \, X_{i,t} + \alpha_I \,(\text{PRET} \cdot X)_{i,t} + \epsilon_{i,t}$. The X vector consists of return consistency (RC), unrealized capital gains (UCG), the capital gains overhang variable (CGO) in Frazzini (2006), earnings surprises (SUE), book-to-market ratios (BM), firm size (SIZE), turnover during the formation period (TURN), idiosyncratic volatility (IVOL), analyst coverage (COV), Amihud's liquidity ratio (AMI), the price delay metric (D) of Hou and Moskowitz (2005), the MAX return variable in Bali, Cakici, and Whitelaw (2011), and the conditional skewness variable (CSKEW) in Harvey and Siddique (2000). 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 while Frazzini (2006) estimates CGO using mutual fund holdings. 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 COV 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 for ID and a subset of firm characteristics that have been linked to momentum in the prior literature. 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 ID from 1980

Specification		PRET	ID	ID xPRET	RC	UCG	CGO	SUE	BM	SIZE	TURN	IVOL	COV	AMI	D	MAX	CSKEW	Adj. R^2
Post 1927	0.0642	0.0109	0.0323	-0.0634														0.035
	11.61	*2.65*	*7.06*	*-3.17*														
Post 1980	0.0824	0.0087	0.1084	-0.2118														0.014
	10.37	*2.31*	*6.54*	*-4.65*														
Disposition	0.0720	0.0128	0.1030	-0.3150	0.0010	0.0094	0.0724											0.026
	11.13	*2.95*	*7.63*	*-8.09*	*0.61*	*3.33*	*5.37*											
All	0.1239	0.0102	0.0794	-0.2497	0.0020	0.0038	0.0651	0.0067	0.0086	-0.0032	-0.0203	-0.0023	0.0057	0.0019	-0.0120	-0.1490	-0.0046	0.074
	10.70	*3.83*	*6.66*	*-9.83*	*1.36*	*1.38*	*6.70*	*13.51*	*4.77*	*-4.34*	*-3.30*	*-0.19*	*3.06*	*2.44*	*-3.08*	*-8.42*	*-1.53*	
Disposition	0.0700	0.0097	0.1169	-0.3096	-0.0016	0.0245	0.0831											0.043
interactions	*10.89*	*2.03*	*8.25*	*-7.00*	*-0.84*	*3.40*	*2.67*											
All	0.1169	0.0129	0.0781	-0.2703	-0.0031	0.0202	0.0669	0.0072	0.0118	-0.0033	-0.0179	0.0035	0.0055	0.0024	-0.0134	-0.1295	-0.0035	0.090
interactions	*10.45*	*1.16*	*6.55*	*-8.39*	*-1.76*	*5.10*	*6.14*	*14.02*	*6.93*	*-4.65*	*-3.01*	*0.26*	*2.63*	*2.01*	*-3.36*	*-6.71*	*-1.18*	

Continuation of Panel A: Interaction terms

Specification	PRETx RC	PRETx UCG	PRETx CGO	PRETx SUE	PRETx BM	PRETx SIZE	PRETx TURN	PRETx IVOL	PRETx COV	PRETx AMI	PRETx D	PRETx MAX	PRETx CSKEW
Disposition	0.0254	-0.0027	0.0119										
interactions	*4.92*	*-0.86*	*1.29*										
All	-0.0053	0.0323	0.0718	-0.0006	0.0103	0.0009	-0.0160	-0.0358	-0.0043	-0.0053	-0.0071	0.0869	-0.0112
interactions	*-1.94*	*5.87*	*4.83*	*-0.53*	*5.74*	*0.83*	*-2.38*	*-3.71*	*-1.29*	*-2.06*	*-1.24*	*2.73*	*-2.00*

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

		PRET	ID	RC	UCG	BM	SIZE	TURN	IVOL	COV
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
	interaction beta for PRET		-0.2703	-0.0053	0.0323	0.0103	0.0009	-0.0160	-0.0358	-0.0043
	return: above mean		-0.003	-0.005	0.015	0.014	0.014	-0.016	-0.020	-0.006
	return: below mean		0.029	0.001	0.002	-0.002	0.009	-0.006	0.000	0.002
	absolute return difference		0.032	0.006	0.013	0.016	0.005	0.010	0.019	0.008
	difference relative to ID			17.59%	41.02%	49.54%	14.89%	32.13%	58.83%	23.65%
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
	interaction beta for PRET		-0.2703	-0.0053	0.0323	0.0103	0.0009	-0.0160	-0.0358	-0.0043
	return: above mean		0.000	0.001	-0.001	-0.009	-0.003	0.004	0.005	0.002
	return: below mean		-0.008	0.000	0.004	0.005	-0.002	0.001	0.000	0.000
	absolute return difference		0.008	0.001	0.005	0.015	0.001	0.003	0.005	0.002
	difference relative to ID			13.41%	63.21%	189.91%	15.43%	32.66%	58.43%	26.43%

Table 7: Residual Information Discreteness

This table reports on the ability of the information discreteness proxy (ID) to explain cross-sectional variation in momentum after orthogonalizing ID against an array of firm characteristics starting in 1980. 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. The proxy for residual information discreteness (RES ID) is estimated from equation (11) as the $\epsilon_{i,t}^{ID}$ residuals from regressing ID on the absolute value of PRET, return consistency, book-to-market ratios, firm size, turnover during the formation period, idiosyncratic volatility, analyst coverage, and institutional ownership. 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 (10) that parallel those reported in Table 6 with ID replaced by RES ID. All t-statistics are Newey-West adjusted with six lags and reported in italics.

Panel A: Double-sorts involving PRET and RES ID from 1980

	winner				loser	average	unadjusted six-month		three-factor six-month		unadjusted three-year		three-factor three-year	
RES ID	1	2	3	4	5	RES ID	return	t-stat	alpha	t-stat	return	t-stat	alpha	t-stat
discrete	7.56	7.79	7.13	7.26	6.58	0.07	0.98	*0.69*	3.71	*3.26*	-7.37	*-1.46*	-5.64	*-1.29*
2	9.79	8.48	8.05	7.49	6.09	0.03	3.70	*2.49*	7.01	*4.17*	-4.37	*-0.89*	-3.03	*-0.65*
3	9.99	8.68	8.55	7.74	5.79	0.00	4.20	*3.20*	7.19	*5.84*	-0.13	*-0.03*	2.31	*0.48*
4	9.33	9.12	8.40	7.85	5.10	-0.02	4.23	*3.28*	6.96	*5.57*	3.26	*0.63*	7.13	*1.32*
continuous	9.87	9.35	8.63	7.47	3.14	-0.07	6.73	*4.66*	9.53	*6.77*	8.93	*1.49*	13.79	*2.43*
continuous - discrete						-0.13	5.75	*4.86*	5.83	*4.68*	16.30	*2.08*	19.43	*2.96*

Panel B: Fama-MacBeth regressions of momentum on residual ID from 1980

Specification		PRET	RES ID	RES ID xPRET	RC	UCG	CGO	SUE	BM	SIZE	TURN	IVOL	COV	AMI	D	MAX	CSKEW	Adj. R^2
	0.1057	0.0284	0.0968	-0.3623														0.014
	10.47	*6.71*	*8.44*	*-10.20*														
Disposition	0.0665	0.0315	0.1046	-0.3971	0.0015	0.0111	0.0811											0.038
	9.98	*8.04*	*8.34*	*-11.97*	*0.84*	*3.58*	*1.58*											
All	0.1130	0.0311	0.0859	-0.3699	-0.0001	0.0036	0.0628	0.0057	0.0093	-0.0030	-0.0228	0.0000	0.0063	0.0025	-0.0088	-0.1341	-0.0039	0.073
	9.85	*9.28*	*7.79*	*-12.00*	*-0.05*	*1.23*	*1.63*	*11.69*	*5.10*	*-3.98*	*-3.72*	*0.00*	*3.32*	*3.13*	*-2.26*	*-7.78*	*-1.28*	
Disposition	0.0648	0.0184	0.1134	-0.3980	-0.0041	0.0296	0.0950											0.043
interactions	*9.90*	*4.30*	*9.13*	*-11.32*	*-2.14*	*6.91*	*5.67*											
All	0.1089	0.0169	0.0764	-0.3436	-0.0066	0.0184	0.0652	0.0066	0.0122	-0.0031	-0.0201	0.0034	0.0062	0.0030	-0.0112	-0.1163	-0.0025	0.089
interactions	*9.70*	*1.60*	*6.88*	*-9.68*	*-3.89*	*4.71*	*5.99*	*12.90*	*7.06*	*-4.30*	*-3.36*	*0.25*	*2.89*	*2.47*	*-2.79*	*-6.08*	*-0.83*	

Continuation of Panel B: Interaction terms

Specification	PRETx RC	PRETx UCG	PRETx CGO	PRETx SUE	PRETx BM	PRETx SIZE	PRETx TURN	PRETx IVOL	PRETx COV	PRETx AMI	PRETx D	PRETx MAX	PRETx CSKEW
Disposition	0.0307	0.0095	0.0448										
interactions	*5.80*	*3.41*	*3.87*										
All	0.0072	0.0285	0.0469	-0.0002	0.0119	0.0012	-0.0139	-0.0135	-0.0056	-0.0033	-0.0033	0.0837	-0.0110
interactions	*2.80*	*6.12*	*3.50*	*-0.15*	*6.91*	*1.21*	*-2.18*	*-1.53*	*-1.61*	*-1.35*	*-0.62*	*2.72*	*-1.93*

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 the information discreteness proxy (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, $\text{SURP}_{i,t} = \beta_0 + \beta_1\,\text{ID}_{i,t} + \beta_2\,\text{PRET}_{i,t} + \beta_3\,(\text{ID}\cdot\text{PRET})_{i,t} + \beta_4\,\text{DISP}_{i,t} + \beta_5\,\text{COV}_{i,t} + \beta_6\,\text{BM}_{i,t} + \beta_7\,\text{SIZE}_{i,t} + \beta_8\,\text{TURN}_{i,t} + \beta_9\,\text{IO}_{i,t} + \epsilon_{i,t}$. Besides ID, PRET, and their interaction, the independent variables are analyst forecast dispersion (DISP), analyst coverage (COV), 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 ID defined by analyst forecasts. This alternative proxy is denoted ID_f and defined in equation (13) 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 (10) that replace ID in Table 6 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 from 1982

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

Panel B: Sequential double-sort involving PRET and ID_f from 1982

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 from 1982

Specification		PRET	ID_f	ID_f xPRET	RC	UCG	CGO	SUE	BM	SIZE	TURN	IVOL	COV	AMI	D	MAX	CSKEW	Adj. R^2
	0.0711	0.0214	0.0398	-0.1283														0.037
	10.33	*3.32*	*4.92*	*-6.94*														
Disposition	0.0609	0.0071	0.0500	-0.1307	0.0114	0.0483	0.0881											0.071
	9.01	*0.89*	*6.18*	*-6.80*	*3.29*	*5.60*	2.37											
All	0.0739	0.0145	0.0566	-0.1519	0.0161	0.0391	0.036243	0.0018	0.0231	-0.0009	-0.0097	0.0255	0.0047	-0.5022	-0.0139	-0.1561	-0.0085	0.131
	3.71	*2.95*	*6.31*	*-6.65*	*2.64*	*4.66*	0.66	*3.68*	*6.78*	*-0.71*	*-1.29*	*0.95*	*2.67*	*-0.60*	*-1.96*	-4.41	-1.68	
Disposition	0.0589	0.0026	0.0557	-0.1374	0.0078	0.0593	0.0845											0.084
interactions	*8.75*	*0.26*	*6.70*	*-6.91*	*1.74*	*6.67*	*1.62*											
All	0.0657	0.0807	0.0599	-0.1465	0.0142	0.0535	0.1259	0.0016	0.0147	-0.0001	-0.0067	0.0284	0.0004	-0.1329	-0.0105	-0.2315	-0.0056	0.165
interactions	*2.45*	*1.61*	*8.07*	*-9.92*	*1.15*	*5.20*	*2.80*	*2.05*	*1.93*	*-0.11*	*-0.59*	*1.16*	*0.15*	*-0.89*	*-1.58*	*-2.96*	*-0.70*	

Continuation of Panel C: Interaction terms

Specification	PRETx RC	PRETx UCG	PRETx CGO	PRETx SUE	PRETx BM	PRETx SIZE	PRETx TURN	PRETx IVOL	PRETx COV	PRETx AMI	PRETx D	PRETx CSKEW	PRETx MAX
Disposition	-0.0024	0.0302	0.0728										
interactions	*-0.44*	*2.13*	*0.57*										
All	-0.0030	0.0348	-0.0456	-0.0033	0.0079	-0.0042	-0.0071	-0.1098	0.0035	0.4830	-0.0496	0.2743	-0.0192
interactions	*-0.42*	*2.51*	*-0.59*	*-1.27*	*0.55*	*-1.83*	*-0.25*	*-3.15*	*0.62*	*1.26*	*-1.78*	*2.78*	*-1.99*

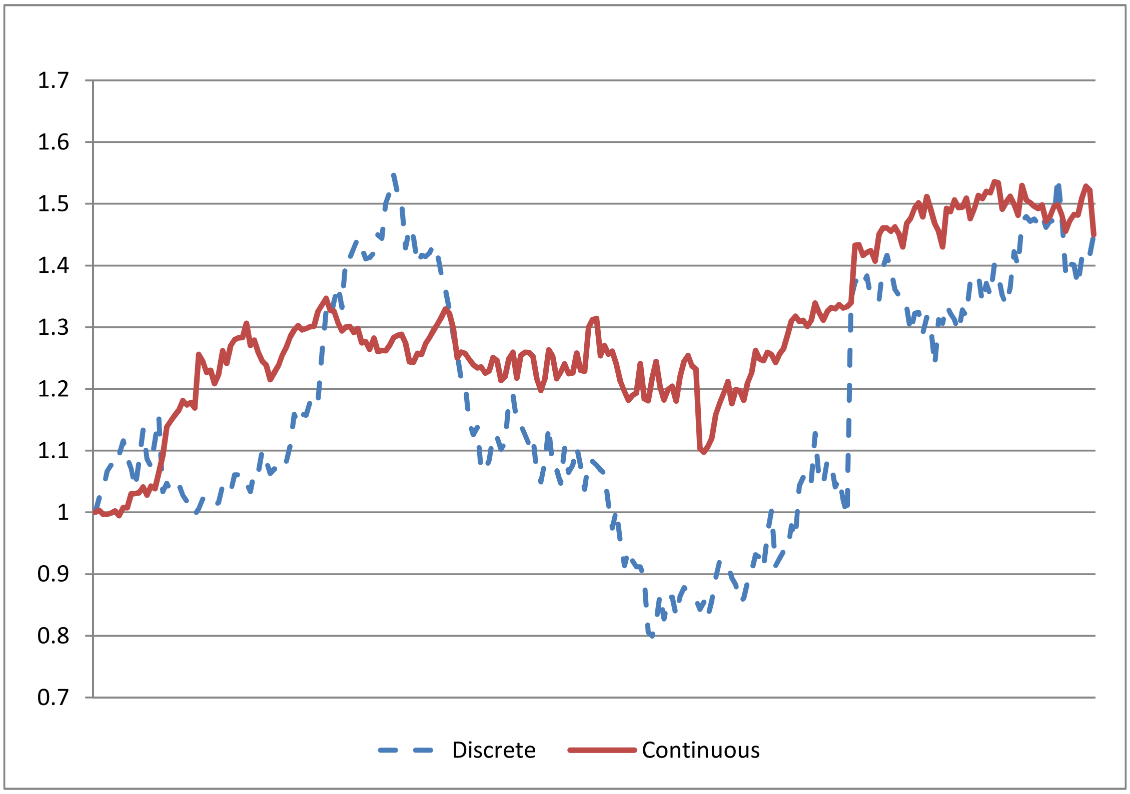

Figure 1 This figure provides a visual illustration of the difference between continuous information versus discrete information. Both firms have the same starting and ending stocks prices but with different intermediate returns over the 250 "daily" periods. ID is defined in equation (1) to capture the 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, ID equals -0.136 for the stock with continuous information and 0.072 for the stock with discrete information.

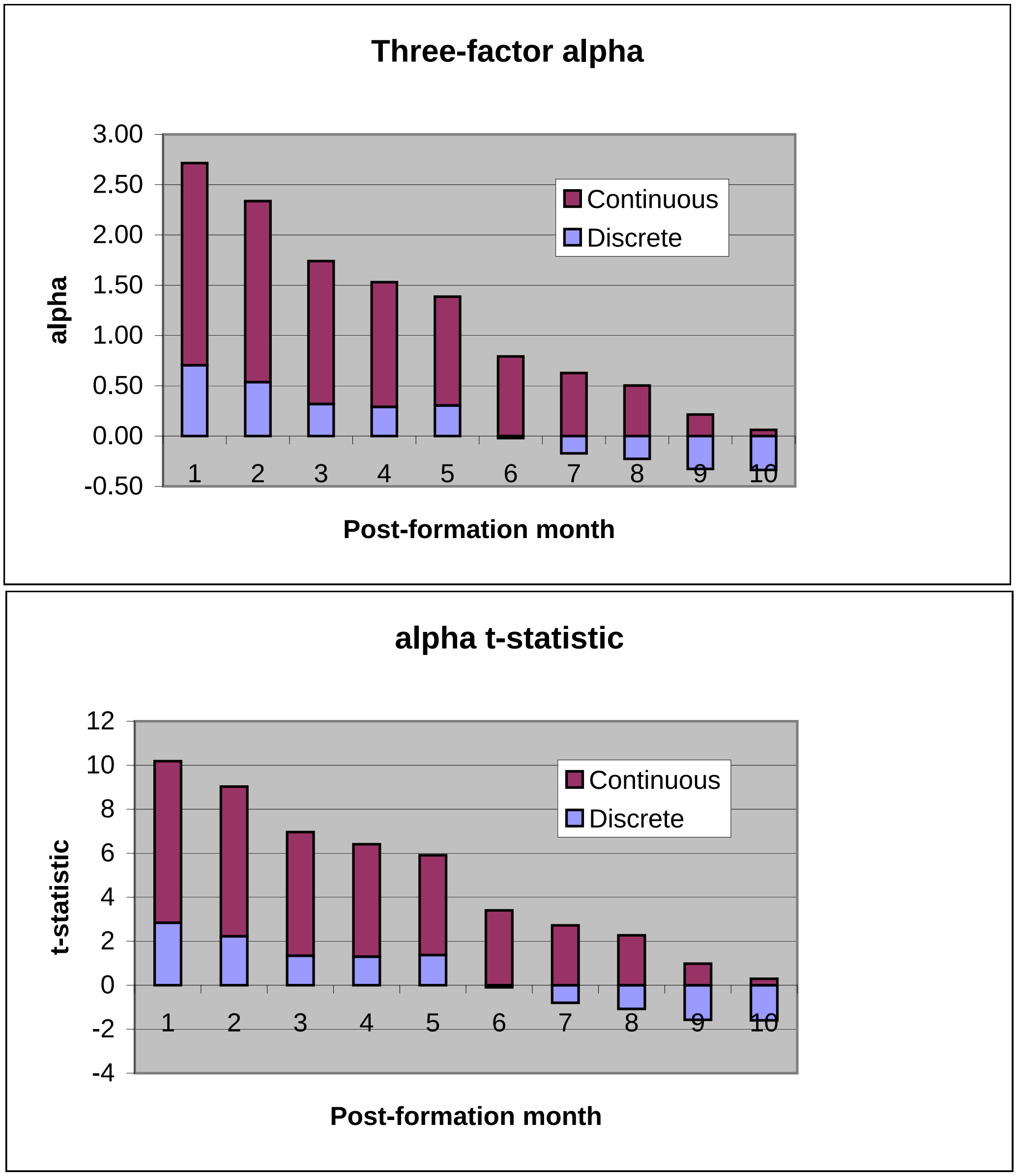

Figure 2 This figure plots risk-adjusted momentum profits in the continuous and discrete information portfolios from one to ten months after portfolio formation during the post-1927 sample period. ID is defined in equation (1) to capture the distribution of daily returns across the formation period. Continuous information arrives frequently in small amounts while discrete information arrives infrequently in large amounts. 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 ID. 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.

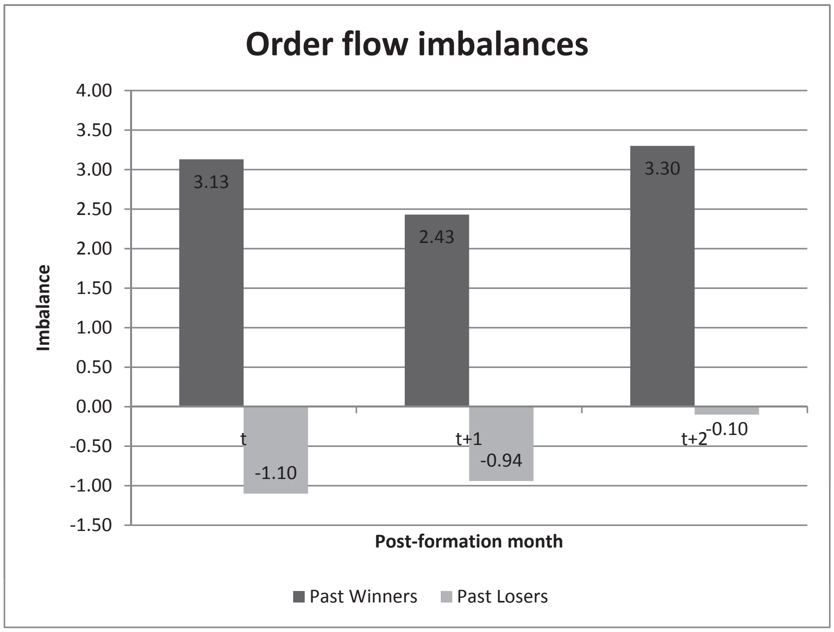

Figure 3 This figure plots post-formation order flow imbalances for past winners and past losers following continuous information during the 1983 to 2004 period. Continuous information arrives frequently in small amounts and is defined by a low ID. ID is defined in equation (1) to capture the distribution 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.