Trended Momentum

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ABSTRACT

Drawing on cognitive psychology and behavioral theories of pattern recognition and heuristic processing, we offer a new perspective on momentum by highlighting how clear price trends shape investor expectations. Trend clarity materially strengthens momentum returns: the highest trend-clarity quintile earns annualized returns of 12.68%, compared with 6.90% for a conventional momentum strategy. We also show that trend clarity affects momentum trading intensity within Hong and Stein's (1999) multi-period return-chasing model. Additional tests indicate that trading on clear trends is a central feature of momentum, distinct from existing explanations and observable across asset classes and global markets.

Keywords: Momentum, Trend Clarity, Behavioral Finance, Cognitive Psychology, Pricing Anomaly.

JEL codes: G11, G12, G14, D83, and D84

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I. Introduction

Momentum investing is one of the most persistent and widely documented anomalies in financial markets. It has been observed across a broad range of asset classes and markets, including equities, bonds, currencies, and commodities (Jegadeesh and Titman, 2011; Asness et al. (2013). Despite the extensive literature and numerous proposed explanations, the phenomenon remains only partially understood. In particular, while standard momentum strategies are defined by cumulative past returns, relatively little attention has been paid to whether the path through which those returns are generated matters for subsequent return continuation.

In this paper, we argue that it does. Our starting point is grounded in cognitive psychology and behavioral decision-making. Investors do not process information in a fully deliberative and frictionless manner; instead, they often rely on simplified representations, intuitive judgment, and cognitively economical heuristics when interpreting complex and noisy information (Simon, 1955; Fiske and Taylor, 1984; Gigerenzer et al., 1999; Kahneman, 2003). In such settings, the way information is presented can affect how readily it is perceived and acted upon. A return history that is smoother, more coherent, and easier to visually summarize may be more salient and more likely to be extrapolated than an equally strong but noisier path. In other words, investors may respond not only to the magnitude of past returns, but also to how clearly those returns express a trend.

This observation motivates our central concept: trend clarity. While trend-chasing is central to many explanations of momentum (De Long et al., 1990; Cutler et al., 1991; Hong and Stein, 1999), the clarity of the trend during the formation period has received little direct attention in empirical work. Traditional momentum strategies following Jegadeesh and Titman

(1993) treat two stocks with the same formation-period return as equivalent, even if one follows a smooth and persistent upward path while the other reaches the same return through a jagged and erratic sequence. As Figure 1 illustrates, stocks with identical formation-period returns can exhibit very different price paths. From the perspective of return-chasing or extrapolative trading, however, these paths are unlikely to be equally informative. A clearer price path, such as Path A in Figure 1, may be easier to recognize, interpret, and act upon, and therefore more likely to induce further trading in the same direction than the noisier paths B and C. We hypothesize that variation in trend clarity helps explain cross-sectional differences in momentum profits.

[Insert Figure 1 here]

To capture this idea empirically, we construct a measure of trend clarity (TC) using daily prices over the formation period from $t-11$ to $t-1$, with month t skipped. Specifically, we regress stock price on time and use the resulting R^2 to measure how clearly the price path follows a linear trend. A higher R^2 indicates a more coherent and visually smooth price trajectory. Because our interpretation relies on investor perception, we validate this measure using an online experiment. Participants compare pairs of stock charts with different R^2 values and assess which exhibits a clearer trend. The results show a strong positive relation between R^2 and perceived trend clarity, supporting the view that our measure aligns with how investors visually interpret return paths.

Our main empirical analysis examines the U.S. equity market over 1926 to 2023. The results show that trend clarity is a powerful conditioning variable for momentum, with profits increasing monotonically across TC quintiles. In equal-weighted portfolios, the winner-minus-loser strategy in the highest-TC quintile earns 6.34% over the subsequent six months (12.68% annualized) compared with 3.45% (6.90% annualized), for the traditional momentum strategy.

Similar patterns appear in value-weighted portfolios, while momentum is weak or absent in the lowest-TC group. These findings suggest that large past price changes alone are not sufficient to generate strong momentum; the clarity with which the trend is expressed also plays a central role.

The positive relation between trend clarity and future momentum survives a wide range of controls and robustness tests. In Fama-MacBeth regressions, the interaction between past returns and TC remains significant after controlling for firm characteristics known to influence momentum, including size, book-to-market, liquidity, volatility, and maximum return effects. The findings are also robust to standard asset pricing adjustments, alternative empirical specifications, different formation windows, and different portfolio cut-offs. We further show that the relation is present out of sample in international equity markets and across other asset classes, supporting the broader relevance of trend clarity as a conditioning variable for momentum.

A key objective of the paper is to relate trend clarity to existing explanations of momentum. First, we connect TC to the multi-period return-chasing framework of Hong and Stein (1999). Although their model does not explicitly incorporate trend clarity, it implies that when investors respond to multiple periods of past returns, clearer trends can generate stronger momentum trading. In this sense, TC provides an empirically tractable way to capture cross-sectional variation in the strength of trend-chasing behavior within an established theoretical framework.

Second, we examine whether TC simply proxies for slower-moving fundamentals. While clearer price trends during the formation period are associated with contemporaneous trends in earnings surprises, these fundamental trends do not persist in a way that can fully account for post-formation return continuation. This evidence suggests that TC does not merely capture stronger fundamentals; rather, the subsequent momentum appears more consistent with how investors respond to and trade on the observed price path.

Third, we examine trading-based evidence. Stocks with clearer past trends exhibit stronger and more persistent directional trading after formation. In particular, post-formation order imbalance is more positive for high-TC winners and more negative for high-TC losers, consistent with intensified trend-chasing behavior. These patterns support the view that trend clarity affects how likely investors are to continue buying past winners and selling past losers.

Fourth, we compare TC with the information discreteness (ID) measure of Da et al. (2014), the closest existing empirical concept. While TC and ID are related, they capture distinct aspects of the formation-period return path. ID reflects whether returns are realized through many small moves or a few discrete jumps, whereas TC captures the linear coherence and perceptual clarity of the overall price trajectory. Empirically, the two measures are only moderately correlated, each retains explanatory power in independent sorts and horse-race regressions, and residualized TC continues to predict momentum. We therefore interpret TC and ID as related but distinct path-based conditioning variables, rather than competing measures of the same phenomenon.

Rather than asserting a one-to-one mapping between TC, ID, and distinct behavioral theories, our interpretation is intentionally measured. Both variables are empirical proxies for how investors process return paths, and both may reflect overlapping behavioral forces in practice. ID is more closely related to the continuity versus discreteness of return realization, while TC reflects how clearly a trend is visually expressed and therefore how likely it is to attract extrapolative trading. These mechanisms need not be mutually exclusive. Instead, the evidence suggests that they capture complementary dimensions of how return histories shape investor behavior and subsequent momentum profits.

The paper makes four main contributions. First, we introduce trend clarity as a new path-based conditioning variable for momentum and show it provides substantial incremental predictive power in the cross-section of returns. Second, we provide a behavioral interpretation of why clearer trends strengthen momentum, drawing on cognitive psychology, bounded rationality, and heuristic processing rather than relying solely on cumulative return measures. Third, we show that the role of trend clarity is robust across markets and asset classes, enhancing both the implementation and the economic interpretation of momentum strategies.

Fourth, we contribute to the practical management of momentum strategies by showing how conditioning on trend clarity improves portfolio construction[1]. Unlike approaches that rely on additional fundamental characteristics (e.g., Sagi and Seasholes, 2007), our approach is directly tied to the core definition of momentum and does not depend on external fundamentals or market state variables. This provides a parsimonious way to enhance momentum strategies and helps mitigate crash risk, as highlighted by Daniel and Moskowitz (2016). Compared to complex dynamic strategies (e.g., Grundy and Martin, 2001; Barroso and Santa-Clara, 2015) our framework offers a simple alternative that operates through portfolio formation rather than market timing. All in all, the results suggest that incorporating trend clarity can improve performance across different market conditions while reducing exposure to momentum crashes.

Overall, our findings suggest that the clarity of the past price path is an economically important and previously underappreciated dimension of momentum. By focusing on how clearly a return trend is expressed, rather than only on its magnitude, we provide a more behaviorally grounded explanation for why some past winners exhibit stronger return continuation than others.

The remainder of the paper is organized as follows. Section II develops the conceptual framework for trend clarity, drawing on cognitive psychology and behavioral decision-making, and introduces the measure along with its experimental validation. Section III presents the main empirical results, including portfolio sorts and Fama–MacBeth regressions. Section IV examines the underlying mechanisms and relates trend clarity to the existing literature, including information diffusion, fundamentals, trading activity, information discreteness, and other momentum-related explanations. Section V provides out-of-sample evidence from international markets and other asset classes, along with robustness tests. Section VI concludes.

II. Trend Clarity: Underlying Reasoning, Measurement, and an Online Experiment

A. Underlying Reasoning

Our underlying reasoning is grounded in cognitive psychology and behavioral theories of decision-making under conditions of limited attention and processing capacity. A central insight from this literature is that individuals do not process all available information in a fully deliberative manner. Instead, they often rely on intuitive, low-cost judgments, particularly in complex environments characterized by abundant information. In this context, investors can be viewed as boundedly rational decision-makers who employ simplified rules and heuristics when forming expectations from noisy market data (Simon, 1955; Gigerenzer et al., 1999; Kahneman, 2003).

This perspective has a natural implication for momentum. Traditional momentum measures focus on cumulative returns over the formation period and implicitly treat two stocks with identical past returns as conveying the same momentum signal. From the standpoint of human judgment, however, these return histories may differ in their interpretability. A stock whose price follows a smoother, more coherent, and more visually stable path may be easier to recognize as "trending" than one that achieves the same cumulative return through a jagged or noisy sequence of movements. If investors rely in part on intuitive pattern recognition and heuristic extrapolation, the clarity of the path itself may affect the strength of their response to past performance.

This argument is closely related to the idea of the cognitive miser view in psychology; which holds that individuals economize on cognitive effort and therefore prefer simpler, more readily interpretable representations of information (Fiske and Taylor (1984), (2020)). In financial markets, where investors face numerous signals and substantial uncertainty, a clear trend may provide precisely such a cognitively economical summary. Rather than processing the full sequence of news and price changes in a fully analytical manner, some investors may be more likely to infer continuation when the past price path is easier to summarize visually and mentally.

A related literature on processing fluency reinforces this intuition. Processing fluency refers to the subjective ease with which information is perceived and understood. Research in cognitive and social psychology shows that stimuli that are easier to process tend to feel more familiar, more persuasive, and more readily accepted in judgment (Reber et al., 2004). Applied to financial markets, a price pattern that is more linear and coherent may be processed more fluently than one that achieves the same endpoint return through a noisier path. Such a pattern may therefore be more salient and more likely to be extrapolated by investors relying on intuitive judgment.

This reasoning also aligns with the broader literature on fast and frugal heuristics. When decision-makers face complex environments, simple decision rules become attractive not because they are fully optimal in a classical sense, but because they economize on time and cognitive resources while still producing workable judgments (Gigerenzer et al., 1999). In this setting, a clear trend can serve as a simple heuristic cue: the more coherent the historical path, the easier it is for investors to classify the stock as one with “momentum” and to project that trend forward.

Our argument therefore departs from the standard momentum definition in an important way. Following Jegadeesh and Titman (1993), most empirical studies define the momentum signal solely based on cumulative returns over a lookback window. While this approach is natural from a return-calculation perspective, it abstracts from how investors may perceive the path of returns. If some market participants respond not only to the magnitude of past returns but also to the clarity with which those returns form a trend, then the conventional momentum variable may be incomplete as a proxy for the signal that is behaviorally salient.

Accordingly, we propose trend clarity as a measure designed to capture how clearly a return path expresses a trend over the formation period. The key idea is not that all investors are technical traders in a narrow sense, nor that trend-chasing is necessarily irrational. Rather, when past price movements form a clearer and more coherent pattern, they become easier to process, easier to classify as meaningful, and more likely to attract extrapolative trading. In this sense, trend clarity serves as a behavioral conditioning variable for momentum: it captures variation in how strongly a given past return signal is likely to be perceived and acted upon.

In summary, our motivation rests on three linked ideas from cognitive psychology and behavioral decision theory. First, investors operate under bounded rationality and often rely on intuitive judgment rather than exhaustive analysis. Second, they conserve cognitive effort and therefore respond more readily to information that is simpler and easier to process. Third, clearer and more coherent price trends are more salient and more fluently processed than equally strong but noisier return paths. Taken together, these considerations suggest that trend clarity should strengthen the momentum effect by increasing the likelihood that past return information is recognized and extrapolated by investors.

B. Trend Clarity Measure and the Perception of Trend Clarity Experiment

We propose using R^2 from a time-trend regression as a measure of trend clarity in time-series data. Specifically, R^2 captures the extent to which variation in prices (or cumulative returns) over the formation period is explained by a deterministic time trend, thereby providing an objective measure of how closely the realized path conforms to a linear trend. This metric maps naturally to our behavioral mechanism; return paths with higher R^2 appear smoother and more coherent, and are therefore easier to process and classify as 'trending' in visual representations such as price charts. As a result, R^2 based trend clarity provides a tractable proxy that links the statistical properties of return paths to their behavioral salience.

To validate the relationship between R^2 and investors' perception of trends, we conduct an online experiment in which participants compare pairs of stock charts for trend clarity (details in Appendix II). We use a pairwise comparison design; each respondent is shown 10 pairs of stock price charts and asked to identify the chart with a clearer trend. The charts are generated to span 10 categories of R^2 values and are paired in three ways - contrasting, moderately distant, and similar in R^2 - to assess participants' ability to discern differences in trend clarity. Each respondent evaluates one batch comprising five pairs of positive return charts and five pairs of negative return charts, presented in randomized order to avoid order effects. Across all participants, 10 different batches are administered in total.

We disseminated the survey via social media (LinkedIn) and academic networks, including students and staff. We obtained 128 valid respondents who completed at least one comparison, yielding a total of 2513 trend evaluations. Appendix II (Figure A1) reports summary statistics for the respondents' demographic, education, and financial experience, showing a reasonably diverse sample. To examine the relationship between R^2 and perceived trend clarity, Figure 2 plots the R^2 distribution for each trend clarity category. The figure indicates a positive correlation between respondents' choice of clearer trends and R^2, although there is substantial variation within each category.

[Insert Figure 2 here]

We further run regression models and report the results in Table 1. In these logistic regressions, the dependent variable is binary; a value of 1 is assigned if respondents rate a trend as clear (answers 4 or 5) and 0 if not clear (answers 1-3). In the ordinal logistic regressions, the dependent variable takes the respondents' ratings from 1 (not clear) to 5 (very clear). The main independent variable is R^2, the R^2 of the chart's time-trend regression. We include a dummy variable, Pos, equal to 1 for positive trends and 0 for negative trends, and an interaction term $R^2 \times$ Pos to test whether the effect of R^2 differs across positive and negative trends.

The coefficients of R^2 are significantly positive across all regression specifications, confirming a positive relationship between trend clarity (TC) and R^2. To consider the economic interpretation, consider model 1: the log odds, log(clear/(not clear)), increase by 3.9879 for a one-unit increase in R^2. For a more measured change, suppose R^2 increases by 0.1 (e.g., from 0.6 to 0.7). Transforming to odds, $e(3.9879\times0.1) = 1.49$, indicating a 49% increase in the odds that a chart is classified as having a clear trend if R^2 increases by 0.1. The interaction analysis between positive and negative trends does not yield significant effects, suggesting that respondents' perception of trend clarity based on R^2 is not affected by trend direction. Overall, the results demonstrate a strong link between R^2 and perceived trend clarity.

[Insert Table 1 here]

III. Results: The Role of Trend Clarity in Momentum Strategy

A. Data

We obtain stock price and return data from the Center for Research in Security Prices (CRSP), focusing on U.S. domestic stocks (share codes 10 and 11) listed on the NYSE, AMEX, and NASDAQ. Accounting data are drawn from the annual and quarterly databases of Compustat. Our primary sample spans from January 1926 to December 2023, though the coverage varies by data availability. For analyses requiring quarterly earnings data, the sample begins in 1964. We also incorporate sentiment data from Jeffrey Wurgler's website (1965 to 2023) for supplementary tests. In additional analyses, we extend the sample to international markets using Compustat Global.

B. Portfolio Sorting

We begin with portfolio sorts. Formation-period return (PRET) is defined as the cumulative stock return measured from $t-11$ to $t-1$, with month t skipped before the $t+1$ to $t+6$ holding period. Trend clarity (TC) is measured as R^2 from a regression of daily stock prices on a time trend over the same formation period, requiring at least 200 daily observations. For each month t, we first sort stocks into quintiles based on PRET and then, within each PRET quintile, we further sort stocks into quintiles based on TC. We compute the holding-period returns and alphas from t+1 to t+6 for each portfolio.

Table 2 reports the equal and value-weighted portfolio returns. The results show that momentum is stronger when past trends are clearer, with a monotonic increase across TC quintiles in the Mom (5-1) column. In particular, the momentum strategy in the highest TC quintile yields a return of 6.34% over the six-month holding period (t = 5.99), more than 80% higher than the unconditional momentum return of 3.45% (t = 3.85). By contrast, momentum is weak and statistically insignificant in the lowest TC group. The difference in momentum returns between the highest and lowest TC quintiles is economically large and statistically significant. Panel B shows similar patterns for value-weighted portfolios, with momentum effects generally stronger, consistent with prior findings in the literature[2].

[Insert Table 2 here]

To control for common factors, we examine portfolio alphas in Table 3. Consistent with prior studies (e.g., Jegadeesh and Titman, 1993), the momentum returns cannot be fully explained by standard factor models based on other cross-sectional characteristics[3]. Importantly, the positive relation between trend clarity and momentum remains robust after controlling for these factors. Notably, although the behavioral factor model of Daniel et al. (2020) explains

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[2] For example, in Chen and Zimmerman's (2022) replication study, the monthly EW return is 0.82% and the VW return is 1.3% in deciles testing.

[3] Due to data availability, alpha of the Fama-French 5-factor model starts from July 1963.

unconditional momentum in our sample, high TC momentum continues to generate significant alpha. Overall, these results suggest that our results are not merely a repackaging of existing firm characteristics that drive cross-sectional returns.

[Insert Table 3 here]

To examine post-formation return dynamics, Figure 3 presents cumulative alphas of the momentum portfolio (winners minus losers) along with their corresponding t-values. The figure reinforces the observation of a monotonic increase in both returns and t-values as trend clarity rises. Two key insights emerge. First, there is little evidence of short-term reversal in high trend clarity groups (3 to 5), whereas significant reversal appears in low TC groups (1 and 2) during the formation month (i.e., the conventional skipping month). This suggests that conditioning on trend clarity can mitigate the impact of short-term reversals in momentum strategies.

[Insert Figure 3 here]

Second, medium-term reversal patterns also vary systematically with trend clarity. Using a t-value threshold of -2 in the equal-weighted results, the lowest TC group exhibits earlier reversal, with cumulative returns becoming statistically indistinguishable from zero by month t+5. This suggests that the short-lived momentum return in months 1 to 4 is temporary and largely reverses thereafter. By contrast, the highest TC group also shows some reversal, but its cumulative returns remain statistically different from zero after 24 months. This indicates that trended momentum is more persistent following portfolio formation.

Overall, these findings highlight the importance of trend clarity as a key determinant of post-formation return dynamics in momentum strategies. Its effects are not explained by existing factor models for cross-sectional returns. Moreover, trend clarity helps account for variation in both short- and medium-term reversal patterns.

C. Fama-MacBeth Regression

To examine the effect of trend clarity on the momentum return controlling for other firm characteristics, we estimate the Fama-MacBeth regression below:

$$r_{i,t+1,t+6} = \alpha + \beta_1 PRET_{i,t} + \beta_2 PRET_{i,t} \times TC_{i,t} + \beta_3 TC_{it} + \sum_{k=1}^{n} \varphi_k \, PRET_{i,t} \times X_{k,i,t}$$
$$+ \sum_{k=1}^{n} \gamma_k X_{k,i,t} + \varepsilon_{i,t+1,t+6} \quad (Eq\ 1)$$

Where $r_{i,t+1,t+6}$ is the cumulative returns from t+1 to t+6, $PRET_{i,t}$ is the past returns from t-11 to t-1, $TC_{i,t}$ is the trend clarity measure and $X_{k,i,t}$ is a list of firm-level characteristics which are defined in the table notes and Appendix I. We conjecture that high trend clarity attracts more momentum traders and this should lead to stronger momentum. We, therefore, expect a positive β_2.

Table 4 reports results from various specifications. Model 1 confirms a strong unconditional momentum effect, as indicated by the positive and significant coefficient on past returns. Model 2 (without controls) and Model 3 (with controls) show that the interaction between past returns and trend clarity is positive and statistically significant. Notably, the adjusted R^2 increases from 1.8% (Model 1) to 2.5% (Model 2) - an improvement of approximately 39% - indicating that trend clarity provides substantial incremental explanatory power for cross-sectional returns beyond unconditional momentum.

[Insert Table 4 here]

In Model 4 we estimate the regression after excluding micro-cap firms, defined as those with market value capitalization below the 20% percentile of NYSE stocks. The results are consistent with those in Model 3.

In summary, the Fama-MacBeth regressions with various controls confirm that the interaction between the past returns and trend clarity significantly predicts the next period return; the higher the trend clarity the stronger the momentum.

IV. What is the Connection between Trend Clarity and Existing Explanations?

In this section, we examine how trend clarity relates to existing explanations of momentum. We first consider the trend-chasing mechanism in Hong and Stein (1999), using simulations to illustrate how multi-period return chasing relates to trend clarity. Empirically, we use firm size and residual analyst coverage as proxies for the speed of information diffusion to test the prediction of a negative relationship between the speed of information diffusion and the effect of trend clarity on momentum.

Second, we examine how trend clarity relates to alternative explanations of momentum. We begin by assessing the link between fundamental earnings trends and price trends to understand the formation of price trends. We then analyze the role of investor activity and sentiment in shaping trend-chasing behavior. Third, we compare trend clarity with the information discreteness measure of Da et al. (2014). Finally, we control for other momentum strategies, including intermediate momentum (IR) and recent momentum (RR) following Novy-Marx (2012), as well as the 52-week high strategy of George and Hwang (2004).

A. Multiperiod Return Chasing in Hong and Stein (1999) and Trend Clarity

Among theoretical studies, Hong and Stein (1999) provide a framework that captures both the initiation of price trends by newswatchers and the trend-chasing of momentum traders.

This framework is closely aligned with the momentum process we study. However, even in this setting, trend-chasing is modeled as return-chasing without explicitly accounting for the clarity of price trends. To bridge this gap, we revisit the Hong and Stein (1999) framework, focusing on its extension to multiple formation periods (Hong and Stein, 1997). While the main conclusions are similar to the one-period case, the multi-period setting allows us to examine how cumulative returns over multi-periods relate to the clarity of price trends.

We examine how trend clarity arises in the Hong and Stein (1999) framework for a fixed formation period. In this model, news shocks about future dividends at time t+z diffuse gradually across newswatchers, generating a price trend beginning at time t. Slower information diffusion (i.e., larger z) implies a more persistent and coherent price path, and thus greater trend clarity. We examine this relationship through simulations with a formation period k to 6 and varying z from 3 to 18, holding other parameters as in the original HS (1999) simulation[4]. We run 30 simulations for each z value with T=250. For each simulation, the momentum trader's intensity parameter ϕ is obtained through optimization according to Equation 7 in HS (1999) (see Internet Appendix I for the detailed simulation setup).

In each simulation, both newswatchers and momentum traders are active at each time t. In the model, momentum trading intensity is the coefficient in front of the sum of the k-period formation returns at each time period t. Similarly, we estimate the time trend in the k-period and

[4] We built our simulation based on the code and notes from Alex Chinco. We are grateful to Alex Chinco for sharing his notes and code. All errors are our responsibility. For more details, visit alexchinco.com/hong-and-stein-1999.

obtain the R^2. Each simulation can be considered an analysis of momentum trading intensity in a particular stock within a market environment. We use the average R^2 of a price trend regression in each simulation to characterize trend clarity created by newswatchers and study its relationship with momentum traders' optimal trading intensity ϕ.

Figure 4 illustrates the relationship between momentum trading intensity (ϕ) and trend clarity (average R^2) across different values of z. Each point represents a simulation, with colors and shapes indicating different z groups. Ellipses show the mean absolute deviation from the median, and a white dot marks the median for each group of 30 simulations. The results show that slower information diffusion (higher z) generates clearer price trends (higher median R^2). Moreover, there is a positive association between trend clarity (median R^2) and momentum trading intensity (median ϕ). Overall, the simulation indicates that in multi-period return chasing framework, trend clarity is a useful predictor of momentum trading intensity, even though the model does not explicitly assume momentum traders are trend aware.[5]

[5] Return chasing works similarly to trend-chasing in the HS1999 model because the price trend is fundamentally created by news watchers, and momentum traders further exacerbate this trend. In this environment, a clear price trend is driven by information useful for predicting future holding returns. Without noise, cumulative past returns are positively associated with trend clarity, making the relationship between clear price trends and return-chasing momentum trading more clearly observable, even if traders are only chasing past returns. In a further simulation reported in the Online Appendix, we show that adding noise traders to the simulation weakens the connection between

[Insert Figure 4 here]

B. Information Diffusion Speed

A further insight from the simulation is that the speed of information diffusion affects the strength of the relation between trend clarity and momentum trading intensity. In Figure 4, the dashed lines represent within-group correlations, showing that higher z values (slower information diffusion) are associated with a stronger positive relation between trend clarity and momentum trading intensity. This is reflected in the steeper slopes of the lines for higher z values, indicating that the link between clearer trends and stronger momentum trading intensifies as information diffuses more slowly. Empirically, this prediction can be tested by examining whether information diffusion moderates the relation between trend clarity and momentum intensity. Following Hong et al. (2000) we use firm size and residual analyst coverage (ResidCov) as proxies for the speed of information diffusion.

Table 5 reports momentum profits (winner minus loser) from triple-sort portfolios (size, momentum, and trend clarity). The results show that the effect of trend clarity on momentum is stronger in small stocks (where information diffusion is slow) than in large stocks, particularly in

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return chasing and trend clarity. Noise reduces overall trend clarity and lowers average return-chasing intensity. Moreover, return-chasing behavior varies more widely in a noisy environment, with intensity fluctuating depending on the realized price path. This makes it more difficult to observe significant effects empirically. The fact that we have strong empirical findings in the US suggests that momentum traders dominate the influence of noise traders in our sample, supporting the importance of trend-chasing in this environment. This is also consistent with the weaker trend clarity effect observed in emerging markets, where noise trading is more prominent.

value-weighted portfolios. These findings further highlight the importance of price trend clarity in shaping the momentum process.

[Insert Table 5 here]

One concern with using firm size as a proxy for information diffusion is that it may also capture attention and limits-to-arbitrage effects. To address this, following Hong et al. (2000), we use residual analyst coverage (ResidCov). Because analyst coverage is typically higher for large firms and is associated with weaker momentum, we construct ResidCov by regressing log(1+analysts) on log(ME) and a NASDAQ dummy each month. The residuals isolate variation in analyst coverage that is orthogonal to firm size.

Table 6 shows that slower information diffusion, proxied by low residual analyst coverage, amplifies the effect of trend clarity on momentum. Both equal- and value-weighted results indicate that the spread between high and low TC momentum is largest when residual analyst coverage is low, though this difference is not statistically significant in value-weighted portfolios.

[Insert Table 6 here]

Overall, we find consistent evidence that slower information diffusion (i.e., delayed reactions from newswatchers) strengthens trend momentum, supporting the theoretical link between trend clarity (TC) and multi-period return chasing in the Hong and Stein (1999) model.

C. Fundamental Earnings Trends

Momentum traders, as trend followers, do not initiate price trends. In the Hong and Stein model, for example, initial trends arise from the gradual diffusion of new information among 'newswatchers'. The extent of this process likely relates to the amount of fundamental news about a firm. To examine the link between fundamentals and price trends, we study how patterns in earnings surprises relate to subsequent trend-chasing behavior.

[Insert Figure 5 here]

Figure 5 plots standardized unexpected earnings (SUE) over the four quarters pre- and post-formation across trend clarity portfolios. The figure highlights two key insights about trend formation and subsequent reversal. First, prior to formation, price trend clarity closely aligns with the SUE trend. As SUE becomes more pronounced and exhibits a steeper trajectory, trend clarity (TC) increases. This pattern suggests that a sequence of positive or negative news contributes to the formation of clear price trends (Panels A and B).

Second, after formation, the magnitude of SUE declines and the trend reverses, indicating a deficiency of fundamentals to back the extrapolation by trend followers. This pattern suggests that post-formation price momentum is a byproduct of over-extrapolation and reflects mispricing, as this price movement is not supported by fundamentals. This also aligns with the theory that future earnings announcements rectify the expectation errors formed by momentum traders, as suggested by La Porta (1996). Notably, for low TC groups (1 and 2), the earnings trend continues into the quarter following formation, whereas this is not observed for high TC groups (4 and 5). This contrast further suggests that post-formation price dynamics diverge more strongly from the fundamental trend in earnings when trends are clearer - consistent with behavior more aligned with momentum investors[6].

In summary, this section establishes that trend clarity is initiated by a clear fundamental trend, as reflected in the earnings surprise. However, the continued price movement in the first six months after formation is not supported by a similar trend in earnings, indicating the influence of non-fundamental momentum investors on the price movement.

D. Momentum Traders' Attention: Trading Volume, Order Imbalance, and Analyst Revisions

The price trend established during the formation period may not only attract fundamental investors, such as newswatchers, but also technical traders, including momentum traders. If so, clearer trends should draw stronger investor attention and induce more persistent post-formation trading in the same direction. Trading volume is a natural proxy for such attention, as clear trends accompanied by high formation-period volume may offer a stronger and more credible signal to momentum traders. Consistent with this idea, Figure 6 shows that among high TC momentum stocks, those with the highest formation-period trading activity (TC3-VOL3)

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[6] The post-earnings announcement drift (PEAD) literature suggests that standardized unexpected earnings (SUE) are positively correlated with future returns. To address concerns that the returns observed in the high TC group may be partially driven by earnings drift, we conducted a triple-sorting exercise. The results, reported in the internet appendix (IA Table 9), show that high TC momentum remains significant across all three SUE groups, and the high-minus-low TC results remain significant even after controlling for SUE.

outperform those with lower activity (TC3-VOL1) in both equal- and value-weighted cumulative returns.

We next examine whether stocks with clearer trends continue to attract stronger post-formation attention and directional trading. Figure 7 provides three pieces of evidence. First, Panel A shows that winner stocks in the high-TC group experience higher abnormal trading volume after formation, whereas low-TC winners exhibit weaker activity relative to their own formation-period benchmark. A similar pattern holds for losers, with high-TC losers also displaying persistently higher abnormal volume. These results suggest that clearer trends continue to attract investor attention after portfolio formation.

Second, Panel B shows that higher attention is accompanied by more directional trading. High-TC winners exhibit persistently positive order imbalance, while high-TC losers exhibit persistently negative order imbalance, indicating continued net buying of past winners and net selling of past losers. By contrast, low-TC groups show much weaker and less persistent imbalances. This pattern is consistent with clearer trends inducing stronger post-formation trend-chasing behavior.

Third, Panel C shows that analyst expectations also continue to adjust after formation. High-TC winners have a higher proportion of upward analyst revisions than low-TC winners, while high-TC losers display a lower proportion of upward revisions than their low-TC counterparts. This suggests that clearer trends are associated not only with stronger trading activity, but also with more persistent expectation updating, especially in the early part of the post-formation period.

[Insert Figures 6 and 7 here]

The analyst-coverage result, the post-formation analyst-revisions, and the trading-volume evidence capture distinct channels that need not move in the same direction. Low analyst coverage proxies for slower diffusion of fundamental information and, therefore, stronger return continuation (Hong and Stein, 1999, 2000). By contrast, post-formation analyst revisions reflect the subsequent adjustment of expectations once the trend has formed. Our finding that high-TC winners continue to receive relatively more upward revisions, while high-TC losers initially receive relatively more downward revisions, suggests that information continues to diffuse after portfolio formation and that analyst expectations adjust more persistently when the prior price trend is clearer. This is consistent with the Hong and Stein (1999, 2000) view that momentum can arise from gradual information diffusion rather than the immediate incorporation of news. Trading volume, in turn, more directly reflects participation and the intensity of price-based trend chasing. This interpretation is also consistent with evidence that momentum is stronger when investor attention is elevated, such as for firms with greater media coverage (Hillert et al., 2014).

Overall, this section shows that the effect of trend clarity is closely linked to investor attention and post-formation trading dynamics. Clearer trends attract greater attention, stronger directional trading, and more persistent revisions in expectations, all of which are consistent with trend clarity strengthening the momentum process.

E. Trend Clarity and Information Discreteness

A related study is Da et al. (2014), which examines the role of price paths in momentum. They suggest that momentum reflects investor underreaction to small, continuous price changes, referred to as "continuous momentum", which helps sustain trends. In contrast, more discrete price changes tend to attract attention from informed investors and arbitrageurs, reducing subsequent price drift.

A simple conjecture is that their continuous momentum may overlap with trend clarity momentum. In the Internet Appendix (IA Figure 1), we examine the construction of these two measures. Our simulation shows that while trend clarity (TC) and information discreteness (ID) are empirically related, they are not identical nor mechanically interlinked. The empirical correlation between these measures is -0.36 in our sample.

To examine the roles of trend clarity (TC) and information discreteness (ID) on momentum, we conduct a triple sort (3x3x3) on past returns, TC, and ID. Table 7 has the following findings. First, Panel A demonstrates a negative relation between TC and ID. In particular, the cell denoting high TC/low ID (bottom-left cell) contains the most stocks, indicating that clear price trends are more likely to be associated with continuous information (low ID). However, the two measures do not align perfectly, suggesting they capture distinct characteristics. Second, Panel B presents momentum strategy returns for each of the nine cells. Momentum is exclusively evident in the high trend clarity groups (in the 3rd row) and the continuous information groups (in the 1st column). There is no momentum effect in any other portfolios. Consistent with Da et al. (2014), momentum is stronger with continuous information. Importantly, TC and ID independently impact momentum returns. As shown by the diff (3-1) row and column, the disparities between the 3 and 1 sorted groups are highly significant across all groups, even when controlling for each other. If the differences between these two sorting measures were due to noise, we would not observe these significant effects among the subgroups. Furthermore, the portfolio that unifies the highest trend clarity and continuous information produces the highest momentum return (EW return of 5.62%, t=5.07). This again suggests the complementary contribution of these two measures to the momentum phenomenon[7].

[Insert Table 7 here]

We further confirm the independent effect of these two conditional variables through Fama-MacBeth regressions in an Internet Appendix (IA Table 11). Both variables exhibit independent predictive power, with PRET×TC and PRET×ID being highly significant across all specifications. To account for the correlation and overlapping effects of the two variables, we examine ResidTC by running a cross-sectional regression of trend clarity (TC) on PRET, information discreteness (ID), and market value each month, then obtaining the residual from the regression. Using this ResidTC, both the portfolio sorting (IA Table 12) and Fama-MacBeth regressions (IA Table 13) confirm that TC is distinct from the low ID momentum effect. Overall, these results show that information discreteness and trend clarity are related but distinct conditioning variables for momentum.

In summary, the evidence in this section shows that trend clarity is not subsumed by the information discreteness measure of Da et al. (2014). While the two variables are correlated and both help explain the cross-section of momentum returns, they capture distinct aspects of the formation-period return path. Information discreteness reflects whether returns are realized through many small moves or a few discrete jumps, whereas trend clarity captures the linear coherence and perceptual clarity of the overall price trend. The evidence further shows that trend

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[7] The findings are consistent in both the equal- or value-weighted computations and regardless of portfolio returns or alphas. We report the results of alphas analyses in an Internet Appendix (IA Table 10).

clarity contains incremental predictive content beyond information discreteness, and the post-formation trading patterns are more consistent with trend clarity being linked to trend-chasing behavior.

Our interpretation is that the two measures proxy for distinct channels through which investors process return information. Information discreteness relates to the continuity of information realization, whereas trend clarity reflects how clearly a trend is expressed and hence how easily it may attract extrapolative trading. These forces need not be mutually exclusive. In practice, both may operate simultaneously, with each measure capturing complementary aspects of investor responses to price dynamics. Ignoring either would provide an incomplete picture of momentum.

F. Trended Momentum: Controlling for Other Momentum Strategies

Finally, to further distinguish the TC explanation from existing momentum-related strategies, we control for intermediate momentum (IR) and recent momentum (RR) strategies, following Novy-Marx (2012) and the 52-week high strategy based on George and Hwang (2004). Table 8 reports the findings.

[Insert Table 8 here]

Novy-Marx (2012) evaluates intermediate (IR) and recent (RR) momentum strategies using returns in t+1 as the dependent variable. George and Hwang (2004) investigate the 52-week high strategy with 6-month holding periods. We find that the IR strategy outperforms the RR strategy in month t+1, consistent with Novy-Marx's (2012) findings. For post-formation returns from t+1 to t+6, we show that clear trend momentum earns significant returns of 2.62%, controlling for other strategies, while momentum with less clear trends yields negative and insignificant returns. Additionally, in the post-estimation test, traditional winner stocks earn significantly higher returns when the trend is clear (for this test, (high TC dummy - low TC dummy) x winner dummy, the slope is 0.0222, t=3.08)[8]. Overall, momentum, conditional on trend clarity remains robust over intermediate horizons, even after accounting for alternative momentum strategies[9].

V. Out-of-Sample Tests and Robustness Checks

A. Out-of-Sample Test: Trended Momentum Around the World

Prior studies show that momentum effects are generally stronger in developed markets than in emerging markets (Rouwenhorst, 1999; Griffin et al., 2003). Cai et al. (2023) attribute this difference to a more limited presence of newswatchers in emerging markets. Building on this idea, we posit that if momentum is partly driven by investors chasing past return trends, then weaker or less clearly defined trends (i.e., lower R^2) may help to explain cross-country variation in momentum effects.

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[8] The TC effects are not significant in the first month (t+1). In the Internet appendix (IA Figure 2), we run Fama-MacBeth regressions for single-month returns using a similar specification as in Table 4 and show consistent findings that PRET*TC is not significant in the first two months but becomes highly significant (t-value above 3) from months 3 to 6. This suggests that TC momentum is a gradual, continued process post-formation.

[9] George and Hwang (2004) document significant returns for the 52-week high strategy over a 6-month holding period. In our sample, we find positive but insignificant returns for this strategy in our regression. However, using the same period (July 1963 to December 2001) as George and Hwang, we recover significant 52-week high momentum. They use terciles instead of quintiles to identify winner and loser stocks, and with terciles, the 52-week high strategy performs better. This suggests that the success of the 52-week high strategy may depend on the specification and time period.

We examine the role of trend clarity in shaping momentum across global markets, covering 21 developed and 35 emerging markets (see IA Table 6 for country classifications). In each country, we implement the same TC double-sorting procedure as in the U.S. analysis, using terciles instead of quintiles to adjust for smaller stock numbers in emerging markets. Figure 8 reports the distribution of country-level momentum returns (winner-minus-loser portfolios) across three TC groups for developed and emerging markets. The vertical dashed line indicates the average momentum return within each market type.

[Insert Figures 8 and 9 here]

For equal-weighted portfolios, the contrast across market types is particularly pronounced. In developed markets, momentum returns increase with trend clarity. Differences between high TC and low TC momentum returns are statistically significant (at the 10% level) in 71% of countries (16 out of 21), indicating that the positive role of trend clarity observed in the U.S. generalizes to most developed markets.

In contrast, momentum in emerging markets is weaker, consistent with prior evidence (Rouwenhorst, 1999; Griffin et al., 2003). Positive average returns are observed only in the highest TC group. Differences between high TC and low TC momentum returns are statistically significant (at the 10% level) in just 46% of countries (16 out of 35).

We further examine whether differences between the two market types are driven by differences in the level of trend clarity. Because TC groups are determined within each country-year, the absolute level of R^2 in the high TC group may be lower in emerging markets than in developed markets. Figure 9 provides some support for this, with average R^2 values of 46% in developed markets and 44% in emerging markets (see IA Table 7 for details). However, the difference is too small to account for the observed variance in momentum outcomes. Instead, the key difference appears to lie in how investors respond to a given level of trend clarity. The sensitivity of momentum to TC is stronger in developed markets, suggesting that, for a given R^2, investors in developed markets treat clearer trends as a stronger momentum trading signal than those in emerging markets[10].

In summary, the global evidence underscores the importance of trend clarity for momentum. In emerging markets, only the strongest trends generate momentum, whereas in developed markets, the effect is more pervasive.

B. Out-of-Sample Test: Other Asset Classes

In this section, following Asness et al. (2013; hereafter AMP), we extend our trended-momentum tests to other asset classes, including currencies, government bonds, and commodities. Portfolio construction follows our equity analysis, with three differences. First, the test assets are currency, government-bond, and commodity contracts rather than individual stocks. Second, due to smaller cross-sections within each asset class, we form two momentum portfolios (loser and winner) and three Trend Clarity (TC) groups; in the pooled analysis, the larger universe allows for three or four TC groups. Third, data availability varies across markets, resulting in shorter or differing sample periods relative to the equity tests. We report the details below.

For currencies, we obtain monthly spot exchange rates from Bloomberg for 20 currencies: Australia, Brazil, Canada, China, Denmark, the Euro area, Hong Kong, India, Japan, Malaysia, New Zealand, Norway, Singapore, South Africa, South Korea, Sweden, Switzerland,

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Taiwan, the UK, and the US. The sample period is 1980–2023. Currency returns are computed as the log difference in the spot exchange rate between month *t–1 and* month *t*. We exclude carry from interest-rate differentials, because interest rates typically vary slowly over short horizons, making it difficult to identify trends in carry-related returns over the formation window.

Panel A of Table 9 shows that winner-minus-loser (WML) returns increase with TC. Momentum is economically large and statistically significant only in the high-TC group, indicating that TC is an informative conditioning variable for currency momentum[11].

[Insert Table 9 here]

We next analyze 20 ten-year government bond markets: Australia, Canada, China, Denmark, France, Germany, India, Italy, Japan, Malaysia, Mexico, Norway, Singapore, South Africa, South Korea, Spain, Sweden, Switzerland, the UK, and the US. Bond returns are from Datastream, and the daily yields used to estimate TC are from Bloomberg. The sample period is

[11] Returns in the sorted portfolios are negative for both winner and loser legs, while WML is positive. To reconcile this pattern with the existing literature, we perform two checks. First, we re-examine unconditional currency momentum. Following AMP, we form three portfolios based on past returns and find significant unconditional momentum in our sample, alongside negative average returns for each leg. This outcome likely reflects the influence of a strong-dollar period in the more recent part of the sample. Second, restricting the sample to match AMP's endpoint (through July 2011), we obtain positive average returns for winner currencies and stronger unconditional momentum. We report these results in the Internet Appendix.

1990–2023. Panel B shows that momentum is not statistically significant within any TC group, and there is no clear monotonic relation between WML returns and TC[12].

For commodities, we follow Bianchi et al. (2015) to identify 27 series from Datastream. The sample period is 1980–2023. Panel C shows that WML returns increase with TC, with the strongest momentum return in the high-TC group.

Finally, we also pool currencies, government bonds, and commodities to examine trended momentum in a broader non-equity universe. While liquidity and transaction costs differ across asset classes, this pooled analysis assesses whether TC retains its differentiating power in a heterogeneous setting. Panel D shows that momentum strengthens with TC. The larger pooled sample also allows for finer TC groupings to increase statistical power. Panel E, which uses four TC groups, shows a larger and more significant spread between high- and low-TC momentum, consistent with our main equity results.

The evidence across non-equity markets indicates that TC enhances momentum performance beyond equities. At the same time, the absence of a TC effect in government bonds suggests that the mechanism may be weaker in markets less influenced by retail participation and sentiment-driven trading, consistent with a behavioral explanation.

C. Out-of-Sample Test: Trended Factor Momentum

[12] In the Internet Appendix (IA Table 15), we show that the unconditional bond momentum in our full sample is negative and statistically insignificant. We also replicate the unconditional momentum test using only the ten bond markets in AMP. In that restricted sample, average returns increase from losers to winners and the implied momentum spread is economically worthwhile although it remains statistically insignificant, consistent with AMP.

As an out-of-sample test of the broader relevance of trend clarity, we examine whether TC also helps explain momentum in characteristic-based factor returns. If TC captures a general tendency for clearer trends to attract stronger extrapolative trading and more persistent return continuation, its effect should extend beyond individual stocks to traded factor portfolios, where return series may also display varying degrees of trend clarity.

We use both equal-weighted (EW) and value-weighted (VW) long-short returns constructed on individual firm characteristics as factor returns. The factor data are from the Chen and Zimmermann open-source asset pricing dataset covering January 1965 to December 2023 and include 179 factors. Using daily factor returns, we construct a cumulative return index as the factor "price" series for each factor. We then estimate trend clarity (TC) from these series as the R^2 of a fitted time trend, following the same procedure as in the stock-level analysis. Monthly factor returns are used to compute formation-period factor returns, with the most recent month skipped. For unconditional factor momentum, we form three portfolios based on formation-period factor returns. For TC-conditional factor momentum, we form 3×3 portfolios by independently sorting on formation-period factor returns and TC, and we examine subsequent six-month returns.

[Insert Table 10 here]

Table 10 provides strong evidence that TC is an effective conditioning variable for factor momentum. The winner-minus-loser (WML) return in the high-TC group is significantly larger than in the low-TC group. For EW factors, conditioning on high TC increases six-month momentum returns by 1.24% relative to unconditional momentum (2.48% annualized).

These results are important for two reasons. First, they show that the predictive role of TC extends beyond individual stocks to factor portfolios, indicating that TC captures a broader feature of return dynamics. Second, they reinforce our main finding that clearer trends are associated with stronger subsequent momentum. In other words, when past performance follows a more coherent and stable path, return continuation is stronger not only for stocks but also for factors. This is consistent with the view that trend clarity enhances the salience and interpretability of past returns, making them more likely to be extrapolated. Overall, the factor results provide out-of-sample support for the central conclusion that trend clarity is a powerful conditioning variable for momentum.

D. Robustness Check: Mitigating Momentum Crashes and Post-Publication Decay

Momentum crashes, as outlined by Daniel and Moskowitz (2016), pose a significant risk to momentum strategies. We examine whether incorporating trend clarity could help mitigate the impact of these crashes.

Table 11 reports momentum returns during 105 identified crash months. Following Daniel and Moskowitz (2016), these periods typically coincide with market rebounds, when prior 'loser' stocks experience sharp reversals. A 'market rebound'- and thus a crash month – is defined as a period in which the past two-year market return is negative, while the current month exhibits a positive market excess return.

[Insert Table 11 here]

Table 11 confirms the presence of momentum crashes, with all the TC sorted strategies generating negative returns during these periods. Notably, the decline is smallest and statistically insignificant in the highest TC quintile, while the largest and most significant losses occur in the lowest TC group. These results suggest that trend clarity mitigates the severity of momentum crashes. Accordingly, strategies that emphasize high TC momentum can reduce downside risk during crash periods.

Moreover, a long-short portfolio strategy, which involves long positions in the clearest trend momentum (WML [winner minus loser] in the high TC) and short positions in the least clear momentum portfolio (WML in the low TC), yields a significant positive return of 9.76% and 9.62% six-month return for Equal Weighted (EW) and Value Weighted (VW) portfolios, respectively. We refer to this as the long-short TC momentum strategy. This is a strong performance[13].

A large literature examines methods to mitigate momentum risk. Grundy and Martin (2001) show that momentum has a significantly negative beta following bear markets and propose hedging market exposure to stabilize returns. However, Daniel and Moskowitz (2016) argue that real-time beta usage does not prevent crashes. Similarly, Barroso and Santa-Clara (2015) use the realized variance of daily returns to predict momentum risk.

Our 'trended momentum' approach offers an alternative risk management strategy by focusing on portfolio construction rather than market timing. As shown in Table 2, the long-short TC momentum strategy delivers stable six-month returns of 5.78% (EW) and 5.49% (VW) over the full sample period, including 87 crash months. These returns are accompanied by strong statistical significance (t-statistics above 6.7). This performance reflects two sources of advantage: weak momentum in low TC portfolios during normal periods and stronger reversals

[13] However, it is important to note that this return is not obtainable on its own without an effective forecast model to predict momentum crashes. The purpose of this analysis is to quantify the incremental benefit of taking into consideration trends when investing with a momentum strategy.

during crash periods. Together, these effects enhance the overall risk-return profile of the strategy.

Our findings suggest that trend clarity is a key conditioning variable for momentum strategies. It can both mitigate the drawbacks of unconditional momentum – by focusing on high TC portfolios – and exploit reversals in low TC portfolios through a long-short TC momentum strategy. This approach offers a simpler alternative to enhancing momentum performance, without the complexities of building dynamic strategies based on forecasting market states, as recommended by Daniel and Moskowitz (2016) or Barroso and Santa-Clara (2015).

Another challenge for anomaly-based strategies is post-publication decay. McLean and Pontiff (2016) show that anomaly returns weaken after publication as mispricing becomes widely recognized. The momentum effect was first documented in 1993. Using Fama-MacBeth regressions (IA Table 8), we find that the unconditional momentum effect (PRET) is not significant in the post-publication period, whereas trend clarity (PRET x TC) retains its significance and shows a stronger magnitude. These results suggest that trend-based momentum is less susceptible to post-publication decay and differs from traditional momentum by capturing a more persistent component of return predictability.

E. Other Robustness Checks

We conduct a series of robustness checks using alternative research designs. To mitigate the impact of small stocks, we apply NYSE-based quintile breakpoints for sorting variables (IA Table 1) and exclude stocks priced below $5 (IA Table 2). To account for more recent momentum effects (Novy-Marx, 2012), we shortened the formation period to 6 months instead of 12 (IA Table 3). We also examine independent double sorts on past returns and trend clarity (IA Table 4). Across all specifications, the results remain consistent, reinforcing the role of trend clarity (TC) as a key determinant of momentum returns. We further consider the role of investor sentiment. Stambaugh et al. (2012) show that mispricing is more pronounced when sentiment is high. Consistent with this, we find that unconditional momentum weakens during low-sentiment periods (IA Table 5). However, momentum conditional on high TC remains significant regardless of sentiment, suggesting that the trend-chasing mechanism operates independently of general investor sentiment.

VI. Conclusions

Momentum investing is persistent and widespread across asset markets around the world, yet its underlying drivers remain only partially understood. In this paper, we argue that one important and previously underappreciated element is the clarity of the past price path. Drawing on cognitive psychology and behavioral decision-making, we propose that investors may respond not only to the magnitude of past returns but also to how clearly those returns form a trend. Smoother and more coherent price paths are easier to perceive, interpret, and extrapolate.

We introduce the concept of trend clarity and demonstrate its empirical importance for understanding momentum. Measured as the R^2 from a time-trend regression of prices during the formation period, trend clarity captures the linear coherence and perceptual clarity of the return path. We show that momentum profits are substantially stronger when past price trends are clearer, and that this effect remains robust after controlling for firm characteristics, factor models, and other established explanations of momentum. The evidence also shows that trend clarity provides incremental predictive content beyond related measures such as information discreteness.

Our findings also highlight the broader relevance of trend clarity for both theory and practice. Empirically, the effect extends beyond the U.S. equity market to international markets and other asset classes. Conceptually, trend clarity links momentum to how investors process and trade on return histories, with post-formation trading evidence showing that clearer trends attract stronger trend-chasing behavior. From a practical perspective, incorporating trend clarity improves the implementation of momentum strategies and helps mitigate crash risk. Overall, our results suggest that trend clarity is an economically important path-based conditioning variable for momentum and a useful component for future theoretical and empirical work on return continuation.

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APPENDIX

Appendix I. Variable Definitions

Formation-period return (PRET). PRET is the cumulative return measured from t−11 to t−1, with month t skipped before the t+1 to t+6 holding period. Data source: CRSP Monthly File.

Trend clarity (TC). TC is the R^2 from the regression of daily stock price (CRSP-adjusted prices, constructed with CRSP cumulative adjustment factors) on a date sequence over the same formation period as PRET, requiring at least 200 daily observations. Data source: CRSP Daily File.

Information discreteness (ID). Following Da et al. (2014) we first count the percentage of positive and negative daily returns in the past 12 months skipping most recent month (to be consistent with the formation period of past 12-month return), we then multiply it by the sign of the past return (1 if the past return is positive and -1 if the past return is negative). Data source: CRSP Daily File.

Firm size (ME). It is the market value defined as the stock price times the number of shares outstanding. Data source: CRSP Monthly File.

Residual trend clarity (ResidTC). We run a cross-sectional regression of trend clarity (TC) on the past 12-month return (PRET), information discreteness (ID) and firm size (ME), i.e. $TC = \alpha + \beta_1 PRET + \beta_2 ID + \beta_3 ME + \varepsilon$ to acquire the residual as residual trend clarity. Data source: CRSP Monthly and Daily File.

Residual information discreteness (ResidID). We run a cross-sectional regression of information discreteness (ID) on past 12-month return (PRET), trend clarity (TC) and firm size

(ME), i.e. $ID = \alpha + \beta_1 PRET + \beta_2 TC + \beta_3 ME + \varepsilon$ to obtain the residual as residual information discreteness. Data source: CRSP Monthly and Daily File.

Book to market ratio (BM). It is book value over market value. Book value is stockholders' equity, plus balance-sheet deferred taxes and investment tax credits if available, minus the book value of the preferred stock. Depending on availability, we use the redemption, liquidation, or par value if available to estimate the value of the preferred stock. Data source: Compustat Fundamentals Annual and CRSP Monthly File.

Dollar trading volume (DVOL). It is the average monthly dollar trading volume in the past 12 months (requiring at least 11 months). Monthly dollar trading volume is stock price times the number of shares traded. Following Gao and Ritter (2010), we adjust the number of shares traded as follows: divide volume of NASDAQ stocks by 2 before Jan 2001, by 1.8 until the end of 2001, by 1.6 between 2002 and 2003 and leave other periods unchanged. Data source: CRSP Monthly File.

Trading turnover (VOL). It is the average monthly trading turnover in the past 12 months (requiring at least 11 months). Monthly trading turnover is the number of shares traded scaled by the number of shares outstanding. Number of shares traded is adjusted (see DVOL). Data source: CRSP Monthly File.

Idiosyncratic volatility (IVOL). We estimate residuals by running a regression of the daily stock return on daily market return (CRSP value-weighted index return) in each month (requiring at least 15 days in a month). Then we compute the standard deviation of the residuals. Data source: CRSP Daily File.

Illiquidity (ILLIQ). It is the average daily illiquidity over the past 12 months. Daily illiquidity is computed as the absolute value of stock return divided by the dollar trading volume.

Dollar trading volume is stock price times the number of shares traded. We require at least 100 days during the past 12 months. Data source: CRSP Daily File.

Maximum daily return (MDR). It is the maximum daily return in a month (requiring at least 15 days in a month). Data source: CRSP Daily File.

Appendix II. Experiment Design

Introduction and Motivation

The perception of trend clarity in stock price charts holds substantial implications for both individual investors and financial institutions. However, the link between a statistical measure of trend and individuals' perception of such a trend has not been exhaustively explored in the academic literature.

To address this gap, our study investigates the relationship between a clear statistical measure, the R^2 value of the time trend in stock price charts, and survey respondents' perception of trend clarity. By doing so, we reveal how statistical measures of trends align with perceived trend clarity.

Experimental Design

We adopted a pairwise comparison design to collect the data. Respondents are randomly presented with 10 pairs of stock price charts, and for each pair, they are asked to select the chart with the perceived clearer trend. This design allows us to control for personal variations in trend perception by directly comparing two charts within the same context. We also ask a list of optional demographic, educational and financial experience questions at the end.

In order to ensure a diverse range of trend clarity, we constructed 10 different batches, each containing a unique combination of 10 pairs of stock price charts. These batches are designed to cover various scenarios of trend clarity, which will allow us to capture a wide array of data for subsequent analysis.

Summary of Pairing Design

We randomly generate a return series for a period of 250 days from a normal distribution and calculate the cumulative return over this period. One can consider the cumulative return plus one as representing the price movement. We then calculate the R^2 of the time series regression of this price on the day variable. We assign R^2 into 10 groups ranging from 0 to 9. For example, an R^2 of 0.09 will be in group 1 and 0.82 will be in Group 8.

Our experiment employs a systematic approach to pairing stock price charts based on their R^2 measures. This approach seeks to gauge respondents' abilities to discern trends with varying degrees of clarity. Our pairing strategy includes three types of pairs: Contrasting, moderately distant pairs and similar pairs.

Each batch includes two contrasting pairs (C1, C2), two moderately distant pairs (M1, M2), and one similar pair (S). The combinations are random with the restrictions applied, and they follow the same pattern in both upward and downward trends. For example,

Batch 1:

- Up: C1(9,0), C2(8,1), M1(5,3), M2(7,4), S(5,5)
- Down: C1(0,9), C2(1,8), M1(3,5), M2(4,7), S(5,5)

Batch 2:

- Up: C1(8,2), C2(7,1), M1(4,2), M2(5,1), S(3,4)
- Down: C1(2,8), C2(1,7), M1(2,4), M2(1,5), S(4,3)

…

Furthermore, we have ensured counterbalancing within each pair, where the charts with higher and lower R^2 measures are presented randomly in order. Each respondent will evaluate one batch, consisting of five pairs in a randomized order to avoid any order effects. In total, we have designed 10 different batches.

For the selected pairs, the cumulated returns are scaled to be the same and presented in a plot. Simulating real-world practice, the graphs are always rescaled to present the data series in full as much as possible. The experiment can be accessed through the following link. https://leedsubs.eu.qualtrics.com/jfe/form/SV_9StPcMAkNzdLPCu

Distributions

We disseminated the survey via social media (LinkedIn) and academic networks, including students and staff. We obtained 128 valid respondents who completed at least one comparison, yielding a total of 2513 trend evaluations. Appendix II (Figure A1) reports summary statistics for the respondents' demographic, education, and financial experience, showing a reasonably diverse sample. To examine the relationship between R^2 and perceived trend clarity, Figure 2 plots the R^2 distribution for each trend clarity category. The figure indicates a positive correlation between respondents' choice of clearer trends and R^2, although there is substantial variation within each category.

As we can see below from the demographic, education and financial experience data, we have a reasonably diverse set of respondents.

Figure A1. Summary of Respondent Characteristics

Q12.1 - What is your age group?

- Under 18: 1

- 18-24: 50
- 25-34: 30
- 35-44: 10
- 45-54: 5
- 55-64: 2
- 65+: 1

Q12.2 - What is your gender?

- Male: 50
- Female: 20
- Non-binary / third gender: 2
- Prefer not to say: 3

Q12.3 - What is your ethnicity?

- White: 45
- Black or African: 1
- Hispanic or Latino: 2
- Asian: 10
- Chinese: 15
- Prefer not to say: 5

Q12.4 - What is your highest level of education?

- No education: 0

- Primary education: 1
- Secondary education: 5
- Vocational school: 3
- Some college: 10
- Associate's degree: 5
- Bachelor's degree: 35
- Master's degree: 25
- Doctoral or professional degree: 10
- Prefer not to say: 2

Q12.5 - What is your field of study/work?

- Natural Science: 2
- Engineering: 8
- Medical: 2
- Agricultural: 1
- Social Science: 3
- Humanities: 2
- Business: 45
- Law: 2
- Computer: 3
- Arts: 2
- Education: 1

Q12.6 - Do you have any experience with stock trading?

- No experience at all: 20
- Some knowledge, but never traded: 40
- Yes, I've traded occasionally: 25
- Yes, I've traded regularly in the past: 10
- Yes, I trade regularly now: 5

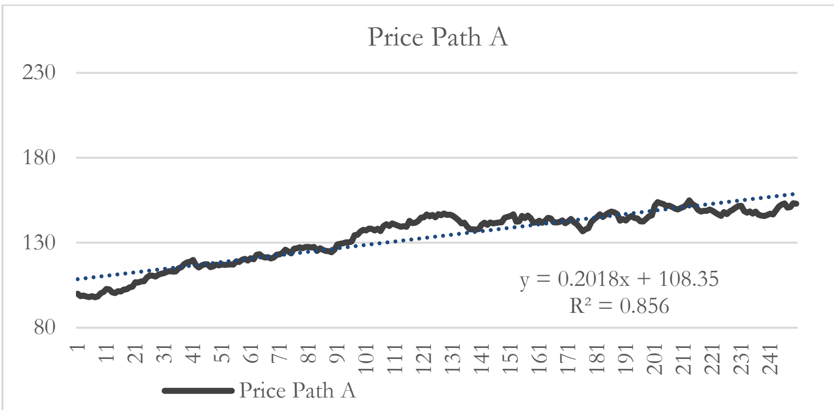
Q12.7 - How often do you interpret data using charts or graphs?

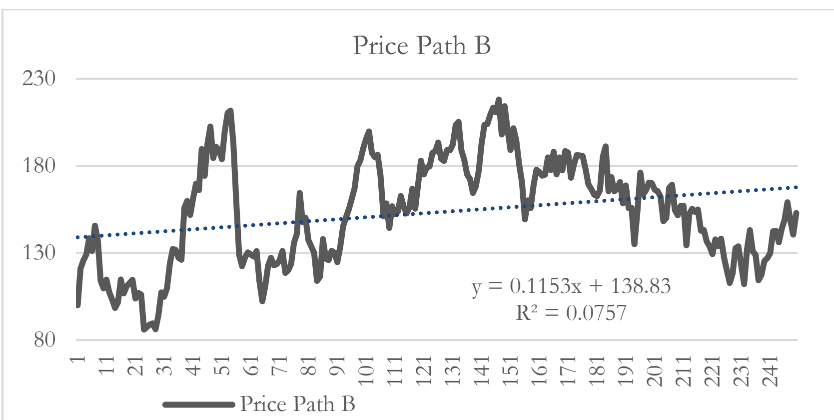
- Never (I don't use charts or graphs): 5
- Rarely (less than once a month): 10
- Occasionally (about once a month): 30
- Frequently (about once a week to once a day): 40
- Very frequently (almost daily): 15

Figures

Figure 1. Momentum Price Paths

This figure illustrates three different paths that produce the same total return of 52% in a hypothetical period of 250 days. It also reports a fitted trend line and its R^2.





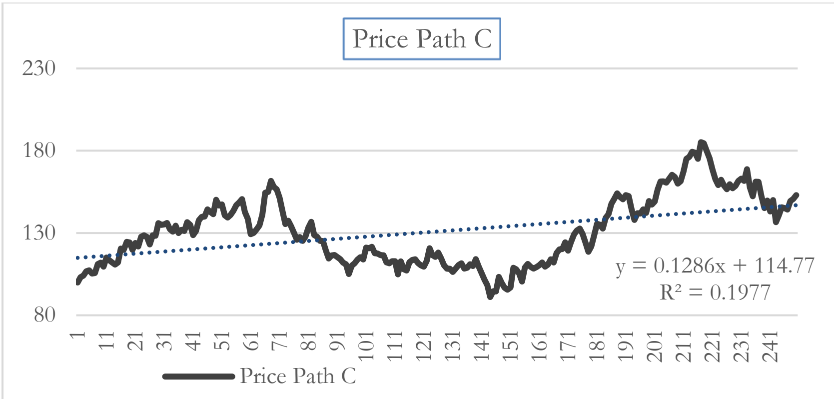

Price Path C
230
180
130
80
1
11
21
31
41
51
61
71
81
91
101
111
121
131
141
151
161
171
181
191
201
211
221
231
241
y = 0.1286x + 114.77
R² = 0.1977
Price Path C

Figure 2. Distribution of R^2 Values Across Different Trend Clarity Categories

This figure illustrates the distribution of R^2 values within each category of trend clarity as perceived by respondents. The trend clarity is rated on a scale from 1 to 5, where 1 represents the least clear trend and 5 indicates the clearest trend. The data are derived from 128 respondents, encompassing a total of 2513 valid responses.

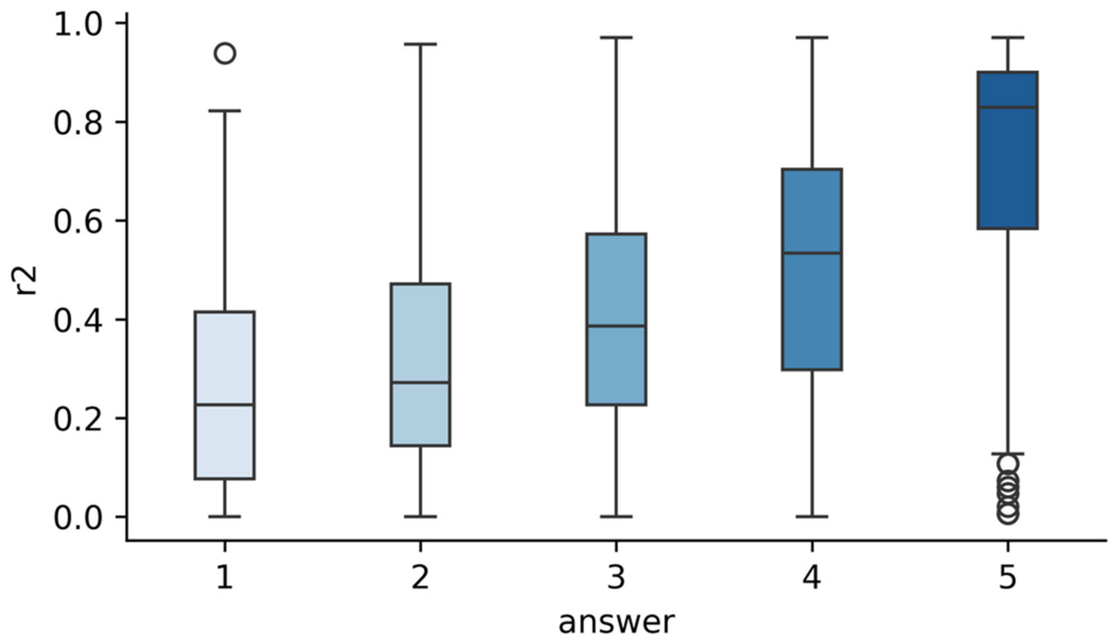
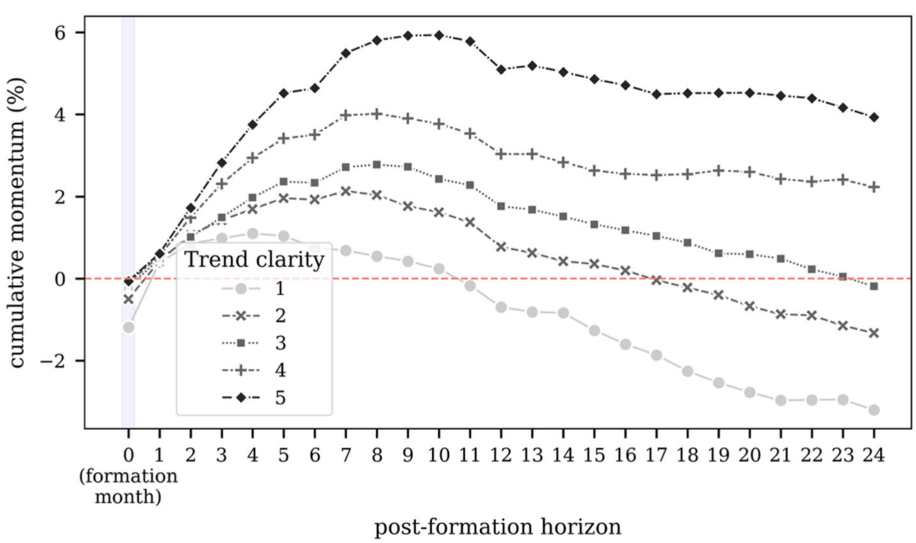


Figure 3. Post-formation Alphas by Trend Clarity

The figure plots post-formation alphas (risk-adjusted returns) with respect to the Fama-French 3-factor model for momentum portfolios (winner minus loser) conditional on trend clarity (TC). The sample used to construct portfolios is from Dec 1926 to Dec 2023. We rank stocks into quintiles based on formation-period returns (PRET) in each month. Within each PRET quintile, we assign stocks into quintiles based on trend clarity. Trend clarity is the R^2 from the regression of daily stock price on a date sequence over the same formation period as PRET, requiring at least 200 days. Panels A and B plot equal-weighted alphas and value-weighted alphas, respectively. Panel A1 (B1) plots cumulative alphas from 0 (formation month) to 24 (24 months after formation). Panel A2 (B2) plots corresponding t-values for cumulative alphas.

Panel A: equal-weighted

Panel A1: Cumulative Alpha



Panel A2: t-Stats of Cumulative Alpha

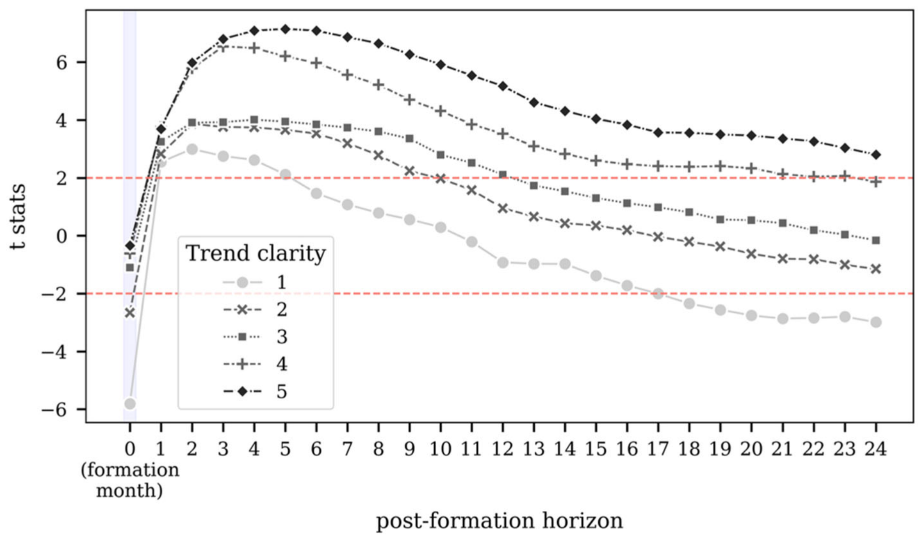
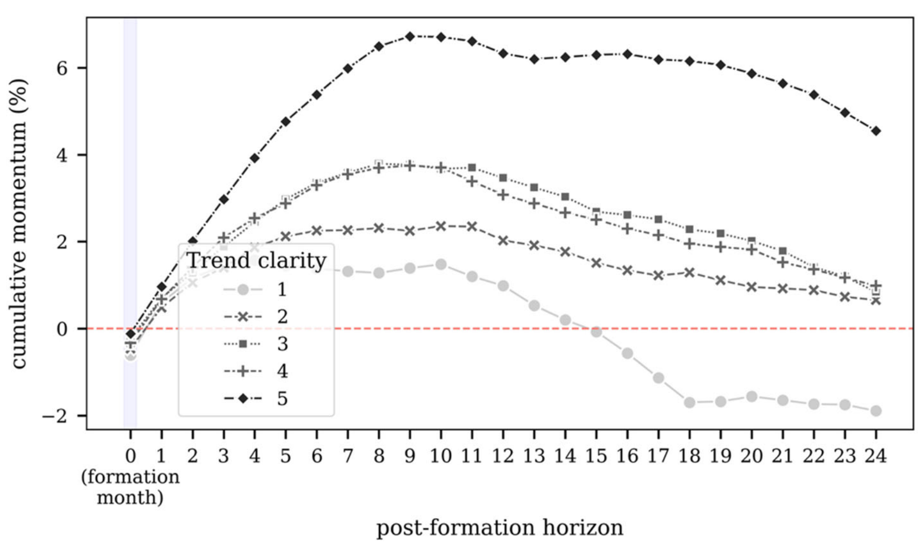


Figure 3. Continued

Panel B: value-weighted

Panel B1: Cumulative Alpha



Panel B2: t-Stats of Cumulative Alpha

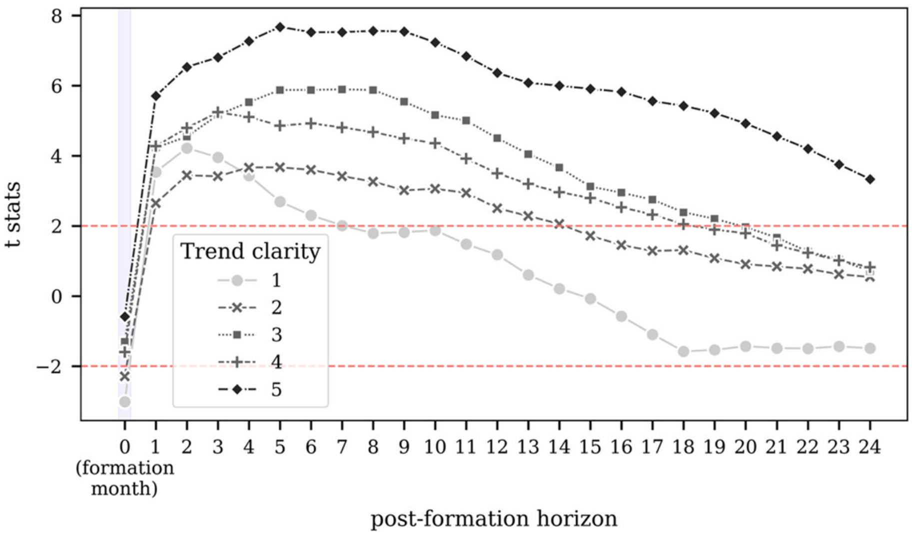
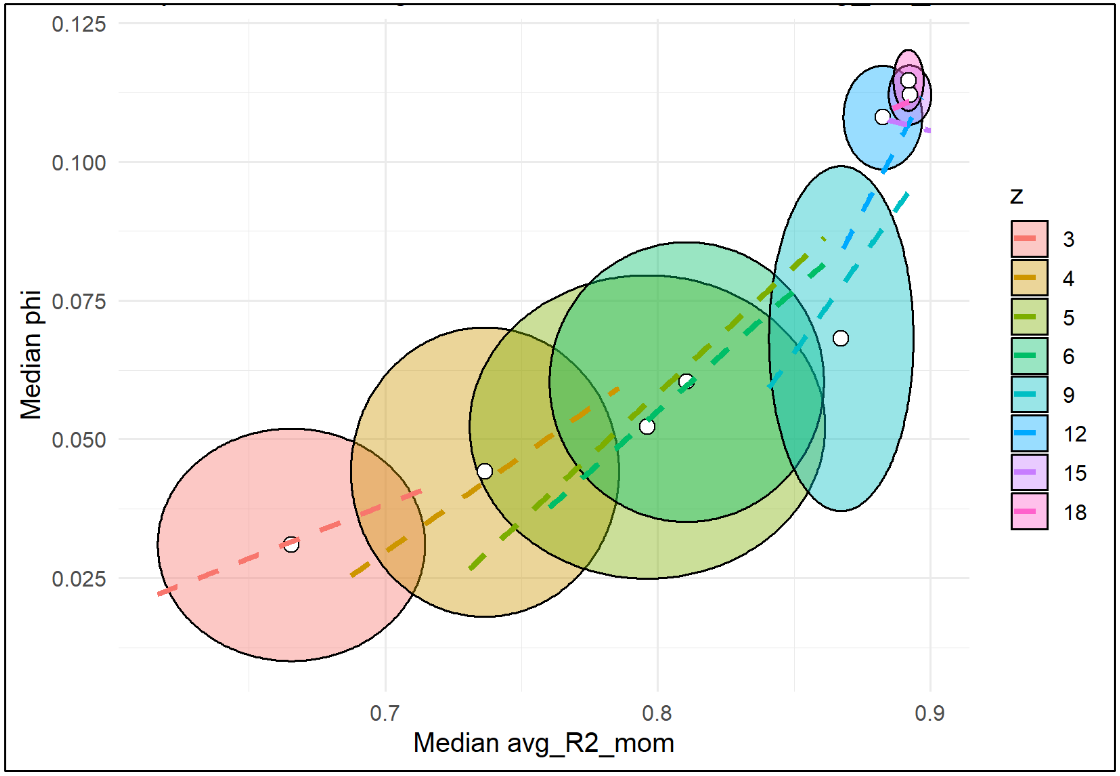

Trend clarity
1
2
3
4
5
t stats
post-formation horizon
0 (formation month)

Figure 4. Trend Clarity and Momentum Intensity with Different News Watcher Efficiency: A Simulation Summary

This figure is an ellipse plot illustrating the relationship between momentum trading intensity (ϕ) and trend clarity (average R^2) across different values of newswatcher efficiency (z). A higher z indicates lower newswatcher efficiency. Each ellipse represents a set of 30 simulations for a given z value, with different colors indicating different z groups. The median values for each group are marked by white dots, while the ellipses show the mean absolute deviation from the median. The dashed lines indicate the trend within each group. The simulation settings are as follows: formation period k=6, z values ranging from 3 to 18, momentum holding period j=12, momentum trader risk tolerance γ=1/3, news shock standard deviation σe=0.5, and the time period of the simulation T=250.

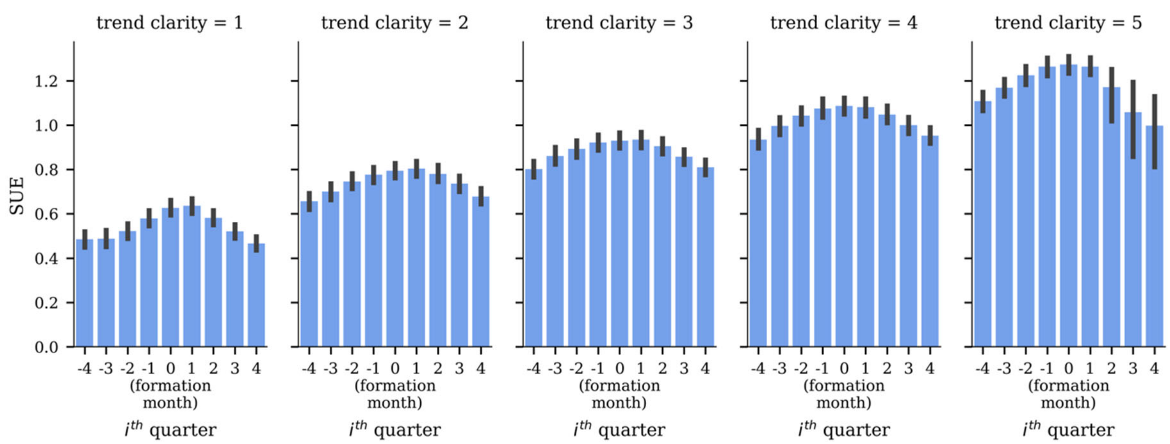


0.125
0.100
0.075
0.050
0.025
Median phi
0.7
0.8
0.9
Median avg_R2_mom
z
3
4
5
6
9
12
15
18

Figure 5. SUE and Trend Clarity

This figure plots the standardised unexpected earnings (SUE) for high and low trend clarity portfolios. We rank stocks into quintiles based on formation-period returns (PRET) and further rank them into quintiles based on trend clarity (TC). TC is the R^2 from the regression of stock daily price on a date sequence during the same formation period as PRET, requiring at least 200 days. SUE is the difference between current earnings and earnings 4 quarters before scaled by the standard deviation of the difference over the past 8 quarters. Panel A plots the SUE 4 quarters before and after formation for winner stocks and Panel B plots the SUE 4 quarters before and after formation for loser stocks. The black vertical line indicates a 95% confidence interval.

Panel A: winner stocks



Panel B: loser stocks

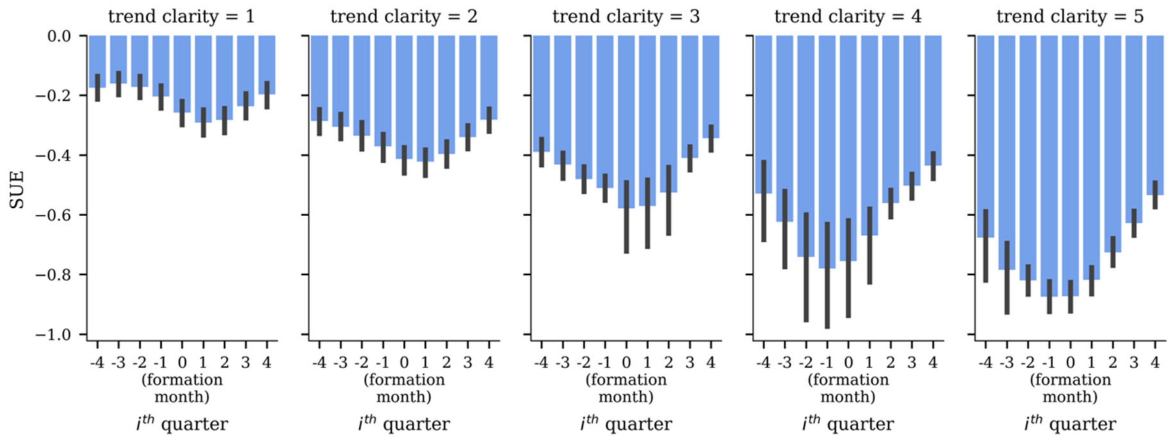
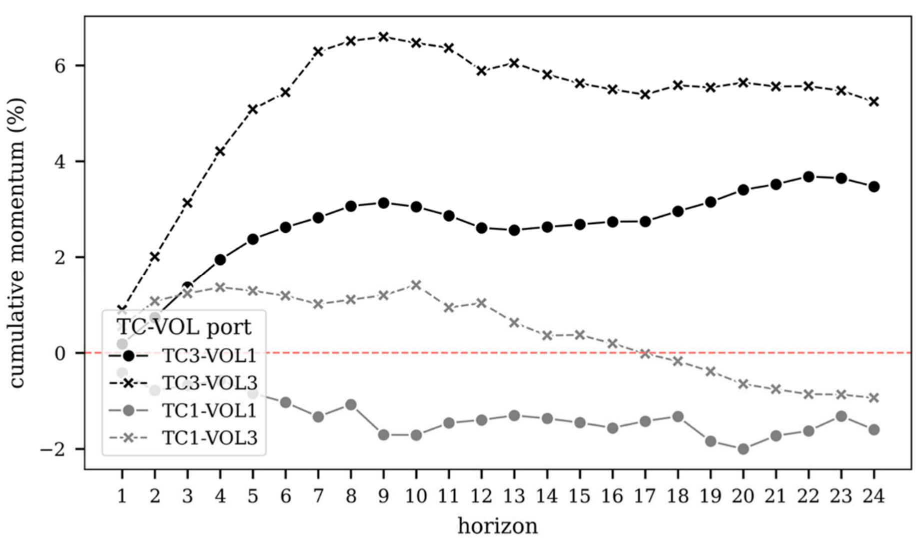

trend clarity = 1
trend clarity = 2
trend clarity = 3
trend clarity = 4
trend clarity = 5
SUE
0.0
−0.2
−0.4
−0.6
−0.8
−1.0
-4 -3 -2 -1 0 1 2 3 4
(formation
month)
i^{th} quarter

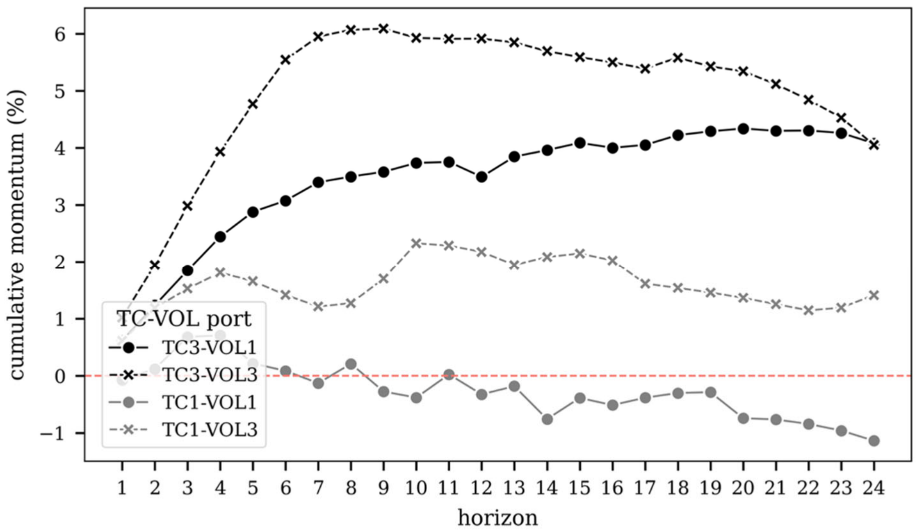
Figure 6. Formation Period Trading Volume Effect on Trend Momentum

This figure plots post-formation cumulative alphas (risk-adjusted returns) from t+1 to t+24 for momentum conditional on trend clarity (TC) and trading volume (VOL). The sample used to construct portfolios is from Dec 1925 to Dec 2023. We independently rank stocks into 3 groups based on trading volume, formation-period return (PRET), and trend clarity in each month. VOL is the average turnover ratio (traded volume divided by the total number of shares outstanding) over the past 12 months. TC is the R^2 from the regression of daily stock price on a date sequence over the same formation period as PRET, requiring at least 200 days. Market value is stock price times the number of shares outstanding. Panels A and B report equal- and value-weighted momentum profits, respectively. t-stats are based on Newey-West standard errors (with 6 lags). Significance levels of 1%, 5%, and 10% are indicated by ***, **, and *.

Panel A: equal-weighted



Panel B: value-weighted



cumulative momentum (%)
horizon
TC-VOL port
TC3-VOL1
TC3-VOL3
TC1-VOL1
TC1-VOL3

Figure 7. Post-formation Trading Activity, Order Imbalance, and Analyst Revisions

This figure plots three post-formation variables for winner and loser portfolios in the high- and low-trend-clarity groups. To remain consistent with the portfolio return construction, in each month we first sort stocks into quintiles based on formation-period returns (PRET) and then further sort them into quintiles based on trend clarity. Trend clarity is measured as R^2 from a regression of daily stock price on a time trend over the same formation period as PRET, requiring at least 200 daily observations.

Panel A plots post-formation abnormal trading volume. Monthly stock trading volume is defined as the number of shares traded divided by shares outstanding. For each post-formation month, we compute the average trading volume of the winner and loser portfolios in the high- and low-trend-clarity groups. Abnormal trading volume is then calculated as the percentage change in monthly portfolio trading volume relative to the portfolio's average trading volume over the previous 12 months.

Panel B plots post-formation order imbalance (OIB). For each stock, order imbalance is defined as

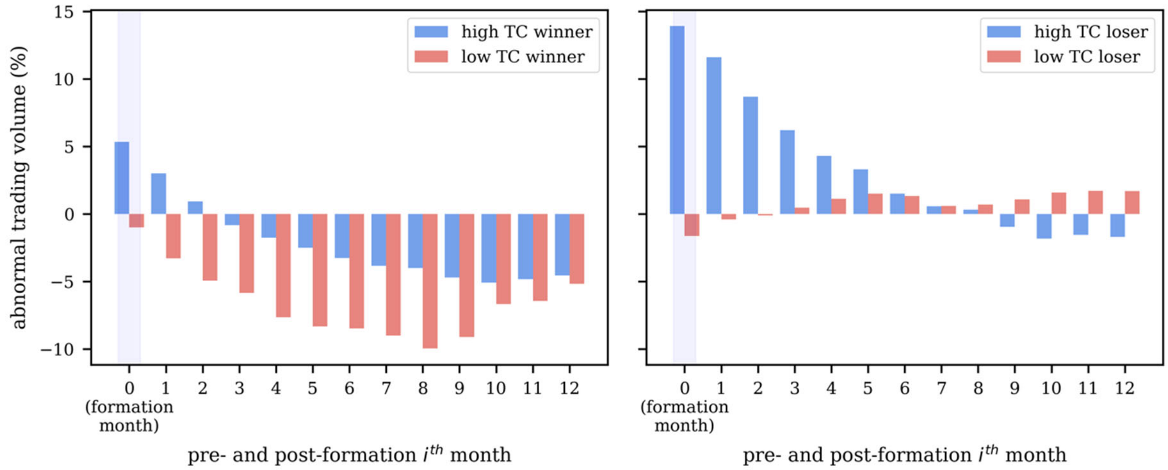
$$OIB = \frac{\text{number of buyer-initiated trades} - \text{number of seller-initiated trades}}{\text{total number of buyer- and seller-initiated trades}} \times 100.$$

Buyer- and seller-initiated trades are identified using the Lee and Ready (1991) algorithm based on TAQ data. Following Da et al. (2013), we adjust OIB by subtracting the cross-sectional monthly average across all stocks. We then compute the average adjusted OIB for the winner and loser portfolios in the high- and low-trend-clarity groups for each post-formation month.

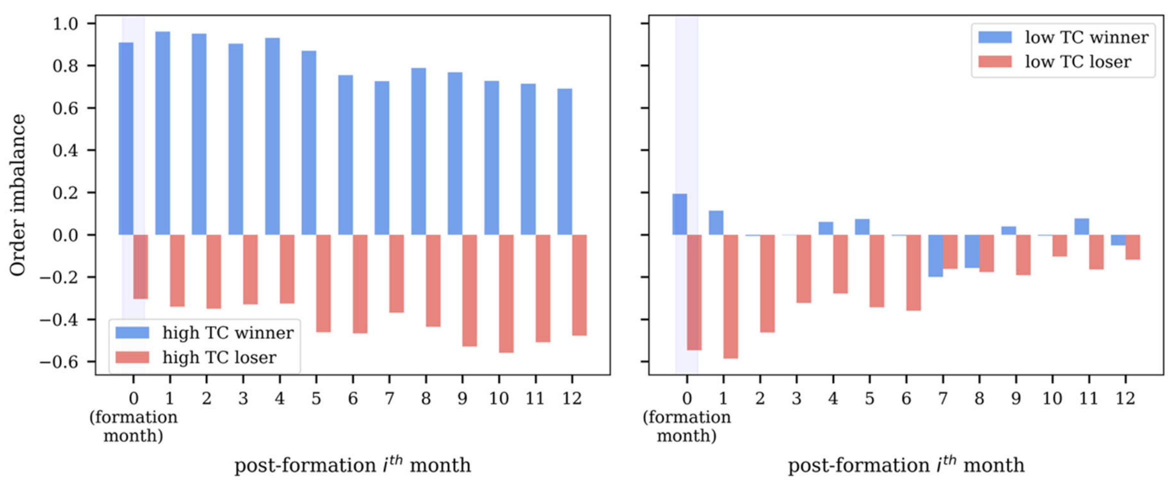
Panel C plots the post-formation percentage of analyst upward revisions. For each stock-month, this measure is defined as the number of upward analyst earnings forecast revisions divided by the sum of upward and downward revisions. We compute the average percentage of upward revisions for the winner and loser portfolios in the high- and low-trend-clarity groups in each post-formation month. Higher values indicate that analysts are, on average, more likely to revise earnings expectations upward than downward.

Figure 7 Continued.

Panel A. Abnormal Trading Volume



Panel B. Order Imbalance



Panel C. Analyst Revisions

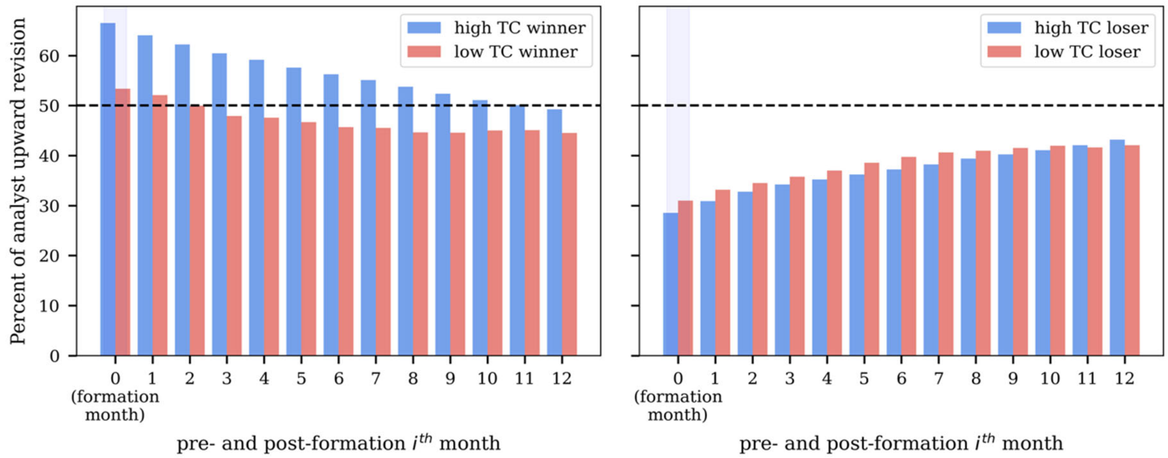


Figure 8. Distribution of Country Momentum Return by Market Type

This figure presents the distribution of average momentum returns across trended groups by market type (21 developed and 35 emerging). For each market, stocks are initially sorted into terciles based on past return performance monthly. Subsequently, these stocks are allocated to terciles according to trend clarity (TC) within each past-return tercile monthly. Past return is defined as the formation-period return (PRET), measured from t−11 to t−1 with month t skipped. Trend clarity is the R^2 from the regression of the daily stock price on a date sequence over the same formation period as PRET, requiring at least 150 days. The winners-minus-losers (WML) holding-period returns from t+1 to t+6 are determined for each TC tercile portfolio in each market (refer to the Internet Appendix for the detailed breakdown). Panels A and B illustrate the distribution of equal- and value-weighted returns of the countries within each market type. The vertical dashed lines represent the average unconditional momentum return, disregarding price trend, for all countries within the respective market type.

Panel A: Equal-Weighted Returns

Panel B: Value-Weighted Returns

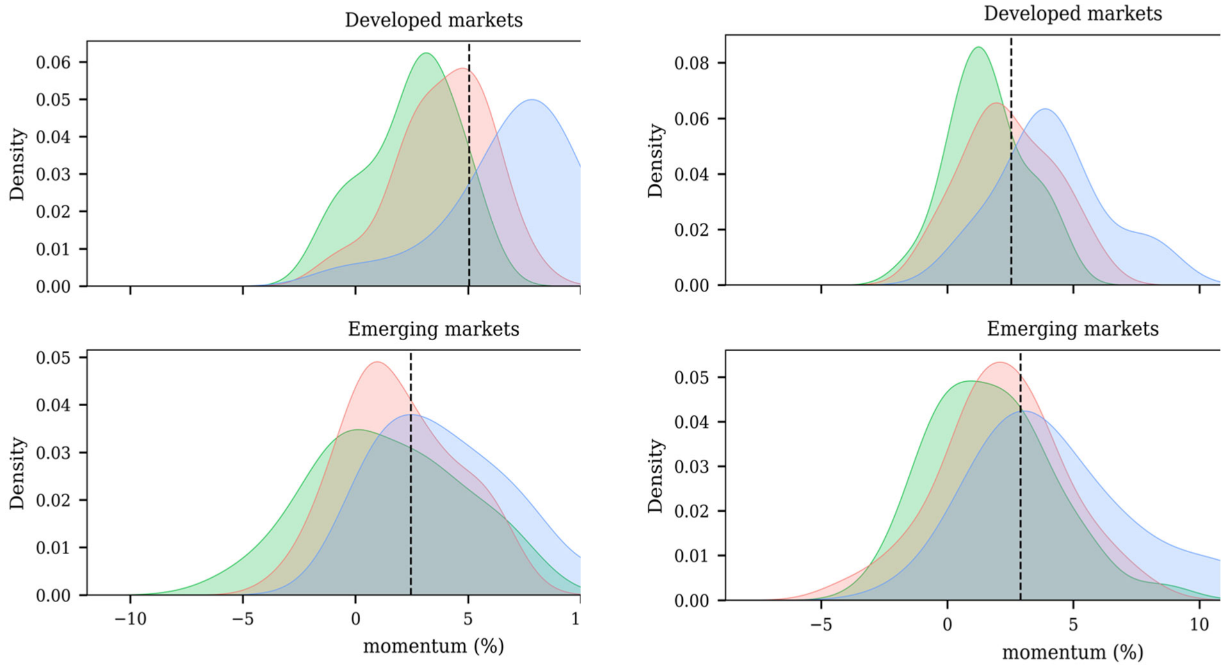
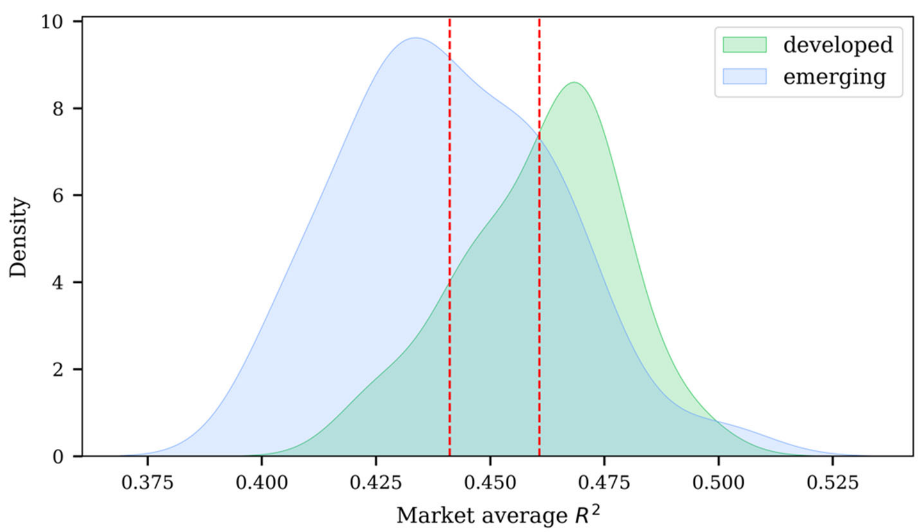

Developed markets
Density
0.06
0.05
0.04
0.03
0.02
0.01
0.00
Emerging markets
Density
0.05
0.04
0.03
0.02
0.01
0.00
−10
−5
0
5
1
momentum (%)
Developed markets
Density
0.08
0.06
0.04
0.02
0.00
Emerging markets
Density
0.05
0.04
0.03
0.02
0.01
0.00
−5
0
5
10
momentum (%)

Figure 9. Market Average R^2 Distribution by Market Type

The figure plots the distribution of average R^2. The average R^2 is computed for each market and the distributions of the average R^2 are plotted for developed and emerging markets. R^2 is estimated from the regression of daily stock price on date sequence in the past 12 months (requiring at least 150 days). Developed and emerging markets are based on the MSCI market development classification. MSCI classifies market into developed, emerging, frontier and standalone markets. Emerging markets for the plot include emerging, frontier and standalone markets (labelled by MSCI).



Tables

Table 1. Analysis of Respondents' Perception of Trend Clarity in Relation to R^2 Values

This table presents the results of regression analyses exploring the relationship between respondents' perception of trend clarity and R^2 values in stock charts. In the logistic regression model, the dependent variable is binary, indicating clear trends (assigned a value of 1 for responses of 4 or 5) and unclear trends (assigned a value of 0 for responses between 1 and 3). The ordinal logistic regression model uses respondents' ratings, which range from 1 (not clear) to 5 (very clear), as dependent variables. 'R^2' represents the R^2 value of the chart, while 'Pos' is a dummy variable indicating the trend direction (1 for positive, 0 for negative). The term '$R^2 \times$ Pos' denotes the interaction between R^2 and the positive trend dummy. The analysis is based on 2513 valid responses. The final row of the table illustrates the change in odds ratio associated with a 0.1 increase in R^2, calculated using the coefficient from the R^2 variable. Significance levels of 1%, 5% and 10% are indicated by ***, ** and *.

	Logistic		Ordinal logistic	
	model 1	model 2	model 3	model 4
R^2	3.9879***	3.7681***	4.3314***	4.1582***
	(22.25)	(15.07)	(28.70)	(20.64)
$R^2 \times$ Pos		0.4689		0.3772
		(1.30)		(1.42)
Pos		-0.5342***		-0.4795***
		(-2.75)		(-3.31)

Obs	2513	2513	2513	2513
Increase in odds by 0.1 increase of R^2	49.0%	45.8%	54.2%	51.6%

Table 2. Trend Clarity and Momentum: Portfolio Returns2

This table reports post-formation returns (in percentage) over the 6 months from t+1 to t+6 for sequentially sorted portfolios. The sample spans from Dec 1925 to Dec 2023 using CRSP data. Stocks are first sorted into quintiles based on an 11-month cumulative return measured from $t-11$ to $t-1$, with month t skipped (PRET), and then into quintiles based on trend clarity (TC) within each PRET quintile. Trend clarity (TC) is the R^2 from the regression of daily stock price on date sequence in the same formation period as PRET (requiring at least 200 days). Unconditional momentum portfolio returns are derived from a univariate sort on PRET. Panels A and B present equal- and value-weighted returns, with t-statistics based on Newey-West standard errors (with six lags). Significance at 1%, 5%, and 10% is indicated by ***, **, and *, respectively.

Panel A: Equal-Weighted Returns

	1 (loser)	2	3	4	5 (winner)	WML (5-1)	t
1 (low TC)	7.28	7.37	7.75	7.87	7.84	0.56	0.61
2	6.58	7.51	7.91	8.43	8.96	2.38***	2.59
3	6.10	7.06	7.86	8.43	9.46	3.36***	3.54
4	5.03	6.78	7.56	8.51	9.54	4.51***	4.66
5 (high TC)	3.69	5.96	6.79	8.15	10.02	6.34***	5.99
diff (5-1)						5.78***	6.80
unconditional	5.70	6.95	7.57	8.26	9.16	3.45***	3.85

Panel B: Value-Weighted Returns

	1 (loser)	2	3	4	5 (winner)	WML (5-1)	t
1 (low TC)	4.89	5.18	5.93	6.20	6.03	1.15	1.28
2	4.47	5.76	6.01	6.01	7.05	2.58**	2.52
3	3.49	5.52	5.99	6.22	7.33	3.84***	4.33
4	3.61	5.37	5.45	6.82	7.71	4.10***	4.26
5 (high TC)	2.16	4.78	5.46	6.53	8.80	6.63***	6.30
diff (5-1)						5.49***	6.75
unconditional	3.60	5.34	5.59	6.38	7.75	4.15***	4.54

Table 3. Trend Clarity and Momentum: Portfolio Alphas

This table presents the alphas (risk-adjusted returns) of momentum (winner-minus-loser) conditional on trend clarity (TC) over the 6-month post-formation period. First, stocks are divided into quintiles each month based on an 11-month cumulative return measured from $t-11$ to $t-1$, with month t skipped (PRET). Within each quintile, stocks are further sorted into quintiles based on the TC. TC is determined by the R^2 from regressing daily stock prices against the date sequence over the same formation period as PRET, requiring a minimum of 200 trading days. Risk-adjusted returns are computed using 4 different asset pricing models including the Fama-French 3- and 5-factor models (Fama and French, 1993, 2015), q5 (Hou et al., 2019), and BF3 (Daniel et al., 2020). Due to factor returns availability, the sample for the Fama-French 3-factor model is from July 1926 to Dec 2023. For the Fama-French 5-factor model, the sample is from July 1963 to Dec 2023. The risk-adjusted returns based on q5 model is from Jan 1967 to Dec 2023. The behavioral factor model (BF3) alpha is based on a sample from July 1972 to Dec 2022. The unconditional momentum portfolio alphas are based on the univariate sort involving PRET only. Panels A and B display the equal- and value-weighted alphas from above modes, respectively. t-stats are based on Newey-West standard errors (with 6 lags). Significance levels of 1%, 5% and 10% are indicated by ***, ** and *.

Panel A: Equal-Weighted Alphas

	FF3	FF5	q5	BF3
1 (low TC)	0.75	0.09	-0.26	-0.23
	(1.47)	(0.22)	(-0.65)	(-0.56)
2	1.92***	0.95**	0.55	0.48

	(3.53)	(1.98)	(1.23)	(1.02)
3	2.33***	1.13**	0.82*	0.72
	(3.85)	(2.02)	(1.73)	(1.30)
4	3.50***	1.70***	1.13**	1.01*
	(5.97)	(3.06)	(2.19)	(1.75)
5 (high TC)	4.64***	2.39***	1.64***	1.43**
	(7.09)	(3.95)	(2.79)	(2.32)
unconditional	2.63***	1.27**	0.78*	0.69
	(4.96)	(2.56)	(1.72)	(1.39)

Panel B: Value-Weighted Alphas

	FF3	FF5	q5	BF3
1 (low TC)	1.37**	0.98**	0.59	0.67
	(2.30)	(2.03)	(1.15)	(1.42)
2	2.25***	1.30**	0.92*	1.09**
	(3.60)	(2.47)	(1.70)	(1.99)
3	3.35***	1.94***	1.71***	1.75***
	(5.88)	(3.93)	(3.52)	(3.46)
4	3.30***	2.00***	1.63***	1.76***
	(4.92)	(3.46)	(2.92)	(3.18)
5 (high TC)	5.38***	3.50***	2.96***	2.86***
	(7.52)	(5.62)	(4.70)	(4.42)
unconditional	3.41***	2.13***	1.72***	1.85***
	(5.91)	(4.25)	(3.40)	(3.56)

Table 4. Fama-MacBeth Regression

This table reports the Fama-MacBeth regression of post-formation returns from t+1 to t+6 on the 11-month cumulative return measured from $t-11$ to $t-1$, with month t skipped (PRET) and the interaction of PRET and trend clarity (TC) with/without controls. We run the regression in each month and then report the time-series average of slopes. The control variables include idiosyncratic volatility (IVOL), market value (ME), book to market ratio (BM), illiquidity (ILLIQ), trading turnover (VOL), maximum daily return (MDR) and dollar trading volume (DVOL) and one-year daily return volatility (RetVOL). Micro firms are defined as firms with a market value less than the 20% percentile of the market value of NYSE stocks. We map the independent variables to [0,1] interval to reduce the impact of outliers and high correlations among them to better capture the effect of independent variables on the dependent variable. Please see Appendix I for detailed definitions of variables. t-stats are based on Newey-West standard errors (with 6 lags). Significance levels of 1%, 5% and 10% are indicated by ***, ** and *.

	model 1		model 2		model 3		model 4 Ex. micro stocks	
	coeff	t	coeff	t	coeff	t	coeff	t
const	0.0532***	3.42	0.0833***	4.63	0.2853***	6.09	0.0882***	2.59
PRET	0.0419***	3.88	-0.0056	-0.47	-0.1458**	-2.55	0.0773	1.54
PRET x TC			0.0663***	4.27	0.0708***	5.91	0.0629***	5.71
TC			-0.0448***	-4.38	-0.0402***	-5.59	-0.0282***	-4.95
PRET x IVOL					0.0310**	2.07	0.0393***	3.13
PRET x ME					0.0588	1.00	0.0037	0.13
PRET x ILLIQ					0.1607***	2.85	-0.0894*	-1.82
PRET x BM					-0.0376***	-2.86	-0.0455***	-3.48
PRET x VOL					0.0252	0.94	0.0295	1.32
PRET x MDR					0.0614***	5.12	0.0221**	2.39
PRET x DVOL					0.1221	1.54	-0.1002	-1.63
PRET x RetVOL					-0.1002***	-4.51	-0.0014	-0.09
IVOL					-0.0476***	-4.70	-0.0349***	-4.59

ME			0.0171	0.35	-0.0021	-0.10
ILLIQ			-0.2483***	-5.12	-0.0285	-0.80
BM			0.0659***	6.54	0.0454***	4.75
VOL			0.0008	0.05	-0.008	-0.58
MDR			-0.0304***	-3.76	-0.0063	-1.23
DVOL			-0.3127***	-5.56	-0.0428	-1.01
RetVOL			0.1072***	4.34	0.0162	1.25
adj. R^2	0.018	0.025	0.076		0.103	
obs	3502725	3411983	2507510		1156971	
avg. num. stock	3006	2928	3453		1593	

Table 5. Information Diffusion (Size) and Trended Momentum

This table reports momentum returns (winner minus loser) over the 6-month post-formation period from t+1 to t+6 of triple-sorted portfolios. The sample used to construct portfolios is from Dec 1925 to Dec 2023. We independently rank stocks into 3 groups based on market capitalization (proxy of information diffusion speed) following Hong et al. (2000), 11-month cumulative return measured from $t-11$ to $t-1$, with month t skipped (PRET) and trend clarity (TC) in each month. TC is the R^2 from the regression of daily stock price on date sequence over the same formation period as PRET (requiring at least 200 days). Market value is stock price times the number of shares outstanding. Panels A and B report equal- and value-weighted momentum profits, respectively. t-stats are based on Newey-West standard errors (with 6 lags). Significance levels of 1%, 5% and 10% are indicated by ***, ** and *.

Panel A: Equal-Weighted Returns

	1 (small)	2	3 (big)	diff (3-1)
1 (low TC)	-0.32	0.94	1.03	1.36**
	(-0.41)	(1.16)	(1.44)	(1.97)
2	2.44***	2.94***	2.01***	-0.43
	(3.04)	(4.02)	(3.08)	(-0.59)
3 (high TC)	5.33***	6.13***	4.86***	-0.47
	(5.49)	(6.67)	(5.90)	(-0.54)
diff (3-1)	5.65***	5.19***	3.83***	-1.83**
	(7.00)	(5.58)	(4.95)	(-2.06)

Panel B: Value-Weighted Returns

	1 (small)	2	3 (big)	diff (3-1)
1 (low TC)	0.74	1.07	0.93	0.20
	(0.92)	(1.35)	(1.28)	(0.26)
2	3.13***	2.79***	1.24*	-1.90***
	(4.24)	(3.86)	(1.71)	(-2.62)
3 (high TC)	6.73***	5.96***	4.18***	-2.55***
	(7.13)	(6.52)	(5.17)	(-2.70)
diff (3-1)	6.00***	4.89***	3.25***	-2.74***
	(6.72)	(5.25)	(4.11)	(-2.69)

Table 6. Information Diffusion (Residual Analyst Coverage) and Trended Momentum

This table reports momentum returns (winner minus loser) over the 6-month post-formation period from t+1 to t+6 for triple-sorted portfolios. The sample spans from Jan 1976 to Dec 2023, given the availability of analyst coverage data. Stocks are independently ranked into 3 groups each month based on residual analyst coverage (ResidCov), which measures information diffusion speed (following Hong et al., 2000), 11-month cumulative return measured from $t-11$ to $t-1$, with month t skipped (PRET), and trend clarity (TC). TC is the R^2 from the regression of daily stock prices on the time sequence over the same formation period as PRET, requiring at least 200 days. Market value (ME) is calculated as stock price times the number of shares outstanding. ResidCov is the residual from a cross-sectional regression of log(1+number of analysts) on log(ME) and a NASDAQ dummy. The number of analysts refers to those with 1-year EPS forecasts, with missing data filled by 0. Panels A and B report equal- and value-weighted momentum returns, respectively, with t-statistics based on Newey-West standard errors (with 6 lags). Significance levels of 1%, 5%, and 10% are denoted by ***, **, and *, respectively.

Panel A: Equal-Weighted Returns

	1 (low ResidCov)	2	3 (high ResidCov)	diff (3-1)
1 (low TC)	0.30	0.40	-0.28	-0.58
	(0.24)	(0.38)	(-0.24)	(-0.54)
2	3.56***	2.52**	0.12	-3.44***
	(3.42)	(2.55)	(0.09)	(-3.62)
3 (high TC)	7.45***	6.07***	2.91*	-4.54***
	(5.84)	(4.01)	(1.75)	(-4.39)

diff (3-1)	7.15***	5.67***	3.19***	-3.96***
	(6.65)	(4.59)	(2.78)	(-3.07)

Panel B: Value-Weighted Returns

	1 (low ResidCov)	2	3 (high ResidCov)	diff (3-1)
1 (low TC)	-0.22	0.02	1.11	1.33
	(-0.17)	(0.02)	(1.02)	(1.12)
2	1.25	0.12	1.46	0.21
	(1.19)	(0.10)	(1.25)	(0.24)
3 (high TC)	5.28***	4.06***	5.68***	0.40
	(3.92)	(2.76)	(3.64)	(0.31)
diff (3-1)	5.50***	4.04***	4.57***	-0.93
	(3.94)	(3.02)	(3.36)	(-0.60)

Table 7. Information Discreteness, Trend Clarity and Momentum

This table reports momentum returns (winner minus loser) in the post-formation period from t+1 to t+6 of triple-sorted portfolios. The sample used to construct portfolios is from Dec 1925 to Dec 2023. We rank stocks independently into 3 groups based on information discreteness (ID), trend clarity (TC) and 11-month cumulative return measured from $t-11$ to $t-1$, with month t skipped (PRET) in each month. Trend clarity (TC) is the R^2 from regression of daily stock price on date sequence in the same formation period as PRET (require at least 200 days). Following Da et al. (2014), ID is computed as ID=sign(PRET)×[%neg−%pos] where %pos and %neg denote the respective percentage of positive and negative daily returns during the same formation period as PRET. The column and row labelled avg are the time-series average of the cross sectional mean across 3 ID or TC groups in each month. Panel A reports the average number of stocks the 3 by 3 portfolios based on TC and ID. Panels B and C report equal- and value-weighted returns respectively. t-stats are based on Newey-West standard errors (with 6 lags). Significance levels of 1%, 5% and 10% are indicated by ***, ** and *.

Panel A: Average Number of Stocks

	1 (info continuous)	2	3 (info discreteness)
1 (low TC)	191	322	462
2	280	344	351
3 (high TC)	503	310	162

Panel B: Equal-Weighted Returns

	1 (info continuous)	2	3 (info discreteness)	diff (3-1)	avg
1 (low TC)	2.14*	-0.71	-1.27	-3.40***	0.05
	(1.95)	(-0.66)	(-1.40)	(-2.99)	(0.06)
2	2.94***	0.91	0.18	-2.75***	1.34*
	(3.06)	(1.08)	(0.23)	(-2.98)	(1.78)
3 (high TC)	5.62***	2.76***	2.38***	-3.24***	3.58***
	(5.07)	(3.07)	(2.70)	(-3.46)	(4.13)
diff (3-1)	3.48***	3.47***	3.64***		3.53***
	(3.59)	(3.49)	(3.85)		(4.33)
avg	3.56***	0.99	0.43	-3.13***	
	(3.75)	(1.18)	(0.58)	(-3.60)	

Panel C: Value-Weighted Returns

	1 (info continuous)	2	3 (info discreteness)	diff (3-1)	avg
1 (low TC)	1.61*	0.55	-0.21	-1.82*	0.65
	(1.74)	(0.61)	(-0.19)	(-1.78)	(0.78)
2	1.99**	1.12	-0.61	-2.60***	0.84
	(2.47)	(1.23)	(-0.75)	(-3.97)	(1.11)
3 (high TC)	5.22***	3.15***	2.97***	-2.25***	3.78***
	(5.72)	(3.54)	(3.53)	(-2.97)	(4.81)
diff (3-1)	3.61***	2.60***	3.17***		3.13***
	(3.89)	(2.87)	(2.62)		(3.82)
avg	2.94***	1.61**	0.72	-2.22***	
	(3.91)	(2.04)	(1.00)	(-4.04)	

Table 8. Trended Momentum: Controlling for Other Momentum Strategies

This table reports Fama-MacBeth regression of trend momentum return with the control of other momentum strategies including intermediate momentum (IR) and recent momentum (RR) following Novy-Marx (2012) and 52-week high based on George and Hwang (2004). Following George and Hwang (2004), we create dummy variables to enable us to control different strategies in isolation. Specifically, the dummy variables indicate whether a stock belongs to winner or loser group in each month for different strategies. We apply quintiles to determine winners and losers. The winner (loser) dummy is 1 if it is in quintile 5 (1) otherwise 0 based on the 11-month cumulative return measured from $t-11$ to $t-1$, with month t skipped. High (low) TC dummy is 1 if it is in quintile 5 (1) based on trend clarity. Similarly, we create dummy variables for IR, RR and 52-week high strategies. Previous month return (RET(t)) and market value (ME) are also included to mitigate the impact of bid-ask bounce and to control for the size effect. The dependent variable includes returns in t+1 and returns over a 6-month period from t+1 to t+6. t-stats are based on Newey-West standard errors (with 6 lags). Significance levels of 1%, 5% and 10% are indicated by ***, ** and *.

	Ret(t+1)		Ret(t+1, t+6)	
	coeff	t	coeff	t
const	0.0120***	4.89	0.0755***	6.55
winner dummy	0.0029***	4.53	0.0098***	2.98
loser dummy	-0.0020**	-2.37	-0.0035	-1.26
winner dummy x high TC dummy	0.0011	1.28	0.0116***	3.48
winner dummy x low TC dummy	-0.0010	-0.43	-0.0107*	-1.75
loser dummy x high TC dummy	0.0007	0.65	-0.0146***	-3.74

loser dummy x low TC dummy	0.0020	0.53	0.0030	0.44
IR winner dummy	0.0015**	2.13	0.0007	0.28
IR loser dummy	-0.0019***	-2.67	0.0001	0.03
RR winner dummy	0.0006	0.84	0.0113***	3.59
RR loser dummy	0.0008	1.18	-0.0087***	-3.35
52-week high winner dummy	-0.0003	-0.36	-0.0039	-0.87
52-week high loser dummy	0.0009	0.63	-0.0073	-1.13
high TC dummy	-0.0002	-0.34	-0.0050	-1.64
low TC dummy	0.0000	0.05	0.0012	0.63
ME	-0.0000*	-1.87	-0.0000**	-2.38
Ret(t)	-0.0695***	-15.68	-0.0358***	-3.21
adj. R^2	0.052		0.055	
obs	3404110		3407946	
avg_n	2921		2925	
Post estimation				
(winner dummy - loser dummy) x high TC dummy	0.0005	0.37	0.0262***	5.37
(winner dummy - loser dummy) x low TC dummy	-0.0031	-0.68	-0.0136	-1.48
(high TC dummy - low TC dummy) x winner dummy	0.0022	0.82	0.0222***	3.08
(high TC dummy - low TC dummy) x loser dummy	-0.0014	-0.34	-0.0176**	-2.11
winner dummy - loser dummy	0.0049***	4.24	0.0134***	3.33
IR winner dummy - IR loser dummy	0.0034***	3.07	0.0006	0.12
RR winner dummy - RR loser dummy	-0.0002	-0.15	0.0199***	4.93
52-week high winner dummy - 52-week high loser dummy	-0.0012	-0.57	0.0034	0.33

Table 8. Trended Momentum in Non-Equity Asset Classes

This table reports average monthly returns for momentum-sorted portfolios formed within Trend Clarity (TC) groups across non-equity asset classes. For each asset class, assets are first assigned to TC groups (low to high). Within each TC group, assets are sorted into two momentum portfolios based on past returns: Loser (1) and Winner (2). WML is the winner-minus-loser return (2–1). The t-statistic corresponds to WML. "diff" reports the difference in WML between the highest and lowest TC groups. Panels A–C use three TC groups due to limited cross-sectional size within each asset class. Panels D–E pool currencies, government bonds, and commodities; the larger pooled universe allows either three TC groups (Panel D) or four TC groups (Panel E). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Currencies

	1 (loser)	2 (winner)	WML (2-1)	t
1 (low TC)	-0.89	-0.51	0.38	1.04
2	-0.54	-0.08	0.46	1.14
3 (high TC)	-2.37	-0.16	2.21***	3.81
diff (3-1)			1.83***	2.83

Panel B: Government Bonds

	1 (loser)	2 (winner)	WML (2-1)	t
1 (low TC)	3.68	3.56	-0.11	-0.26
2	3.50	3.47	-0.03	-0.08
3 (high TC)	3.47	3.06	-0.41	-0.84
diff (3-1)			-0.29	-0.58

Panel C: Commodities

	1 (loser)	2 (winner)	WML (2-1)	t
1 (low TC)	-1.62	-0.87	0.76	0.65
2	-2.01	0.15	2.15**	2.16
3 (high TC)	-2.52	0.11	2.62**	2.08
diff (3-1)			1.87	1.29

Panel D: All Non-Equity Asset Classes (Pooled; 2 × 3)

	1 (loser)	2 (winner)	WML (2-1)	t
1 (low TC)	-0.97	0.43	1.40***	2.78
2	-1.15	1.25	2.40***	4.28
3 (high TC)	-1.76	1.27	3.03***	3.75
diff (3-1)			1.63*	1.82

Panel E: All Non-Equity Asset Classes (Pooled; 2 × 4)

	1 (loser)	2 (winner)	WML (2-1)	t
1 (low TC)	-0.88	0.13	1.02**	2.00
2	-1.24	1.35	2.58***	4.59
3	-1.27	1.18	2.45***	4.04
4 (high TC)	-1.83	1.30	3.14***	3.50
diff (4-1)			2.12**	2.05

Table 9. Trended Factor Momentum

This table reports subsequent six-month returns for factor momentum portfolios. The sample is January 1965 to December 2023 and includes 179 factors from the Chen and Zimmermann open-source asset pricing dataset. For each factor, a daily cumulative return index is constructed from daily factor returns and used to estimate Trend Clarity (TC) via the R^2 measure. Momentum is based on formation-period factor returns, with the most recent month skipped. In the TC-conditional test, factors are independently sorted into three momentum portfolios (Loser–Winner) and three TC groups (Low–High) to form 3×3 portfolios. WML is Winner minus Loser (3–1), with the corresponding t-statistic reported. "diff (High–Low)" reports the difference in WML between the high- and low-TC groups. The "unconditional" row reports standard (unconditional) factor momentum without conditioning on TC. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.R^2

Panel A: Equal-Weighted Factors

	1 (loser)	2	3 (winner)	WML (3-1)	t
1 (low TC)	2.12	3.06	6.21	4.09***	4.87
2	1.95	3.33	6.23	4.28***	4.79
3 (high TC)	0.77	3.3	6.83	6.06***	6.56
diff (3-1)				1.97***	2.74
unconditional	1.6	3.23	6.42	4.82***	5.85

Panel B: Value-Weighted Factors

	1 (loser)	2	3 (winner)	WML (3-1)	t

1 (low TC)	1.6	2.09	4.09	2.49***	3.00
2	1.24	2.11	4.13	2.89***	3.38
3 (high TC)	0.46	1.69	4.57	4.11***	4.71
diff (3-1)				1.62**	2.45
unconditional	1.09	1.96	4.27	3.18***	4.01

Table 10. Momentum Crash Period Analysis

In this table we report post-formation returns over t+1 to t+6 of momentum returns conditional on trend clarity (TC) during the 105 crash months. The sample used to construct portfolios is from Dec 1925 to Dec 2023. We first sort stocks into quintiles based on the 11-month cumulative return measured from $t-11$ to $t-1$, with month t skipped (PRET), and the stocks are then assigned to quintiles based on TC within each past return quintile in each month t. Trend clarity is the R^2 from the regression of daily stock price on date sequence over the same formation period as PRET (require at least 200 days). Following Daniel and Moskowitz (2016), the crash period is determined by the market rebounds when market return over the past 2 years is negative in month t (ex-ante) and market excess return is positive in month t+1 (not ex-ante). The unconditional momentum portfolio returns are based on the univariate sort involving PRET only. Panels A and B report equal- and value-weighted returns respectively. t-stats are based on Newey-West standard errors (with six lags). Significance levels of 1%, 5% and 10% are indicated by ***, ** and *.

Panel A: Equal-Weighted Returns

	1 (loser)	2	3	4	5 (winner)	return (5-1)	t
1 (low TC)	38.20	30.66	25.47	22.82	24.14	-14.06***	-2.65
2	36.08	29.49	25.39	22.89	25.45	-10.64*	-1.87
3	33.23	27.05	23.00	22.70	25.03	-8.20	-1.59
4	33.72	24.90	23.47	21.92	22.99	-10.73**	-2.12
5 (high TC)	25.77	21.37	19.24	18.93	21.47	-4.29	-0.90
diff (5-1)						9.76**	2.19

unconditional	33.36	26.74	23.26	21.85	23.75	-9.60**	-1.98

Panel B: Value-Weighted Returns

	1 (loser)	2	3	4	5 (winner)	return (5-1)	t
1 (low TC)	30.01	21.44	16.14	15.45	17.42	-12.59***	-2.65
2	27.78	20.49	18.26	14.26	17.04	-10.74*	-1.88
3	24.98	20.07	16.38	15.19	16.68	-8.31*	-1.92
4	27.45	20.55	15.90	14.69	15.64	-11.81***	-3.26
5 (high TC)	18.76	17.30	13.90	13.71	15.78	-2.97	-0.84
diff (5-1)						9.62***	3.12
unconditional	24.43	19.47	15.27	14.20	16.19	-8.25**	-2.02

Trended Momentum

Internet Appendix I: Multi-Period Momentum Chasing and Trend Clarity

Introduction

This appendix connects the paper's trend clarity measure to the return-chasing mechanism in Hong and Stein (1999). In the Hong and Stein framework, news about future dividends diffuses gradually across newswatchers. This gradual diffusion generates a sequence of price changes that momentum traders can chase. The main paper uses this framework to motivate why clearer price trends should be associated with stronger momentum trading. Here, we provide the simulation details behind that argument.

The appendix has two purposes. First, we extend the momentum-trader forecasting rule from a one-period return to a cumulative k-period formation return. This extension matches the empirical design of the paper, where momentum is measured over a multi-month formation period rather than from a single price change. Second, we use simulations to study how trend clarity relates to the optimized momentum-trading intensity. The key result is that slower information diffusion produces clearer price trends and is associated with higher optimal momentum-trading intensity.

We also report a supplementary noise-trader exercise. This exercise adds independent supply shocks to the simulated price process while leaving the newswatcher information structure unchanged. The results are consistent with the economic interpretation in the paper: noise trading weakens the mapping between observed price trends and momentum-trading intensity, but the positive relation between trend clarity and momentum intensity remains visible.

Multi-Period Momentum Chasing

Hong and Stein Setup

Hong and Stein (1999) model a market populated by two groups of boundedly rational agents: newswatchers and momentum traders. Newswatchers observe private information about fundamentals but do not infer information from prices. Because information diffuses gradually across newswatchers, prices underreact in the short run. Momentum traders, in contrast, forecast future price changes using past price changes. Their return-chasing demand can amplify price continuation and eventually contribute to overreaction.

The model therefore contains both ingredients that are central to the paper. Newswatchers initiate price trends through gradual information diffusion, while momentum traders chase observed returns. Trend clarity summarizes whether the resulting price path is coherent enough to attract stronger return chasing.

A k-Period Formation Window

In the baseline Hong and Stein framework, momentum traders condition on a simple past price change. To align the model with the empirical formation window in the paper, we allow momentum traders to condition on the cumulative price change over k periods. Let

$$X_t = \sum_{i=1}^{k} \Delta P_{t-i}.$$

The momentum-trader order flow is

$$F_t = A + \phi X_t,$$

where A is a constant and ϕ measures the intensity with which momentum traders respond to the cumulative formation-period return.

The optimal response coefficient can be written as

$$\phi = \gamma \frac{\mathrm{Cov}(P_{t+j} - P_t, X_t)}{\mathrm{Var}(X_t)\mathrm{Var}_M(P_{t+j} - P_t)},$$

where γ is the aggregate risk tolerance of momentum traders, j is the holding horizon, and $\mathrm{Var}_M(P_{t+j} - P_t)$ is the conditional variance of the forecast error from the perspective of momentum traders. This expression shows that momentum-trading intensity is stronger when the cumulative formation-period price change has more predictive content for future holding-period price changes.

Trend clarity is closely related to this predictive content. A price path generated by gradual information diffusion is more useful to momentum traders when the formation-period return is not only large but also coherent. We therefore measure trend clarity in the simulated price path using the average R^2 from a time-trend regression over the k-period formation window.

Comparative Statics

We simulate the price process following the Hong and Stein framework and use the simulated data to optimize ϕ. The simulation varies the information-diffusion speed, denoted by z, while holding the remaining parameters fixed. Specifically, we set

$$j = 12, \quad k = 6, \quad g = 1/3, \quad \sigma_\epsilon = 0.5, \quad T = 250.$$

We consider $z \in \{3, 4, 5, 6, 9, 12, 15, 18\}$. For each value of z, we simulate 30 price paths. Larger z corresponds to slower information diffusion and therefore a more gradual price discovery process.

For each simulation, we compute the average formation-period trend clarity as follows. At each time t, we regress the past k simulated prices on a linear time trend and record the regression R^2. We then average this R^2 over the simulation window. Each simulated path produces one pair consisting of average trend clarity and the optimized momentum-trading intensity ϕ. Across the 8 values of z and 30 paths for each value, this procedure yields 240 simulation observations.

Figure 1 shows that slower information diffusion produces clearer price trends and higher optimized momentum-trading intensity. The median R^2 rises as z increases, and the

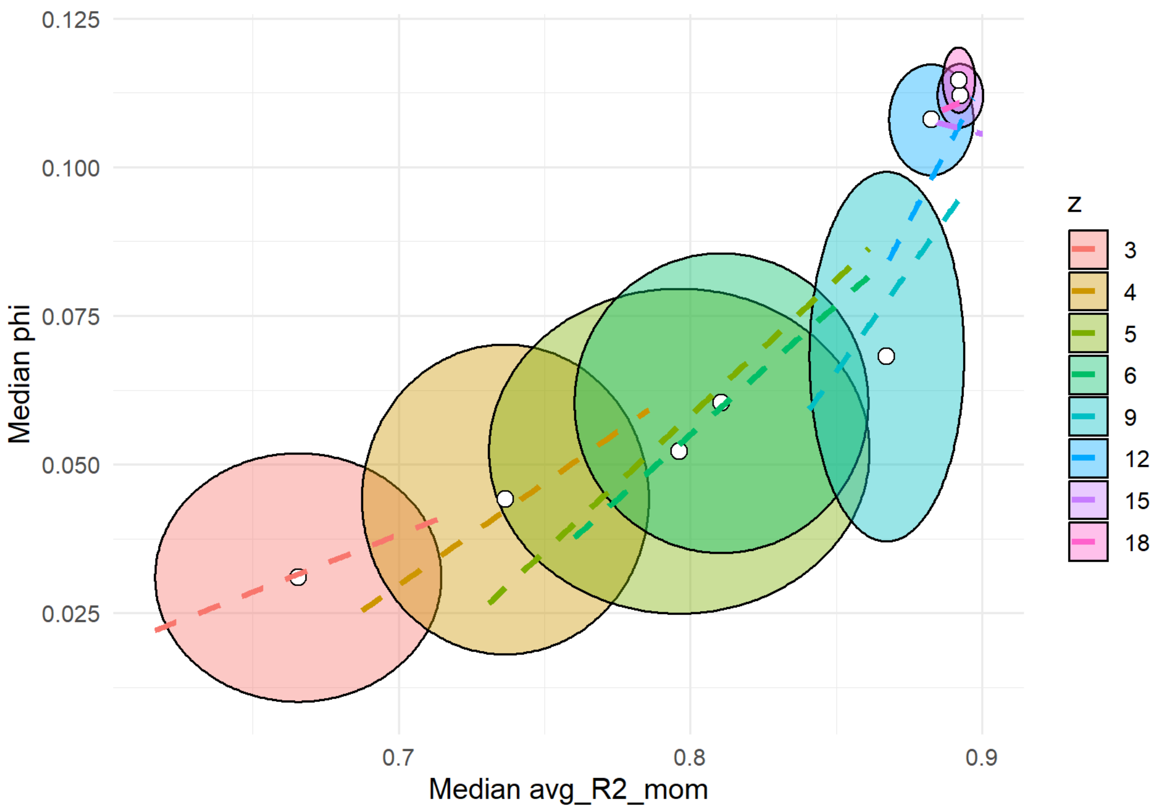


Figure 1: Trend Clarity and Momentum-Trading Intensity Across Information-Diffusion Speeds. This figure plots optimized momentum-trading intensity, ϕ, against average formation-period trend clarity, measured by the average R^2 from a time-trend regression over the k-period formation window. Points are grouped by z, the speed of information diffusion. Larger z indicates slower information diffusion.

median ϕ also increases. The result supports the paper's interpretation that trend clarity captures a feature of the price path that is relevant for momentum trading, even in a framework where momentum traders are modeled as return chasers rather than explicitly as trend-clarity investors.

The simulation also allows us to distinguish between trend clarity in the price path before momentum-trader feedback and trend clarity in the price path after momentum-trader demand is incorporated. Empirically, we observe realized prices that include the effects of all traders. In the simulation, however, we can separately examine the price path generated by newswatchers before the optimized momentum-trader demand feeds back into prices.

Figure 2 shows a similar positive relation when trend clarity is measured from the ex ante price path generated by newswatchers. This pattern indicates that the relation between trend clarity and momentum intensity is not mechanically driven by the momentum-trader feedback in the realized price path.

Noise-Trader Extension

Simulation Design

The second exercise adds independent noise-trader supply shocks to the simulated price process. The purpose is not to introduce a new theoretical mechanism, but to examine whether the positive relation between trend clarity and momentum intensity survives when prices contain additional non-fundamental noise.

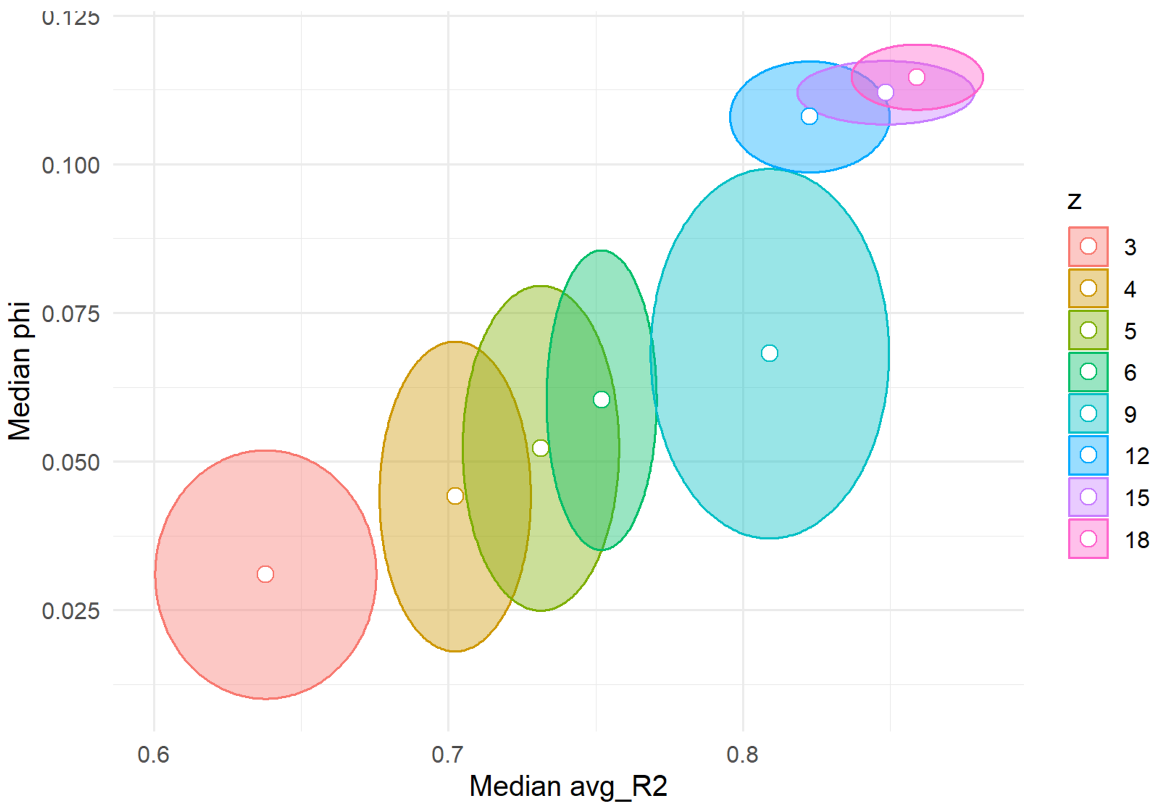


Figure 2: Ex Ante Trend Clarity and Momentum-Trading Intensity. This figure plots optimized momentum-trading intensity, ϕ, against trend clarity measured from the simulated price path generated by newswatchers before momentum-trader feedback.

Let N_t denote an independent noise-trader supply shock:

$$N_t \sim N(0, \sigma_N^2).$$

The supply absorbed by newswatchers is modified to include this shock:

$$S_t = Q - jA - \sum_{\ell=1}^{j} \phi X_{t-\ell} + N_t,$$

where $X_{t-\ell}$ is the cumulative k-period price change used by momentum traders. The newswatcher signal structure is otherwise unchanged. We then recompute the optimized momentum-trading intensity using the simulated price process that includes the noise shocks.

We set

$$z = 12, \quad j = 12, \quad k = 6, \quad g = 1/3, \quad \sigma_\epsilon = 0.5, \quad T = 250.$$

We vary the standard deviation of the noise shock over

$$\sigma_N \in \{0.02, 0.04, 0.06, 0.08, 0.10\}.$$

These values correspond to 4%, 8%, 12%, 16%, and 20% of $\sigma_\epsilon = 0.5$, respectively.

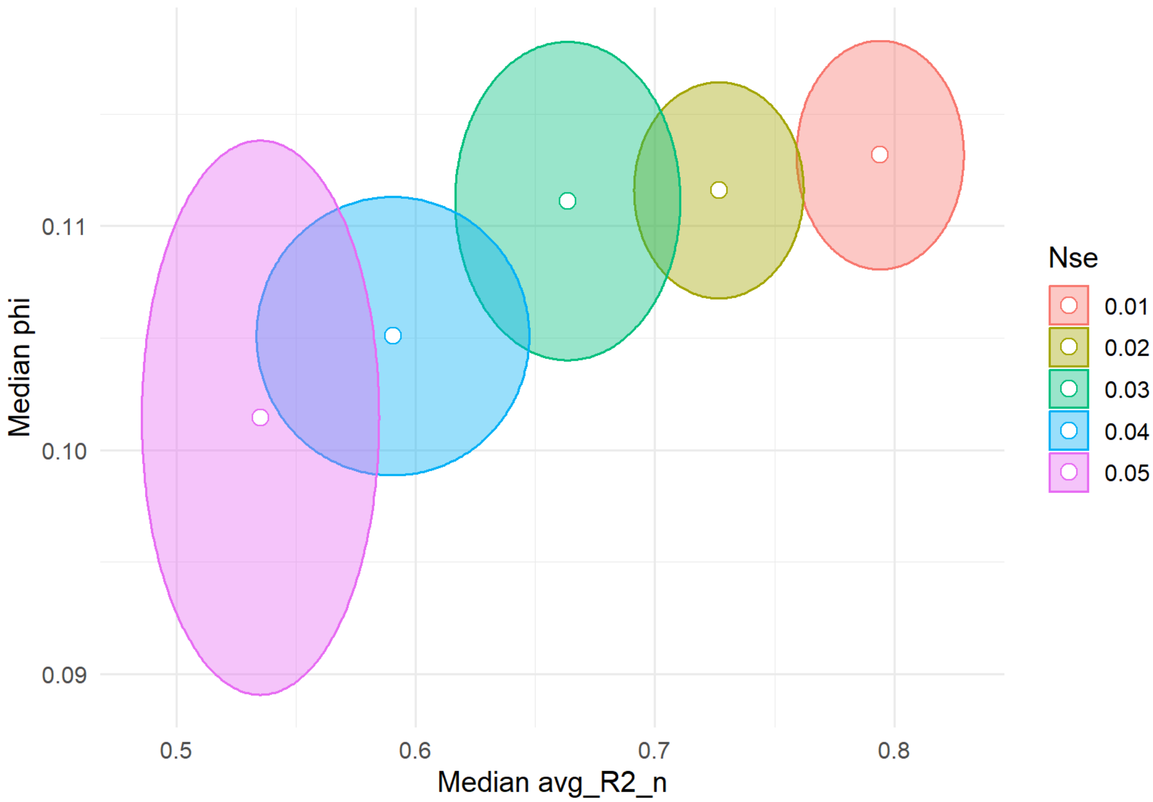


Figure 3: Noise Trading, Ex Ante Trend Clarity, and Momentum-Trading Intensity. This figure plots optimized momentum-trading intensity, ϕ, against trend clarity measured from the simulated price path before momentum-trader feedback, with independent noise-trader shocks added to the price process.

Simulation Results

Figure 3 shows that greater noise trading reduces overall trend clarity and lowers the median optimized momentum-trading intensity. The positive relation between trend clarity and momentum intensity remains visible, but the dispersion of ϕ rises as the price path becomes noisier.

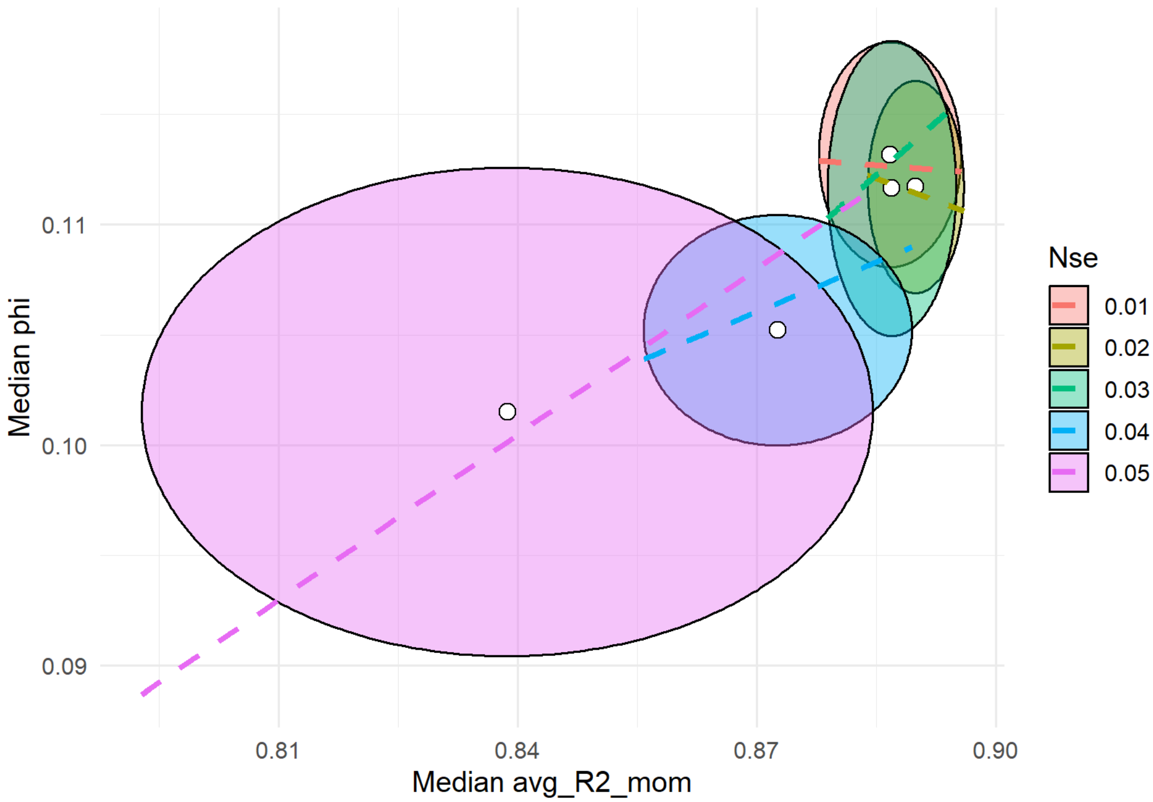


Figure 4: Noise Trading, Realized Trend Clarity, and Momentum-Trading Intensity. This figure plots optimized momentum-trading intensity, ϕ, against realized trend clarity measured from the simulated price path after momentum-trader feedback, with independent noise-trader shocks added to the price process.

Figure 4 shows that the relation between realized trend clarity and momentum intensity becomes less precise when noise trading is present. This result is useful for interpreting the empirical measure. Observed prices contain both information-driven trends and non-fundamental noise; as a result, realized trend clarity should be informative but imperfect. The simulation therefore supports the paper's empirical use of trend clarity while also clarifying why the relation need not be deterministic.

Conclusion

The simulations show that trend clarity is naturally linked to momentum-trading intensity in a multi-period version of the Hong and Stein framework. When information diffuses more slowly, price discovery is more gradual, price trends are clearer, and optimized momentum-trading intensity is higher. Adding independent noise-trader shocks weakens the mapping between observed price trends and momentum intensity, but it does not eliminate the positive relation. These results support the paper's interpretation of trend clarity as an empirically useful measure of the price-path information that can attract and strengthen momentum trading.

References

Hong, H.; and J. C. Stein. "A Unified Theory of Underreaction, Momentum Trading, and Overreaction in Asset Markets." NBER Working Paper No. 6324 (1997).

Hong, H.; and J. C. Stein. "A Unified Theory of Underreaction, Momentum Trading, and Overreaction in Asset Markets." *Journal of Finance*, 54 (1999), 2143–2184.

Trended Momentum
Internet Appendix II: Tables and Figures

IA Table 1. Trend Clarity and Momentum: NYSE Breakpoints (Section V.E)
This table reports post-formation returns over the 6-month period from t+1 to t+6 of the sequentially sorted portfolios. The sample used to construct portfolios is from CRSP between Dec 1925 and Dec 2023. We first sort stocks into quintiles based on the 11-month cumulative return measured from t-11 to t-1, with month t skipped (PRET) in each month and the stocks are then assigned to quintiles based on trend clarity (TC) within each PRET quintile in each month. Trend clarity (TC) is the R-squared from the regression of daily stock price on date sequence in the same formation period as PRET (requiring at least 200 days). The quintile cutoff is based on NYSE stocks only. Panels A and B report equal- and value-weighted returns, respectively. t-stats are based on Newey-West standard errors (with 6 lags). Significance levels of 1%, 5% and 10% are indicated by ***, ** and *.

Panel A: Equal-Weighted Returns

	1 (loser)	2	3	4	5 (winner)	return (5-1)	t
1 (low TC)	7.65	7.67	8.00	7.98	8.14	0.50	0.58
2	7.07	7.83	8.12	8.38	9.26	2.19**	2.53
3	6.56	7.42	7.93	8.57	9.62	3.06***	3.61
4	5.58	7.19	7.79	8.41	9.69	4.11***	4.60
5 (high TC)	4.13	6.43	6.95	8.16	10.14	6.01***	5.99
diff (5-1)						5.51***	6.82

Panel B: Value-Weighted Returns

	1 (loser)	2	3	4	5 (winner)	return (5-1)	t
1 (low TC)	5.35	5.86	6.00	6.10	6.18	0.83	0.99
2	5.39	5.74	6.32	5.97	7.17	1.78*	1.92
3	4.35	5.51	5.96	6.39	7.41	3.06***	3.54
4	4.37	5.74	5.88	6.64	7.73	3.36***	3.80
5 (high TC)	3.11	5.15	5.80	6.53	8.88	5.77***	5.86
diff (5-1)						4.94***	6.29

IA Table 2. Trend Clarity and Momentum: Excluding Stocks with Price less than 5 dollars (Section V.E)
This table reports post-formation returns over the 6-month period from t+1 to t+6 of the sequentially sorted portfolios. The sample used to construct portfolios is from CRSP between Dec 1925 and Dec 2023 and stocks are excluded if price is less than 5 dollars. We first sort stocks into quintiles based on the 11-month cumulative return measured from t-11 to t-1, with month t skipped (PRET) in each month, and the stocks are then assigned to quintiles based on trend clarity (TC) within each PRET quintile in each month. Trend clarity (TC) is the R-squared from the regression of daily stock price on date sequence in the same formation period as PRET (requiring at least 200 days). Panels A and B report equal- and value-weighted returns, respectively. t-stats are based on Newey-West standard errors (with 6 lags). Significance levels of 1%, 5% and 10% are indicated by ***, ** and *.

Panel A: Equal-Weighted Returns

	1 (loser)	2	3	4	5 (winner)	return (5-1)	t
1 (low TC)	6.70	7.20	7.52	7.65	8.21	1.52**	2.33
2	6.41	7.21	7.73	8.26	8.99	2.57***	3.52
3	5.73	6.67	7.58	8.27	9.22	3.49***	4.90
4	5.23	6.52	7.24	8.23	9.49	4.25***	5.76
5 (high TC)	4.44	6.20	6.71	8.18	10.08	5.64***	6.68
diff (5-1)						4.13***	6.16

Panel B: Value-Weighted Returns

	1 (loser)	2	3	4	5 (winner)	return (5-1)	t
1 (low TC)	4.77	5.43	5.77	5.74	6.32	1.55*	1.96
2	4.92	5.58	5.99	5.99	7.24	2.33***	2.93
3	4.30	5.41	5.87	6.49	7.49	3.19***	3.96
4	3.67	5.21	5.66	6.67	7.71	4.03***	4.83
5 (high TC)	3.00	5.17	5.65	6.79	9.12	6.12***	6.55
diff (5-1)						4.57***	6.47

IA Table 3. Trend Clarity and Momentum: 6-month Formation Period (Section V.E)

This table reports post-formation returns over the 6-month period from t+1 to t+6 of the sequentially sorted portfolios. The sample used to construct portfolios is from CRSP between Dec 1925 and Dec 2023. We first sort stocks into quintiles based on the past 6-month returns skipping the most recent month (PRET) in each month, and the stocks are then assigned to quintiles based on trend clarity (TC) within each PRET quintile in each month. Trend clarity is the R-squared from the regression of daily stock price on date sequence in the past 6 months (skip the most recent month to be consistent with the past return formation period and require at least 100 days). Panels A and B report equal- and value-weighted returns, respectively. t-stats are based on Newey-West standard errors (with 6 lags). Significance levels of 1%, 5% and 10% are indicated by ***, ** and *.

Panel A: Equal-Weighted Returns

	1 (loser)	2	3	4	5 (winner)	return (5-1)	t
1 (low TC)	6.37	7.39	8.14	8.05	9.05	2.68***	3.40
2	5.89	7.37	7.70	8.23	9.28	3.39***	4.32
3	5.89	7.42	7.89	8.34	9.37	3.48***	4.37
4	5.38	6.83	7.60	8.19	9.48	4.10***	5.06
5 (high TC)	4.07	6.30	7.23	7.84	10.02	5.95***	6.72
diff (5-1)						3.27***	5.17

Panel B: Value-Weighted Returns

	1 (loser)	2	3	4	5 (winner)	return (5-1)	t
1 (low TC)	4.55	5.69	6.14	6.36	6.66	2.11***	2.87
2	4.07	5.50	6.06	6.48	7.32	3.25***	4.32
3	4.14	5.62	6.17	6.53	7.32	3.18***	3.82
4	4.00	5.58	5.90	6.61	7.81	3.81***	4.82
5 (high TC)	2.93	5.09	5.55	6.43	8.47	5.54***	6.02
diff (5-1)						3.44***	5.25

IA Table 4. Trend Clarity and Momentum: Independent Sort (Section V.E)

This table reports post-formation returns over the 6-month period from t+1 to t+6 of the sequentially sorted portfolios. The sample used to construct portfolios is from CRSP between Dec 1925 and Dec 2023. We independently sort stocks into quintiles based on the 11-month cumulative return measured from t-11 to t-1, with month t skipped (PRET) and quintiles based on trend clarity (TC) within each PRET quintile in each month. Panels A and B report equal- and value-weighted returns, respectively. t-stats are based on Newey-West standard errors (with 6 lags). Significance levels of 1%, 5% and 10% are indicated by ***, ** and *.

Panel A: Equal-Weighted Returns

	1 (loser)	2	3	4	5 (winner)	return (5-1)	t
1 (low TC)	7.32	8.11	8.44	8.42	7.26	-0.06	-0.05
2	7.52	8.38	8.36	8.63	8.09	0.58	0.49
3	7.19	7.88	8.43	8.96	9.25	2.06*	1.92
4	6.43	7.03	7.65	9.07	9.85	3.42***	2.92
5 (high TC)	4.35	5.89	7.53	8.49	10.13	5.78***	4.63
diff (5-1)						5.84***	4.56

Panel B: Value-Weighted Returns

	1 (loser)	2	3	4	5 (winner)	return (5-1)	t
1 (low TC)	4.83	5.87	6.33	6.81	5.19	0.36	0.28
2	4.85	6.04	6.00	6.44	6.01	1.16	1.02
3	4.75	6.33	6.14	6.31	6.98	2.23**	2.04
4	4.09	5.23	5.90	7.08	7.70	3.61***	3.23
5 (high TC)	2.89	4.79	6.13	6.84	9.06	6.16***	5.19
diff (5-1)						5.81***	4.52

IA Table 5. Sentiment and Trended Momentum (Section V.E)

This table reports post-formation returns over the 6-month period from t+1 to t+6 of the sequentially sorted portfolios in high and low sentiment periods. The sentiment is from Jeffrey Wurgler's website. High (low) sentiment is the months when sentiment is above (below) the median of sentiment. Sentiment data is available from July 1965 to Dec 2023. We first sort stocks into quintiles based on the 11-month cumulative return measured from t-11 to t-1, with month t skipped (PRET) in each month t, and the stocks are then assigned to quintiles based on trend clarity (TC) within each PRET quintile in each month t. Trend clarity (TC) is the R-squared from the regression of daily stock price on date sequence in the same formation period as PRET (requiring at least 200 days). The unconditional momentum portfolio returns are based on the univariate sort involving PRET only. Panels A and B report equal- and value-weighted returns, respectively. t-stats are based on Newey-West standard errors (with 6 lags). Significance levels of 1%, 5% and 10% are indicated by ***, ** and *.

Panel A: Equal-Weighted Returns

	high sentiment				low sentiment			
	1 (loser)	5 (winner)	return (5-1)	t	1 (loser)	5 (winner)	return (5-1)	t
1 (low TC)	1.53	3.63	2.11*	1.80	10.76	9.41	-1.35	-0.69
2	1.20	5.51	4.31***	3.27	10.15	10.78	0.63	0.30
3	0.81	6.85	6.04***	4.42	10.03	10.97	0.94	0.40
4	0.08	7.38	7.30***	4.61	8.59	11.16	2.58	1.13
5 (high TC)	-0.60	8.11	8.70***	4.63	7.11	11.64	4.53**	2.04
diff (5-1)			6.60***	4.93			5.88***	4.97
unconditional	0.57	6.29	5.72***	4.16	9.29	10.78	1.50	0.71

Panel B: Value-Weighted Returns

	high sentiment				low sentiment			
	1 (loser)	5 (winner)	return (5-1)	t	1 (loser)	5 (winner)	return (5-1)	t
1 (low TC)	1.31	3.60	2.29	1.54	7.11	6.77	-0.33	-0.19
2	1.02	4.35	3.34**	2.09	6.20	8.00	1.80	0.79
3	1.08	5.55	4.47***	2.72	5.44	8.24	2.80	1.51
4	0.54	5.91	5.36***	2.82	5.35	8.55	3.20*	1.68
5 (high TC)	-0.33	7.41	7.75***	3.72	2.96	10.33	7.37***	3.70
diff (5-1)			5.45***	3.68			7.70***	5.95
unconditional	1.01	5.88	4.87***	2.89	5.10	8.90	3.81**	1.99

IA Table 6. List of Non-US markets (Section V.A)
The table lists non-US markets. Markets are classified by MSCI into developed, emerging, frontier and standalone. We further group markets into two categories. Markets are labelled emerging if the market is not classified as developed by MSCI.

market	avg num of stocks	unique num of stocks	num of months	classification
ARE	70	146	184	emerging
ARG	62	93	189	emerging
AUS	849	3552	445	developed
AUT	61	155	261	developed
BEL	122	267	291	developed
BGD	221	380	203	emerging
BGR	82	198	184	emerging
BRA	164	334	198	emerging
CAN	1653	6152	471	developed
CHE	186	449	371	developed
CHL	93	223	270	emerging
CHN	1862	4977	297	emerging
DEU	729	1734	291	developed
DNK	128	366	345	developed
EGY	144	247	230	emerging
ESP	139	411	291	developed
FIN	121	276	290	developed
FRA	606	1541	291	developed
GBR	1085	4927	445	developed
GRC	209	406	254	emerging
HKG	984	2925	409	developed
HRV	66	140	159	emerging
IDN	282	926	350	emerging
IND	1622	5345	366	emerging
ISR	265	809	315	developed
ITA	269	746	291	developed
JAM	71	89	61	emerging
JOR	133	237	203	emerging
JPN	2899	5934	445	developed
KOR	1203	3581	408	emerging
KWT	131	222	206	emerging
LKA	201	327	221	emerging
MAR	60	91	185	emerging
MEX	83	194	238	emerging
MUS	63	73	87	emerging
MYS	654	1429	405	emerging
NGA	111	206	191	emerging
NLD	121	314	291	developed
NOR	159	663	351	developed
NZL	92	278	351	developed
OMN	68	115	156	emerging
PAK	251	558	306	emerging
PER	76	115	75	emerging
PHL	160	330	317	emerging
POL	390	1190	329	emerging
ROU	77	184	165	emerging
RUS	179	389	145	emerging
SAU	149	278	222	emerging
SGP	382	1108	398	developed
SWE	360	1446	363	developed
THA	405	1139	408	emerging
TUR	356	587	219	emerging
TWN	1009	2642	420	emerging
USA	2925	25355	1165	developed
VNM	533	998	180	emerging
ZAF	242	866	353	emerging

IA Table 7. R2 Across Markets and Trend Groups (Section V.A)

The table reports the average and percentiles of R-squared. In each month, all stocks in each market are ranked into 3 groups based on R-squared. Then, the average and percentiles of R-squared in each group are calculated across the same market type (developed and emerging). R-squared is estimated from the regression of daily stock price on date sequence in the past 12 months (requiring at least 150 days). Developed and emerging markets are based on the MSCI market development classification. Markets are classified by MSCI into developed, emerging, frontier and standalone. We further group markets into two categories. Markets are labelled emerging if the market is not classified as developed by MSCI.

	trend clarity	average	p10	p30	p50	p70	p90
developed	1 (low TC)	0.15	0.13	0.14	0.14	0.15	0.17
emerging	1 (low TC)	0.14	0.12	0.13	0.14	0.15	0.16
developed	2	0.44	0.42	0.44	0.44	0.45	0.46
emerging	2	0.43	0.40	0.42	0.44	0.45	0.46
developed	3 (high TC)	0.73	0.72	0.73	0.73	0.74	0.75
emerging	3 (high TC)	0.72	0.71	0.72	0.73	0.73	0.75
developed	full sample	0.46	0.44	0.45	0.47	0.47	0.47
emerging	full sample	0.44	0.41	0.43	0.44	0.45	0.47

IA Table 8. Momentum Post Publication Decay (Section V.D)

Panel A: momentum decay

	EW		VW	
	Fama-French	Chen-Zimmermann	Fama-French	Chen-Zimmermann
pre-pub	0.92***	0.93***	1.36***	1.44***
	(3.39)	(3.37)	(5.11)	(5.34)
post-pub	0.64*	0.73	0.69	1.16**
	(1.66)	(1.57)	(1.53)	(2.25)
pct of decay	30.4%	21.5%	49.3%	19.4%

Panel B: Fama-MacBeth regression

	pre pub		post pub	
	coeff	t	coeff	t
const	0.0740***	3.99	0.0615***	3.51
PRET	0.5481***	4.78	0.2796	1.42
PRET x TC	7.9628***	3.47	8.4861***	2.86
TC	0.0062	0.16	-0.0718	-1.10
PRET x ID	-12.4812***	-5.01	-7.1466*	-1.81
PRET x IVOL	-3.4654	-0.99	-3.9895	-1.14
PRET x ME	12.3006	1.46	10.7826	0.63
PRET x ILLIQ	0.0258	0.01	30.1421***	2.84
PRET x BM	-2.2570	-1.03	-6.2336**	-2.18
PRET x VOL	-0.5327	-0.13	-2.8600	-0.48
PRET x MDR	12.0809***	4.11	6.6714***	2.64
PRET x DVOL	1.7794	0.19	23.6701	1.33
ID	0.1360***	3.07	0.1408***	3.76
IVOL	-0.1979*	-1.78	-0.0581	-0.25
ME	0.8625***	3.75	0.4220	0.74
ILLIQ	0.2794	1.45	-2.3588***	-5.97
BM	0.5411***	5.03	0.4195**	2.27
VOL	0.2359**	2.11	0.4258*	1.95
MDR	-0.0268	-0.42	0.0877	1.03
DVOL	-0.9395***	-3.89	-3.3228***	-5.33
adj. r2	0.092		0.055	
obs	957194		1550291	
avg. num. stock	2615		4306	

IA Table 9. Earnings Surprise and Trend Clarity (Section IV.C)

This table reports momentum returns (winner minus loser) in the post-formation period from t+1 to t+6 of triple-sorted portfolios. The sample is from Mar 1965 to Dec 2023 due to the availability of quarterly earnings. We rank stocks independently into 3 groups based on standardized unexpected earnings (SUE), trend clarity (TC) and the 11-month cumulative return measured from t-11 to t-1, with month t skipped (PRET) in each month. Trend clarity (TC) is the R-squared from the regression of daily stock price on date sequence in the same formation period as PRET (requiring at least 200 days). Following Da et al. (2014), ID is computed as ID=sign(PRET)×[%neg−%pos] where %pos and %neg denote the respective percentage of positive and negative daily returns during the same formation period as PRET. SUE is the difference of earnings between the current quarter and four quarters before being scaled by the earnings difference over the past eight quarters. The column and row labelled avg are the time-series average of the cross sectional mean across 3 SUE or TC groups in each month. Panel A reports the returns of unconditional SUE portfolios. Panels B and C report equal- and value-weighted returns, respectively. t-stats are based on Newey-West standard errors (with 6 lags). Significance levels of 1%, 5% and 10% are indicated by ***, ** and *.

Panel A: unconditional returns of SUE portfolios

	1 (low SUE)	2	3 (high SUE)	return (3-1)	t
EW	5.73	7.61	8.22	2.49***	7.32
VW	5.29	5.57	5.99	0.70*	1.67

Panel B: triple-sort equal-weighted returns

	1 (low SUE)	2	3 (high SUE)	diff (3-1)	avg
1 (low TC)	-0.11	-1.09	-0.65	-0.54	-0.62
	(-0.12)	(-1.08)	(-0.62)	(-0.63)	(-0.69)
2	0.32	0.12	1.01	0.69	0.48
	(0.34)	(0.11)	(1.03)	(1.11)	(0.51)
3 (high TC)	3.17**	2.60*	2.99**	-0.18	2.92**
	(2.50)	(1.95)	(2.13)	(-0.22)	(2.32)
diff (3-1)	3.28***	3.69***	3.64***		3.53***
	(3.13)	(3.75)	(3.28)		(4.27)
avg	1.13	0.54	1.12	-0.01	
	(1.17)	(0.52)	(1.08)	(-0.02)	

Panel C: triple-sort value-weighted returns

	1 (low SUE)	2	3 (high SUE)	diff (3-1)	avg
1 (low TC)	-0.45	-0.18	0.52	0.97	-0.04
	(-0.41)	(-0.19)	(0.47)	(1.07)	(-0.04)
2	-0.20	-0.33	0.86	1.06	0.11
	(-0.19)	(-0.32)	(0.87)	(1.34)	(0.12)
3 (high TC)	2.77**	4.01***	4.37***	1.60	3.71***
	(2.17)	(3.25)	(3.85)	(1.59)	(3.39)
diff (3-1)	3.22***	4.19***	3.85***		3.75***
	(2.72)	(3.59)	(3.39)		(4.45)
avg	0.71	1.17	1.92**	1.21**	
	(0.70)	(1.26)	(2.08)	(2.27)	

IA Table 10. Information Discreteness, Trend Clarity and Momentum: Alpha Analysis (Section IV.E)
This table reports momentum (winner minus loser) alphas (risk-adjusted returns based on the Fama-French 3-factor model) in the post-formation period from t+1 to t+6 of triple-sorted portfolios. The sample is from July 1926 to Dec 2023 (factor returns are available from July 1926). We rank stocks independently into 3 groups based on information discreteness (ID), trend clarity (TC) and the 11-month cumulative return measured from t-11 to t-1, with month t skipped (PRET) in each month. Trend clarity (TC) is the R-squared from the regression of daily stock price on date sequence in the same formation period as PRET (requiring at least 200 days). Following Da et al. (2014), ID is computed as ID=sign(PRET)×[%neg−%pos] where %pos and %neg denote the respective percentage of positive and negative daily returns during the same formation period as PRET. The column and row labelled avg are the time-series average of the cross sectional mean across 3 ID or TC groups in each month. Panel A reports the average number of stocks the 3 by 3 portfolios based on TC and ID. Panels B and C report equal- and value-weighted returns respectively. t-stats are based on Newey-West standard errors (with 6 lags). Significance levels of 1%, 5% and 10% are indicated by ***, ** and *.

Panel A: Equal-Weighted Alphas

	1 (info continuous)	2	3 (info discreteness)	diff (3-1)	avg
1 (low TC)	2.17***	0.00	-1.22**	-3.39***	0.32
	(3.19)	(0.00)	(-2.07)	(-4.30)	(0.66)
2	2.84***	0.84*	-0.30	-3.14***	1.12**
	(4.67)	(1.86)	(-0.65)	(-5.59)	(2.56)
3 (high TC)	4.59***	1.74***	1.23**	-3.36***	2.52***
	(6.54)	(2.98)	(2.24)	(-5.59)	(4.63)
diff (3-1)	2.43***	1.74***	2.45***		2.21***
	(3.52)	(2.73)	(3.54)		(4.31)
avg	3.20***	0.86*	-0.10	-3.30***	
	(5.54)	(1.91)	(-0.23)	(-6.47)	

Panel B: Value-Weighted Alphas

	1 (info continuous)	2	3 (info discreteness)	diff (3-1)	avg
1 (low TC)	1.82***	0.87	-0.14	-1.95**	0.85*
	(2.72)	(1.54)	(-0.18)	(-2.21)	(1.70)
2	1.90***	1.18**	-0.58	-2.49***	0.83*
	(3.19)	(2.17)	(-1.07)	(-4.25)	(1.77)
3 (high TC)	4.14***	2.70***	2.53***	-1.61***	3.12***
	(6.38)	(4.28)	(4.32)	(-2.70)	(5.85)
diff (3-1)	2.33***	1.82**	2.67***		2.27***
	(3.16)	(2.52)	(3.10)		(4.00)
avg	2.62***	1.58***	0.60	-2.02***	
	(5.06)	(3.39)	(1.30)	(-4.51)	

IA Table 11. A FM Regression Including Information Discreteness and its Interaction (Section IV.E)

This table reports the Fama-MacBeth regression of post-formation returns from t+1 to t+6 on the 11-month cumulative return measured from t-11 to t-1, with month t skipped (PRET) and the interaction of PRET and trend clarity (TC) with/without controls. We run the regression in each month and then report the time-series average of slopes. The control variables include information discreteness (ID), idiosyncratic volatility (IVOL), market value (ME), book to market ratio (BM), illiquidity (ILLIQ), trading turnover (VOL), maximum daily return (MDR) and dollar trading volume (DVOL). Micro firms are defined as firms with a market value less than the 20% percentile of the market value of NYSE stocks. We map the independent variables to [0,1] interval to reduce the impact of outliers and high correlations among them to better capture the effect of independent variables on the dependent variable. Please see Appendix I for detailed definitions of variables. t-stats are based on Newey-West standard errors (with 6 lags). Significance levels of 1%, 5% and 10% are indicated by ***, ** and *.

	model 1		model 2		model 3		model 4		model 5	
									Ex. micro stocks	
	coeff	t	coeff	t	coeff	t	coeff	t	coeff	t
const	0.0532***	3.42	0.0833***	4.63	0.0476**	2.21	0.1888***	4.42	0.0421	1.11
PRET	0.0419***	3.88	-0.0056	-0.47	0.0452**	2.19	-0.064	-1.14	0.1226**	2.42
PRET x TC			0.0663***	4.27	0.0366**	2.35	0.0500***	3.90	0.0465***	4.00
TC			-0.0448***	-4.38	-0.0238**	-2.24	-0.0269***	-3.47	-0.0184***	-3.13
PRET x ID					-0.0942***	-4.21	-0.0799***	-5.37	-0.0508***	-4.03
PRET x IVOL							-0.0197	-1.18	0.0380***	3.08
PRET x ME							0.1088*	1.82	0.0075	0.26
PRET x ILLIQ							0.0837	1.63	-0.1037**	-2.23
PRET x BM							-0.0394***	-2.96	-0.0481***	-3.64
PRET x VOL							0.0228	0.84	0.0326	1.45
PRET x MDR							0.0591***	4.94	0.0227**	2.31
PRET x DVOL							0.0154	0.19	-0.1231**	-2.05
ID					0.0648***	5.29	0.0512***	5.90	0.0273***	4.05
IVOL							0.0021	0.14	-0.0289***	-3.35
ME							-0.0157	-0.32	-0.0031	-0.16
ILLIQ							-0.1374***	-3.17	0.0043	0.11
BM							0.0639***	6.13	0.0470***	4.84
VOL							0.0176	1.06	-0.0027	-0.20
MDR							-0.0281***	-3.58	-0.0059	-1.09
DVOL							-0.2049***	-3.46	-0.0109	-0.23
adj. r2	0.018		0.025		0.032		0.074		0.101	
obs	3502725		3411983		3411771		2507485		1156971	
avg. num. stock	3006		2928		2928		3453		1593	

IA Table 12. Residual Trend Clarity (Section IV.E)

This table reports post-formation returns over the 6-month period from t+1 to t+6 of the sequentially sorted portfolios. The sample used to construct portfolios is from Dec 1925 to Dec 2023. We first sort stocks into quintiles based on the 11-month cumulative return measured from t-11 to t-1, with month t skipped (PRET) in each month, and the stocks are then assigned to quintiles based on residual trend clarity (ResidTC) within each PRET quintile in each month. To estimate ResidTC, we run cross-sectional regression of trend clarity (TC) on information discreteness (ID) and log market value in each month and obtain the residual from the regression. Trend clarity (TC) is the R-squared from the regression of daily stock price on date sequence in the past 12 months (skip the most recent month to be consistent with past return formation period and require at least 200 days). Following Da et al. (2014), ID is computed as ID=sign(PRET)×[%neg−%pos] where %pos and %neg denote the respective percentage of positive and negative daily returns during the same formation period as PRET. Panels A and B report equal- and value-weighted returns, respectively. t-stats are based on Newey-West standard errors (with 6 lags). Significance levels of 1%, 5% and 10% are indicated by ***, ** and *.

Panel A: Equal-Weighted Returns

	1 (loser)	2	3	4	5 (winner)	WML (5-1)	t
1 (low TC)	6.01	7.06	7.78	8.09	8.24	2.23**	2.25
2	6.49	7.11	7.81	8.17	9.22	2.73***	2.87
3	5.58	7.27	7.76	8.33	9.52	3.94***	4.2
4	5.39	6.99	7.53	8.53	9.47	4.08***	4.22
5 (high TC)	5.2	6.23	6.98	8.27	9.4	4.19***	4.36
diff (5-1)						1.97**	2.39

Panel B: Value-Weighted Returns

	1 (loser)	2	3	4	5 (winner)	WML (5-1)	t
1 (low TC)	4.1	5.28	5.97	6.38	6.92	2.82***	2.86
2	4.35	5.33	6.04	6.12	7.39	3.04***	3
3	4.02	5.47	5.73	6.41	7.93	3.91***	3.83
4	3.03	5.52	5.75	6.69	8.07	5.04***	5.13
5 (high TC)	2.9	5.05	5.28	6.47	8.1	5.20***	5.08
diff (5-1)						2.38***	2.82

IA Table 13. FM Regression Including Information Discreteness and its Interaction (Section IV.E)

This table reports the Fama-MacBeth regression of post-formation returns from t+1 to t+6 on the 11-month cumulative return measured from t-11 to t-1, with month t skipped (PRET) and the interaction of PRET and trend clarity (measured by residual trend clarity, ResidTC) with/without controls. We run the regression in each month and then report the time-series average of slopes. The control variables include information discreteness (measured by residual information discreteness, ResidID), idiosyncratic volatility (IVOL), log market value (ME), book to market ratio (BM), illiquidity (ILLIQ), trading turnover (VOL), maximum daily return (MDR) and log dollar trading volume (DVOL). Micro firms are defined as firms with a market value less than the 20% percentile of the market value of NYSE stocks. We use ResidTC and ResidID to reduce the impact of high correlations to better capture the effect of independent variables on the dependent variable. Please see Appendix I for detailed definitions of variables. t-stats are based on Newey-West standard errors (with 6 lags). Significance levels of 1%, 5% and 10% are indicated by ***, ** and *.

	model 1		model 2		model 3	
					Ex. micro stocks	
	coeff	t	coeff	t	coeff	t
const	0.0690***	6.05	0.0792***	5.14	0.1063***	4.84
PRET	0.0139	1.43	0.0757**	2.54	0.0602	1.21
PRET x ResidTC	0.0283*	1.93	0.0316***	3.06	0.0320***	2.85
ResidTC	-0.0094	-1.38	-0.0114***	-3.28	-0.0029	-0.84
PRET x ResidID	-0.3337***	-3.82	-0.2897***	-5.93	-0.2049***	-4.41
PRET x IVOL			-0.4720*	-1.90	-0.0473	-0.14
PRET x ME			0.0149**	2.46	0.0055	0.69
PRET x ILLIQ			-993.1077*	-1.90	15653.6364	0.05
PRET x BM			0.0086**	2.08	-0.0054	-0.63
PRET x VOL			-0.1661	-1.34	-0.1639	-1.08
PRET x MDR			0.2490***	5.21	0.1625**	2.03
PRET x DVOL			-0.0098*	-1.76	-0.004	-0.50
ResidID	0.1543***	5.72	0.1251***	7.73	0.0578***	3.52
IVOL			-0.5608***	-2.84	-0.8805***	-4.50
ME			-0.0103**	-2.24	-0.0053	-1.29
ILLIQ			1469.9317***	3.64	-501020.3443**	-2.32
BM			0.0142***	3.99	0.0090*	1.72
VOL			-0.2549***	-4.67	-0.1115*	-1.65
MDR			-0.0071	-0.23	0.0788**	1.98
DVOL			0.0041	1.24	-0.0006	-0.15
adj. r2	0.028		0.075		0.103	
obs	3407943		2507485		1156971	
avg. num. stock	2925		3453		1593	

IA Table 14. Correlations Between Past Returns, Trend Clarity and Information Discreteness (Appendix I)

Panel A: raw variables

	PRET	PRET*TC	PRET*ID	TC	ID
PRET	1	0.94	-0.65	0.13	0.14
PRET*TC	0.94	1	-0.71	0.19	0.07
PRET*ID	-0.65	-0.71	1	-0.09	0.03
TC	0.13	0.19	-0.09	1	-0.37
ID	0.14	0.07	0.03	-0.37	1

Panel B: normalized variables

	PRET	PRET*TC	PRET*ID	TC	ID
PRET	1	0.19	-0.15	0.07	0.16
PRET*TC	0.19	1	-0.39	0.01	-0.01
PRET*ID	-0.15	-0.39	1	-0.01	0.00
TC	0.07	0.01	-0.01	1	-0.36
ID	0.16	-0.01	0.00	-0.36	1

Panel C: residual trend clarity and residual information discreteness

	PRET	PRET*ResidTC	PRET*ResidID	TC	ID
PRET	1	0.16	-0.21	0.03	0.03
PRET*ResidTC	0.16	1	0.28	0.17	0.06
PRET*ResidID	-0.21	0.28	1	0.05	0.22
TC	0.03	0.17	0.05	1	0.34
ID	0.03	0.06	0.22	0.34	1

The correlation structure of the main variables complicates regression tests. Panel A shows that PRET×TC has a low correlation with TC (19%) but a high correlation with PRET (94%), due to the nature of TC. Since TC, as an R-squared measure, ranges from 0 to 1 and has a smaller standard deviation (0.3 vs. 0.58 for PRET), its variation is limited. Moreover, TC cannot change the sign of PRET and acts more as a scale factor. As a result, PRET dominates PRET×TC, making it difficult to isolate the effect of TC in regressions. PRET×ID has a slightly lower correlation with PRET (-0.65), as ID ranges from -1 to 1 and can change the sign of PRET, reducing its dominance.

Normalized variables, which capture variations relative to the cross-sectional mean, reduce correlation and minimize the impact of extreme values, as seen in Panel B. This approach better captures the effect of TC, ensuring more consistent results with portfolio analysis.

We also run regressions using raw variables, winsorized at 1% and 99%. To address correlation issues, we use residual trend clarity (ResidTC) and residual information discreteness (ResidID), making them orthogonal to past returns, ID, and TC. Cross-sectional regressions allow us to extract the residuals, reducing correlations. Panel C confirms much lower correlations among variables, and the use of raw variables does not change the results.

IA Table 15. Unconditional Momentum in Non-Equity Asset Classes

This table reports average monthly returns for unconditional momentum portfolios formed within each asset class. Assets are sorted into three portfolios based on past returns: Loser (1), Middle (2), and Winner (3). WML is the winner-minus-loser return (3–1), with the corresponding t-statistic reported in the final column. "AMP sample end" restricts the sample to end in July 2011 to match Asness et al. (2013). "10 bonds in AMP" restricts the bond universe to the ten countries studied in AMP. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: currencies (full sample)

1 (Loser)	2	3 (Winner)	WML (3–1)	t (3–1)
-1.75	-0.72	-0.01	1.74***	3.61

Panel B: currencies (AMP sample end)

1(Loser)	2	3 (Winner)	WML (3–1)	t (3–1)
-1.78	-0.48	0.35	2.13***	3.50

Panel C: government bonds (full sample)

1 (Loser)	2	3 (Winner)	WML (3–1)	t (3–1)
3.74	3.22	3.40	-0.34	-0.72

Panel D: government bonds (10 bonds in AMP)

1 (Loser)	2	3 (Winner)	WML (3–1)	t (3–1)
2.89	3.07	3.18	0.29	0.66

Panel E: commodities (full sample)

1 (Loser)	2	3 (Winner)	WML (3–1)	t (3–1)
-2.45	-1.03	0.13	2.58**	2.34

IA Table 16. Trend Clarity and Momentum: Portfolio Returns (Monthly)1

This table reports post-formation *monthly* average returns (in percentage) over the 6 months from t+1 to t+6 for sequentially sorted portfolios using overlapping portfolios in the spirit of Jegadeesh and Titman (1993). The sample spans from Dec 1925 to Dec 2023 using CRSP data. Stocks are first sorted into quintiles based on an 11-month cumulative return measured from $t-11$ to $t-1$, with month t skipped (PRET), and then into quintiles based on trend clarity (TC) within each PRET quintile. Trend clarity (TC) is the R-squared from the regression of daily stock price on date sequence in the same formation period as PRET (requiring at least 200 days). Unconditional momentum portfolio returns are derived from a univariate sort on PRET. Panels A and B present equal- and value-weighted returns, with t-statistics based on Newey-West standard errors (with six lags). Significance at 1%, 5%, and 10% is indicated by ***, **, and *, respectively.

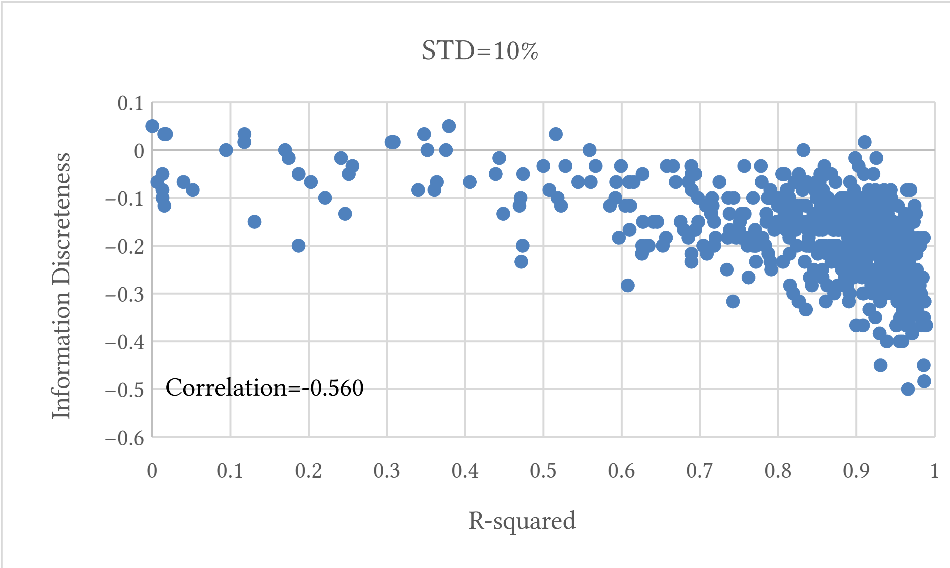
Panel A: Equal-Weighted Returns

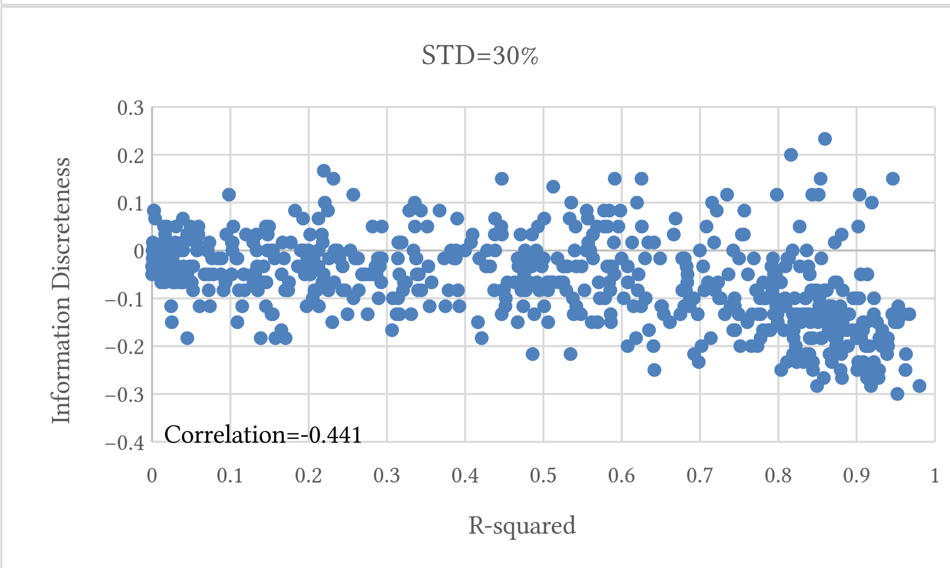
	1 (loser)	2	3	4	5 (winner)	WML (5-1)	t
1 (low TC)	1.39	1.30	1.30	1.32	1.28	-0.11	-0.64
2	1.28	1.29	1.33	1.38	1.45	0.17	0.94
3	1.20	1.22	1.31	1.35	1.51	0.31*	1.72
4	1.06	1.14	1.23	1.38	1.53	0.47**	2.48
5 (high TC)	0.93	1.01	1.11	1.30	1.60	0.67***	3.28
diff (5-1)						0.78***	6.04
unconditional	1.17	1.19	1.26	1.35	1.47	0.30*	1.68

Panel B: Value-Weighted Returns

	1 (loser)	2	3	4	5 (winner)	WML (5-1)	t
1 (low TC)	0.86	0.87	1.00	1.00	0.97	0.12	0.67
2	0.77	0.97	0.99	0.99	1.12	0.35*	1.82
3	0.63	0.93	1.00	1.03	1.18	0.55***	2.90
4	0.63	0.91	0.91	1.12	1.25	0.61***	3.20
5 (high TC)	0.44	0.81	0.90	1.06	1.41	0.96***	4.80
diff (5-1)						0.85***	6.33
unconditional	0.64	0.89	0.93	1.05	1.24	0.60***	3.31

IA Figure 1. The Relationship Between ID and R2 in Simulated Returns. (Section IV.E)
In this figure we report the scatter plots for the ID and R2 measures for 600 simulated paths. The return is generated in a lognormal distribution with the expected return of 25% over 120 periods. In panel A the standard deviation is set at 10%, while in Panel B it is 30%.



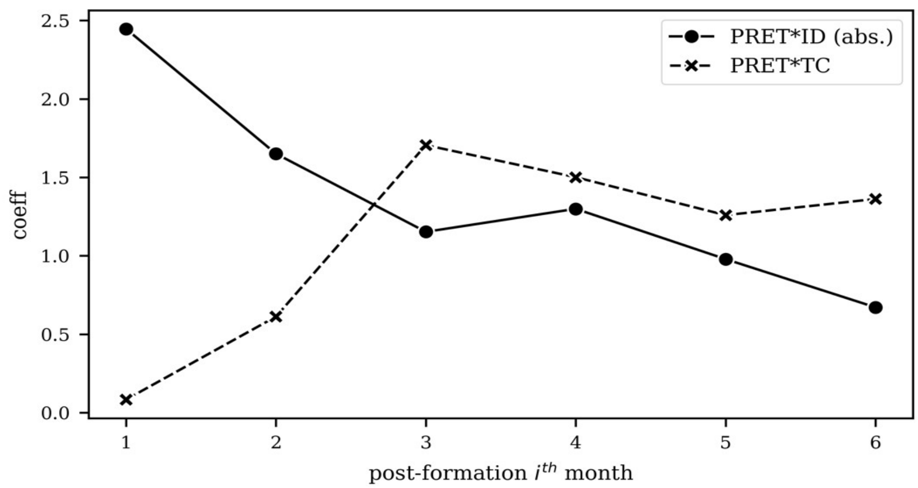


ID is determined by the proportion of positive versus negative daily returns over the formation period. A higher percentage of positive returns suggests a continuous flow of information, while returns concentrated in a few days indicate more discrete information flow. Thus, ID measures the frequency difference between positive and negative daily returns. In contrast, TC captures the overall price trend. These measures are naturally related, especially when the magnitude of daily returns is similar (i.e., lower standard deviation). However, when daily returns vary more, the ID measure can remain stable even as the price trend weakens.

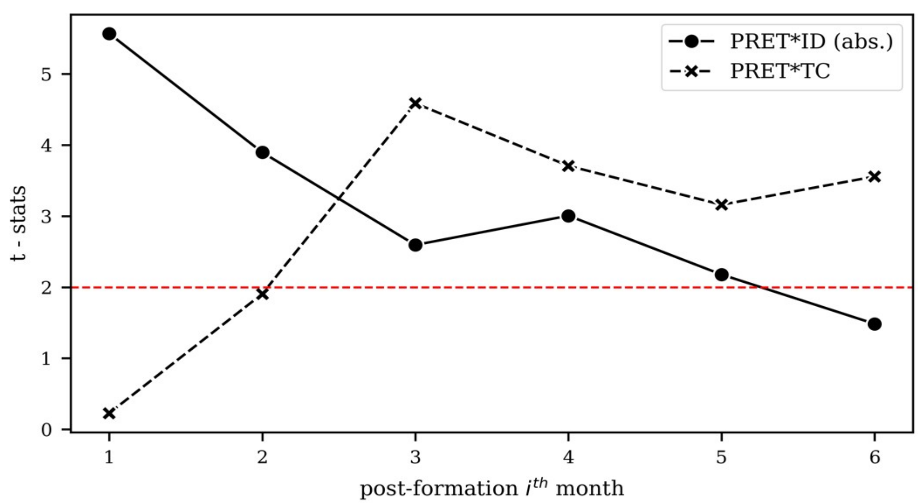
Figure 1 shows scatter plots of ID and TC from simulated return paths with identical expected returns. The plots confirm a generally negative but weak correlation between ID and TC, with a wide range of TC values for a given ID. The ID range broadens as the return process's standard deviation increases. Our simulation's correlation is higher than that of -0.36 in the sample statistic, suggesting that there is further noise in the empirical signal that weakens their link further. Overall, this supports the conclusion that ID and TC are distinct and not mechanically linked.

IA Figure 2. Fama-MacBeth Regression: Coefficient in Post-Formation Single Month
This figure plots the Fama-MacBeth regression of each post-formation single return from t+1 to t+6 on the 11-month cumulative return measured from t-11 to t-1, with month t skipped (PRET) and the interaction of PRET and trend clarity (TC) with/without controls. We run the regression in each month and then plot the time-series average of slopes. The control variables include information discreteness (ID), idiosyncratic volatility (IVOL), market value (ME), book to market ratio (BM), illiquidity (ILLIQ), trading turnover (VOL), maximum daily return (MDR) and dollar trading volume (DVOL). Following Freyberger et al. (2020) and Kozak et al. (2020), we normalize independent variables to reduce the impact of outliers and high correlations among them to better capture the effect of independent variables on the dependent variable. We take the absolute of slopes of PRET*ID as momentum is stronger when ID is low. Please see Appendix I for detailed definitions of variables and the procedures of normalization. t-stats are based on Newey-West standard errors. Significance levels of 1%, 5% and 10% are indicated by ***, ** and *.

Panel A: coefficients



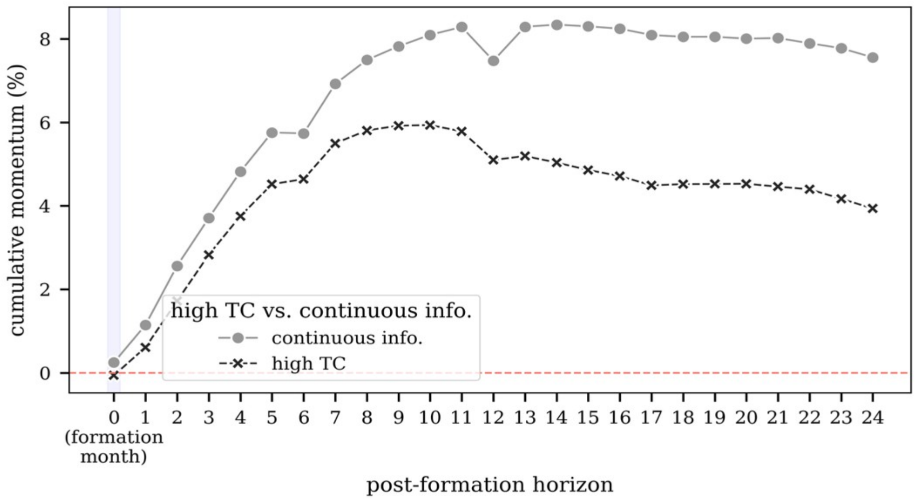
Panel B: t-stats



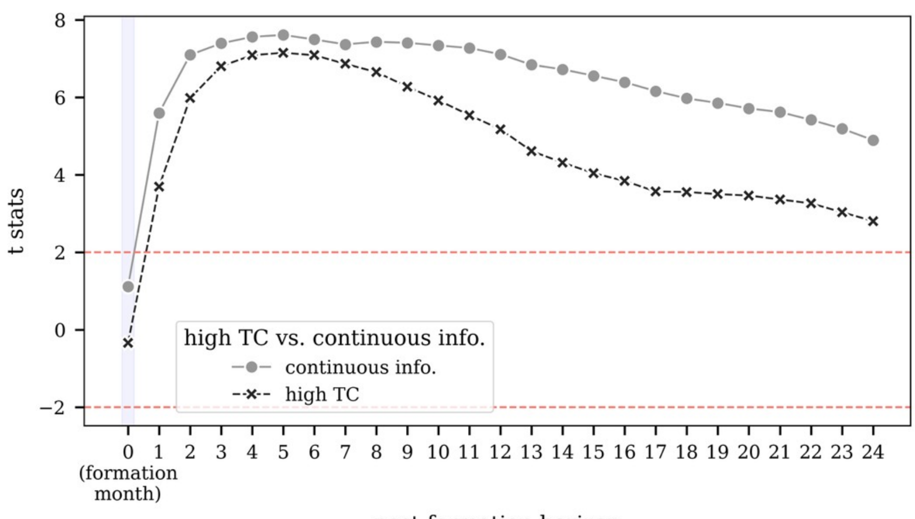
IA Figure 3. Comparison of Post-formation Alphas
The figure plots post-formation alphas (risk-adjusted returns) with respect to the Fama-French 3-factor model for momentum portfolios (winner minus loser) of high trend clarity (TC) and continuous information groups. The sample used to construct the portfolio is from Dec 1925 to Dec 2023. We rank stocks into quintiles based on the 11-month cumulative return measured from $t-11$ to $t-1$, with month t skipped (PRET) in each month. Within each quintile, we assign stocks into quintiles based on trend clarity and use quintile 5 as the high TC group. Similarly, we

assign stocks into quintiles based on information discreteness (ID) and use quintile 1 as the continuous information group (i.e. low discreteness means high continuation). Trend clarity (TC) is the R-squared from the regression of daily stock price on date sequence in the same formation period as PRET (require at least 200 days). Information discreteness is computed as according to Da et al. (2014): ID=sign(PRET)×[%neg−%pos] where %pos and %neg denote the percentage of positive and negative daily returns during PRET period. Panels A and B plot equal-weighted alphas and value-weighted alphas, respectively. Panel A1 (B1) plots cumulative alphas. Panel A2 (B2) plots corresponding t values for cumulative alphas.

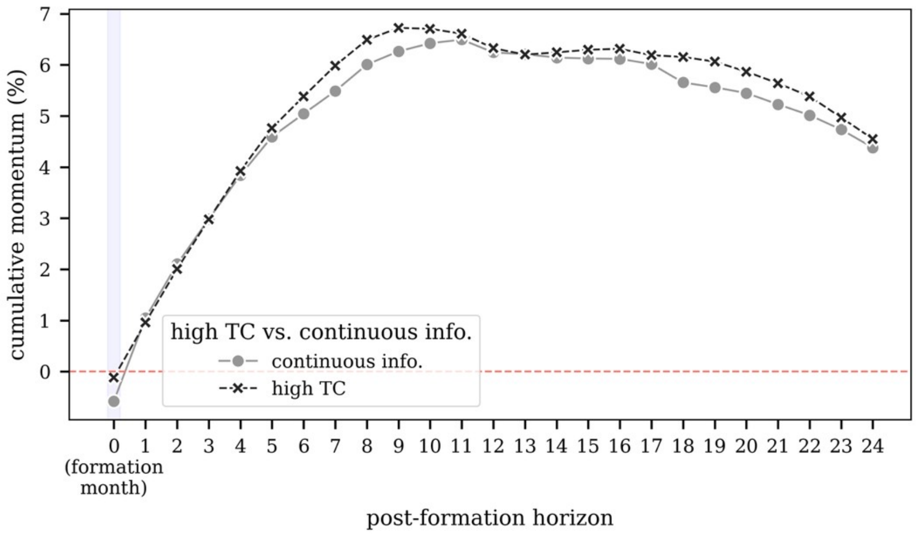
Panel A1: equal-weighted cumulative alpha



Panel A2: equal-weighted cumulative alpha t values



Panel B1: value-weighted cumulative alpha



Panel B2: value-weighted cumulative alpha t values