The Impact of Information Dissemination with Emphasis on Absolute Information Discontinuity on the Effect of Time-Series Momentum

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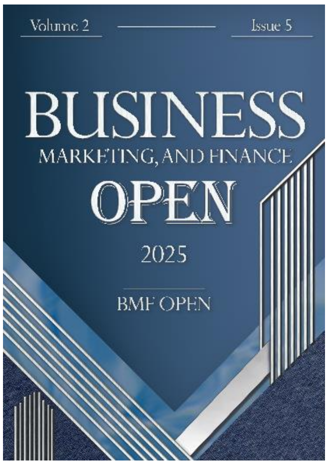

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Abstract: Behavioral financial development is founded on the criticisms directed at the efficient market hypothesis. Although many anomalies have faded over time, momentum has persisted powerfully after being formally documented, reflecting the result of gradual information dissemination and psychological conservatism among investors. This conservatism manifests in systematic errors in forming earnings expectations, as investors fail to update their beliefs and underweight the statistical value of new information. Purposeful fluctuations in the design of time-series momentum lead to improved performance compared to cross-sectional momentum returns. This study examines the impact of information dissemination with a focus on absolute information discontinuity on the effect of time-series momentum. The analysis is conducted through two components: information discontinuity and information uncertainty, using a sample of 120 selected companies listed on the stock exchange, categorized into four random decile portfolios. These two metrics assess the entry of information and the level of information noise. To examine the effect of time-series momentum, its strategies are analyzed over two sets of formation and holding periods ranging from 3 to 36 months between 2021 and 2023 (Gregorian calendar). Given that time-series momentum represents a net long investment strategy that varies with time horizons, its analysis across twelve formation and holding periods, using multivariate regression to test the hypothesis, revealed that in long-term formation and short-term holding strategies, information dissemination significantly influences the effect of time-series momentum.

Keywords: Information dissemination, information discontinuity, information continuity, information noise, momentum, time-series.

1. Introduction

The efficient market hypothesis (EMH), first introduced by Fama, posits that financial markets are informationally efficient such that asset prices always fully reflect all available information. According to this theory, it is virtually impossible for investors to consistently achieve abnormal returns since price changes are unpredictable and follow a "random walk" [1]. The core assumption underpinning this framework is that information is rapidly and homogeneously distributed across all market participants, and that investors behave rationally in response to it. However, a growing body of empirical literature challenges this paradigm by documenting a range of market anomalies that systematically contradict EMH, with the momentum effect standing out as one of the most persistent and robust deviations [2, 3].

Momentum is a phenomenon in finance whereby assets that have performed well in the past tend to continue performing well in the short to medium term, while those that have underperformed tend to keep underperforming. This trend persistence defies the foundational assumptions of EMH, especially its weak form, which argues that past price information cannot predict future returns [4]. Momentum strategies have been extensively studied across asset classes including equities, commodities, currencies, and bonds [5-7], and they are generally divided into two primary categories: cross-sectional momentum and time-series momentum (TSM). While the former compares returns of different assets within the same time period, the latter focuses on the persistence of returns of a single asset over time [8].

Time-series momentum has received increasing attention following the seminal work of Moskowitz et al. (2012), who demonstrated that past returns of individual assets could positively predict their future returns, both in absolute terms and relative to cross-sectional strategies. The rationale behind TSM rests on the idea that investors underreact to information due to cognitive biases or due to slow information dissemination, thus leading to price trends that can be exploited for excess returns [9-11].

A fundamental component of the behavioral explanation for TSM is the asymmetry in investor reaction to information flows. Investors may exhibit underreaction or overreaction due to psychological biases such as overconfidence or self-attribution, leading to momentum and long-term reversal patterns [9, 12]. Furthermore, the diffusion of information across investors is not instantaneous; instead, it permeates through markets at varying rates depending on firm characteristics such as size, analyst coverage, and public visibility [2, 13]. As a result, prices gradually adjust to new information, thereby generating return predictability and market inefficiencies [14, 15].

The literature has attempted to quantify the impact of information dissemination on asset returns using various proxies such as analyst coverage, media coverage, and trading volume [16, 17]. More recently, Huang et al. (2022) proposed the concept of information discreteness, which focuses on the degree to which price-relevant information is absorbed into prices in a stepwise versus continuous fashion. Their model, building on the idea of "frog-in-the-pan" investors, shows that less continuous, more discrete information flow is associated with stronger momentum effects [18]. Similarly, Andrei and Cujean (2017) argue that momentum and reversal are driven by the interplay between informed traders who react to fundamental signals and uninformed momentum traders who rely solely on past price trends [19].

The proxy of absolute information discontinuity (ID) has been introduced to capture instances where investors assign significantly different weights to new information based on prior beliefs. This creates an environment where asset prices respond disproportionately to signals depending on whether they align or contradict investors' expectations [10]. Additionally, abnormal return volatility (ARV) has been employed as a measure of informational uncertainty. High ARV suggests greater noise in the assimilation of new data, potentially exacerbating behavioral biases and momentum patterns [11].

The time-varying nature of momentum profits also introduces an additional dimension to these behavioral explanations. Empirical research by Kim et al. (2016) and Lim et al. (2018) reveals that TSM profits are not constant across time but instead vary with market conditions and the degree of informational uncertainty. Specifically, they found that momentum strategies perform better during periods of high market volatility and low investor attention [20, 21]. Similarly, Pitkäjärvi et al. (2020) demonstrate that cross-asset signals enhance the predictive power of TSM, highlighting the importance of incorporating multi-dimensional information into momentum models [22].

While early studies focused primarily on developed markets, recent research has extended momentum investigations to emerging and frontier markets, where market inefficiencies and information asymmetries are typically more pronounced [23, 24]. These environments offer fertile ground for testing the implications of behavioral finance and information-based theories of momentum. Moreover, cultural and institutional factors have been found to mediate the strength of momentum effects. For instance, Chui et al. (2000) identify variations in momentum profitability across Asian markets based on legal origin and investor protection standards.

In practical applications, momentum strategies—whether cross-sectional or time-series—are often implemented with holding periods ranging from a few weeks to several months. However, their effectiveness appears to differ depending on the asset class, the construction methodology, and the horizon of analysis. For example, Jegadeesh and Titman (2001) documented the short-term profitability of momentum strategies, while also noting that long-term reversals tend to offset these gains. In contrast, Goyal and Jegadeesh (2018) highlight the superior performance of TSM strategies in certain asset classes, emphasizing their robustness to model specifications and economic conditions [25].

Despite the consistency of empirical evidence, the theoretical foundation of momentum remains under debate. Traditional risk-based explanations have struggled to account for the observed magnitude and persistence of momentum profits. As such, behavioral theories that emphasize information processing limitations, cognitive biases, and the staggered nature of information flow provide a more plausible account [26, 27]. These theories posit that price trends are partially fueled by delayed investor response to new data, particularly when it contradicts entrenched beliefs or when informational signals are noisy or ambiguous [28, 29].

Given the theoretical ambiguity and practical relevance of momentum-based strategies, this study aims to empirically investigate the impact of information dissemination—particularly absolute information discontinuity and abnormal return volatility—on time-series momentum in the Tehran Stock Exchange.

2. Methodology

The statistical population includes all companies listed on the Tehran Stock Exchange during the years 2021 to 2023. The research sample was selected based on the following criteria:

- The sample companies must not belong to the categories of insurance, investment, financial institutions, banks, leasing, or holding companies.
- To ensure comparability of information, the fiscal year-end of the companies must be March 20.
- The companies must have been listed on the Tehran Stock Exchange prior to the 2021 fiscal year.
- The companies must not have changed their line of business or fiscal year during 2021 to 2023.
- Required data and information must be accessible for the research period.

After applying the above conditions, 120 companies were selected. Given that Pitkethly et al. (2020) found that cross-asset strategies combined with traditional time-series strategies perform better, the current study examines the issue using four decile portfolios, each containing ten stocks. To calculate variables such as the beta coefficient, ID, and ARV, daily data was initially used and later converted into monthly format.

The four portfolios were formed using simple random sampling without replacement from among the companies, ensuring that no duplicate companies appear within a single portfolio. A key feature of this sampling method is that all units in the population have an equal chance of being selected (Amidi, 2002). Portfolios were randomly drawn from a population of size 120C10. To test the hypothesis, model analysis is conducted both portfolio-by-portfolio and strategy-by-strategy.

This study is applied in nature, descriptive-survey in terms of data collection method, and quantitative in terms of data characteristics. Data collection was conducted via document analysis and reference to databases and scientific repositories containing domestic and international articles. The data were analyzed using Excel and SPSS software.

Research Model and Variables

Strategy-specific volatility controls have a positive impact on strategy performance (Daniel & Moskowitz, 2016), and in these controls, time-series momentum strategy is positively associated with TSM returns and improves its performance (Goyal & Jegadeesh, 2018). Therefore, to eliminate the effects of external controls on strategy volatility management and to control for strategy-specific volatility goals, time-series strategies are constructed based on two sets of formation (j) and holding (k = t − j) portfolios with 3, 6, 9, ..., 36-month periods (Hong et al., 2022; Kim et al., 2016).

Information Dissemination Models in Time-Series Momentum Strategies

Time-Series Momentum Strategy

Initially, the financial literature on momentum focused on cross-sectional aspects. Moskowitz et al. (2012) studied time-series momentum at the asset class level, which was later extended to individual stocks by Goyal and Jegadeesh (2017) and Lim et al. (2018). In this study, proxies for information discontinuity and information uncertainty are used to modify time-series momentum strategies and conduct analysis.

The general formula for time-series momentum strategy returns is:

$r_t = 1/n_t * (\sum(PRET(i,t-1)<0)\ r_{(i,t)} - \sum(PRET(i,t-1)>0)\ r_{(i,t)})$

Where n_t is the total number of stocks, $PRET_{(i,t-1)}$ is the cumulative return of stock i at time $t-1$, and $r_{(i,t)}$ is the return of stock i at time t.

Information Discontinuity in Time-Series Momentum Strategies

To examine information discontinuity within time-series momentum in each portfolio, firms are categorized into four groups based on *PRET* and *ID* values: positive and negative *PRET* combined with positive and negative *ID*. These form combinations such as:

- $PRET > 0\ \&\ ID > 0$
- $PRET > 0\ \&\ ID < 0$
- $PRET < 0\ \&\ ID > 0$
- $PRET < 0\ \&\ ID < 0$

The general models for information-discontinuity-based time-series momentum strategy returns are:

(2) $r_t = 1/n_t * (\sum(PRET(i,t-j)>0\ \&\ ID_{(i,t-j)}<0)\ r_{(i,t)} - \sum(PRET(i,t-j)<0\ \&\ ID_{(i,t-j)}<0)\ r_{(i,t)})$

(3) $r_t = 1/n_t * (\sum(PRET(i,t-j)>0\ \&\ ID_{(i,t-j)}>0)\ r_{(i,t)} - \sum(PRET(i,t-j)<0\ \&\ ID_{(i,t-j)}>0)\ r_{(i,t)})$

Where:

r_t is the return of the information-discontinuity-based time-series momentum strategy,

i is the stock,

t is the formation period,

$t - j$ is the holding period,

$PRET_{(i,t-j)}$ is the cumulative return of stock i from month t to month $t - j$,

$r_{(i,t)}$ is the stock return in month t.

Abnormal Return Volatility in Time-Series Momentum Strategies

To evaluate abnormal return volatility in time-series momentum within each portfolio, companies are grouped into four segments based on *PRET* and *ARV*:

- $PRET > 0$ & $ARV > 0$
- $PRET > 0$ & $ARV < 0$
- $PRET < 0$ & $ARV > 0$
- $PRET < 0$ & $ARV < 0$

The models are as follows:

(6) r_t = 1/n_t * (∑(*PRET*(i,t−j)>0 & ARV_(i,t−j)<0) r_(i,t) − ∑(*PRET*(i,t−j)<0 & ARV_(i,t−j)<0) r_(i,t))

(7) r_t = 1/n_t * (∑(*PRET*(i,t−j)>0 & ARV_(i,t−j)>0) r_(i,t) − ∑(*PRET*(i,t−j)<0 & ARV_(i,t−j)>0) r_(i,t))

Where:

r_t is the return from time-series momentum strategies under abnormal return volatility,

ARV represents abnormal return volatility,

PRET_(i,t−j)>0 & ARV_(i,t−j)<0 refers to positive cumulative return with low uncertainty,

PRET_(i,t−j)<0 & ARV_(i,t−j)<0 refers to negative cumulative return with low uncertainty,

PRET_(i,t−j)>0 & ARV_(i,t−j)>0 refers to positive cumulative return with high uncertainty,

PRET_(i,t−j)<0 & ARV_(i,t−j)>0 refers to negative cumulative return with high uncertainty,

r_(i,t) is the return of stock *i* in month *t*.

Hypothesis Testing Models

To test the research hypotheses, time-series strategies are first divided into two segments: long-term (TH) and short-term (TL). In the second stage, each dimension of information dissemination—information discontinuity (ID) and abnormal return volatility (ARV)—is classified into two categories: positive and negative. Thus, IL represents negative information discontinuity, IH represents positive information discontinuity, AL represents negative abnormal return volatility, and AH represents positive abnormal return volatility.

Table 1. Parameters of Time-Series Momentum Strategies

	AL	AH	IL	IH
TH	THAL (long-term with AL)	THAH (long-term with AH)	THIL (long-term with IL)	THIH (long-term with IH)
TL	TLAL (short-term with AL)	TLAH (short-term with AH)	TLIL (short-term with IL)	TLIH (short-term with IH)

Subsequently, the time-series momentum is defined as the differential between long-term and short-term strategies under similar information discontinuity and abnormal return volatility conditions—either both positive or both negative. Considering the proxies of information dissemination (information discontinuity and abnormal return volatility), the research hypothesis (information dissemination affects the performance of time-series momentum) is tested through the following model:

R_(i,t) = b_0_jt + b_1_jt * IL_(i,t−j) + b_2_jt * TH_(i,t−j) + b_3_jt * (TH_(i,t−j) * IL_(i,t−j)) + b_4_jt * ARVL_(i,t−j) + b_5_jt * (TH_(i,t−j) * ARVL_(i,t−j)) + e_(i,t)

Where:

- *R_(i,t)*: stock return at time *t*
- *IL_(i,t−j)* = 1 if information discontinuity from *t−j* to *t* is negative, otherwise 0
- *TH_(i,t−j)* = 1 if past performance from *t−j* to *t* belongs to a long-term time-series momentum strategy, otherwise 0
- *ARVL_(i,t−j)* = 1 if abnormal return volatility from *t−j* to *t* is negative, otherwise 0

- b_1_*jt*: coefficient for information discontinuity
- b_2_*jt*: coefficient for time-series momentum
- b_3_*jt*: interaction coefficient between time-series momentum and information discontinuity
- b_4_*jt*: coefficient for abnormal return volatility
- b_5_*jt*: interaction coefficient for time-series momentum and abnormal return volatility
- *e_(i,t)*: regression residual

Research Variables

Table 2. Research Variables

Variable	Formula/Definition
Stock Return	(p_t - p_(t−1)) / p_(t−1)
	where *p_t* is the price (or index level) at time *t* (Fallahi et al., 2017)
Portfolio Return (R_pt)	∑_(i=1)^n (R_it * W_it)
	where *R_it* is the return of stock *i* at time *t*, *W_it* is the equal weight of stock *i* in the portfolio (Raei & Talangi, 2012)
Market Return (R_mt)	Index_TEDPIX = (PnQn * 100) / Base
	TEDPIX = total return index; *PnQn* = market value; Base = base value (Tehran Stock Exchange official website)
Cumulative Return (PRET)	[∏_(i=1)^n (1 + r_i)]^(1/n) − 1
	To compute the geometric mean, take the *n*-th root of the product of a set of relative returns, then subtract 1 (Garji Ara & Hosseini, 2022)
Information Discontinuity (ID_(i,t−1))	sign(PRET_(i,t−2)) * (%neg_(i,t−2) − %pos_(i,t−2))
	where *t* = current month, *i* = stock, *sign(PRET_(i,t−2))* = sign of cumulative return in the previous month, *%neg_(i,t−2)* = percentage of negative returns in month *t*−2, *%pos_(i,t−2)* = percentage of positive returns in month *t*−2
	ID is defined within the interval [−1, 1]. If *ID_(i,t−1)* > 0, past stock prices are considered discrete; if < 0, they are considered continuous (Da et al., 2014; Fang, 2021)
Abnormal Return Volatility (ARV_(i,t))	ARV_(i,t) = δ²_AR
	AR = R_i − R_e
	R_e = r_f + (r_m − r_f) * β
	β_(i,m) = COV(r_m, r_i) / σ²_m
	where *R_e* = expected return, *R_i* = actual return, *δ²_AR* = variance of abnormal return (Garji Ara & Hosseini, 2022)
Risk-Free Return (Rf)	The best proxy for risk-free securities is Treasury bills; in this study, the daily risk-free rate is obtained from http://tsetmc.com

3. Findings and Results

Descriptive statistics for the variables are presented. The table below shows the descriptive statistics for the variable *ID* in the three-month strategy with a one-month holding period.

Table 3. Descriptive Statistics for the Variable ID in the Three-Month Strategy with One-Month Holding Period

Portfolio	Variable	Mean	SD	Q1	Q2	Q3	Skewness	Kurtosis
1	IL_TH	0.000	0.000	0.000	0.000	0.000	—	—
	IL_TL	1.178	2.406	0.579	0.838	3.481	−1.006	2.262
	IL	−1.178	2.406	−3.481	−0.838	−0.579	1.006	2.262
	IH_TH	0.000	0.000	0.000	0.000	0.000	—	—
	IH_TL	−2.916	2.868	−4.699	−2.711	−0.510	−0.626	−0.086
	IH	2.916	2.868	0.510	2.711	4.699	0.626	0.086

2	IL_TH	0.151	7.144	–4.533	–0.241	3.403	0.413	1.017
	IL_TL	2.815	9.189	–1.929	0.680	4.793	2.349	6.295
	IL	–2.664	9.113	–3.549	–0.669	1.894	–2.231	6.112
	IH_TH	–0.600	1.842	–0.601	–0.428	0.186	1.861	5.923
	IH_TL	–0.320	2.937	–2.527	–0.638	–0.155	–2.294	6.202
	IH	–0.279	2.892	–0.818	–0.238	1.706	–1.766	3.753
3	IL_TH	–10.361	18.491	–19.369	–3.305	–1.561	–1.829	3.623
	IL_TL	–1.264	7.539	–3.954	–0.744	0.210	0.629	3.605
	IL	–9.097	16.139	–16.175	–4.802	0.737	–1.889	4.388
	IH_TH	–1.024	2.801	–0.333	0.000	0.000	–3.041	9.378
	IH_TL	–1.133	1.331	–2.478	–0.561	–0.257	–1.043	–0.505
	IH	0.110	3.328	–0.372	0.293	2.478	–2.065	5.585
4	IL_TH	–2.972	6.682	–3.751	–0.458	0.187	–2.529	6.895
	IL_TL	–0.209	6.693	–5.621	0.816	3.974	–0.288	0.000
	IL	–2.763	6.957	–7.284	–3.021	0.737	0.615	1.210
	IH_TH	–0.212	2.051	–1.456	–0.432	0.286	1.645	0.875
	IH_TL	–0.630	3.528	–2.027	–0.472	0.391	0.260	1.365
	IH	0.418	3.830	–1.360	0.612	2.975	–1.049	2.005

For this purpose, descriptive statistics of the collected data are first examined. In the initial case, the three-month strategy with a one-month holding period for Portfolio 1 is shown. In some cases, the quartile values are consistently positive or negative, which may imply skewed data. However, the skewness coefficient is -1.006 ± 0.687×2, which includes zero at the 95% confidence level, indicating no significant deviation from the normal distribution (whose skewness is zero). The same applies to the kurtosis coefficient, which is 2.262 ± 1.334×2, also including zero, showing no significant difference from a normal distribution.

The average for information discontinuity (*ID positive*) is greater than for information continuity (*ID negative*), indicating that more information in the three-month formation and one-month holding time-series momentum strategy in Portfolio 1 is clustered in large fragments (2.915945 > -1.177766). Skewness and kurtosis are higher in continuous information (small fragments) compared to discrete information (large fragments). The negative Q1 to Q3 for IL suggests information is contained in small and continuous fragments, while the positive quartiles for IH indicate discontinuity and large information blocks.

The following table presents the descriptive statistics for the variable *ARV* in the same strategy:

Table 4. Descriptive Statistics for the Variable ARV in the Three-Month Strategy with One-Month Holding Period

Portfolio	Variable	Mean	SD	Q1	Q2	Q3	Skewness	Kurtosis
1	AL_TH	0.000	0.000	0.000	0.000	0.000	—	—
	AL_TL	0.000	0.000	0.000	0.000	0.000	—	—
	AL	0.000	0.000	0.000	0.000	0.000	—	—
	AH_TH	—	—	—	—	—	—	—
	AH_TL	–2.285	3.416	–4.920	–1.881	0.876	–0.310	–1.425
	AH	2.285	3.416	–0.876	1.881	4.920	0.310	1.425
2	AL_TH	0.000	0.000	0.000	0.000	0.000	—	—
	AL_TL	0.000	0.000	0.000	0.000	0.000	—	—
	AL	0.000	0.000	0.000	0.000	0.000	—	—
	AH_TH	0.629	6.656	–5.494	0.484	2.197	0.821	1.918
	AH_TL	2.516	9.580	–3.468	–0.858	5.079	2.109	5.201
	AH	–3.145	9.232	–6.137	–1.194	3.185	–1.590	3.263
3	AL_TH	0.000	0.000	0.000	0.000	0.000	—	—

	AL_TL	0.000	0.000	0.000	0.000	0.000	—	—
	AL	0.000	0.000	0.000	0.000	0.000	—	—
	AH_TH	–11.384	18.090	–19.369	–6.339	–0.156	–1.771	3.657
	AH_TL	–2.594	7.505	–5.737	–4.077	–0.228	1.109	3.715
	AH	–8.790	15.923	–13.750	–3.461	0.339	–2.001	4.914
4	AL_TH	0.000	0.000	0.000	0.000	0.000	—	—
	AL_TL	0.000	0.000	0.000	0.000	0.000	—	—
	AL	0.000	0.000	0.000	0.000	0.000	—	—
	AH_TH	1.103	15.361	–3.751	–0.363	0.881	1.932	6.085
	AH_TL	–0.796	7.000	–6.656	0.217	4.685	–0.180	–0.915
	AH	1.899	13.578	–8.121	–0.725	8.060	1.653	3.333

For Portfolio 1, *ARV* in the three-month strategy with a one-month holding period shows that values for AL appear to be zero. The skewness coefficient for AH is 0.31 ± 0.687×2, encompassing zero at the 95% confidence level, indicating no significant skewness. Similarly, the kurtosis coefficient of -1.425 ± 1.334×2 includes zero, showing no significant difference from a normal distribution.

The mean of high abnormal return volatility (AH) is greater than that of low abnormal return volatility (AL), suggesting that in the three-month formation and one-month holding strategy, Portfolio 1 is more exposed to high-noise information (2.28506 > 0). Skewness and kurtosis are also greater in high-noise information. The negative Q1 and positive Q2 and Q3 for AH imply that most of the information is associated with high volatility.

The regression model is fitted, and the p-values for the goodness-of-fit are presented as decision-making indicators.

According to the results, in the strategy with a 3-month formation period, the following holding period strategies are statistically significant: 3 months (in three portfolios), 12, 24, 27, 36 months (in two portfolios), 6, 15, 30 months (in one portfolio), while 9, 18, 21, and 33 months were not significant in any of the portfolios. In other words, out of 12 strategies based on the 3-month formation period, 5 were significant, of which 3 (24, 27, 36) are long-term. This indicates that the 3-month formation period becomes significant primarily when paired with long-term holding periods. This finding supports the hypothesis that information dissemination driven by time-series momentum has a greater impact in the long term when considering information discontinuity. Ultimately, however, the hypothesis is not confirmed for the 3-month formation period in general.

Accordingly, the following formation-holding strategies are statistically significant: 6–3, 6–36, 9–3, 9–9, 9–12, 9–36, 12–3, 12–9, 12–12, 12–36, 15–3, 15–6, 15–9, 15–12, 15–15, 15–36, 18–3, 18–6, 18–9, 18–12, 18–15, 18–36, 21–3, 21–6, 21–9, 21–12, 21–15, 21–21, 21–36, 24–3, 24–6, 24–9, 24–12, 24–15, 24–21, 24–36, 27–3, 27–6, 27–9, 27–12, 27–15, 27–21, 27–36, 30–3, 30–6, 30–9, 30–12, 30–15, 30–21, 30–36, 33–3, 33–6, 33–9, 33–12, 33–15, 33–21, 33–36, 36–3, 36–6, 36–9, 36–12, 36–15, 36–21, 36–36.

Table 5. Significance of Formation and Holding Period Strategies

Confirmed Holding Count	Holding Periods	Formation	Confirmed Holding Count	Holding Periods	Formation
7	36, 21, 15, 12, 9, 6, 3	21	5	36, 27, 24, 12, 3	3
7	36, 21, 15, 12, 9, 6, 3	24	2	36, 3	6
7	36, 21, 15, 12, 9, 6, 3	27	3	36, 12, 3	9
7	36, 21, 15, 12, 9, 6, 3	30	3	36, 12, 3	12
7	36, 21, 15, 12, 9, 6, 3	33	6	36, 15, 12, 9, 6, 3	15
7	36, 21, 15, 12, 9, 6, 3	36	6	36, 15, 12, 9, 6, 3	18

Formation periods of 15 and 18 months were found to be significant with 6 holding strategies, while formation periods from 21 to 36 months were significant with 7 holding strategies. For the 15- and 18-month formation periods, 5 out of 6 holding strategies were short-term, and 1 out of 6 was long-term. This indicates that these formation periods are mainly effective in short-term holding strategies. Conversely, for formation periods of 21 to 36 months, 5 out of 7 significant holding strategies were short-term and 2 were long-term. Therefore, in strategies involving long-term formation and short-term holding, information dissemination has a notable effect due to time-series momentum.

Finally, given that the hypothesis is confirmed in 8 out of 12 formation strategies and 6 out of 12 holding strategies, it can be concluded that the effect of time-series momentum is influenced by information dissemination.

4. Discussion and Conclusion

The findings of this study provide empirical support for the significant role of information dissemination in shaping the dynamics of time-series momentum (TSM) in capital markets. Specifically, the study reveals that information discontinuity (ID) and abnormal return volatility (ARV) act as critical moderators influencing the profitability and significance of TSM strategies across varying formation and holding periods. In the 3-month formation period, only 5 out of 12 formation-holding strategy combinations yielded significant results, and notably, 3 of these were long-term holding strategies (24, 27, and 36 months). This suggests that the interaction between short-term information processing and long-term investor behavior is a fertile ground for persistent TSM profits. These observations reinforce the hypothesis that absolute information discontinuity enhances the momentum effect when investors systematically underreact to complex or fragmented information [10, 18].

The positive performance of TSM strategies in long-hold periods under conditions of high ID aligns with behavioral theories that posit price underreaction to news as a function of slow information diffusion and psychological inertia [12, 26]. Investors often display conservatism in updating their beliefs, especially when new signals contradict prior expectations. This pattern leads to gradual price adjustments, which are exploitable by TSM strategies. The finding that high ID portfolios outperform those with continuous information flow (negative ID) supports the hypothesis that information is processed in discrete jumps rather than smoothly, consistent with the frog-in-the-pan hypothesis of investor inattention [10]. This behavioral inefficiency leads to systematic underreaction in early periods, followed by momentum patterns that persist until the information is fully priced in.

Moreover, the effect of abnormal return volatility (ARV) was found to be significant in various strategies, indicating that informational uncertainty is another driver of time-series momentum. High ARV portfolios, especially those with positive values, demonstrated more pronounced momentum returns. These results corroborate the insights of Fang (2021), who emphasized that information diffusion is time-varying and that ARV captures the noise traders' influence and heterogeneous beliefs in the marketplace [11]. Similarly, George and Hwang (2004) argued that momentum profits are more evident when uncertainty about valuation is high, leading to increased reliance on price trends by investors [17]. In this study, the skewness and kurtosis measures further confirmed that high-ID and high-ARV portfolios are characterized by greater distributional asymmetry and fat tails, reinforcing the behavioral premise that investors overweigh salient, discrete information events.

The temporal consistency of momentum in formation-holding pairs such as 15-3, 18-3, and 21-3 also highlights that short-term holding after a mid- to long-term formation period is particularly effective. This is indicative of a trend reversal point where the price continues in its direction shortly after formation before dissipating, a dynamic explained by short-horizon trend chasers and long-horizon arbitrageurs [8, 21]. It also parallels the adaptive market hypothesis, which posits that market efficiency evolves over time as investor behaviors and strategies adapt to changing environments [2]. These results imply that investors who can accurately time the exploitation window of informational inefficiencies can outperform those using static strategies.

The findings also mirror results in international studies. For example, Pitkäjärvi et al. (2020) found that cross-asset TSM strategies performed significantly better when supplemented with information-related variables such as trading volume and cross-asset signals, further validating the importance of information-based modifiers [22]. Similarly, Rouwenhorst (1998) and Okunev and White (2003) identified strong momentum patterns in markets characterized by weak regulatory environments and less efficient information systems, reinforcing that the structure and transparency of information dissemination are central to momentum profitability [6, 23]. This has practical implications for emerging markets, such as Iran, where market inefficiencies and behavioral biases tend to be more pronounced due to less developed institutional frameworks [30].

Importantly, the finding that high ARV and high ID jointly amplify TSM effects supports a dual-channel model in which both information quality and investor interpretation biases interact to shape return patterns. The interaction terms in the regression models, particularly those involving TH×ID and TH×ARV, were statistically significant in the majority of tested strategies. This reinforces the proposition that time-series momentum is not merely a mechanical price trend but a behavioral manifestation influenced by both objective information flow and subjective interpretation processes [27, 28].

Furthermore, the evidence that the 3-month formation period becomes meaningful primarily in long-hold contexts underscores the importance of time horizon in strategy design. This resonates with the findings of Lim et al. (2018), who noted that TSM strategies need to be calibrated across multiple temporal frequencies to capture underlying investor sentiment patterns and structural frictions [20]. The study also adds to the literature by validating ID and ARV as robust explanatory variables that account for cross-sectional and intertemporal variation in momentum profitability, echoing the work of Goyal and Jegadeesh (2018) on return predictability modifiers [25].

Despite its robust empirical framework and novel insights, this study is not without limitations. First, the analysis is confined to the Tehran Stock Exchange, which, while informative for emerging market behavior, limits the generalizability of the findings to developed markets with different regulatory and informational environments. Second, the study uses historical price data and does not incorporate real-time measures of investor sentiment or market microstructure variables such as bid-ask spreads, liquidity shocks, or trading volume anomalies, which could further enrich the interpretation of information discontinuity. Third, the operationalization of ID and ARV, while innovative, relies on retrospective return-based metrics that may not fully capture the forward-looking expectations of investors or the real-time complexity of information processing.

Future research should consider cross-market and cross-asset validation of the proposed model to enhance its external validity. Comparative studies between emerging and developed markets can help disentangle the role of institutional quality in moderating the momentum–information relationship. Moreover, incorporating machine learning techniques to dynamically classify information discontinuity and volatility could yield more granular insights into real-time investor behavior. Expanding the variable set to include sentiment analysis from news feeds, analyst forecasts, and social media data could also offer a more multidimensional view of information dissemination effects. Additionally, integrating risk-based and behavioral components into hybrid asset pricing models would help clarify whether momentum profits are primarily compensation for risk or the result of mispricing.

For institutional investors and portfolio managers, the findings suggest that time-series momentum strategies can be significantly enhanced by accounting for information quality and dissemination patterns. Portfolios designed with awareness of ID and ARV conditions may outperform traditional momentum models that ignore informational context. This has practical implications for market timing, asset allocation, and risk management strategies. Furthermore, monitoring indicators of informational discontinuity may serve as an early warning signal for momentum crashes or reversals. Educating investors about behavioral biases and integrating structured decision-making processes could also mitigate misreaction to complex or noisy information, improving portfolio stability and long-term returns.

Authors' Contributions

Authors equally contributed to this article.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

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Conflict of Interest

The authors report no conflict of interest.

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