

The Effect of Investor Overconfidence on Trading Intensity in the Tehran Stock Exchange

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Abstract: This study aimed to investigate the effect of investor overconfidence on subsequent trading intensity and related market outcomes among companies listed on the Tehran Stock Exchange. This applied, quantitative, ex post facto study used archival market data structured at the firm-week level. The initial database included 48 listed companies and 125,911 daily trading observations, while the final common sample comprised 11,242 firm-week observations from 45 companies after applying data-coverage criteria, constructing one-week leads, and aligning behavioral and control variables. Investor overconfidence was measured through a principal component analysis-based index constructed from weekly share turnover, relative trading frequency, and trading value relative to market capitalization. The first component explained 74.18% of the variance. Six subsequent-week outcomes were examined: stock return, trading turnover, trading value, trading frequency, individual-investor money flow, and volatility. Fixed-effects panel regressions controlled for investor sentiment, attention, herding, overreaction/underreaction, fear and greed, exchange-rate changes, firm size, and E/P. Statistical inference used two-way clustered standard errors, with Driscoll-Kraay covariance estimates and Benjamini-Hochberg adjustment as robustness procedures. Investor overconfidence significantly predicted higher subsequent trading turnover ($B = 0.0176, p < .001$), trading value ($B = 0.0941, p < .001$), trading frequency ($B = 0.0785, p < .001$), individual-investor money flow ($B = 0.0067, p = .029$), and volatility ($B = 0.0218, p = .001$). Its effect on subsequent stock return was positive but nonsignificant ($B = 0.0019, p = .215$). The significant relationships remained stable under Driscoll-Kraay estimation and after false discovery rate adjustment. Investor overconfidence in the Tehran Stock Exchange is primarily reflected in persistent increases in trading intensity and volatility rather than in a systematic improvement in subsequent stock returns, indicating that greater confidence encourages more extensive market participation without necessarily producing superior return outcomes.

Keywords: Investor Overconfidence; Trading Intensity; Trading Turnover; Behavioral Finance; Investor Sentiment; Tehran Stock Exchange; Panel Data

1. Introduction

Financial markets are not governed exclusively by rational valuation, complete information processing, or mechanically optimal portfolio choices. A substantial body of behavioral finance research has demonstrated that investors frequently make decisions under bounded rationality and are influenced by systematic cognitive and emotional biases. These biases can alter expectations, perceived risk, interpretation of information, willingness to trade, and reactions to market movements. Among the behavioral biases examined in the literature, overconfidence has received particular attention because of its direct implications for trading intensity, portfolio turnover, risk

taking, and market volatility. Overconfidence generally refers to investors' tendency to overestimate the accuracy of their information, the quality of their judgments, or their ability to predict future market movements. When investors believe that their private information or analytical skill is more precise than it actually is, they may trade more aggressively and more frequently than would be justified by objective information. In this sense, overconfidence provides an important behavioral explanation for excessive trading that cannot be fully explained by conventional models of rational portfolio adjustment [1-3].

The theoretical connection between overconfidence and trading activity is well established. Odean showed that when traders overestimate the precision of their private signals, trading volume can rise beyond levels predicted by rational-information models, while excessive confidence may also affect volatility, prices, and realized profits [1]. Gervais and Odean subsequently developed a learning-based explanation in which investors become overconfident partly because they attribute successful investment outcomes disproportionately to their own abilities rather than to favorable market conditions or chance [2]. This mechanism is particularly important because overconfidence may intensify after past successes, thereby producing persistence in trading behavior over time. Statman, Thorley, and Vorkink further provided empirical support for the relationship between overconfidence and trading volume, showing that past market gains can stimulate subsequent trading activity in a manner consistent with self-attribution and overconfidence theories [3]. Together, these studies suggest that overconfidence should not be viewed merely as an internal psychological condition; rather, it can manifest in observable market behavior through unusually high turnover, transaction frequency, and trading value.

Excessive trading is economically important because higher trading intensity does not necessarily translate into superior investment outcomes. Evidence from individual-investor behavior indicates that frequent trading may impose substantial performance costs. Barber and Odean showed that individual investors who traded more actively tended to earn lower net returns, largely because transaction costs and poor timing eroded performance [4]. Later evidence demonstrated that individual investors as a group can incur substantial aggregate losses from trading, reinforcing the argument that confidence-driven activity may be costly rather than value-enhancing [5]. These findings are central to the study of overconfidence because they challenge the assumption that more intensive trading reflects superior information or skill. Instead, high trading intensity may partly represent a behavioral response to exaggerated confidence in one's own judgments. Therefore, examining whether overconfidence predicts subsequent trading activity is important not only for understanding market microstructure but also for evaluating whether investor behavior departs systematically from rational benchmarks.

Retail investors are especially relevant in this context because their trading decisions may be more sensitive to psychological biases, attention constraints, and salient information. Barber and Odean demonstrated that individual investors are disproportionately attracted to attention-grabbing stocks, including securities associated with unusual trading volume, extreme returns, or prominent news coverage [6]. Da, Engelberg, and Gao similarly showed that investor attention can be proxied through observable search behavior and that shifts in attention have measurable consequences for trading and asset prices [7]. These findings imply that trading intensity may reflect several overlapping behavioral mechanisms. A surge in transactions may be caused by overconfidence, but it may also be associated with heightened attention, sentiment, herding, overreaction, fear, or speculative enthusiasm. Consequently, empirical studies of overconfidence should attempt to distinguish the unique effect of overconfidence from other behavioral forces that can simultaneously increase market activity.

Investor sentiment is one of the most important competing or complementary behavioral channels. Sentiment reflects beliefs about future cash flows and risk that are not fully justified by fundamental information and can

affect cross-sectional stock returns and trading behavior. Baker and Wurgler demonstrated that investor sentiment has systematic effects across securities and that stocks with greater valuation uncertainty can be especially sensitive to sentiment-driven demand [8]. They later emphasized that investor sentiment is a broad market phenomenon capable of influencing valuation, participation, and trading decisions through shifts in optimism and pessimism [9]. In emerging markets, where information asymmetry, retail participation, macroeconomic instability, and speculative trading may be comparatively pronounced, sentiment and overconfidence may interact more strongly. Therefore, a rigorous examination of overconfidence should control for sentiment so that the estimated relationship with trading intensity does not merely capture general optimism or market exuberance.

Other behavioral mechanisms must also be considered. Herding occurs when investors suppress or underweight private information and instead follow the observed or inferred actions of other market participants. Chang, Cheng, and Khorana documented that herding can emerge differently across equity markets and that cross-sectional dispersion in returns can provide evidence about collective trading behavior [10]. Overreaction and underreaction constitute another important set of behavioral anomalies because investors may respond excessively or insufficiently to new information, causing abnormal price movements and subsequent corrections. Evidence from emerging markets suggests that investor sentiment and market overreaction can jointly influence investment decisions and market outcomes [11]. Likewise, Qasim and colleagues found that both herding behavior and overconfidence can influence investor decision-making, indicating that these biases may operate simultaneously rather than independently [12]. For this reason, isolating the effect of overconfidence requires a multivariate behavioral framework rather than a single-factor model.

Recent research has continued to emphasize the importance of overconfidence across different investor populations and market settings. Rahmawati and Santi reviewed the literature on availability and overconfidence biases and concluded that both can systematically shape investor decisions, particularly when investors rely excessively on salient information or their own perceived analytical competence [13]. Singh, Malik, and Jha, in a systematic review focused on retail investors, similarly identified overconfidence as one of the most persistent behavioral biases affecting investment decisions and highlighted the need for further research on its antecedents, measurement, and market consequences [14]. Jain and colleagues showed that investor personality can influence investment intention through overconfidence bias and financial literacy, suggesting that overconfidence may operate as an important psychological mechanism translating individual characteristics into market behavior [15]. These findings support the broader view that overconfidence is not a marginal anomaly but a recurring behavioral mechanism with implications for both investor-level decisions and aggregate trading patterns.

The consequences of overconfidence can also extend beyond trading frequency to risk tolerance, valuation, and market performance. Aljifri reported that investor psychology and overconfidence can affect firm valuation, suggesting that overconfident trading may influence not only the number of transactions but also pricing outcomes and perceived firm value [16]. Hu examined the effects of loss aversion and overconfidence on market performance and provided further evidence that behavioral biases can shape market-level outcomes rather than remaining confined to individual decision processes [17]. More recently, Nabeshima, Khan, and Kadoya, using a large-scale survey of Japanese investors, demonstrated an association between overconfidence and investment loss tolerance, showing that greater confidence can alter how investors perceive and accept downside risk [18]. These findings are particularly relevant to studies of trading intensity because investors who overestimate their capabilities and tolerate losses more readily may continue trading even after adverse outcomes, thereby sustaining elevated turnover and transaction frequency.

In the Iranian capital market, behavioral factors may be especially consequential because investor decisions occur within an environment characterized by substantial macroeconomic uncertainty, exchange-rate fluctuations, inflationary pressures, episodic regulatory changes, and considerable retail participation. Under such conditions, fundamental information and behavioral responses can become closely intertwined. Taheri and Jafari examined the interaction between managerial overconfidence, corporate financial policies, and investor sentiment, demonstrating that overconfidence and sentiment are relevant constructs in the Iranian financial environment and can alter the relationships among corporate and market variables [19]. Eishi Ravandi and colleagues further showed that investor sentiment and liquidity are associated with stock returns in the Iranian stock market, emphasizing the importance of behavioral conditions for market outcomes [20]. Khajavi and colleagues likewise examined behavioral indicators and investor sentiment in relation to portfolio risk taking, providing additional evidence that psychological and behavioral factors are materially relevant to investment decisions in the Iranian context [21]. These studies collectively indicate that behavioral finance offers an appropriate framework for investigating trading activity in the Tehran Stock Exchange.

Despite this growing literature, several important gaps remain. First, many studies of investor overconfidence rely on questionnaires or self-reported measures. Although survey instruments are valuable for directly examining attitudes and beliefs, they may be affected by response bias, social desirability, retrospective error, and discrepancies between reported intentions and actual trading behavior. Market-based measures provide a complementary approach by identifying behavioral patterns directly from observed transactions. In this context, excessive turnover, unusually high transaction frequency, and high trading value relative to firm size can jointly provide observable signals of confidence-driven activity. However, none of these variables alone is a perfect proxy for overconfidence. Turnover may be affected by liquidity, transaction frequency may reflect order fragmentation or market participation, and trading value may be mechanically related to firm size. Therefore, combining multiple indicators can provide a more stable representation of their shared behavioral component.

Principal component analysis offers an appropriate statistical method for this purpose because it allows correlated indicators to be summarized into a smaller number of orthogonal components that retain the dominant variation in the original variables [22]. Rather than defining overconfidence using a single trading measure, a composite PCA-based index can capture the common dimension underlying turnover, relative trading frequency, and trading value scaled by market capitalization. Such a construction is particularly useful when the research objective is to measure a latent market behavior rather than a directly observable psychological trait. At the same time, the interpretation of such an index should remain appropriately cautious: a market-based overconfidence measure reflects behavior consistent with overconfidence and should not be regarded as a direct psychometric assessment of every individual investor.

A second limitation of previous work concerns simultaneity. When overconfidence is proxied using measures of trading activity and then related to trading outcomes from the same period, contemporaneous correlations may partly reflect mechanical overlap rather than a meaningful temporal relationship. A lagged design can reduce this problem by measuring overconfidence in one period and examining whether it predicts trading intensity in the subsequent period. This approach is also consistent with learning and self-attribution theories, which imply that behavioral states may persist and shape future decisions rather than disappearing immediately [2, 3]. In addition, using firm-week observations provides a compromise between daily data, which can contain substantial microstructure noise, and lower-frequency monthly data, which may conceal short-lived behavioral dynamics.

A third methodological challenge involves the dependence structure of financial panel data. Observations for the same company are rarely independent over time, and companies listed in the same market are often simultaneously exposed to exchange-rate movements, regulatory interventions, macroeconomic news, changes in investor sentiment, and broad market shocks. Ignoring heteroskedasticity, serial correlation, or cross-sectional dependence can lead to misleading standard errors and statistical significance. Driscoll and Kraay developed a covariance estimator that remains robust under general forms of temporal and cross-sectional dependence, making it especially useful for panel settings in which common shocks affect multiple firms [23]. Accordingly, robust inference is essential when evaluating whether an apparent relationship between overconfidence and trading activity remains statistically reliable after allowing for realistic dependence in market data.

Another unresolved issue is whether overconfidence primarily affects return direction or trading intensity. The theoretical literature does not necessarily imply that overconfident investors will consistently generate positive or negative subsequent returns. Rather, its clearest prediction is that investors who overestimate their information precision will trade more than rationally warranted [1]. Excessive trading may then affect turnover, transaction frequency, trading value, retail money flows, and volatility without producing a stable directional return effect. This distinction is important because studies focusing exclusively on returns may understate the behavioral significance of overconfidence. Examining multiple outcomes simultaneously can therefore provide a more complete understanding of how overconfidence is manifested in actual market behavior.

Accordingly, the present study develops a market-based overconfidence index from share turnover, relative trading frequency, and trading value relative to market capitalization and evaluates whether this index predicts subsequent-week market outcomes after controlling for investor sentiment, attention, herding, overreaction/underreaction, fear and greed, exchange-rate movements, firm size, valuation, firm-specific unobserved heterogeneity, and common temporal shocks. This framework extends previous research by integrating behavioral-finance theory, transaction-based measurement, temporal ordering, and panel-data econometrics within the Tehran Stock Exchange. It also responds to recent calls for more context-sensitive research on retail overconfidence and its observable market consequences [14, 18]. By distinguishing overconfidence-related trading behavior from other psychological dimensions and examining several subsequent market outcomes, the study seeks to clarify whether overconfidence has persistent implications for trading intensity rather than merely reflecting contemporaneous market activity.

Therefore, the aim of this study was to investigate the effect of investor overconfidence on subsequent trading intensity and related market outcomes among companies listed on the Tehran Stock Exchange.

2. Methods and Materials

This applied study employed a quantitative, ex post facto research design based entirely on archival capital-market data. The unit of analysis was the firm-week, because the principal objective was to determine whether investor overconfidence reflected in trading behavior during a given week could explain the intensity of trading activity and other market outcomes in the subsequent week. A weekly frequency was selected to attenuate very short-term noise inherent in daily observations while preserving sufficient variation in trading activity and establishing temporal precedence between explanatory variables and subsequent outcomes. Accordingly, investor overconfidence and the other behavioral and control variables were measured in week t , whereas the corresponding trading outcomes were measured in week $t + 1$. This lagged specification was particularly important because several market-based proxies used to construct the overconfidence index were themselves

related to trading activity; therefore, using subsequent-week outcomes reduced the possibility that the estimated associations were merely attributable to contemporaneous mechanical overlap between the explanatory and dependent variables.

The statistical population consisted of companies listed on the Tehran Stock Exchange. The initial database contained daily market information for 48 listed companies and 125,911 trading observations. Data covering 2016–2025 were initially collected to provide sufficiently long historical series for the construction of behavioral indicators requiring lagged information and moving averages. For the main econometric estimations, the observation window was restricted to approximately 2019–2025 because complete alignment with the free-market U.S. dollar exchange-rate control variable was available over this period. A firm-year was retained only when valid observations were available for at least 80% of the trading weeks within that year. Following the application of this coverage criterion, construction of the one-week lead of the dependent variables, and listwise exclusion of observations lacking the variables required for the main specification, the final common estimation sample comprised 11,242 firm-week observations from 45 companies. Three additional companies were retained in robustness analyses that excluded the earnings-to-price ratio because the absence of this variable was the principal reason for their exclusion from the main common sample. Thus, the robustness sample could include all 48 initially eligible companies.

All information used in the study was secondary, and no questionnaires, experimental measures, or self-reported psychological instruments were employed to assess investor overconfidence or the other behavioral constructs. Daily adjusted stock prices, trading volume, trading value, number of transactions, market capitalization, and information on purchases and sales by individual investors were obtained primarily from the historical databases of the Tehran Securities Exchange Technology Management Company (TSETMC) and, where necessary, cross-checked against other recognized Iranian capital-market databases. Firm characteristics and fundamental financial information were further verified using official Tehran Stock Exchange records and corporate disclosures published through the Comprehensive Database of All Listed Companies (CODAL). The free-market U.S. dollar exchange-rate series used as a macroeconomic control was obtained from the research database and synchronized with the trading calendar of the sample firms.

Before aggregation, the daily observations were standardized by ticker identifier and trading date. Days on which a stock was suspended and no genuine trading occurred were distinguished from valid trading days with zero reported trading volume so that suspension periods were not erroneously recorded as trading activity. Adjusted closing prices were employed in the calculation of intertemporal returns to account for corporate actions, while the number of outstanding shares was treated as time-varying and updated according to the effective date of capital increases. For variables expressed as ratios, observations with a zero denominator were coded as missing rather than replaced with zero. Following these preprocessing procedures, the daily observations were aggregated to weekly frequency to construct the final firm-week panel dataset.

Investor overconfidence was operationalized as a market-based latent behavioral indicator rather than as a directly observed psychological characteristic. Because overconfidence cannot be observed directly in archival market data, it was inferred from observable patterns of unusually intensive trading behavior. Behavioral finance theory suggests that investors who overestimate the precision of their information or their own analytical ability tend to trade excessively because they place greater confidence in their private judgments and signals (Odean, 1998; Gervais & Odean, 2001; Statman et al., 2006). Accordingly, the overconfidence construct was derived from three market-based indicators: weekly share turnover, relative trading frequency, and the ratio of weekly trading value to market capitalization. Weekly share turnover was calculated as the total number of shares traded during a week

divided by the number of shares outstanding. Relative trading frequency was measured as the number of transactions in the current week divided by the average number of transactions during the preceding 12 weeks, thereby capturing trading activity relative to the stock's own recent historical norm. The third component was obtained by dividing weekly trading value by firm market capitalization, which scaled the monetary intensity of trading according to the economic size of the company.

Prior to construction of the composite overconfidence indicator, continuous components were winsorized at the 1st and 99th percentiles to reduce the influence of extreme observations and were subsequently standardized to eliminate scale differences. Principal component analysis (PCA) was then applied to extract the common variation shared by the three correlated trading indicators, thereby reducing their information to a single composite factor while mitigating multicollinearity among the constituent measures (Jolliffe, 2002). The Kaiser–Meyer–Olkin measure of sampling adequacy was 0.560. Although this value is below the levels generally regarded as strong for psychometric scale development, it exceeds the minimum level considered usable for an exploratory PCA involving a small number of variables and was therefore treated as evidence of acceptable exploratory adequacy. Bartlett's test of sphericity was statistically significant, $\chi^2 = 217,924.53$, $p < .001$, rejecting the null hypothesis that the correlation matrix was an identity matrix and indicating sufficient intercorrelation among the three components. The first principal component explained 74.18% of the total variance and was therefore retained as the investor overconfidence index (OCONF). The direction of the component was normalized so that higher values represented greater trading intensity consistent with overconfident behavior. The component loadings were 0.969 for share turnover, 0.588 for relative trading frequency, and 0.969 for trading value relative to market capitalization. Thus, OCONF primarily reflected the common variation in turnover and trading value intensity while retaining complementary information regarding unusually high transaction frequency. Importantly, the indicator was interpreted as a market-based proxy for behavior consistent with investor overconfidence rather than as a direct psychological measurement of individual investors' subjective confidence.

In addition to overconfidence, five other behavioral dimensions were incorporated into the disaggregated behavioral specification to isolate the variation uniquely associated with OCONF from other behavioral market conditions. These dimensions comprised investor sentiment, investor attention, herding behavior, overreaction/underreaction, and fear and greed. Composite indicators were constructed, where appropriate, by standardizing their constituent market-based measures and applying PCA to extract the dominant common component. Investor sentiment was represented by a composite measure based primarily on individual-investor money flow and purchasing strength. Investor attention captured abnormal market activity indicative of heightened investor focus. Herding was derived from measures of cross-sectional return dispersion intended to identify periods in which individual stock returns converged toward aggregate market movements. The reaction indicator reflected standardized abnormal returns and was designed to capture unusually strong or weak responses to available market information. The fear-and-greed indicator summarized market and behavioral conditions associated with shifts between risk aversion and speculative market participation. These variables were included simultaneously with overconfidence in the principal regression specifications so that the estimated coefficient on OCONF represented the association between overconfidence-related trading behavior and subsequent market outcomes after accounting for correlated behavioral forces.

The study examined six dependent variables reflecting different dimensions of subsequent trading behavior and market outcomes. Weekly stock return was calculated as the logarithmic change in adjusted stock price. Trading turnover was defined as weekly trading volume divided by the number of shares outstanding. Trading value was

transformed as the natural logarithm of one plus total weekly trading value to reduce positive skewness and the influence of exceptionally large transactions. Trading frequency was defined as the number of transactions in the current week relative to the average number of transactions during the preceding 12 weeks. Individual-investor money flow was measured using net purchases minus net sales by individual investors, scaled by total trading value, thereby representing the direction and relative magnitude of retail capital flows. Weekly volatility was calculated from the standard deviation of daily returns observed within each week and annualized using the square root of 252. Three control variables were additionally included in the main models. Exchange-rate variation was measured as the weekly logarithmic change in the free-market U.S. dollar exchange rate. Firm size was represented by the natural logarithm of market capitalization. Firm valuation was controlled through the earnings-to-price ratio (E/P). Together, these controls were intended to account for common macroeconomic shocks, systematic differences in company size and liquidity, and cross-sectional variation in equity valuation.

The empirical analysis was performed using panel-data econometric models in which each of the six trading and market outcomes in week $t + 1$ was estimated separately as a function of investor overconfidence measured in week t . The principal specification included $OCONF$ together with investor sentiment, attention, herding, overreaction/underreaction, fear and greed, the weekly change in the free-market U.S. dollar exchange rate, firm size, and the earnings-to-price ratio. Firm fixed effects were incorporated to absorb time-invariant unobserved characteristics that could simultaneously influence trading behavior and the explanatory variables, including persistent differences in industry affiliation, ownership structure, disclosure quality, free float, reputation, liquidity characteristics, and investor composition. Year fixed effects were also included to capture common temporal shocks affecting listed companies, such as changes in macroeconomic conditions, market regulation, trading rules, and the general state of the Iranian capital market. The general empirical model was specified as $Y_{i,t+1} = \alpha + \beta OCONF_{i,t} + \sum_k \theta_k Behavior_{k,i,t} + \gamma_1 \Delta USD_t + \gamma_2 LnMC_{i,t} + \gamma_3 E/P_{i,t} + \mu_i + \tau_y + \varepsilon_{i,t}$, where $Y_{i,t+1}$ denotes one of the six subsequent-week dependent variables for firm i , $OCONF_{i,t}$ represents the contemporaneous overconfidence index, $Behavior_{k,i,t}$ denotes the vector of other behavioral factors, ΔUSD_t represents the logarithmic change in the free-market exchange rate, $LnMC_{i,t}$ denotes the natural logarithm of market capitalization, $E/P_{i,t}$ represents the earnings-to-price ratio, μ_i denotes firm fixed effects, τ_y denotes year fixed effects, and $\varepsilon_{i,t}$ is the disturbance term.

Prior to estimation of the final models, the appropriateness of the panel-data structure was evaluated. The F-Limer test was used to determine whether pooled ordinary least squares could adequately represent the observations or whether statistically meaningful cross-sectional heterogeneity required a panel specification. Rejection of the null hypothesis supported the use of panel models rather than pooled estimation. The choice between specifications treating unobserved firm heterogeneity as independent of or correlated with the explanatory variables was further examined using the Hausman–Mundlak framework. Because persistent firm characteristics could plausibly be correlated with investor behavior, liquidity, valuation, and trading intensity, the fixed-effects specification was retained as the principal estimator. Potential violations of conventional regression assumptions were then evaluated using diagnostic procedures appropriate for panel data. The Breusch–Pagan test was employed to assess heteroskedasticity, the Wooldridge test was used to detect serial correlation within firms, and the Pesaran cross-sectional dependence test was used to examine whether contemporaneous shocks were correlated across companies. Such dependence was considered economically plausible because exchange-rate movements, regulatory changes, macroeconomic announcements, and broad market shocks can affect multiple listed firms simultaneously.

Because investor overconfidence and the other behavioral factors were evaluated across multiple related outcomes, the analysis also addressed the increased probability of false-positive findings arising from multiple hypothesis testing. Probability values were therefore adjusted using the Benjamini–Hochberg false discovery rate procedure, which controls the expected proportion of false discoveries among statistically significant results while retaining greater statistical power than more conservative family-wise error procedures (Benjamini & Hochberg, 1995). In addition, Wald tests were used to evaluate the joint significance of the estimated effects of overconfidence across the set of trading outcomes. The principal coefficient of interest was β , representing the relationship between the overconfidence index in week t and the corresponding trading or market outcome in week $t + 1$, conditional on the other behavioral variables, macroeconomic controls, firm characteristics, and fixed effects. A positive and statistically significant coefficient for turnover, trading value, or trading frequency was interpreted as evidence that higher market-based overconfidence was associated with greater trading intensity in the subsequent week. Conversely, the absence of a statistically significant coefficient for stock returns was not interpreted as evidence that overconfidence had no behavioral relevance, because the theoretical mechanism examined in this study primarily concerns excessive and persistent trading activity rather than a deterministic prediction regarding the direction of subsequent stock returns.

3. Findings and Results

The final analytical sample consisted of 11,242 firm–week observations obtained from 45 companies listed on the Tehran Stock Exchange. The original database contained 48 companies and 125,911 daily trading observations; however, three companies were excluded from the common main-model sample because complete information on the E/P control variable was unavailable over the required estimation window. The resulting panel was unbalanced because the number of valid trading weeks differed across companies and years as a result of trading suspensions, listing characteristics, missing fundamental information, and the requirement that each firm-year contain at least 80% valid weekly observations. On average, each company contributed approximately 249.82 firm–week observations to the main sample. The behavioral indicators were constructed using the longer historical series beginning in 2016, whereas the principal econometric analyses were conducted over the common estimation period corresponding approximately to 2019–2025. After aggregation to weekly frequency, creation of the one-week lead in the dependent variables, construction of 12-week rolling measures, and simultaneous alignment of behavioral and control variables, 11,242 observations remained available for the principal fixed-effects regressions. Inspection of the annual distribution of observations showed that the panel retained broad coverage throughout the principal estimation period and that the results were not generated by concentration of the observations in a single year or a small group of companies.

Table 1. Descriptive Statistics of the Main Study Variables

Variable	N	Mean	SD	Minimum	Median	Maximum
Weekly stock return (R)	11,242	0.0068	0.0714	-0.2386	0.0029	0.2841
Trading turnover (TVR)	11,242	0.0863	0.1187	0.0004	0.0471	0.6825
Log trading value (VALUE)	11,242	15.924	1.493	11.806	15.981	19.187
Relative trading frequency (FT)	11,242	1.082	0.641	0.118	0.914	4.736
Individual-investor money flow (MF)	11,242	0.0182	0.1845	-0.6173	0.0114	0.6416
Weekly volatility (VOL)	11,242	0.3716	0.2189	0.0417	0.3174	1.2468
Investor overconfidence (OCONF)	11,242	0.000	1.000	-1.684	-0.219	4.527
Investor sentiment (SENT)	11,242	0.000	1.000	-3.186	-0.037	3.481

Investor attention (ATTN)	11,242	0.000	1.000	-2.672	-0.164	4.216
Herding behavior (HERD)	11,242	0.000	1.000	-3.021	0.058	3.317
Overreaction/underreaction (REACT)	11,242	0.000	1.000	-3.414	-0.021	3.692
Fear and greed index (FGI)	11,242	0.000	1.000	-2.948	0.046	3.562
Weekly change in USD exchange rate (Δ USD)	11,242	0.0038	0.0281	-0.0862	0.0011	0.1094
Firm size (LnMC)	11,242	29.146	1.537	25.681	29.091	33.216
Earnings-to-price ratio (E/P)	11,242	0.0738	0.0941	-0.1817	0.0613	0.3824

As shown in Table 1, the mean weekly stock return was 0.0068, corresponding to an average weekly return of approximately 0.68%, although the relatively large standard deviation of 0.0714 indicates considerable variation in returns across firms and weeks. Trading turnover averaged 0.0863, indicating that, on average, approximately 8.63% of outstanding shares were exchanged during a typical firm-week. The median turnover of 0.0471 was substantially lower than the mean, suggesting a positively skewed distribution in which a subset of weeks was characterized by unusually intensive trading. The mean relative trading frequency was 1.082, indicating that the number of transactions in an average week was approximately 8.2% above the firm's preceding 12-week average. Its maximum of 4.736 demonstrates that some observations exhibited trading frequencies more than four times their recent historical norms. Individual-investor money flow had a small positive mean of 0.0182 but ranged from -0.6173 to 0.6416, demonstrating substantial switching between net individual-investor selling and buying across firm-weeks. Average annualized within-week volatility was 0.3716, with marked dispersion across observations. The PCA-derived behavioral variables had means close to zero and standard deviations equal to one as a consequence of their standardization. OCONF was moderately right-skewed, with a median of -0.219 and a maximum of 4.527, indicating that exceptionally high overconfidence-related trading episodes occurred relatively infrequently but were economically substantial. The control variables also displayed sufficient variation for panel estimation: weekly exchange-rate changes fluctuated between -0.0862 and 0.1094, while firm size and E/P exhibited meaningful cross-sectional and temporal heterogeneity. Overall, these descriptive results confirmed that the sample contained considerable variation in trading intensity, behavioral conditions, market outcomes, and firm characteristics, providing an appropriate empirical basis for the subsequent panel-data analyses.

Table 2. Principal Component Analysis for the Investor Overconfidence Index

Indicator	Result	
Kaiser–Meyer–Olkin measure	0.560	
Bartlett's test, χ^2	217,924.53	
Bartlett's test, p-value	<0.001	
Eigenvalue of first component	2.225	
Variance explained by first component	74.18%	
Number of retained components	1	
Component of OCONF	PC1 Loading	Squared Loading
Share turnover	0.969	0.939
Relative trading frequency	0.588	0.346
Trading value/market capitalization	0.969	0.939

Table 2 presents the empirical assessment of the market-based investor overconfidence index. The Kaiser–Meyer–Olkin statistic was 0.560. Although this value does not represent a particularly strong level of sampling adequacy in psychometric applications, it was considered usable for the present exploratory PCA because only three theoretically related market indicators were entered and the objective was to summarize their common

market variation rather than to validate a multi-item psychological scale. More importantly, Bartlett's test of sphericity was highly significant, $\chi^2 = 217,924.53$, $p < .001$, confirming that the correlation matrix was significantly different from an identity matrix and that the three indicators contained sufficient shared information for component extraction. The first component had an eigenvalue of 2.225 and accounted for 74.18% of the total variance, indicating that nearly three quarters of the variation in the three trading-intensity measures could be represented by one common dimension. Share turnover and trading value relative to market capitalization both showed very high positive component loadings of 0.969, whereas relative trading frequency had a smaller but still positive loading of 0.588. The squared loadings indicated that the first component captured approximately 93.9% of the variance in both share turnover and trading value intensity and approximately 34.6% of the variance in relative transaction frequency. The uniformly positive direction of the loadings is important because it indicates that the component did not represent a contrast between different dimensions of trading; rather, it captured their simultaneous increase. Consequently, higher OCONF scores reflected weeks in which turnover, transaction frequency relative to historical norms, and trading value relative to firm size jointly increased. These findings supported retention of the first principal component as the study's market-based proxy for investor overconfidence.

Table 3. Panel-Data Specification and Diagnostic Tests

Dependent Variable	F-Limer Statistic	Hausman–Mundlak χ^2	Breusch–Pagan χ^2	Wooldridge F	Pesaran CD
Stock return	8.74***	31.62***	286.41***	19.84***	14.27***
Trading turnover	27.53***	46.18***	514.36***	58.47***	21.61***
Log trading value	83.16***	71.94***	648.25***	96.31***	28.43***
Trading frequency	19.68***	42.75***	402.17***	44.92***	18.86***
Individual money flow	6.92***	23.87**	238.56***	15.73***	12.48***
Volatility	31.47***	38.26***	371.91***	63.18***	25.74***

The diagnostic results reported in Table 3 strongly supported the use of a fixed-effects panel-data framework and robust covariance estimators. The F-Limer statistics were statistically significant for all six dependent variables, with values ranging from 6.92 for individual-investor money flow to 83.16 for trading value. Thus, the null hypothesis that all firm-specific effects were jointly equal to zero was rejected, indicating that pooling all observations without accounting for cross-sectional firm heterogeneity would be inappropriate. The Hausman–Mundlak statistics were also significant across the models, providing evidence that unobserved firm-specific characteristics were systematically related to the explanatory variables. This result favored fixed effects over a conventional random-effects specification. The Breusch–Pagan tests were significant at $p < .001$ in all models, indicating substantial heteroskedasticity. Similarly, the Wooldridge tests rejected the null hypothesis of no first-order serial correlation, demonstrating that disturbances within the same company were correlated across adjacent periods. The Pesaran CD statistics were likewise statistically significant in every equation, establishing the presence of cross-sectional dependence among firms. Such a result was expected in the Tehran Stock Exchange because common market shocks, exchange-rate movements, macroeconomic announcements, regulatory changes, and broad changes in investor sentiment can simultaneously affect multiple listed companies. Taken together, these findings indicated that conventional homoskedastic standard errors would produce unreliable statistical inference. Therefore, the substantive models were estimated using firm and year fixed effects together with two-way clustered standard errors at the firm and week levels. Driscoll–Kraay standard errors were subsequently employed as an additional robustness check.

Table 4. Fixed-Effects Panel Regression of Investor Overconfidence and Behavioral Factors on Subsequent-Week Market Outcomes

Predictor	Return	Turnover	Log Trading Value	Trading Frequency	Money Flow	Volatility
OCONF	0.0019 (1.24)	0.0176*** (6.84)	0.0941*** (5.91)	0.0785*** (7.12)	0.0067* (2.18)	0.0218*** (3.47)
SENT	0.0048** (2.77)	0.0049* (2.31)	0.0316** (2.89)	0.0194** (2.74)	0.0271*** (5.38)	-0.0062 (-1.41)
ATTN	0.0026 (1.58)	0.0097*** (4.23)	0.0618*** (4.76)	0.0447*** (5.09)	0.0051 (1.64)	0.0159** (2.91)
HERD	-0.0037* (-2.11)	0.0062** (2.71)	0.0275* (2.34)	0.0258** (2.96)	-0.0038 (-1.29)	0.0187*** (3.52)
REACT	0.0126*** (6.47)	0.0038 (1.71)	0.0217* (2.09)	0.0146* (2.18)	0.0031 (1.08)	0.0249*** (4.66)
FGI	0.0054** (2.93)	0.0057** (2.83)	0.0362** (3.14)	0.0221** (2.95)	0.0118*** (3.79)	-0.0097* (-2.17)
ΔUSD	-0.0827** (-2.95)	0.0214 (1.49)	0.1837* (2.12)	0.0741 (1.59)	-0.0416* (-2.08)	0.0972*** (3.81)
LnMC	-0.0014 (-0.66)	-0.0138*** (-4.26)	0.6415*** (18.37)	-0.0517*** (-5.19)	0.0019 (0.53)	-0.0286*** (-4.37)
E/P	0.0181* (2.09)	-0.0096 (-1.43)	-0.0824* (-2.15)	-0.0358 (-1.71)	0.0157 (1.41)	-0.0421* (-2.26)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,242	11,242	11,242	11,242	11,242	11,242
Firms	45	45	45	45	45	45
Within R^2	0.084	0.263	0.418	0.296	0.119	0.238

Table 4 reports the principal tests of the study hypotheses. Investor overconfidence in week t was positively and significantly associated with several dimensions of trading activity in week $t + 1$, even after simultaneously controlling for five additional behavioral factors, exchange-rate changes, firm size, valuation, firm fixed effects, and year fixed effects. The coefficient of OCONF for subsequent-week turnover was positive and statistically significant ($B = 0.0176$, $t = 6.84$, $p < .001$). Given the operational definition of turnover, this result indicates that a one-standard-deviation increase in the overconfidence index was associated, on average, with an increase of approximately 0.0176 in the proportion of outstanding shares traded during the following week, conditional on the remaining variables. OCONF also had a positive effect on log trading value ($B = 0.0941$, $t = 5.91$, $p < .001$), showing that higher overconfidence-related activity was followed by significantly greater monetary trading intensity. The strongest standardized-pattern evidence was observed for trading frequency: OCONF significantly predicted an increase in relative transaction frequency in the following week ($B = 0.0785$, $t = 7.12$, $p < .001$). Thus, elevated overconfidence was not limited to contemporaneously high activity but showed persistence into the next trading period.

A smaller positive relationship was observed between OCONF and subsequent individual-investor money flow ($B = 0.0067$, $t = 2.18$, $p = .029$), suggesting that periods of greater overconfidence-related activity were followed by a modest shift toward net buying by individual investors. Overconfidence also predicted higher subsequent volatility ($B = 0.0218$, $t = 3.47$, $p = .001$), indicating that the increased trading activity associated with overconfidence was accompanied by greater short-term price variability. In contrast, the relationship between OCONF and subsequent stock return was positive but statistically nonsignificant ($B = 0.0019$, $t = 1.24$, $p = .215$). This finding is substantively important because it suggests that the principal empirical consequence of overconfidence in the present sample was greater trading intensity rather than a systematic increase or decrease in subsequent returns. In other words, more confident trading behavior was reliably associated with greater turnover, value, frequency, and volatility, but it did not generate a predictable directional return advantage.

The coefficients of the additional behavioral variables further indicated that the OCONF effect was not merely a proxy for general market optimism or heightened activity. Investor sentiment positively predicted subsequent return, turnover, trading value, frequency, and individual money flow, whereas investor attention was particularly strongly associated with turnover, value, frequency, and volatility. Herding was positively related to trading

activity and volatility but negatively related to subsequent stock returns. Overreaction/underreaction displayed its largest associations with stock return and volatility, while the fear-and-greed index was positively related to return, trading activity, and individual-investor money flow and negatively associated with volatility. Among the control variables, exchange-rate appreciation was negatively associated with subsequent stock returns and individual money flow but positively associated with volatility. Firm size was strongly positively related to the logarithm of trading value but negatively related to turnover, relative trading frequency, and volatility, indicating that large firms generated greater absolute trading value while exhibiting lower trading intensity relative to their size. The within- R^2 values ranged from 0.084 for stock returns to 0.418 for trading value, indicating that explanatory power was strongest for measures of trading activity and weaker for subsequent return, which is consistent with the substantially greater unpredictability of short-horizon stock returns.

Table 5. Robustness of the Overconfidence Effect Using Driscoll–Kraay Covariance Estimation

Outcome	Main FE Coefficient	Main p-value	Driscoll–Kraay Coefficient	DK SE	DK t	DK p-value
Stock return	0.0019	0.215	0.0019	0.0016	1.19	0.234
Trading turnover	0.0176	<0.001	0.0176	0.0031	5.68	<0.001
Log trading value	0.0941	<0.001	0.0941	0.0189	4.98	<0.001
Trading frequency	0.0785	<0.001	0.0785	0.0128	6.13	<0.001
Individual money flow	0.0067	0.029	0.0067	0.0031	2.16	0.031
Volatility	0.0218	0.001	0.0218	0.0072	3.03	0.003

The robustness estimates presented in Table 5 demonstrate that the substantive conclusions were not dependent on the use of two-way clustered standard errors. Re-estimation with Driscoll–Kraay covariance matrices and four temporal lags produced the same coefficient estimates because the underlying fixed-effects specification was unchanged, while allowing statistical inference to remain robust to a more general structure of serial and cross-sectional dependence. The overconfidence coefficient remained highly significant for turnover ($B = 0.0176$, $t = 5.68$, $p < .001$), trading value ($B = 0.0941$, $t = 4.98$, $p < .001$), and trading frequency ($B = 0.0785$, $t = 6.13$, $p < .001$). Its positive relationship with volatility also remained statistically significant ($B = 0.0218$, $t = 3.03$, $p = .003$). The smaller effect on individual-investor money flow was preserved as well ($B = 0.0067$, $t = 2.16$, $p = .031$), although its lower statistical strength compared with the core trading-intensity outcomes indicates that the money-flow relationship should be interpreted more cautiously. Conversely, the association with subsequent return remained nonsignificant ($B = 0.0019$, $t = 1.19$, $p = .234$). The near-identical inferential pattern obtained under the two covariance estimators indicates that the principal results were not artifacts of a particular assumption regarding the error structure. Most importantly, OCONF continued to predict higher subsequent turnover, monetary trading activity, transaction frequency, and volatility under a covariance estimator designed specifically to address cross-sectional dependence and temporal autocorrelation.

Table 6. Multiple-Testing Adjustment and Joint Significance of Investor Overconfidence Effects

Outcome	OCONF Coefficient	Raw p-value	Benjamini–Hochberg Adjusted p-value	Result after FDR Adjustment
Stock return	0.0019	0.215	0.215	Not significant
Trading turnover	0.0176	<0.001	<0.001	Significant
Log trading value	0.0941	<0.001	<0.001	Significant
Trading frequency	0.0785	<0.001	<0.001	Significant
Individual money flow	0.0067	0.029	0.035	Significant
Volatility	0.0218	0.001	0.002	Significant
Joint Wald test across six outcomes	—	$\chi^2(6) = 89.34$	<0.001	Jointly significant

Table 6 evaluates whether the observed findings remained statistically reliable after accounting for the simultaneous testing of overconfidence across six related outcomes. Application of the Benjamini–Hochberg false discovery rate procedure did not alter the main conclusions. The adjusted probability values for trading turnover, trading value, and trading frequency remained below 0.001, providing particularly strong evidence that these associations were not attributable to multiplicity. The overconfidence–volatility relationship also remained statistically significant after adjustment, with an FDR-corrected $p = .002$. The weaker relationship with individual-investor money flow remained below the 0.05 threshold after adjustment ($p_{FDR} = .035$), although it was clearly less robust than the associations with the three direct trading-intensity measures. In contrast, the nonsignificant return coefficient remained nonsignificant after correction ($p_{FDR} = .215$). The joint Wald test further rejected the null hypothesis that the overconfidence coefficients across the six outcomes were jointly equal to zero, $\chi^2(6) = 89.34$, $p < .001$. This result establishes that, when the collection of market consequences was considered jointly, investor overconfidence had a statistically detectable overall relationship with subsequent market behavior.

Taken together, the findings provide a coherent empirical pattern. Investor overconfidence measured from contemporaneous market behavior showed its strongest and most persistent associations with subsequent trading intensity rather than with the direction of stock returns. Higher values of the OCONF index were followed by greater share turnover, greater monetary trading value, more frequent transactions relative to recent historical norms, and higher volatility. A smaller positive association was also observed with the net money flow of individual investors. These relationships persisted after controlling for investor sentiment, investor attention, herding, overreaction/underreaction, fear and greed, exchange-rate movements, firm size, valuation differences, unobserved time-invariant firm characteristics, and common annual shocks. They also remained evident under two alternative methods of robust statistical inference and after adjustment for multiple hypothesis testing. Therefore, the empirical evidence indicates that investor overconfidence in the Tehran Stock Exchange is manifested primarily through sustained increases in trading activity and market intensity rather than through a consistently positive or negative effect on subsequent stock returns.

4. Discussion and Conclusion

The present study investigated the effect of investor overconfidence on subsequent trading intensity and related market outcomes in the Tehran Stock Exchange using a market-based composite index and firm–week panel data. The findings showed that investor overconfidence in week (t) was positively and significantly associated with trading turnover, trading value, trading frequency, individual-investor money flow, and market volatility in week (t+1), whereas its effect on subsequent stock returns was positive but statistically nonsignificant. More specifically, the overconfidence index significantly predicted higher turnover (($B=0.0176$), ($p<.001$)), greater trading value (($B=0.0941$), ($p<.001$)), higher relative transaction frequency (($B=0.0785$), ($p<.001$)), greater individual-investor money flow (($B=0.0067$), ($p=.029$)), and increased volatility (($B=0.0218$), ($p=.001$)). These relationships remained stable after controlling for investor sentiment, attention, herding, overreaction/underreaction, fear and greed, exchange-rate changes, firm size, valuation, firm fixed effects, and year fixed effects. The results were also robust to Driscoll–Kraay covariance estimation and remained statistically significant after Benjamini–Hochberg false discovery rate correction. The overall pattern therefore indicates that overconfidence primarily manifests through persistence in trading intensity and market activity rather than through a systematic direction in subsequent stock returns.

The positive relationship between investor overconfidence and subsequent share turnover is consistent with one of the central predictions of behavioral finance. Overconfident investors tend to overestimate the precision of their private information and the quality of their analytical judgments and therefore perceive a greater expected benefit from trading than objectively justified. Odean demonstrated theoretically that when investors assign excessive precision to their own information, trading volume increases because investors disagree more strongly about asset values and act more aggressively on their beliefs [1]. The present finding that greater overconfidence in one week predicts higher turnover in the following week is therefore consistent with the argument that confidence-driven trading is persistent rather than purely contemporaneous. Gervais and Odean further explained that overconfidence may emerge and strengthen through biased learning, particularly when investors attribute successful outcomes to their own ability while underweighting the role of luck or favorable market conditions [2]. Such a mechanism can generate repeated trading because previous market participation reinforces perceived competence and encourages further transactions. The current results extend this theoretical logic to the Tehran Stock Exchange by demonstrating that a market-based overconfidence factor predicts subsequent increases in turnover even after other behavioral variables are held constant.

The observed positive association between overconfidence and trading value provides further evidence that the effect is not limited to a greater number of small transactions. Higher OCONF scores were followed by greater monetary value of trading in the subsequent week, suggesting that overconfident behavior is accompanied by a broader increase in the economic magnitude of market participation. This result strongly aligns with the evidence reported by Statman, Thorley, and Vorkink, who found that trading volume behaves in a manner consistent with investor overconfidence and self-attribution mechanisms [3]. Their findings suggest that favorable experiences or rising confidence can stimulate subsequent market activity, thereby linking psychological biases with observable trading volume. Similarly, the present study indicates that when turnover, relative transaction frequency, and trading value jointly signal greater overconfidence in the current period, trading activity remains elevated in the following period. This temporal persistence strengthens the interpretation that the relationship is behavioral rather than merely a mechanical consequence of using trading-based indicators.

The positive effect of overconfidence on relative trading frequency reinforces this conclusion. Among the principal trading-intensity outcomes, transaction frequency displayed one of the strongest associations with overconfidence. This result is theoretically plausible because overconfident investors are more likely to believe that they repeatedly identify profitable trading opportunities and may consequently adjust their portfolios more frequently than warranted by new fundamental information. Such behavior corresponds closely with the excessive-trading hypothesis developed in earlier behavioral finance research [1, 4]. Barber and Odean showed that individual investors who traded most frequently tended to earn poorer net performance than less active investors, demonstrating that high activity cannot automatically be interpreted as superior information processing [4]. Barber and colleagues later documented substantial aggregate losses attributable to individual investor trading, further showing that persistent market participation may impose economic costs when investors overestimate their ability to identify profitable opportunities [5]. Accordingly, the current finding suggests that overconfidence may be one of the behavioral mechanisms sustaining repeated trading in the Iranian stock market.

The significant positive relationship between overconfidence and subsequent individual-investor money flow provides additional evidence regarding the behavioral character of the observed trading pattern. Although the magnitude of this effect was smaller than that observed for turnover, value, and frequency, it remained statistically significant after multiple-testing adjustment. This implies that higher overconfidence was followed by a modest

shift toward stronger net buying by individual investors. Such a result may reflect the tendency of confident investors to interpret information optimistically or to believe that they can successfully identify undervalued securities. Research on attention-driven trading provides a related explanation. Barber and Odean showed that individual investors disproportionately purchase attention-grabbing stocks because the set of available buying choices is extremely large and attention serves as a filtering mechanism [6]. Da, Engelberg, and Gao likewise demonstrated that heightened investor attention can influence trading and asset demand [7]. Although attention was controlled separately in the present model, the positive OCONF coefficient indicates that overconfidence explains additional variation in individual-investor buying behavior beyond the effect of attention alone.

The finding that overconfidence significantly increased subsequent volatility is also consistent with behavioral market theory. When investors trade aggressively on subjective beliefs that they perceive as highly precise, disagreement can translate into more frequent revisions of market prices and greater short-term price fluctuations. Odean's theoretical framework explicitly connects overconfidence with not only trading volume but also volatility and market prices [1]. Similarly, Hu reported that overconfidence and loss aversion can influence broader market performance, indicating that psychological biases may affect market-level dynamics rather than remaining confined to individual decisions [17]. Aljifri likewise demonstrated that investor psychology and overconfidence can have implications for firm valuation, supporting the proposition that investor beliefs can be transmitted into observable market outcomes [16]. The positive relationship between OCONF and volatility in the present study therefore suggests that confidence-driven trading may contribute to a more unstable short-term pricing environment by intensifying transactions based on heterogeneous and potentially excessively precise private beliefs.

In contrast, investor overconfidence did not significantly predict subsequent stock returns. This result is theoretically meaningful and does not contradict the broader behavioral interpretation. Overconfidence theory offers a clearer prediction regarding the volume and intensity of trading than regarding the direction of future returns. If overconfident investors simultaneously hold optimistic and pessimistic private signals but overestimate their respective precision, their disagreement can increase transactions without producing a stable positive or negative average return effect. The nonsignificant return coefficient is therefore consistent with the proposition that the primary observable consequence of overconfidence is excessive market participation rather than a reliable ability to forecast price direction [1, 3]. The result also accords with evidence that active individual investors do not necessarily obtain superior investment performance despite their willingness to trade frequently [4, 5]. In practical terms, stronger confidence may cause investors to trade more without providing them with an informational advantage capable of generating systematically higher subsequent returns.

The results also remained significant after controlling for investor sentiment, which is important because confidence and optimism can be conceptually related. Baker and Wurgler demonstrated that investor sentiment can affect the cross-section of stock returns and that securities characterized by greater valuation uncertainty may be especially exposed to sentiment-driven demand [8]. They further emphasized that shifts between optimism and pessimism can influence market participation and valuation more broadly [9]. In the present study, sentiment independently predicted several outcomes, including return, turnover, trading value, transaction frequency, and money flow. Nevertheless, the overconfidence coefficient remained significant for the major trading-intensity measures after sentiment was incorporated into the model. This distinction indicates that overconfidence should not be reduced to general optimism. Sentiment reflects how favorably or unfavorably investors perceive market prospects, whereas overconfidence concerns the perceived precision of one's own judgment or information. An

investor can therefore be pessimistic yet overconfident in that pessimistic judgment, or optimistic without necessarily believing that his or her information is superior. The empirical separation of these effects strengthens the validity of the present findings.

The significant effects of investor attention, herding, overreaction/underreaction, and fear and greed further demonstrate the multidimensional nature of behavioral influences in the Tehran Stock Exchange. Investor attention was positively associated with subsequent turnover, trading value, transaction frequency, and volatility, consistent with evidence that securities attracting unusual attention can experience stronger investor participation [6, 7]. Herding was positively associated with trading activity and volatility, which corresponds with the broader literature showing that investors may cluster around collective market behavior, especially when uncertainty is high or private information is weak [10]. Qasim and colleagues similarly found that herding and overconfidence jointly affect investment decision-making, indicating that these biases frequently coexist rather than operate in isolation [12]. The fact that overconfidence remained statistically significant after these variables were included confirms that its effect on trading intensity was not simply a statistical reflection of correlated behavioral tendencies.

The observed relationships are also compatible with evidence on market overreaction and behavioral decision-making in emerging markets. Parveen and colleagues reported that investor sentiment and market overreaction can influence investment decisions and market behavior, emphasizing the importance of psychological mechanisms in markets where uncertainty and information asymmetry are substantial [11]. Rahmawati and Santi likewise concluded that overconfidence and availability-related biases can influence investor decisions by affecting how information is selected and interpreted [13]. The present findings add to this literature by showing that overconfidence has a distinct temporal relationship with subsequent trading activity even when overreaction and other market-based psychological factors are simultaneously controlled. This finding is particularly relevant because it suggests that different behavioral biases have partially independent market consequences and should therefore be modeled jointly rather than treated as interchangeable manifestations of irrational behavior.

The findings also support recent research emphasizing the importance of investor characteristics and psychological heterogeneity. Jain and colleagues demonstrated that investor personality can affect investment intention through overconfidence, highlighting the mediating role of perceived competence and subjective confidence in financial decision-making [15]. Nabeshima, Khan, and Kadoya further reported that overconfidence is associated with greater investment loss tolerance among Japanese investors, indicating that highly confident investors may remain willing to bear adverse outcomes and continue participating in the market [18]. This mechanism may help explain the persistence identified in the current study: if overconfident investors exhibit greater tolerance for losses or interpret setbacks as temporary, they may continue trading rather than reduce activity after unfavorable results. Singh, Malik, and Jha likewise identified overconfidence as a persistent and influential retail-investor bias and called for further research into its measurement and consequences across institutional and market settings [14]. The present study responds to this need by employing an archival, market-based index rather than relying exclusively on self-reported confidence.

The Iranian evidence is also consistent with previous studies documenting the relevance of behavioral factors in the Tehran Stock Exchange. Eishi Ravandi and colleagues found that investor sentiment and liquidity influence stock returns in the Iranian stock market, demonstrating that behavioral conditions and trading-market characteristics are closely connected [20]. Khajavi and colleagues similarly emphasized the role of behavioral indicators and investor sentiment in shaping portfolio risk-taking decisions [21]. Taheri and Jafari also showed that overconfidence and investor sentiment are meaningful components of financial relationships in the Iranian context,

particularly when interacting with corporate financial policies [19]. The present findings extend these studies by shifting attention from contemporaneous behavioral associations toward the temporal persistence of market-based overconfidence and by showing that its principal effect appears in subsequent trading intensity rather than subsequent return direction.

An important methodological contribution of the study is the use of a composite PCA-based proxy for overconfidence. The first principal component explained 74.18% of the total variance in share turnover, relative trading frequency, and trading value relative to market capitalization, with particularly strong loadings for turnover and trading value. Principal component analysis is appropriate when several correlated indicators are intended to represent a common underlying empirical dimension because it summarizes shared variation while reducing redundancy among the original measures [22]. The findings therefore support the interpretation of OCONF as a composite measure of trading behavior consistent with overconfidence rather than as a direct psychological scale. This distinction is important because no archival proxy can establish the internal psychological state of individual investors with certainty. Nevertheless, the temporal predictive power of the index, combined with its robustness to alternative statistical inference and behavioral controls, supports its usefulness as a market-level indicator of overconfidence-related trading intensity.

Finally, the robustness analyses reinforce confidence in the statistical interpretation of the findings. Financial panel data are frequently affected by heteroskedasticity, temporal dependence, and common shocks across securities. The persistence of the principal coefficients under Driscoll–Kraay covariance estimation indicates that the results were not dependent on conventional independence assumptions and remained detectable when more general cross-sectional and temporal dependence were accommodated [23]. Moreover, the Benjamini–Hochberg adjustment showed that the significant effects on turnover, trading value, frequency, money flow, and volatility were not eliminated after accounting for multiple testing. Collectively, these findings indicate that investor overconfidence in the Tehran Stock Exchange is most clearly expressed through sustained increases in market participation and trading intensity. Overconfident investors appear to trade more, trade with greater monetary intensity, participate more frequently, and contribute to higher short-term volatility, yet this increased activity does not translate into a systematic subsequent return advantage.

The present study has several limitations that should be considered when interpreting the findings. First, investor overconfidence was inferred from observable trading behavior rather than measured directly through psychological assessment, meaning that the OCONF index captures market activity consistent with overconfidence but cannot establish the subjective beliefs of individual investors. Second, the analysis was conducted at the firm–week level and therefore could not identify individual trading histories or distinguish heterogeneous effects across specific categories of retail investors. Third, although the lagged research design reduces contemporaneous mechanical relationships, it does not by itself establish strict causality because unobserved time-varying factors may influence both current overconfidence proxies and subsequent trading outcomes. Fourth, the principal sample contained 45 Tehran Stock Exchange companies with sufficiently complete data, which may limit generalizability to less liquid firms, companies with shorter listing histories, or securities traded in other Iranian markets. Finally, macroeconomic and regulatory conditions in Iran during the study period were unusual in several respects, including substantial exchange-rate instability and market interventions, and these institutional characteristics should be considered when extrapolating the findings to other financial markets.

Future research should extend the present analysis through several complementary approaches. Studies using investor-level transaction records could directly examine whether investors classified as more overconfident

subsequently trade more frequently, hold less diversified portfolios, realize lower risk-adjusted returns, or respond differently to gains and losses. Combining archival trading information with validated psychometric measures would also make it possible to evaluate the convergent validity of market-based overconfidence indices. Future analyses could distinguish bullish from bearish overconfidence, examine asymmetric effects following prior gains and losses, and test whether overconfidence differs across bull, bear, high-volatility, and crisis periods. Researchers could also investigate whether market liquidity, firm size, ownership concentration, free-float percentage, information transparency, industry characteristics, or investor sophistication moderate the association between overconfidence and trading intensity. Dynamic panel estimators, instrumental-variable strategies, high-frequency transaction data, nonlinear models, and regime-switching frameworks may further strengthen causal interpretation and reveal whether confidence-related trading displays thresholds or persistence across different market regimes.

From a practical perspective, the findings indicate that investors, brokerage firms, market regulators, and financial-education providers should treat unusually intensive trading as a potential behavioral risk signal rather than automatically interpreting it as evidence of superior information. Brokerage platforms can incorporate behavioral feedback mechanisms that allow investors to compare trading frequency, turnover, realized performance, and transaction costs over time, thereby helping users recognize situations in which activity increases without corresponding improvements in returns. Financial-literacy programs should explicitly address overconfidence, self-attribution, attention-driven trading, herding, and the distinction between conviction and informational accuracy. Portfolio managers and risk officers can monitor composite measures of abnormal turnover, transaction frequency, and trading-value intensity as supplementary indicators of speculative pressure. At the market level, regulators may benefit from monitoring periods in which behavioral indicators rise simultaneously with volatility and retail money flows, particularly when such activity is not accompanied by comparable changes in fundamentals. These measures would not seek to restrict legitimate trading but rather to improve investor awareness, market surveillance, and the identification of episodes in which excessive confidence may contribute to unstable trading conditions.

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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