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# Threshold Dynamics of Investor Overconfidence and Trading Activity: Evidence from Indonesia's Stock Market

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**Abstract**
Investor overconfidence significantly influences trading behavior in emerging markets, yet prior research has predominantly assumed linear and static effects, overlooking potential regime-dependent amplification under varying market conditions. This research explores the threshold dynamics of investor overconfidence in the Indonesian equity market using daily data from firms comprising the IDX80 (2015–2024). We proxy for overconfidence using excess turnover and analyze it with fixed-effects panel regression and Hansen's (1999) panel threshold model. We found that excess turnover significantly affects trading activity, that lagged returns reinforce self-attribution bias, and that smaller or undervalued firms primarily garner speculative trading. The threshold analysis revealed regime dependency: firm-specific returns exceeding 1.15% nearly double trading intensity, and if volatility exceeds 2.61%, either condition would have nearly tripled effect. Aggregate returns do not condition the overconfidence–trading link. These findings contribute to behavioral finance by suggesting that overconfidence is not static but intensifies as strong performance and high volatility are observed. Practically, the indicators at the thresholds offer regulators early-warning signals of speculative surges and provide investors with risk management strategies even amid such risks.

Keywords: Investor overconfidence; Behavioral finance; Trading activity; Panel threshold regression; Emerging markets; Indonesia.

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## INTRODUCTION

Investor psychology is critical to how financial markets operate and govern activities, particularly in emerging economies where retail investors are more prominent and institutional protections are poorly developed (Kushwaha et al., 2023). Traditional finance rests on rational expectations and efficient markets but fails to explain the behavioral anomalies in the market associated with high turnover, volatility clustering, and bubbles. Behavioral finance goes further by acknowledging the existence of systematic biases in decision-making (Barberis & Thaler, 2003). For instance, investors' overconfidence bias leads to inflated perceptions of the accuracy of knowledge and signals, making their own positive signals appear more impactful (Odean, 1999; Barber & Odean, 2001). These studies establish that overconfidence is a highly influential cause of speculative trading and mispricing.

More broadly, the literature has long reported how investor sentiment and noise traders disrupt financial markets by producing imprecise prices in the short term, which can harmfully proliferate bubbles. Shiller (2000) illustrates how investor exuberance shapes speculation; De Long et al. (1990) establish, with residual variance due to noise trader risk, how prices remain distorted but deteriorate over time; Baker and Wurgler (2007) more simply argue that prior investor sentiment influences subsequent stock market movements. Both demonstrate the importance of investor psychology in influencing trading behavior.

The Indonesian stock market represents an ideal environment to examine these processes. Specifically, Indonesia is one of Southeast Asia's most active capital markets, exhibiting high trading intensity, a large number of retail investors, and frequent episodes of speculation, such as the post-pandemic rallies of 2021–2022 and, notably in Indonesia, large IPOs such as GOTO. These events demonstrate how changes in belief can induce sudden trading spikes that are inexplicable in the context of fundamentals. Prior research conducted in Indonesia has mostly focused on herding, momentum, and liquidity anomalies (Siregar & Budiarto, 2017; Santoso et al., 2020), often treating behavioral influences as stable and linear. In contrast, the actual behavior of overconfidence has not been examined as potentially non-linear and state-dependent—escalating after rallies and tumultuous periods, rather than exerting a constant influence.

This study addresses this gap using Hansen's (1999) *panel threshold regression* (PTR) applied to firm-level daily data from IDX80 constituents over the time frame of 2015–2024. It assesses whether firm-specific returns, aggregate market returns, or volatility condition the relationship between overconfidence (operationalized through excess turnover) and trading intensity. Using endogenous threshold estimates allows for the discovery of regime shifts in investor behavior that standard linear inference methods fail to capture.

The research responds to key questions and offers three contributions. First, it develops behavioral finance theory by demonstrating overconfidence as amplification rather than an inherent psychological trait. Overconfidence amplifies when thresholds of performance or uncertainty are crossed, making it conditional and non-linear. Second, it provides the first quantitative estimates of behavioral amplification within volatility—documenting, for example, that in Indonesia trading responses may nearly double or triple during high-volatility periods following firm-specific gains. Finally, it offers policy and practical implications by providing regulators and market participants with transparent threshold values to issue signals and develop risk-control measures as early-warning indicators of speculative surges.

## Hypothesis Development

### *Behavioral Finance, Overconfidence, and Trading Activity*

Behavioral finance contradicts the rational expectations model by demonstrating how systematic psychological errors affect the outcomes in the market (Barberis & Thaler, 2003). Overconfidence is possibly the most important bias. Overconfidence occurs when investors overestimate how accurate their private information is, and traders overestimate how good their trading skills are compared to others. This miscalibration is often exacerbated by an illusion of control and a bias of attribution, which leads to excessive and speculative trading (De Bondt & Thaler, 1995; Barberis, Shleifer, and Vishny, 1998). The result is that investors trade excessively, earning lower net returns (Odean, 1999; Barber & Odean, 2000).

Theoretical models have examined the underpinnings of these behaviors. Daniel, Hirshleifer, and Subrahmanyam (1998) show that short-term momentum and long-term reversals directly result from the overconfidence/self-attribution process. Gervais and Odean (2001) show that trades in time series are correlated and that repeatedly trading profitably creates overconfidence that persists. At the aggregate level, Statman, Thorley, and Vorkink

(2006) find overconfidence raises trading volume, while Glaser and Weber (2007) find individuals raised trading volume due to overconfidence. These results imply that overconfidence is not a constant term, but conditional; Chuang and Lee (2006) and Chuang and Susmel (2011) identify regime switching trading, the degree of overconfidence influenced by the degree of volatility (or uncertainty), leading to a case for nonlinear modeling. Overall, prior research reflects a stable association between overconfidence and increased trading. Given this solid foundation, we propose our first hypothesis:

H1: Investor overconfidence has a significant positive effect on trading activity in the Indonesian stock market.

***Nonlinear Dynamics and Thresholds***

Most of the past work regarding binary commitment situations assumes linear models, which means a constant effect is assigned to individuals in terms of the effects from overconfidence across the states (high/low overconfidence). Thus, linear modeling is constant behavior over conditions, whereas what may be happening are nonlinear, threshold dependent behaviors. Performance-contingency amplification emerges in performance contexts in the context where an investor will trade more when they get a positive return. Uncertainty-contingency amplification emerges where investors speculate more during volatile periods and are willing to invest in riskier assets. Traditional interaction terms found in statistical modeling are reasonable for gradual heterogeneity, whereas Hansen's (1999) Panel Threshold Regression (PTR) finds the endogenous number of breakpoints where the endogenous variable discretely changes from action or state change; this sample establishes more of a psychological Tipping Point mechanism that activates only after an amount of performance or amount of uncertainty has been breached.

The research on self-attribution bias (Daniel et al., 1998; Gervais & Odean, 2001) offers a distinct context for performance-based thresholds, indicating that overconfidence bias should affect trading more strongly after positive firm-specific returns. This leads to the second hypothesis:

H2: The positive effect of overconfidence on trading activity should be significantly greater when firm-specific returns are above a certain threshold.

Likewise, noise trader risk models (De Long et al., 1990) imply that periods of high uncertainty may strengthen behavioral biases. Thus, we would anticipate that volatility should serve as a spur for overconfidence-oriented speculation:

H3: The positive effect of overconfidence on trading activity should be significantly stronger when firm-specific volatility is above a certain threshold.

Aggregate market returns are less clearly hypothesized to affect trading. In a retail-driven market such as Indonesia, the focus on stock narrative and speculative story-telling may be medium-sized and more prevalent than or in addition to their use of top-down macroeconomic signals. Thus, while we would suspect some level of effect from aggregate market returns on trading, it would be reasonable to follow up on whether aggregate market returns were conditioning variables for overconfidence-controlled speculation in the same way as firm specific performance. Thus, we test the following:

H4: The positive effect of overconfidence on trading activity is conditioned by aggregate market returns.

## RESEARCH METHOD

This research employed a two-stage empirical strategy to assess the effect of investor overconfidence on trading activity in the Indonesian equity market. The first stage estimated the average effect of excess turnover—our proxy for overconfidence—on daily trading intensity using a baseline fixed-effects panel regression incorporating firm characteristics and risk variables. The second stage applied Hansen's (1999) Panel Threshold Regression (PTR) to examine whether a nonlinear adjustment process existed under varying regimes defined by firm-specific returns, market returns, or volatility. This design provided a better fit than alternative approaches, likely due to the prominent role of retail investors and speculative trading behavior in the Indonesian market.

The dataset contained daily firm-level observations for IDX80 constituents from January 2015 to December 2024. Data collection followed a systematic multi-source approach to ensure accuracy and completeness. Daily stock prices, trading volumes, and shares outstanding were obtained from Yahoo Finance and Investing.com, while market-level data, including the Jakarta Composite Index (IHSG), were sourced from the Indonesia Stock Exchange (IDX) and Bloomberg Terminal. Firm-level fundamentals such as market capitalization, book value, and financial variables were extracted from quarterly and annual financial reports available through IDX filings and company investor relations portals. Data series were cross-validated across sources to address inconsistencies, and missing observations were corrected using forward-fill interpolation for non-trading days. Firms with more than 20% missing data in any calendar year were excluded. Extreme values in turnover and volatility measures were winsorized at the 1st and 99th percentiles to limit the impact of outliers.

After accounting for data availability, the final panel comprised 61 firms and 147,862 firm-day observations. Although the panel was unbalanced due to differing listing periods and occasional trading suspensions, the dense coverage across firms and time provided sufficient variation to capture high-frequency trading dynamics and yield robust statistical inference.

### Variable Definitions

| Variable | Formula | Description | Reference |
|---|---|---|---|
| **Dependent Variable** | | | |
| Turnover | $\frac{Volume_{i,t}}{ShareOutstanding_{i,t}}$ | Daily trading volume divided by shares outstanding, proxy for trading intensity | Barber & Odean (2000) |
| **Key Independent Variable (Overconfidence Proxy)** | | | |
| Excess Turnover | $Turnover_{i,t} - \overline{Turnover_{i,t}}^{(21)}$ | Deviation of turnover from 21-day moving average, capturing abnormal speculative trading | Statman, Thorley & Vorkink (2006) |
| **Threshold Variables** | | | |
| Lagged Return | $\frac{P_{i,t-1} - P_{i,t-2}}{P_{i,t-2}}$ | One-day lagged stock return (%) | Barberis, Shleifer & Vishny (1998) |
| Market Return | $\frac{IHSG_t - IHSG_{t-1}}{IHSG_{t-1}}$ | Daily return of the Jakarta Composite Index | Campbell, Lo & MacKinlay (1997) |
| Volatility | $\sqrt{\frac{1}{21}\sum_{k=1}^{21}(R_{i,t-k} - \overline{R}_{i,t}^{(21)})^2}$ | 21-day rolling standard deviation of stock returns | Campbell, Lo & MacKinlay (1997) |

| Variable | Formula | Description | Reference |
|---|---|---|---|
| **Control Variables** | | | |
| Firm Size | $\ln(MarketCap_{i,t})$ | Natural log of market capitalization | Fama & French (1992) |
| Price-to-Book Ratio (PBV) | $\frac{P_{i,t}}{BookValuePerShare_{i,t}}$ | Proxy for growth opportunities | Fama & French (1992) |
| Amihud Illiquidity | $\frac{\lvert R_{i,t}\rvert}{Turnover_{i,t}}$ | Capturing daily price impact of trading | Amihud (2002) |
| Beta | $R_{i,t} = \alpha_i + \beta_i R_{m,t} + \varepsilon_{i,t}$ | Market risk exposure estimated from market model | Sharpe (1964) |

## RESULTS AND DISCUSSION

### Descriptive Statistics and Correlation Analysis

**Table 2. Descriptive Statistics**

| Variable | Observations | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| Turnover | 147,862 | 0.00 | 0.01 | 0.0001 | 0.245 |
| Excess Turnover | 147,862 | 0.00 | 1.44 | -11.23 | 132.77 |
| Lagged Return | 147,862 | 0.00 | 0.03 | -0.31 | 0.27 |
| Volatility (21d) | 147,862 | 0.02 | 0.02 | 0.0001 | 0.16 |
| IHSG Return | 147,862 | 0.00 | 0.01 | -0.08 | 0.07 |
| Size (ln) | 147,862 | 30.8 | 1.49 | 26.1 | 35.4 |
| PBV | 147,862 | 2.42 | 5.73 | 0.01 | 73.65 |
| Amihud | 147,862 | 0.40 | 12.03 | 0.0001 | 679.5 |
| Beta | 147,862 | 1.05 | 0.68 | -1.5 | 3.4 |

Source: Authors' estimation

In Table 2, we present the descriptive statistics for the main variables in our investigation, which is observed over the 2015–2024 period. Daily turnover, calculated as trading volume divided by shares outstanding, has a relatively low and modest mean consistent with the thin trading in most Indonesian firms. Excess turnover, as the proxy for investor overconfidence is centered near zero but displays significant variability, while the extreme maximum values (>130) suggest temporary surges in speculative activity. The average firm-specific and market (IHSG) returns are near zero, while the volatility depicts a large variation that captures calm and turbulent times. Valuation multiples similarly suggest significant heterogeneity: PBV ranges from bargains to speculative growth stocks, and firm size (log of market capitalization) varies between large blue-chip companies and small issuers. The measure of illiquidity (Amihud) and beta continue to indicate diverse trading environments and risk exposures.

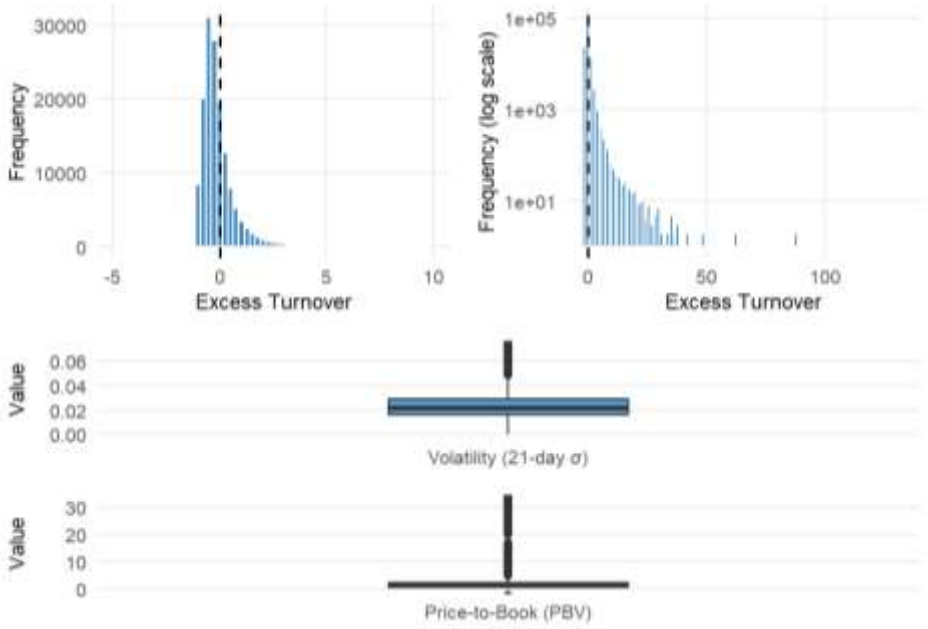


**Figure 1. Distribution of Excess Turnover, Volatility, and PBV**
Source: Authors' calculation

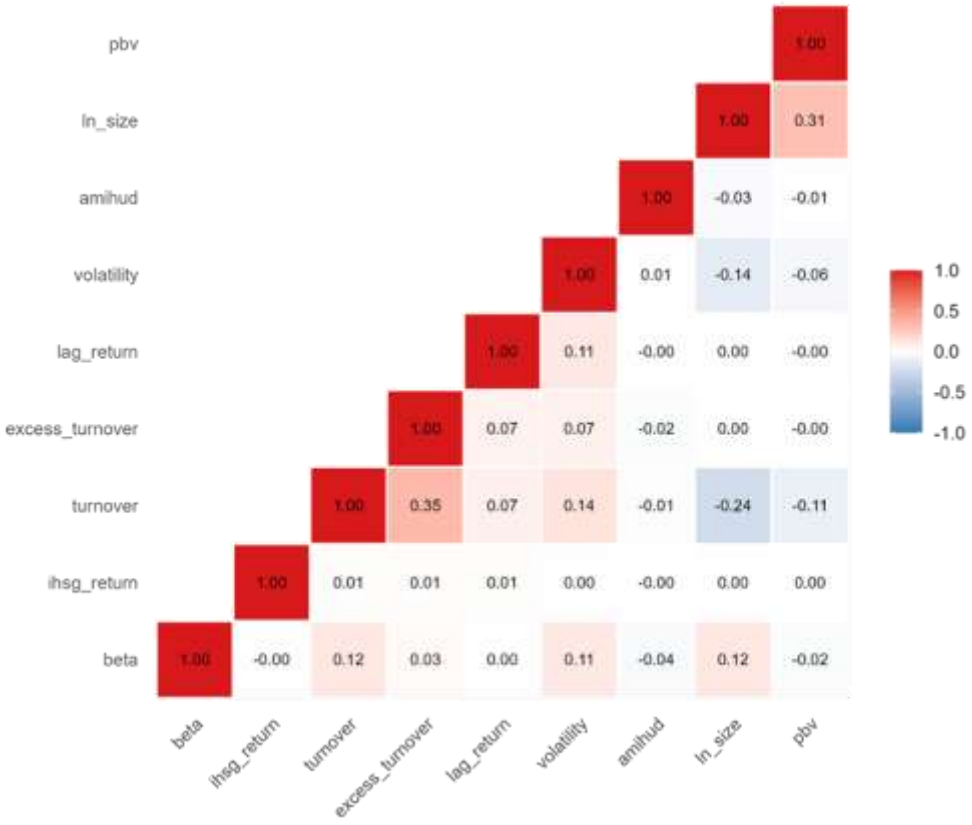


**Figure 2. Correlation Matrix of Key Variables**
**Source: Authors' calculation**

Figure 1 shows these patterns visually. The top panels display the distribution of excess turnover. The first zoomed (−5 to 10) shows that the majority of observations are bunched up tightly around zero suggesting normal day-to-day variation. The log-scaled panel, on the other

hand, shows a long right tail resulting in rarely occurring but high spikes. These spikes occur in conjunction with speculative trading waves as evidenced mostly by trading volume and provide further justification for implementing a threshold regression to account for nonlinear investor responses. The bottom panels provide boxplots for volatility and PBV, while the outliers were trimmed at the 99th percentile for clarity. Volatility is concentrated at relatively low levels, while occasionally this volatile typically occurs in times of market stress. The valuation metric of PBV has a much wider range than volatility with low probability extreme outliers in both directions. Together these figures show a fair degree of skewness and heterogeneity that simple linear models will not be able to properly acknowledge. Figure 2 is the correlation matrix. Overall, pairwise correlations are fairly low (<0.35) suggesting little risk of multicollinearity. Turnover and excess turnover are positively correlated, and firm size and PBV are negatively correlated, which follows valuation trends in emerging markets.

**Baseline regression**

Baseline Panel Regression

**Table 3. Baseline Panel Regression**

| Variable | Coefficient | Robust Std. Error | t-stat | p-value | Significance |
|---|---|---|---|---|---|
| Excess Turnover | 0.0013703 | 8.88E-06 | 154.230 | 0.000 | *** |
| Lagged Return | 0.0071367 | 0.0003675 | 19.420 | 0.000 | *** |
| Size (ln) | -0.0009912 | 1.86E-05 | -53.270 | 0.000 | *** |
| PBV | -0.0000738 | 4.41E-06 | -16.730 | 0.000 | *** |
| Amihud | -2.82E-07 | 1.07E-06 | -0.260 | 0.791 | ns |
| Beta | 0.0008435 | 2.06E-05 | 40.970 | 0.000 | *** |
| Volatility | 0.0148275 | 0.000538 | 27.560 | 0.000 | *** |
| Constant | 0.0316902 | 0.0005687 | 55.720 | 0.000 | *** |
| **Observations** | **147,862** | | | | |
| **Number of firms** | **61** | | | | |
| **$R^2$ (Within)** | **0.1781** | | | | |
| **$R^2$ (Between)** | **0.3638** | | | | |
| **$R^2$ (Overall)** | **0.2031** | | | | |
| **F(7,147794)** | **4574.22** | | | | |
| **ρ (intra-class corr.)** | **0.1138** | | | | |

Source: Authors' estimation

Table 3 shows the results of the fixed-effects panel regression. Excess turnover has a positive and statistically significant coefficient (β=0.00137; p<0.01), which supports the hypothesis that overconfidence increases turnover. Economically, a one-unit increase in excess turnover translates into a turnover increase of 0.00137. This is approximately 14% of the average amount of daily turnover. These results suggest that abnormal speculative activity has a substantial impact on turnover in the market. The other coefficients are as we would expect. Lagged returns is positive significant (β=0.0071), suggesting that self-attribution bias operates

in the context where prior gains trigger more turnover. Firm size is negative, indicating that smaller firms attract higher levels of speculative activity relative to larger firms, while PBV is also negative and suggests that turnover is even more pronounced in firms that are undervalued. Beta and volatility are both positive and statistically significant, suggesting that more risky trading cannot be undone by the fact that riskier trading drives turnover in excess of expected turnover. Amihud illiquidity is a non-significant variable which suggests that overconfidence in the context of generating speculative activity, dominates liquidity when considering trading activity.

**Model Diagnostics**

**Table 4. Model Diagnostics**

| Test | Statistic | p-value | Significance |
|---|---|---|---|
| Hausman (FE vs RE) | $\chi^2 = 1.15$ | 0.359 | ns |
| Wooldridge Serial Correlation | F = 212.5 | 0.000 | *** |
| Pesaran CD (Cross-sectional dep.) | CD = 18.3 | 0.000 | *** |

Source: Authors' estimation

The diagnostic tests further confirm that the specification is appropriate - serial correlation is likely present, and correlation across the pooled cross-section across time is very likely to be present, although robust clustered standard errors and Driscoll–Kraay corrected SEs will yield reliable inference. Together these results provide strong evidence that overconfidence considerably shapes trading activity in Indonesia, which further justifies the threshold analysis.

Threshold regressions

**Table 5. Threshold Regression Result**

| Threshold Variable | Tau (τ) | β_L (Low Regime) | β_H (High Regime) | Δ (β_H-β_L) | $\chi^2$ | p-value | 95% CI for Δ |
|---|---|---|---|---|---|---|---|
| Lagged Return | 0.0115 | 0.00112 | 0.00193 | 0.00081 | 13.600 | 0.000 | [0.00036, 0.00127] |
| IHSG Return | -0.0059 | 0.0011 | 0.00149 | 0.00039 | 1.880 | 0.170 | n.s. |
| Volatility (21d) | 0.0261 | 0.00076 | 0.00223 | 0.00148 | 11.000 | 0.001 | [0.00061, 0.00223] |

Source: Authors' estimation using Hansen (1999) panel threshold regression methodology

**Lagged Return Threshold**

Supporting H2, a statistically significant boundary is found at 1.15%. Below this bound, excess turnover has a small effect (β_L = 0.00112) on trading. Above this bound the coefficient increases to β_H = 0.00193, which is nearly double the effect. Economically, when a stock posts a gain of 1.15% or more on a particular day, the intensity of overconfidence driven trading amplifies by around 18% relative to average of the sample settled with self-attribution theory.

**Market Return (IHSG) Threshold**

In contrast, the result for market returns leads us to reject H4. The estimated threshold at –0.59% is also statistically insignificant (p = 0.170). This suggests that Indonesian investors seem rather unfazed by aggregate behavior of the broader market, and provide stronger reaction to firm specific cues, which is a sign of a retail driven market where stock selection and speculative stories outweigh top-down effect.

**Volatility Threshold**

Align with H3, a significant threshold emerges at 2.61% (21-day volatility). In tranquil times (below 2.61%), we estimated that the effect of overconfidence is small ($\beta\_L = 0.00076$). Then when volatility crosses the boundary, the coefficient increases to $\beta\_H = 0.00223$, or nearly three times larger. In economic terms, that shift in average daily turnover correlates to that of around 22%, which shows uncertainty and increases overconfidence driven speculation.

Following these statistical results, this section discusses these results as they relate to behavioral finance theory and the recent empirical literature as well, identifying theoretical contributions and practical implications.

**Overconfidence and trading activity**

The baseline results lend direct evidence that overconfidence does play a significant role in trading behavior in Indonesia. The positive and significant impact of excess turnover fits well within the established literature showing overconfident investors trade too frequently and earn lower net returns (Odean, 1999; Barber & Odean, 2000). Recent studies generally reinforce this narrative: Chen and Gong (2021) document that miscalibration and aggressiveness in trading are both central avenues by which overconfidence is exhibited in emerging markets, and Chuang, Lee, and Wang (2020) show that self-attribution bias can explain post-return trading patterns in Asian markets.

Also, the impact of lagged returns on turnover suggests a strong role of self-attribution (Daniel, Hirshleifer, & Subrahmanyam, 1998; Gervais & Odean, 2001). Recent evidence from the region in Southeast Asia by Nguyen and Pham (2023) also showed that after a positive price movement investors outweigh their personal skill, which adds to the behavioral rationale.

The negative relation of firm size and PBV with turnover suggests that speculative activity is directed toward small and undervalued firms, which aligns with studies by Bakar and Yi (2021) conducted in Malaysia and Al-Mamun et al. (2022) in ASEAN markets, confirming the retail-driven speculation focuses on small issuers. The positive influences of beta and volatility align with research by Verma and Panwar (2025), who identify high-risk stocks as focal points of speculative trading in Asia.

**Regime Dependence of Overconfidence**

The threshold regression results provide new evidence that overconfidence is non-linear and has regime dependence. The significant lagged return threshold at 1.15% suggests that, when faced with positive shocks, speculative trading amplifies, consistent with recent evidence

provided by Li, He, and Zhao (2022), who found a return-induced optimism led to excessive turnover in Chinese A-shares.

The volatility threshold at 2.61% also suggests that uncertainty serves to amplify speculation. This finding relates to the noise trader risk model (De Long et al., 1990) and corresponds to recent cross-market studies by Akhtar, Faff, and Oliver (2021), who find that volatility shocks exacerbate the behavioral response of retail traders, and Zhang and Chen (2024), who find identified volatility thresholds act as triggers for momentum-based speculation.

In contrast, the relatively small importance of the market return threshold indicates Indonesian investors are purely more sensitive to firm-specific signals than to aggregate market signals. That finding is consistent with Indonesia's domestic retail-based market structure (OJK, 2021), and recent work by Budiman, Pradana, and Sari (2025) reported that Indonesian investors relied primarily on stock-level narratives and behavioral biases (primarily overconfidence and mental accounting) than macroeconomic signals.

The findings also contribute to behavioral finance literature by showing overconfidence can be dependent on a few thresholds of performance and uncertainty in emerging markets. Prior work in China (Chen, Rui, & Xu, 2012), India (Kumar, 2022), and Turkey (Bayar & Yildirim, 2017) have suggested similar nonlinearities, however, this is the first study to demonstrate those nonlinearities in Indonesia using high-frequency panel data. More contemporaneous studies, such as He, Li, and Shen (2019) for China, and Verma & Panwar (2025) for a broader Asia context, have highlighted that volatility and changes in stable periods should be considered, and that is corroborated in the data here.

For regulators, the identification of firm-specific return and volatility levels provides potentially actionable early-warning signals for speculative bubbles. This fits well with the how the recent literature of market surveillance has suggested regulators use threshold-based triggers for monitoring financial stability in emerging market context (World Bank, 2022; IMF, 2023). For investors, the findings highlight the dangers of over-trading; specifically, when the firm is in a high-volatility regime or it is trading strongly after being in a low volatility regime, emphasizing the importance of the ability to constructively ignore market noise and stick to a disciplined risk-adjusted trading strategy (Brière & Szafarz, 2021). Ultimately, this work expands our own understanding of theory by arguing that overconfidence is also likely to be regime dependent not simply a trait and contributes to practice by providing measurable thresholds capable of being used by regulators or investors to monitor instances of speculative irrationality in emerging markets.

## CONCLUSION

This study provided empirical evidence on the threshold dynamics of investor overconfidence in the Indonesian equity market, using firm-level daily data from IDX80 constituents (2015–2024). Overconfidence, measured by excess turnover, exhibited a positive and statistically significant effect on trading activity, with the relationship found to be nonlinear and conditional upon firm returns and volatility. Trading responses nearly doubled when total firm returns exceeded 1.15% and tripled under volatility above 2.61%, supporting the view that overconfidence is a regime-dependent bias rather than a fixed trait. By applying Hansen's

(1999) panel threshold regression, this study identified measurable tipping points that amplify speculative behavior, offering actionable insights for regulators and investors in managing risk during high-performance or high-uncertainty regimes. A key suggestion for future research is to expand the range of overconfidence proxies, incorporate additional macro-financial thresholds, conduct cross-country comparisons among ASEAN or other emerging markets, and explore advanced modelling approaches such as double-threshold, time-varying threshold frameworks, or machine learning-enhanced predictive models to refine the understanding and forecasting of behavioral amplification.

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