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Beyond Fundamentals: How Investor Overconfidence Shapes Firm Valuation in India

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Beyond Fundamentals: How Investor Overconfidence Shapes Firm Valuation in India

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Abstract

Purpose: This study investigates the impact of investor overconfidence on firm valuation within India's dynamic and rapidly evolving equity market. Anchored in behavioural finance theory, which posits that cognitive biases and limits to arbitrage generate persistent mispricing, the analysis explores how overconfident trading behaviour contributes to valuation distortions. Overconfident investors tend to trade excessively and react asymmetrically to gains versus losses, leading to systematic deviations from firms' intrinsic values.

Methodology: Utilizing a balanced panel of 1,367 continuously listed non-financial firms over the period April 2000 to March 2023, the study employs firm-fixed effects regressions and dynamic panel estimations using the Arellano-Bond Generalized Method of Moments (GMM). This methodological approach addresses potential issues of unobserved heterogeneity and endogeneity. To enhance empirical robustness, multiple proxies for investor overconfidence are implemented, including abnormal trading volume, turnover ratios, and changes in share issuance.

Findings: The results reveal a statistically significant positive association between investor overconfidence and firm valuation. This indicates that behavioural biases among investors contribute to sustained pricing inefficiencies, with overconfidence playing a key role in driving firm valuations above their intrinsic worth. The findings underscore the persistence of behavioural anomalies in price formation, especially within the context of an emerging market like India.

Unique Contribution to Theory, Policy, and Practice: Theoretically, this study enriches the behavioural finance literature by providing robust evidence that overconfidence-induced trading behaviour influences firm valuation, supporting the view that psychological factors can lead to systematic mispricing. From a policy perspective, the findings highlight the need for regulatory frameworks that mitigate sentiment-driven inefficiencies in capital markets.

Keywords: *Asset Pricing, Overconfidence Bias, Behavioural Finance, Firm Valuation, Panel Data Models, Generalized Method of Moments, Emerging Markets*

1. Introduction

Traditional asset pricing models grounded in the Efficient Market Hypothesis (EMH) posit that investors process information rationally and prices fully reflect available data (Fama, 1970). However, persistent anomalies such as excess volatility, momentum, and post-earnings announcement drift challenge this assumption (Shleifer, 1997; Hirshleifer, 2001). In response, behavioral finance integrates psychological insights to explain deviations from rational behavior (Barberis & Thaler, 2003; Kahneman & Tversky, 1979), with investor overconfidence emerging as a pivotal cognitive bias. Overconfident investors overestimate the accuracy of their private information, leading to excessive trading, underreaction to public signals, and mispricing (Odean, 1998; Daniel, Hirshleifer, & Subrahmanyam, 1998; Barber & Odean, 2001).

Theoretical models such as those by Barberis, Shleifer, and Vishny (1998), and Hong and Stein (2007) explain how mispricing persists when arbitrage is limited or costly. While these frameworks are well-developed in mature markets, their application in emerging economies remains limited, despite structural characteristics, such as institutional voids, higher information asymmetry, and unsophisticated investor bases, that often intensify behavioral distortions (Morck, Yeung, & Yu, 2000; Mitra & Bhaduri, 2015). India exemplifies such conditions, with a growing but fragmented equity market, high retail investor participation, and evolving regulatory norms that may amplify cognitive biases like overconfidence. Although investor sentiment has attracted growing attention in Indian markets, few studies rigorously examine how overconfidence impacts firm valuation. Most research focuses on micro-level trading behavior (Barber & Odean, 2001; Kumari & Mahakud, 2015), with limited exploration of aggregate-level mispricing. This study addresses that gap by constructing robust, market-based proxies of investor overconfidence and empirically evaluating its influence on firm-level valuation distortions in India. Grounded in bounded rationality (Simon, 1955) and prospect theory (Kahneman & Tversky, 1979), this paper also builds on behavioral asset pricing models (Daniel et al., 1998; Barberis et al., 1998), which argue that sentiment-driven misbeliefs are not promptly arbitraged away. De Long et al. (1990) further demonstrate how noise traders, overconfident agents acting on misperceived signals, can drive persistent mispricing. Empirical studies support this view, showing that overconfidence leads to excessive trading, reliance on salient private signals, and price reversals, particularly in small-cap, illiquid, and volatile stocks (Glaser & Weber, 2007; Brown & Cliff, 2005; Siganos et al., 2017). In the Indian context, early contributions by Kumari and Mahakud (2015) and Kumar and Goyal (2016) provide indicative evidence of sentiment-induced distortions, but comprehensive firm-level analyses remain sparse.

This study contributes to behavioral finance in five significant ways. *First*, it develops and validates multiple volume-based proxies for investor overconfidence, in line with Chuang and Lee (2006) and Statman et al. (2006). *Second*, it employs panel-data techniques, fixed effects, random effects, and dynamic GMM estimators (Arellano & Bond, 1991; Roodman, 2009) to address endogeneity and firm heterogeneity. *Third*, it provides one of the first large-sample studies on firm-level valuation effects of overconfidence in India, where investor heterogeneity, driven by

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digitally enabled retail investors and institutional participants, offers a unique empirical setting (SEBI, 2023). *Fourth*, the study contextualizes overconfidence within emerging market frictions such as policy uncertainty, informational asymmetry, and volatility (Bekaert & Harvey, 2003). *Finally*, the triangulation of overconfidence measures, based on turnover anomalies, divergence from analyst forecasts, and excess trading volumes, adds robustness, responding to recent methodological calls in the Review of Financial Studies and Journal of Financial Economics (Deaves et al., 2009; Glaser & Weber, 2007). Overall, this research extends behavioral asset pricing into underexplored institutional contexts and provides insights relevant for regulators, investors, and policymakers seeking to mitigate valuation inefficiencies arising from cognitive biases.The rest of the paper is organized as follows: Section 2 reviews the theoretical literature; Section 3 outlines the methodology and variable construction; Section 4 presents results; and Section 5 concludes with implications and future research directions.

Theoretical Framework and Related Literature

Traditional finance theory assumes that agents are fully rational, maximize utility, and form expectations using Bayesian principles, resulting in efficient markets where prices reflect all available information (Fama, 1970; Von Neumann & Morgenstern, 1944; Muth, 1961). Within this paradigm, psychological factors are largely considered noise, with arbitrage assumed to eliminate mispricing (Ross, 1976). However, anomalies such as momentum (Jegadeesh & Titman, 1993), excess volatility (Shiller, 1981), and post-earnings announcement drift (Bernard & Thomas, 1989) challenge this rational framework. Behavioural finance addresses these inconsistencies by incorporating insights from cognitive psychology, particularly bounded rationality and limits to arbitrage (Simon, 1955; Shleifer & Vishny, 1997), emphasizing that psychological biases can exert systematic effects on market outcomes (Barberis & Thaler, 2003; Hirshleifer, 2001).

Investor overconfidence, a key behavioral bias, refers to the overestimation of one's predictive abilities and the reliability of private information. It leads to excessive trading (Odean, 1998; Barber & Odean, 2000), inflated valuations (Gervais & Odean, 2001), and feedback loops that fuel speculative dynamics (Scheinkman & Xiong, 2003). Theoretical models by Daniel et al. (1998) and Hong and Stein (2007) demonstrate how overconfident investors underreact to public signals and overreact to private beliefs, creating persistent mispricing, especially when arbitrage is delayed or costly. Empirically, overconfidence increases trading intensity and volatility (Hilary & Hsu, 2011), but firm-level evidence from emerging markets remains sparse, despite contextual features like retail dominance, high information asymmetry, and regulatory frictions (Chopra et al., 1992; Kumari & Mahakud, 2015). This study builds on these theoretical foundations by empirically linking aggregate investor overconfidence to firm-level valuation anomalies in India.

Investor Overconfidence in Financial Decision-Making

Overconfidence, a pervasive cognitive distortion, results in overestimated knowledge and underestimated risks, leading to suboptimal investment choices. Originating in the psychology of heuristics (Kahneman & Tversky, 1974), this bias is well-established in financial behavior. Odean

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(1998) found that overconfident investors trade excessively, eroding net returns. Daniel et al. (1998) further argued that overconfidence skews attention toward private signals, distorting price formation. Barber & Odean (2000, 2001) confirmed that men, typically more overconfident than women, traded more frequently and earned lower returns. Glaser & Weber (2007) and Deaves et al. (2009) reinforced these findings across demographic and experiential dimensions. Psychological underpinnings such as self-attribution bias (Miller & Ross, 1975), illusion of control (Langer, 1975), and confirmation bias (Russo & Shoemaker, 1992) further entrench overconfident behavior. Demographic and cultural influences also matter: Chen et al. (2007) showed higher overconfidence-driven trading among Chinese investors, while Bar-Yosef & Venezia (2006) emphasized the roles of education and income. In India, Chandra (2008) observed suboptimal portfolio allocations due to overconfidence; similarly, Lai et al. (2013) and Chuang and Lee (2006) found persistent overconfident behavior among Asian investors across market cycles.

Overconfidence is also central to asset pricing anomalies and corporate financial decisions. It leads to inflated investment-cash flow sensitivity among managers who overestimate project returns (Chiu et al., 2022), and distorts asset pricing by contributing to a misaligned Security Market Line (Chen, Li, & Yu, 2020). Zhou (2011) and Han et al. (2020) find that overconfidence drives excessive volatility and volume, especially when public information is mistaken for private insight, reinforcing price instability and SML anomalies.

Moreover, overconfidence disproportionately affects retail investors during market upswings, where limited information processing capacity amplifies losses (Barber & Odean, 2016). Measurement has evolved from trading-based proxies to survey-based methods capturing overprecision and overplacement biases, offering richer behavioral integration into econometric models (Glaser & Weber, 2011; Grežo, 2020). Statman et al. (2006) and Meier (2018) linked aggregate confidence to trading volumes and risk tolerance, emphasizing the macro-level implications of micro-level psychological distortions. In sum, overconfidence is not merely an individual bias but a structural force shaping trading behavior, pricing dynamics, and capital allocation, particularly salient in emerging markets. This study builds on this foundation by developing a triangulated measurement framework of investor overconfidence and examining its valuation effects in the Indian equity market.

Overconfidence Bias in the Indian Stock Market

Overconfidence bias, where investors overestimate their knowledge and underestimate risks, is well-established in behavioral finance literature (Bremer & Kato, 1996; Huddart et al., 2009). In emerging markets like India, its manifestation is shaped by distinct features such as high market volatility, evolving regulation, and a demographically diverse investor base. Empirical studies confirm the presence of overconfidence among Indian investors. Prosad et al. (2015) used VAR models on NIFTY 50 data (2006–2013), detecting both overconfidence and disposition effects, with the former being more prominent. Mushinada & Veluri (2018) employed EGARCH models and identified self-attribution bias linked to heightened trading volumes and volatility. Similarly, Kumar & Prince (2022) found overconfidence to be more pronounced during bullish pre-crash periods, indicating the influence of market conditions on investor psychology. Sushmita et al. (2018) observed heuristics-driven decisions in the BSE SENSEX, while Kansal & Singh (2018) noted that high income, frequent trading, and large-cap exposure increase susceptibility to overconfidence, though demographic variables like age and gender were not significant. Recent studies highlight the evolving and multifaceted nature of overconfidence. Nair and Shiva (2024) developed a formative index capturing four dimensions—accuracy, perceived control, positive illusions, and past success, underscoring its psychological complexity. Mushinada and Veluri (2019) found a strong covariance between self-attribution and overconfidence, suggesting the interaction of multiple behavioral traits in shaping investment behavior. Moreover, sectoral and temporal heterogeneity is evident: Kumar and Prince (2022) observed intensified overconfidence during regulatory and pre-election phases, while Safeeda and Ganesh (2024) documented stronger effects in high-beta and small-cap stocks post-COVID.

Despite these insights, much of the existing research remains limited in scope, either temporally constrained or focused on generalized market patterns. There is a paucity of studies that isolate the firm-level impact of overconfidence or explore its dynamic behavior across investor types and market phases. Calls for more granular, multidimensional proxies (Glaser & Weber, 2011; Deaves et al., 2009) remain largely unaddressed in the Indian context.

This study addresses this gap by integrating firm-specific proxies and dynamic panel econometric methods to examine how overconfidence distorts firm valuation across market cycles. In doing so, it contributes to a deeper behavioral understanding of asset pricing in emerging economies.

Research Design

Data, sample, and variable measurement

This study employs an unbalanced quarterly panel of non-financial firms listed on the National Stock Exchange (NSE) of India from April 2000 to March 2023. The extended time frame spans key macroeconomic events, such as the global financial crisis, COVID-19, and India's digital equity market transformation, allowing analysis of overconfidence across diverse market regimes. Quarterly frequency enables finer modeling of intra-year sentiment dynamics, consistent with behavioral finance literature (Baker and Wurgler, 2002, 2006, 2007, 2012; Huang et al., 2015). The sample excludes financial firms due to their structurally distinct balance sheets and regulatory environments (Fama & French, 1992; Booth et al., 2001), as well as firms undergoing major structural events (e.g., M&A, delistings), to preserve data integrity. All market and financial variables are sourced from the CMIE Prowess database. To mitigate outlier effects, continuous variables are winsorized at the 1st and 99th percentiles. The dependent variable is Tobin's Q, approximated as: (Market value of equity + Book value of debt) / Book value of total assets (Chung & Pruitt, 1994). This ratio captures both intrinsic firm value and market expectations, making it suitable for analyzing sentiment-induced mispricing (Gompers et al., 2003; Dittmar & Mahrt-Smith, 2007).

The model controls for key firm-level characteristics:

Market Capitalization ($MktCap_{it}$): Serves as a proxy for firm size and investor visibility. Larger firms face lower information asymmetry, higher analyst coverage, and reduced mispricing (Liu & Magnan, 2011; Merton, 1987).

Return on Assets (ROA_{it}): Measures operational profitability, reflecting both managerial efficiency and capital productivity. ROA is positively associated with firm value, though its effect may be distorted under speculative sentiment (Baker et al. 2012; Hassan, 2018).

Leverage ($Leverage_{it}$): Defined as total debt over total assets, leverage captures financial risk and is sensitive to both fundamentals and behavioral distortions. Overconfident investors often underweight downside risk, amplifying misvaluation in high-leverage firms (Feng & Wu, 2018; El Ghoul et al., 2017).

Turnover ($Turnover_{it}$): Used as a sentiment proxy, abnormal turnover signals speculative trading and belief over precision (Statman et al., 2006; Glaser & Weber, 2007). In sentiment-driven environments, turnover also correlates with herding and bubble-like valuations, especially in retail-dominated markets like India. This empirical specification blends neoclassical and behavioral elements to isolate the effects of overconfidence on firm valuation in an emerging market setting.

Investor Overconfidence

Overconfidence bias, a central construct in behavioral finance, refers to investors' systematic overestimation of private signal precision and underestimation of risks (Odean, 1998; Daniel et al., 1998). As overconfidence is inherently latent, this study adopts a multi-proxy approach grounded in established literature (Glaser & Weber, 2007; Deaves et al., 2009). This design enhances construct validity and aligns with best practices in behavioral asset pricing, which infer sentiment from behaviorally indicative observables (Barberis et al., 2007; Huang et al., 2015).

Change in the Trading Volume

Trading volume is a well-established proxy for investor overconfidence, reflecting the tendency of investors to trade excessively based on overestimated private signal precision (Odean, 1998; Barber & Odean, 2002). This is particularly pronounced in emerging markets, where retail dominance and limited arbitrage intensify behavioral frictions (Chuang & Lee, 2006). Following standard literature, the change in trading volume (Δtv_t) is defined as:

$$\Delta tv_{it} = \frac{tv_{it} - tv_{it-1}}{tv_{it-1}}$$

A positive Δtv_t reflects increased trading aggressiveness tied to overconfidence, validated across market phases and investor types (Deaves et al., 2009). It is particularly insightful during bullish trends, speculative windows, or earnings announcements.

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Turnover Rate

The turnover rate (TR) serves as another reliable proxy, especially when direct sentiment measures are unavailable. It captures trading intensity and beliefs about private signal accuracy (Statman et al., 2006). Overconfident investors trade more, underestimate risks, and contribute to market volatility (Barber & Odean, 2001). Turnover is also linked with liquidity and investor disagreement (Griffin et al., 2007; Tekce & Yilmaz, 2015). In emerging markets, where arbitrage is limited, turnover becomes even more reflective of behavioral patterns (Li & Zhang, 2020). It is computed as:

$$turn_{it} = \frac{tv_{it}}{nso_{it}}$$

Where nso_{it} denotes shares outstanding. This normalized measure enables cross-sectional and panel analyses.

The increase in the number of shares outstanding

Equity issuance serves as an indirect proxy for investor overconfidence, particularly when firms exploit perceived overvaluation driven by exuberant sentiment (Malmendier & Tate, 2005; Baker & Wurgler, 2002). This proxy extends beyond managerial overconfidence to reflect broader sentiment-driven issuance patterns (Polk & Sapienza, 2008). Elevated issuance often coincides with bullish or speculative phases (Gilchrist et al., 2005), especially in markets with pronounced valuation asymmetries.

The operational variable is the positive change in outstanding shares:

$$iso_{it} = \begin{cases} iso_{it}, & if\ iso > 0 \\ \theta, & if\ iso \leq 0 \end{cases}$$

Where iso_{it} denotes the quarterly change, and θ is a small constant to maintain panel consistency.

This ensures analytical tractability across firms.

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Table 1: Operationalization of Variables

Variables	Definition	Measurement and Sources
Tobin's Q ratio (Tobin's Q)	Measures firm valuation by comparing the market value of assets to their replacement cost. It serves as a proxy for investment opportunities.	$\text{Tobin'sQ} = \frac{\text{Mkt value of Equity+Total Liabilities}}{\text{Total Assets}}$ Source: CMIE Database for Indian Equity Markets
Market capitalization (MktCap)	Represents the total equity market value of a firm; used as a proxy for firm size.	$\text{MktCap}_{it} = \text{Share price}_{it} *$ $\text{Number of Outstanding Shares}_{it}$ Source: CMIE
Leverage Ratio (Leverage)	Captures capital structure by measuring the proportion of assets financed by debt.	$\text{Leverage} = \frac{\text{Total Debt}}{\text{Total Assets}}$ Source: CMIE
Return on assets (ROA)	Indicates the firm's efficiency in generating profit from its assets.	$\text{ROA}=\frac{\text{Net Profit (after tax)}}{\text{Total Assets}}$
Investor overconfidence (Δtv_{it})	Proxies overconfidence by the change in trading volume relative to the previous period.	$\Delta tv_{it} = \frac{tv_{it}-tv_{it-1}}{tv_{it-1}}$ Source: CMIE

Methodology

To rigorously assess the relationship between investor overconfidence and firm valuation in the Indian equity market, this study adopts a multi-stage econometric strategy embedded within a panel data framework. This framework allows us to exploit both cross-sectional and time-series variation, while controlling for firm-level heterogeneity, dynamic feedback effects, and endogeneity concerns, all of which are crucial for obtaining unbiased estimates in corporate finance research (Baltagi, 2008; Wooldridge, 2010).

We begin by specifying a reduced-form valuation model of the following structure:

$$Q_{it} = \alpha_i + \beta_1 \text{Overconfidence}_{it} + \beta_2 X_{it} + \gamma_t + \mu_i + \varepsilon_{it} \quad \text{(Eq. 1)}$$

Where Q_{it} denotes Tobin's Q for firm *i* at time *t*, $\text{Overconfidence}_{it}$ represents the key behavioural variable proxied through trading dynamics (e.g., changes in trading volume, turnover rate, and share issuance), X_{it} is a vector of control variables (firm size, leverage, profitability), γ_t are time fixed effects capturing macroeconomic and regulatory shocks, μ_i denotes firm-specific unobserved heterogeneity, and ε_{it} is the idiosyncratic error term.

Static Panel Estimators: Benchmark Analysis

We begin with pooled Ordinary Least Squares (OLS), fixed effects (FE), and random effects (RE) estimators. While pooled OLS assumes homogeneity across firms, FE accounts for unobserved, time-invariant firm-level heterogeneity. The specification is:

$$Q_{it} = \alpha_i + \beta_1 \text{Overconfidence}_{it} + \beta_2 X_{it} + \gamma_t + \varepsilon_{it} \qquad \text{(Eq. 2)}$$

To decide between FE and RE, the Hausman (1978) specification test is conducted. The Breusch-Pagan Lagrange Multiplier (LM) test is used to choose between pooled OLS and RE (Greene, 2012).

Addressing Endogeneity: Dynamic Panel GMM Estimators

To address dynamic endogeneity and simultaneity bias, we estimate a dynamic panel model where past firm valuation may influence current valuation, and where overconfidence proxies may be endogenous:

$$Q_{it} = \alpha_i + \delta Q_{it-1} + \beta_1 \text{Overconfidence}_{it} + \beta_2 X_{it} + \gamma_t + \mu_i + \varepsilon_{it} \qquad \text{(Eq. 3)}$$

In this context, the inclusion of the lagged dependent variable induces correlation with the error term, rendering standard estimators inconsistent. Therefore, we employ the Generalized Method of Moments (GMM) approach developed by Arellano and Bond (1991), which uses first-differencing to remove firm effects and instruments lagged levels of regressors to correct for endogeneity However, when the regressors exhibit persistence, the difference GMM may suffer from weak instrument problems. To enhance efficiency and instrument strength, we apply the System GMM estimator proposed by Blundell and Bond (2000). This estimator combines equations in levels and first differences, using appropriate lagged instruments for each system. For the differenced equation, lagged levels are used as instruments. For the level equation, Lagged differences are used as instruments. This methodology is robust to heteroskedasticity and autocorrelation within panels and is particularly suited for datasets with a large number of cross-sections and relatively short time periods (Roodman, 2009).

Diagnostic and Robustness Checks

To validate instrument relevance and model specification, we conduct the following diagnostics:

Hansen J-test of overidentifying restrictions to assess instrument validity. Arellano-Bond test for autocorrelation in first-differenced residuals. Difference-in-Hansen tests for instrument subsets.

Further robustness is ensured by estimating alternative model specifications using different proxies for overconfidence and conducting sub-sample analyses across firm sizes, industry classifications, and market phases.

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Empirical Findings and Discussions

Table 2: Descriptive Statistics and Pairwise Correlations

Panel A: Descriptive Statistics					
Variables	mean	Q1	Median	Q3	Std. Dev.
Tobin's Q	2.735	1.908	2.000	2.786	1.856
MktCap	8.134	7.889	7.999	8.990	1.720
Leverage	0.405	0.358	0.380	0.470	0.224
ROA(%)	4.445	0.990	3.120	5.234	7.456
ΔTV	0.407	0.387	-0.034	-0.045	1.980
Turn	1.567	0.890	0.604	1.876	2.879
iso	0.234	0.003	0.012	0.016	0.678
Panel B: Pairwise Correlations					
Tobin's Q	1.000				
MktCap	0.201	1.000			
Leverage	0.054	0.062	1.0000		
ROA	0.044	0.123	-0.056	1.000	
ΔTV	0.101	-0.056	0.013	0.054	1.000
Panel C: Correlation of investor overconfidence proxies					
ΔTV	1.000				
Turn	0.732	1.000			
iso	0.689	0.778	1.000		

Notes: *Summary statistics show the mean, median, and standard deviation (Std). Q1 and Q3 stand for the first and third quartile; *, # Significance at 1.5% and level, respectively, in the correlation matrix.*

Descriptive Statistics and Preliminary Insights

Table 2 (Panel A) presents summary statistics for key variables over 2000Q2–2023Q1. The mean Tobin's Q of 2.735 (SD = 1.856) reflects considerable dispersion in firm valuations, indicative of sentiment-driven mispricing often seen in emerging markets (Baker & Wurgler, 2006). The average log market capitalization (8.134) denotes a sample dominated by mid- to large-cap firms, consistent with studies linking firm size to valuation premiums and visibility (Hou, Xue, & Zhang, 2015). Leverage averages 0.405, and ROA is 4.445% with substantial heterogeneity (SD = 7.456), in line with Indian capital structure literature (Booth et al., 2001).Behavioural proxies, ΔTV, Turn, and iso, display considerable variation, affirming active investor behavior. High mean turnover (1.567) and trading volume changes suggest frequent retail-driven trading, consistent with overconfidence biases in Indian markets (Chandra, 2008; Prosad et al., 2015). The iso variable,

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with a mean of 0.234, captures sporadic but sentiment-linked equity issuances (Baker & Wurgler, 2002).

Panel B reveals a positive correlation between Tobin's Q and firm size (r = 0.201), supporting the view that larger firms attract valuation premiums. Leverage and ROA show weak correlations with Q, implying limited direct effects outside of controlled regression settings. Panel C shows strong associations among overconfidence proxies, ΔTV–Turn (r = 0.732), Turn–iso (r = 0.778), suggesting shared behavioral underpinnings (Statman et al., 2006), but without multicollinearity concerns (Greene, 2012). Overall, the descriptive patterns provide initial support for the hypothesis that investor overconfidence, reflected in trading activity and equity issuance, plays a role in firm valuation dynamics. These insights motivate the need for rigorous multivariate analysis to address endogeneity and firm-level heterogeneity.

5.1.1 Time-Series Trends of Investor Overconfidence Proxies (April 2000 to March 2023)

The time-series evolution of three investor overconfidence proxies, Change in Trading Volume (ΔTV), Turnover Rate (Turn), and Share Issuance (ISO), reveals strong alignment with market phases. ΔTV and Turn show pronounced spikes during bullish periods (e.g., 2006–2008, 2020–2021), reflecting elevated trading driven by overoptimism and self-attribution bias (Barber & Odean, 2000; Statman et al., 2006). ISO trends, though less frequent, coincide with market highs, suggesting managers issue equity when investor sentiment is strong (Baker & Wurgler, 2007; Malmendier & Tate, 2005). The co-movement of these proxies during high-sentiment periods reinforces their behavioral validity in capturing investor overconfidence across cycles.

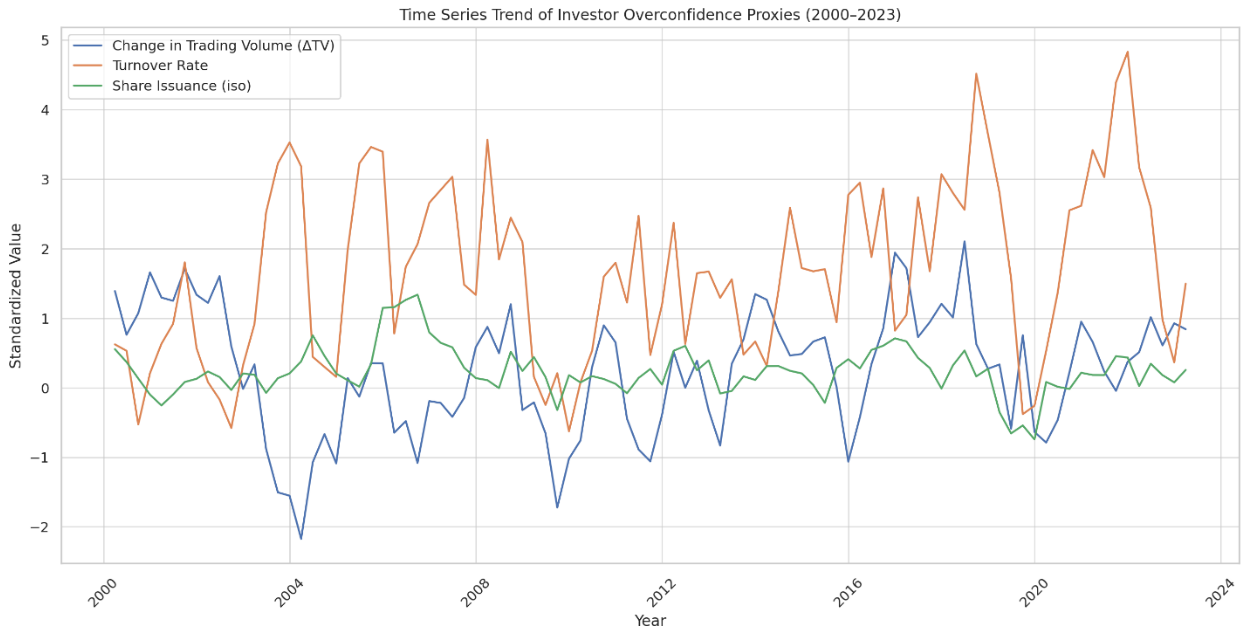

Figure 1: *Time Series Trends of Investor Overconfidence Proxies in the Indian Equity Market (April 2000 to March 2023)*

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5.2 Investor Overconfidence and the Firm Valuation

Table 3: Investor Overconfidence and the Firm Valuation

H_0: Investor overconfidence bias positively affects the valuation of firms in India's emerging stock market.

$$Q_{it} = \alpha_i + \beta_1 \text{Overconfidence}_{it} + \beta_2 X_{it} + \gamma_t + \mu_i + \varepsilon_{it}$$

Variables	Coef.	Se.	t
intercept	−15.6974***	1.234	-7.889
MktCap	2.013***	0.938	6.775
Leverage	4.087***	0.956	2.234
ROA	-0.032	0.023	0.093
Overconfidence	4.356***	0.008	5.234
F-Statistics	22.1534	x^2	320.456

****, **, and * denote statistical significance at the 1%, 5% and 10% levels, respectively. Abbreviations: Coef., coefficient; Se., standard errors; t, t-statistics.*

Table 3 presents the benchmark regression results evaluating the effect of investor overconfidence on firm valuation, proxied by Tobin's Q, while controlling for firm size (MktCap), leverage, and profitability (ROA). The coefficient for Investor Overconfidence is positive and highly significant (β = 4.356, t = 5.234), supporting the hypothesis that psychological biases inflate firm valuation beyond fundamentals. This finding corroborates the behavioral asset pricing framework (Daniel et al., 1998; Gervais & Odean, 2001), emphasizing the role of sentiment-driven mispricing in markets with high retail participation and limited arbitrage, such as India (Kumari & Mahakud, 2015; Adebambo & Yan, 2018). The evidence aligns with Barberis and Thaler's (2003) proposition that non-fundamental behavioral forces shape price levels in emerging markets.

Firm Size (MktCap) shows a strong positive relationship with valuation (β = 2.013, t = 6.775), consistent with informational efficiency theories. Larger firms are more visible, enjoy broader investor bases, and lower asymmetry, thus commanding higher valuations (Fama & French, 1992; Liu & Magnan, 2011). This size premium is amplified in India's retail-dominated market, where firm visibility often substitutes for financial analysis (La Porta et al., 2002). Leverage also exhibits a significant positive effect (β = 4.087, t = 2.234), deviating from classical finance predictions where high debt implies risk and lower valuation (Modigliani & Miller, 1958). Instead, in the Indian context, leverage may signal managerial confidence or growth potential, especially given the importance of banking relationships and credit access (Baker & Wurgler, 2002; Graham & Leary, 2011; Ghosh, 2008).

In contrast, ROA is statistically insignificant (β = –0.032, t = 0.093), suggesting that firm profitability does not significantly influence valuation in this setting. This counters traditional valuation models (Penman & Zhang, 2002) and may indicate inefficiencies or behavioral distortions in how investors process earnings signals in emerging markets (De Bondt & Thaler, 1995; Hirshleifer, 2001). The significant F-statistic (F = 22.15) and chi-square (χ^2 = 320.46) confirm overall model robustness. The results confirm that investor overconfidence is a statistically and economically significant determinant of firm valuation in India. Notably, the insignificance of ROA and the dominance of sentiment-based variables reinforce the idea that behavioral biases—not fundamentals- drive valuation in retail-heavy and inefficient markets (Shleifer & Vishny, 1997; Hong & Stein, 1999). For policymakers, this underscores the urgency of strengthening financial literacy and market transparency. For firms and institutional investors, it signals caution in relying on elevated market valuations during sentiment-driven cycles, especially when planning capital market actions.

5.3. Robustness Analysis: Validating the Overconfidence–Valuation Link

Table 4 presents robustness checks based on three alternative model specifications and subsamples, addressing firm-year heterogeneity and potential structural variations. The coefficient for investor overconfidence remains positive and statistically significant across all models (range: 0.0979–0.1020; SE ≈ 0.0505), reaffirming the stability of the core findings and the behavioral channel in firm valuation. Though the magnitudes are slightly attenuated relative to the baseline estimates, their consistency supports the persistence of sentiment-induced mispricing (Daniel et al., 1998; Odean, 1999). The intercepts remain large and negative, highlighting unexplained cross-sectional variation in firm value despite accounting for key behavioral and financial determinants. Market capitalization maintains a strong positive effect on Tobin's Q (coefficients: 1.953–2.234), indicating that larger firms enjoy valuation premiums, likely due to enhanced visibility, liquidity, and analyst following (Barberis & Shleifer, 2003; Kumar & Lee, 2006). Leverage also exhibits a positive and stable relationship with firm value (1.996–2.224), which may reflect the perception of debt as a credible signal of growth potential in emerging markets. This contrasts with developed market findings where high leverage is often penalized (Rajan & Zingales, 1995; Frank & Goyal, 2009), suggesting an India-specific interpretation shaped by mixed signaling and behavioral effects (Banerjee & De, 2019).Profitability, proxied by ROA, demonstrates a weak and statistically insignificant association with firm valuation across specifications (p-values > 0.10). This supports the view that in sentiment-driven markets, investors often underreact to internal performance metrics, favoring heuristic-based signals (Baker & Wurgler, 2006; Gervais & Odean, 2001). The F-statistics (12.768–15.456) and Chi-square values (204.65–265.32, significant at 1%) confirm the joint explanatory strength of the models. The R^2 values (0.392–0.410) indicate moderate explanatory power, consistent with empirical studies in emerging market contexts where behavioral shocks and sentiment asymmetries often reduce model fit (Chiah & Zhong, 2019; Adebambo & Yan, 2018).

These robustness results validate the theoretical underpinnings of bounded rationality and behavioral asset pricing. The persistent significance of the overconfidence proxy, even after controlling for firm size, leverage, and profitability, demonstrates the embedded role of sentiment in valuation processes (Kahneman & Tversky, 1979; Shefrin & Statman, 1994). Overall, the findings reinforce the study's contribution to behavioral finance by confirming that investor overconfidence is not a spurious anomaly but a structurally relevant force shaping valuations in an emerging market like India.

Table 4: Investor Overconfidence and Indian Firm Valuation

Robustness Checks

$$Q_{it} = \alpha_i + \beta_1 \text{Overconfidence}_{it} + \beta_2 X_{it} + \gamma_t + \mu_i + \varepsilon_{it}$$

Variables	(Δtv_{it})	(iso_{it})	$(turn_{it})$
Intercept	-16.345(4.012)	-17.234(4.876)	-13.112(3.762)
MktCap	2.234(0.453)	1.953(0.352)	2.2090 (0.463)
Leverage	1.996(0.434)	2.123(0.482)	2.224(0.500)
ROA	0.4035 (-0.0214)	0.3625(-0.0130)	0.4412(-0.0237)
Overconfidence	0.1020 (0.0501)	0.0979 (0.0505)	0.0987(0.0506)
F-Statistics	12.768	15.456	14.456
χ^2	204.65***	265.32***	211.45***
R^2	0.392	0.401	0.410
Total Observations	29,086	28,802	27,998

*Notes: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Robust standard errors in parentheses. These results were generated for Δtv, iso, and Turn in the regression analysis, one at a time.*

5.4 System GMM Estimation: Addressing Endogeneity and Dynamic Effects

To address potential endogeneity concerns such as reverse causality, unobserved heterogeneity, and dynamic persistence in firm valuation, Table 5 presents results using the two-step System Generalized Method of Moments (GMM) estimator (Arellano & Bover, 1995; Blundell & Bond, 1998). The dynamic structure of Tobin's Q justifies this method, especially given its autoregressive nature and correlation with investor sentiment. The lagged dependent variable is strongly positive and significant across all specifications ($\beta = 0.713$ to 0.789; $p < 0.01$), indicating valuation persistence consistent with dynamic capital structure adjustment models (Gomes, 2001; Flannery & Rangan, 2006). This further validates the use of GMM to overcome Nickell bias (Nickell, 1981).

Investor overconfidence remains positive and statistically significant ($\beta = 0.119$ to 0.143; $p < 0.05$ or better), reaffirming its role in inflating firm valuations. While these coefficients are smaller than in static regressions (Table 2), their sustained significance after correcting for endogeneity confirms the behavioral pricing effect predicted by Daniel et al. (1998), Gervais and Odean (2001), and Adebambo and Yan (2018). Among controls, market capitalization is only marginally significant in one model (β = 0.0603; $p < 0.1$), indicating limited explanatory power when sentiment and dynamics are accounted for, consistent with critiques of size-based pricing (Fama & French, 1992). Leverage and ROA remain statistically insignificant, suggesting that behavioral factors may overshadow fundamentals in driving short-term valuation in emerging markets (Baker & Wurgler, 2002; Brown & Cliff, 2005). Diagnostic tests confirm model validity. AR(2) p-values exceed 0.10, rejecting second-order serial correlation. Hansen's J and Difference-in-Hansen tests yield high p-values (0.426–0.879), affirming instrument validity. F-statistics are large and significant, underscoring joint model strength. Overall, the robustness of overconfidence effects in the dynamic setting supports behavioral finance theories (Barberis & Thaler, 2003; Kahneman & Tversky, 1979), with practical implications for regulators and investors in sentiment-driven markets.

Table 5: Robustness check with the system GMM Method

Robustness Check with the System GMM Method

$$Q_{it} = \alpha + \delta Q_{it-1} + \beta_1 \text{Overconfidence}_{it} + \beta_2 X_{it} + \gamma_t + \mu_i + \varepsilon_{it}$$

Variables	(Δtv_{it})	(iso_{it})	$(turn_{it})$
intercept	-0.683(0.263)	-0.402(0.201)	-0.389(0.198)
$Tobin's Q_{it-1}$	0.7886*** (0.0921)	0.7623*** (0.0882)	0.7125*** (0.0569)
MktCap	0.0603* (0.0340)	0.0316 (0.0294)	0.0325 (0.0237)
Leverage	−0.1762 (0.1922)	−0.1691 (0.1606)	−0.1468 (0.1082)
ROA	0.0009 (0.0023)	0.0204 (0.0222)	0.0234 (0.0179)
Overconfidence	0.1427*** (0.0297)	0.1187** (0.0459)	0.1319*** (0.0381)
Year Dummaies	included	included	included
F-value	449.80***	684.10***	441.70***
AR(1) test (p-value)	0.284	0.128	0.088
AR(2) test (p-value)	0.488	0.237	0.433
Hansen test of over-identification (p-value)	0.426	0.773	0.879
Diff-in-Hansen tests of exogeneity (p-value)	0.497	0.754	0.868
No. of observations	17, 071	17,071	16,649

*Notes: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Robust standard errors are in parentheses (). Each column displays regression results of a dynamic systems GMM equation where the three alternative proxies of overconfidence (Δtv, iso, and turn) are included in the regression analysis, one at a time. The Arellano-Bond test statistic, AR (1) and AR(2) follow an asymptotic normal distribution, with null (H0): No autocorrelation in the differenced errors. The residual values in the first difference AR (1) can be correlated by construction; however, there should not be a serial correlation in the second difference AR (2). The Hanson test of over-identification (J-statistic) follows a chi-square distribution; with a null hypothesis (H0) =, the instruments as a group are exogenous and specified correctly, which means that instruments in the dynamic system GMM are valid. Difference-in-Hansen exogeneity tests have a null (H0) = instruments in the systems GMM equation are exogenous.*

6. Conclusion of the Study

This study presents compelling evidence that investor overconfidence significantly influences firm valuation in India's equity market, offering behavioural insights beyond the rational expectations paradigm (Fama, 1970). Grounded in the theoretical frameworks of Kahneman and Tversky (1979), Daniel et al. (1998), and Barberis and Thaler (2003), the findings affirm that cognitive biases, particularly overconfidence, systematically distort asset prices. Using quarterly panel data for NSE-listed non-financial firms from 2000 to 2023, the analysis applies fixed-effects and dynamic System GMM estimators, supported by alternative sentiment proxies (turnover, share issuance). Across all models, overconfidence exhibits a consistent and significant positive effect on Tobin's Q, underscoring its role in valuation mispricing. Theoretically, this reinforces behavioural asset pricing models, revealing that sentiment-driven mispricing persists even in institutionally active and relatively liquid emerging markets. Empirically, the study aligns with findings from Brown and Cliff (2005), Adebambo and Yan (2018), and Chiah and Zhong (2019), suggesting that behavioural anomalies are structural, not episodic. From a practical standpoint, the results highlight the importance of incorporating sentiment indicators into valuation frameworks, especially for small- and mid-cap stocks where arbitrage constraints amplify behavioural biases. For policymakers, the findings advocate for integrating behavioural metrics into macroprudential surveillance and promoting investor literacy to mitigate systemic vulnerabilities. In sum, this study contributes novel evidence from a major emerging market, bridging behavioural finance with market-specific frictions. Future research could enhance this behavioural characterisation by leveraging macro sentiment indices, textual analytics, or high-frequency trading data to further unpack the psychology of valuation in developing economies.

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