



Detecting anchoring and disposition effects in the Egyptian stock exchange and their contribution to conditional volatility

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Abstract

This study investigates the empirical presence, persistence and conditional volatility implications of anchoring and the disposition effect among market participants in the Egyptian Stock Exchange (EGX) from 2010 to 2025. Anchoring is measured by whether nearness to the 52-week high (underreaction) and historical high (overreaction) predicts future returns and the disposition effect is estimated through the relationship between win-day and lose-day indicators and abnormal trading volume. Autoregressive moving average generalized autoregressive conditional heteroskedasticity (ARMA-GARCH) models assess the effect of each bias on conditional volatility for the full sample and four politically and economically distinct subperiods. Anchoring exerts a broadly stabilizing effect on volatility that persists across the sample but breaks down under the compounding shocks of the most recent regime. The disposition effect emerges as the most stable of the two biases, present in every subperiod without exception. Across both biases, the ARMA-GARCH estimations confirm that behavioral proxies are statistically significant determinants of conditional volatility, indicating that behavioral factors constitute a material component of equity risk. These findings contribute to the growing body of behavioral finance literature on Egypt with implications for portfolio strategy, volatility risk management and market regulation in Egypt and comparable emerging markets.

1. Introduction

Traditional financial theories assume that investors act rationally, processing information to make optimal decisions and that this rational behavior aggregates into efficient and correctly priced markets. However, the recurring appearance of market anomalies, speculative bubbles and financial crises has repeatedly challenged this assumption leading to behavioral finance emerging as a significant area of study (Kahneman & Tversky, 1979; Shahabuddin & Ali, 2024). Behavioral finance aims to explain real financial behavior by focusing on cognitive errors and psychological biases that influence investors' financial decisions instead of only describing an ideal decision-making framework and traditional proposals (Robert J Shiller, 2003; Thanh & Sahadewo, 2024).

Such cognitive biases as disposition effect and anchoring bias lead to investors' inability to make rational decisions that contribute to market inefficiencies. Disposition effect is manifested in investors' selling winning investments too soon and keeping losing investments for too long due to loss aversion that determines people's preference for avoiding losses over the pursuit of gains, resulting in risk-aversion and premature selling of winning stocks. Anchoring bias leads to investors' reliance on specific values as a reference point while making investment decisions about the future instead of using available information and new data. Consequently, these psychological tendencies contribute to market anomalies such as asset mispricing and excess volatility (Luna & Luna, 2018; Shefrin, 2000).

These dynamics are not merely of academic interest; they are especially consequential in markets characterized by significant macroeconomic and political instability where the information that investors must

process is itself more ambiguous and harder to interpret. The Egyptian Stock Exchange (EGX) offers a particularly compelling setting in which to examine this, as over the 2010-2025 period alone the market has moved through revolution and its aftermath, a subsequent phase of structural economic reform, the global COVID-19 pandemic and a period of acute geopolitical and inflationary pressure tied to regional conflict. Few emerging markets have experienced this density of structurally distinct regimes within a single fifteen-year window making the Egyptian Stock Exchange (EGX) an unusually well-suited setting for testing not only whether anchoring and disposition biases exist but whether their strength is a stable investor trait or a regime-dependent phenomenon that intensifies or weakens with the nature of prevailing uncertainty.

The remainder of this paper is structured as follows. The Literature Review examines the theoretical evolutions from traditional finance to behavioral finance establishing the theoretical grounding and hypothesis for anchoring bias and the disposition effect. Materials and Methods details the dataset, variable proxies for both biases, macroeconomic controls and econometric specifications comprising the panel fixed effects regression and ARMA-GARCH volatility modeling. Descriptive Statistics and Diagnostic Tests presents summary metrics, correlation metrics and panel root properties. Results reports the empirical estimation for return predictability and the drivers of abnormal trading volume and conditional volatility across the full sample and subperiods. Discussion provides a synthesis and critical interpretation of behavioral findings. Finally, Conclusion summarize the key empirical findings and outlines their practical implications for portfolio strategy, risk management and market regulation.

2. Literature Review

2.1. From Traditional Finance to Behavioral Finance

Standard finance assumes that market participants act as fully rational decision-makers “homo economicus” who process all available information in a systematic way to maximize economic utility (Pompian, 2012). The theoretical foundation of standard finance is built upon Expected Utility Theory (Bernoulli, 1954; von Neumann & Morgenstern, 1944) which proposed that rational investors assess risky alternatives by calculating expected utilities weighted by outcome probabilities. Building upon expected utility Markowitz (1952) introduced Modern Portfolio Theory formalizing the principle of mean-variance diversification. Expanding on these concepts, Sharpe (1964) and Lintner (1975) subsequently formulated the Capital Asset Pricing Model (CAPM) which relate the expected returns directly to systematic market risk as measured by beta while Ross (1976) formulated the Arbitrage Pricing Theory (APT) to accommodate multi-factor macroeconomic risk drivers. Central to classical market theory is Efficient Market Hypothesis (EMH) which asserts that financial asset prices fully (Fama, 1970) and rapidly adjust to reflect all available information, rendering systematic market outperformance through technical or fundamental analysis impossible (Aktan, Sahin, & Kucukkaplan, 2018).

Despite the mathematical rigor of traditional theories, empirical observations in actual financial markets often reveal systemic anomalies that challenge classical assumptions. Market anomalies including short-term momentum, post-earnings-announcement drift and the small-cap effect demonstrate persistent deviations from complete informational efficiency (Çömlekçi & Özer, 2018; Fink, 2021). Furthermore, empirical studies on asset pricing models demonstrate that asset prices display excess volatility relative to fundamental dividends (Gervais & Odean, 2001; Shiller, 1980) and that emerging equity markets often breach weak-form efficiency as a result of market frictions, information asymmetry and socio-political shocks (Kamal, 2014; Omran & Farrar, 2006).

In order to explain such discrepancies, behavioral finance emerged as an alternative paradigm that explicitly incorporates cognitive constraints, emotional influences and psychological heuristics into financial modelling (Shahani & Ahmed, 2022; Shiller, 2003). Grounded in Simon (1955) concept of bounded rationality, behavioral finance acknowledges that decision-makers face innate information-processing limitations. Prospect Theory (Kahneman & Tversky, 1979) laid the groundwork for the shift to modern behavioral finance by challenging Expected Utility Theory as a descriptive account for decision making under risk. Prospect Theory demonstrates that individuals evaluate decision outcomes as gains or losses relative to a psychological reference point rather than in terms of absolute final wealth states.

Prospect Theory reveals three key psychological patterns: (1) asymmetric risk preferences where individuals exhibit risk aversion toward gains but risk-seeking behavior toward losses (2) reference-point dependency and (3) loss aversion in which the psychological pain caused by a loss is roughly 2.5 times stronger than the satisfaction obtained from a comparable gain (Ackert & Deaves, 2010; Kahneman & Tversky, 1979). Instead of simply assessing fundamental cash flows, investors use mental shortcuts (heuristics) which are relative to a particular reference price (Pandit, 2021). This architecture which relies on reference points directly give rise to two distinct market anomalies: anchoring bias in which investors assign too much importance to past benchmarks when forming their expectations for returns (Sattar, Toseef, & Sattar, 2020; Tversky & Kahneman, 1974) and the disposition effect where investors realize profits by selling winner stocks and hold losers to defer realizing losses (Kartini & Nahda, 2021; Herish Shefrin & Statman, 1985). The remainder of this review details the theoretical grounding and empirical manifestations of these two specific biases.

2.2. Anchoring Bias

The concept of anchoring bias was initially introduced by [Tversky and Kahneman \(1974\)](#) who defined it as the tendency of people to establish an initial value which they subsequently adjust in order to reach a final response. [Czerwinka \(2017\)](#) goes further to explain anchoring as a psychological behavior wherein the judgment of individuals has been significantly influenced by information received previously. Anchoring results from two distinct processes: adjustment which entails starting from an anchor based on known information and make gradual adjustments in line with beliefs about its accuracy and priming whereby the anchor subtly influences the decision-making process by suggesting a specific line of thought ([Kahneman, 2011](#)). [Tversky and Kahneman \(1974\)](#) demonstrate that in forming expectations, investors normally begin with arbitrary values that serve as anchors for their forecasts, while [Kaestner \(2006\)](#) contends that anchoring leads individuals to reason on the basis of their previous reference points assigning excessive weight to historical information and resulting in inadequate adjustments when new, conflicting information emerges. [Shiller \(2003\)](#) suggests that anchoring can result in biased judgements that differ from a security's true value thus increasing risk.

In the context of investing, anchoring occurs when investors compare potential purchases to specific reference points such as security prices and are believed to frequently wait for securities to reach these reference points prior to making trade decisions ([Baker & Nofsinger, 2002](#)). Research has shown that anchoring positively influences investors' decision-making processes ([Owusu & Laryea, 2023](#)) and empirical studies demonstrate that cognitive biases have a substantial influence on financial decisions ([Banerji, Kundu, & Alam, 2023](#)) commonly observed within managerial and investment contexts ([Suresh, 2024](#)). [Pervez, Shah, and Khattak \(2025\)](#) studied the anchoring bias's influence on stock exchange investors' choices, recruiting 351 investors and using PROCESS Macros ([Hayes, 2018](#)) to test mediation and moderation effects, they found that anchoring bias had a positive effect on the investment decision-making process with risk perception acting as a partial moderator and information asymmetry intensifying the effect.

Since the influential research by [Tversky and Kahneman \(1974\)](#) many studies have examined the anchoring effect across different settings, demonstrating strong and consistent effects in international institutional investment ([Cho & Yang, 2018](#)) horse race betting ([Stone & Cooper, 2001](#)) real estate investing ([Conti, Frühwirth-Schnatter, Heckman, & Piatek, 2014](#); [Ishfaq & Anjum, 2015](#)) analysts' earnings forecasts ([Elhussein & Abdelgadir, 2020](#)) and macroeconomic releases ([Gurdgiev & O'Loughlin, 2020](#)). At its essence, anchoring refers to the tendency to make decisions on the basis of reference points that hold little objective significance causing investors to rely on irrelevant statistics in their decision-making. When analyzing stock market returns, researchers frequently rely on the 52-week high and low as reference points operating under the premise that a stock is unlikely to fall below its 52-week low or rise above its 52-week high ([Nafila & Wibowo, 2020](#)). The use of historical highs was utilized as valuation anchors which became popular with [McMillan \(2005\)](#) and the 52-week high is frequently cited as a reliable indicator of anchoring effects ([Duclos, 2015](#)).

The 52-week high proximity demonstrates a stronger predictive ability for potential returns than the historical high ([Nafila & Wibowo, 2020](#)) where the returns near a 52-week high do not reverse over the long-term suggesting that this level acts as a reliable indicator of underreaction to new information. [George and Hwang \(2004\)](#) similarly argue that closeness to a 52-week high better predicts returns because the current price level reflects the momentum effect more accurately than any past increase and that the 52-week high should be viewed as a reference point for adjusting return estimates. [Cen, Hilary, and Wei \(2013\)](#) in their study of the Helsinki stock exchange discovered that stocks close to a 52-week high tend to perform well when investors use this high as an anchor for valuation even in the face of new positive information implying that equity markets near their 52-week highs can be underpriced. More broadly, [Westerhoff \(2003\)](#) considers anchoring a vital factor in behavior-based asset pricing and [Li and Yu \(2012\)](#) using US stock data found that when a stock's price approaches its 52-week high, market participants often perceive this as merely the result of temporary positive news, [Zhu \(2022\)](#) concluded that from a practical decision-making perspective, anchoring allows decision-makers to reach conclusions rapidly at the expense of accuracy.

The relevance of anchoring extends beyond developed markets. [Kengatharan and Kengatharan \(2014\)](#) examined individual investor behavior on the Colombo Stock Exchange finding that anchoring had the most impact on investment behavior among the biases considered. Similar patterns emerge in the Middle East and North Africa (MENA) region: [Tlili, Chaffai, and Medhioub \(2023\)](#) highlight the role of anchoring bias in how investors make decisions across MENA stock markets showing that investors rely heavily on past price levels and external benchmarks. [Khan and Imam \(2016\)](#) contend that present market values closely mirror earlier prices when recent rates serve as reference points resulting in an unfavorable relationship between return and investment in which investors perceive stocks as cheap when prices decline and expensive when they rise. [George and Hwang \(2004\)](#) attribute the 52-week-high momentum to anchoring and adjustment bias proposing that investors do not place accurate bids particularly near historical highs that are driven by positive news. In summary, this literature suggests that anchoring bias systematically distorts investors' forecasts based on the historical order of market data thereby influencing their assessment of intrinsic value given new information.

2.3. Underreaction and Overreaction

These dynamics become particularly evident around news events. As stated by Fink (2021) companies' market prices are influenced when investors obtain fundamental information and when news deviates from expectations by either exceeding or falling short of them, which triggers distinct market reactions. Within financial theory, the most thoroughly documented of these responses are underreaction and overreaction.

Underreaction happens when investors slowly incorporate new information into the stock price resulting in gradually changing returns in the direction of the original announcement over time. Barberis, Shleifer, and Vishny (1998) define underreaction as a pattern where the average stock return following good news exceeds the average return following bad news when investors fail to fully adjust their expectations to new information, prices change only gradually leading to short-term return continuation. Conservatism bias which is the tendency to underweight useful statistical evidence when it contradicts prior beliefs is often cited as a psychological explanation for this slow adjustment (Edwards, 1968). Empirically, underreaction is typically observable over horizons of one to twelve months generating positive autocorrelation in returns (Barberis et al., 1998; Cutler, Poterba, & Summers, 1991).

Overreaction, by contrast, describes a phenomenon where investors project recent performance into the future with excessive optimism or pessimism forcing asset prices to drift beyond what fundamentals justify because these valuations are unsustainable, the market eventually undergoes a correction manifesting as long-term return reversal (Barberis et al., 1998). While short-to-medium term asset returns frequently show evidence of momentum, empirical evidence demonstrates that these trends tend to reverse over extended horizons from three to five years (Koivuranta, 2026). Jegadeesh and Titman (1993) suggest that investors underreact to immediate, firm-specific information while concurrently overreacting to long-term corporate prospects and De Bondt and Thaler (1985) demonstrate that portfolios of historical "loser" stocks consistently outperform past "winner" stocks over three-to-five-year holding periods as investors overestimate historical performance and underestimate fundamentals.

H₁: Stocks that are closer to their 52-week high (underreaction) exhibit a positive relationship with future returns, implying that investors underreact to recent positive information.

H₂: Stocks that are closer to their historical high (overreaction) exhibit a negative relationship with future returns, implying that investors overreact to positive information.

2.4. Anchoring and Volatility

The effects of the anchoring heuristic are not confined to the conditional mean of returns where they also exert a systematic influence on conditional return variance. The direction of the variance effect is non-linear and context-dependent governed by an asset's proximity to a historical reference point and the degree to which price underreaction is subsequently resolved. Anchoring creates a unique two-phase volatility pattern; a dampening phase as price nears a benchmark followed by a sudden volatility amplification once the threshold is crossed. Driessen, Lin, and Van Hemert (2013) demonstrate that when stock prices advance within three percent of their 52-week high, systematic risk and return variability contract markedly with market beta dropping by approximately 0.18 and idiosyncratic variance declining by roughly 32 percent; a directionally identical, though smaller, reduction occurs as price approaches 52-week lows and this compression extends to option-implied volatility. Iqbal (2022) provides complementary evidence using the KSE-30 index detecting significant ARCH effects at daily and weekly frequencies and a GARCH (1,1) parameter sum below unity confirming that anchoring-induced volatility shocks are stationary and mean-reverting. However, once the reference point is crossed then the dynamic reverses. Driessen et al. (2013) show that crossing a 52-week high induces an immediate 46 percent surge in return variance whereas breaching a 52-week low generates an even larger increase of approximately 111 percent with both effects persisting across several trading sessions before decaying. Psychologically, crossing the anchor invalidates the cognitive benchmark unblocking previously suppressed investor reactions and forcing accumulated news into prices within a compressed trading window.

These findings hold direct methodological implications: behavioral anchoring is operationalized through dual proxies which are nearness to the 52-week high capturing investor underreaction and nearness to the historical high capturing overreaction both grounded in the anchoring and adjustment heuristic proposed by Tversky and Kahneman (1974). George and Hwang (2004) show that investors anchor on salient price benchmarks for instance the 52-week high which produces systematic return predictability and empirical evidence supports that this anchoring mechanism operates symmetrically to suppress return volatility as prices converge toward either 52-week highs or lows.

H₃: Nearness to 52-week high (underreaction) reduces return volatility as price near the reference point limits investors' reactions to news.

H₄: Nearness to historical high (overreaction) reduces return volatility as price anchored near this reference point similarly limits investors' reactions to news.

2.5. Disposition Effect

The disposition effect identified by Hersh Shefrin and Statman (1985) refers to investors' tendency to realize gains quickly while delaying losses. Over the past decades, this phenomenon has been examined extensively

using experimental, empirical and survey-based approaches confirming its prevalence among investors. The concept is explained by Prospect Theory (Kahneman & Tversky, 1979) which suggests that an investor's perception of risk is influenced by a reference point typically the purchase price of an asset: investors tend to be risk-averse when facing gains but willing to take risks when facing losses. Notable studies including Weber and Camerer (1998), Odean (1998), Lehenkari and Perttunen (2004) and Frazzini (2006) have further demonstrated the existence of the disposition effect at the individual investor level. Barber and Odean (1999) examine the disposition effect by analyzing the proportion of gains realized (PGR) and the proportion of losses realized (PLR) and Richards, Rutterford, and Fenton-O'Creevy (2011) find that utilizing stop losses reduces this bias.

Although Prospect Theory focuses primarily on how individuals behave, it is important to study the disposition effect at the market level because the market is shaped by the collective actions of individuals (Kaustia, 2004). One of the significant challenges in this approach is identifying an appropriate reference point since the market-level purchase point is often unavailable and investors are unlikely to remain anchored to their purchase price over time (Baucells, Weber, & Welfens, 2011; Meng & Weng, 2018). At the individual level, research indicates that a stock's historical peak prices significantly influence reference-point formation (Baucells et al., 2011; Gneezy, 2005; Nolte & Schneider, 2018) at the market level where individual purchase prices are unknown, historical prices serve as reference points (Kliger & Kudryavtsev, 2008). Studies by Baker, Pan, and Wurgler (2012) and Ranganathan and Singh (2021) suggest that the 52-week high price is particularly influential being a recent metric commonly reported in financial media with investors tending to sell when stocks reach these historical peaks (Baucells et al., 2011; George & Hwang, 2004; Ma, Wang, & Zhang, 2017). Consequently, stocks classified as "winners" which are those surpassing their previous 52-week highs are expected to exhibit higher abnormal trading volumes than "losers" (Lakonishok and Smidt (1986), Bremer and Kato (1996), Kaustia (2004) and Huddart, Lang, and Yetman (2009).

Most research on the disposition effect has focused on developed markets raising questions about applicability to emerging markets which differ significantly in terms of equity participation, regulation and liquidity. While emerging markets are experiencing rapid growth in capitalization and investor base, many of their investors are inexperienced which leads to biased decision-making (Campbell & Sharpe, 2009) and studies by Feng and Seasholes (2005) and Dhar and Zhu (2006) indicate that inexperienced investors are more susceptible to the disposition effect. Bharandev and Rao (2020) investigate the disposition effect in the Indian stock market using 52-week high and low prices as reference points finding that stocks with more winning days (prices crossing 52-week highs) exhibit higher abnormal trading volumes indicating that investors tend to sell winners to realize gains while losing days (prices below 52-week lows) do not significantly influence trading volumes suggesting that investors hold onto losing stocks. A subsequent ex-post analysis revealed that winning (losing) days are often followed by more winning (losing) days implying that disposition-prone investors may miss further gains or accumulate losses.

H₅: There is a positive (negative or less positive) relationship between the days defined as winning (losing) days and abnormal trading volume, supporting the presence of the disposition effect at the stock level.

2.5.1. Disposition Effect and Volatility

Beyond its role in shaping individual trading decisions, the disposition effect carries an important implication for how volatile a stock's price becomes over time. Grinblatt and Han (2005) demonstrate that the disposition effect introduces a divergence between a stock's observed market price and its underlying fundamental value: investors' reluctance to realize losses combined with their propensity to realize gains prevents new information from being reflected immediately in prices giving rise to underreaction and contributing to momentum patterns in stock returns. Driessen et al. (2013) investigate the behavior of stock return volatility in relation to 52-week highs and lows finding that both option-implied volatility and the volatility of underlying returns decline as prices approach a 52-week high or low but increase significantly following a breakthrough of these levels with idiosyncratic return variance rising by approximately 19 to 46 percent following a breakthrough of the 52-week high and by 43 to 111 percent following a breakthrough of the 52-week low.

H₆: Breaching a 52-week high or low is associated with a significant increase in return volatility.

3. Materials and Methods

This study employs a fixed sample of 30 firms that were constituents of the EGX 30 at the beginning of the observation period and tracks them throughout the sample horizon (2010–2025) including firms subsequently delisted to avoid survivorship bias. Because anchoring and the disposition effect both arise from investor decisions regarding individual securities both biases are examined using firm-level daily panel data comprising daily closing prices, trading volumes and macroeconomic and firm-characteristic variables including interest rates, inflation, exchange rates, GDP growth and market capitalization.

All estimations (panel fixed effects regressions, ARMA GARCH models and unit root tests were performed in "STATA/MP 17". The low frequency macroeconomic series were converted to daily frequency by temporal disaggregation (Sax & Steiner, 2013) subject to an averaging constraint so that the daily values average to the

officially published monthly or annual figures. Daily closing prices and trading volumes were obtained from Egyptian Stock Exchange (EGX) database.

3.1. Measuring Anchoring Proxies

In line with the methodology of Uddin, Gul, and Mubarik (2021) the study will employ two primary anchoring proxies:

Nearness to 52-week high (X52W): This is calculated as the ratio of the lagged stock daily closing price to the highest price of the stock over the past 52 weeks.

Nearness to historical high (XHH): This is calculated as the ratio of the lagged stock daily price to the highest price of the stock from the beginning of sample periods till price at day $t-1$

The formulas for these proxies will be as follows:

$$X_{(52w)} = \frac{P_{t-1}}{P_{52w,t-1}} \text{ and } X_{(HH)} = \frac{P_{t-1}}{P_{max,t-1}} \quad (1)$$

Where; P_t is the price of stock at time t , $P_{52w,t}$ is the 52-week high price at time t and $P_{max,t}$ is the historical high price at time t .

3.2. The Calculation for Daily Returns

The daily returns R_t will be calculated using the natural logarithm of ratio of the closing price for the current day to the closing price of the previous day:

$$R_t = \ln \left[\frac{P_t}{P_{t-1}} \right] \quad (2)$$

Where; P_t is the closing price at the current day and P_{t-1} is the closing price at the previous day.

3.3. Dummy Variables

Two dummy variables will be incorporated into the analysis:

D_t : This dummy variable will take the value of 1 if the stock price reaches or exceeds its historical high price during the day, and 0 otherwise.

I_t : This dummy variable will take the value of 1 if the 52-week high equals the historical value during the day, and 0 otherwise.

The full model, with macroeconomic variables (interest rate, inflation rate and exchange rate, GDP growth rate and firm size) to control for their effects is as follows:

$$R_t = \alpha + \beta_1 R_{(t-1)} + \beta_2 X_{52w} + \beta_3 X_{HH} + \beta_4 D_t + \beta_5 I_t + \beta_6 Intr_t + \beta_7 Inflr_t + \beta_8 ER_t + \beta_9 Firm\ Size_i + \beta_{10} GDP_t + e_i \quad (3)$$

Where $Intr$ is the interest rate, $Infr$ is the inflation rate, ER is the exchange rate, $Firm\ Size$ is the categorized market capitalization (Small, Medium and Large) and GDP is the GDP growth rate.

Based on the model above, if traders or investors fail to fully incorporate the favorable information underlying a stock's approach toward its 52-week high (underreaction), this proximity is expected to be associated with positive expected returns as the residual price adjustment associated with that information is realized over later periods. Conversely, if traders or investors overreact to the favorable information underlying a stock's proximity to its historical high, this proximity is expected to be negatively associated with subsequent returns consistent with the gradual correction of that overreaction. When the stock reaches a new all-time high on a given trading day this is expected to trigger profit taking among current investors thereby exerting a downward pressure on the following day's return. Finally, when the 52-week high and historical high coincide, market participants focus on a single reference point rather than two competing anchors. This single anchor alignment eliminates confounding effects allowing the underreaction to be identified with greater empirical precision.

3.4. Anchoring and Conditional Volatility

Similarly, to assess the contribution of anchoring bias to conditional volatility, the variables underreaction and overreaction as defined above are incorporated into the equation of conditional variance:

$$\sigma_t^2 = \omega + \alpha_1 \epsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \gamma_1 Underreaction_t + \gamma_2 Overreaction_t \quad (4)$$

The coefficients γ_1 and γ_2 capture the marginal contribution of underreaction and overreaction respectively to conditional volatility, besides the effects of past shocks ϵ_{t-1}^2 and past volatility σ_{t-1}^2 . A statistically

significant and negative γ_1 and γ_2 would provide evidence that anchoring driven behavior dampens volatility in Egyptian Stock Exchange (EGX).

3.5. Measuring Disposition Effect Proxies

The disposition-effect analysis adapts the daily-level approach of [Bharandev and Rao \(2020\)](#) testing the relationship between abnormal trading volume and days on which a stock's price crosses its rolling 52-week high or low, calculated over the preceding 252 trading days:

$$52 - \text{week high}_{i,t} = \max_{0 \leq t \leq 252} \text{Closing Price}_{i,t-k} \quad (5)$$

$$52 - \text{week low}_{i,t} = \min_{0 \leq t \leq 252} \text{Closing Price}_{i,t-k} \quad (6)$$

A trading day is classified as a winning day if the closing price exceeds the stock's own 52-week high recorded up to (but not including) that day and a losing day if the closing price falls below its own 52-week low, reference points are recalculated on a rolling basis. Abnormal trading volume ($ABVOL_{i,t}$), following [Barber and Odean \(2008\)](#) is the ratio of a day's trading volume to the stock's average daily volume over the preceding year:

$$ABVOL_{i,t} = \frac{\text{Volume}_{i,t}}{\bar{V}_{i,t}} \quad (7)$$

$$\bar{V}_{i,t} = \frac{\sum_{d=t-252}^{t-1} \text{Volume}_{i,d}}{252} \quad (8)$$

$$\text{Winning Days}_i = \begin{cases} 1, & \text{if } \text{Closing Price}_{i,t} > 52 - \text{week high}_{i,t} \\ 0, & \text{else} \end{cases} \quad (9)$$

$$\text{Losing Days}_i = \begin{cases} 1, & \text{if } \text{Closing Price}_{i,t} < 52 - \text{week low}_{i,t} \\ 0, & \text{else} \end{cases} \quad (10)$$

Winning-day and losing-day dummies are defined as 1 if the closing price exceeds the 52-week high (or falls below the 52-week low) and 0 otherwise. Under the disposition effect, once a stock reaches a new 52-week high, shareholders holding unrealized gains are more likely to sell, increasing trading activity while when a stock falls below its 52-week low, loss-averse investors are expected to hold rather than sell. $ABVOL_{i,t}$ is regressed on the winning-day and losing-day dummies, controlling for macroeconomic conditions and firm size:

$$ABVOL_i = \alpha + \beta_1 (\text{WinningDay}_i) + \beta_2 (\text{LosingDay}_i) + \beta_3 \text{Intr}_t + \beta_4 \text{Infl}_t + \beta_5 \text{ER}_t + \beta_6 \text{Firm Size}_i + \beta_7 \text{GDP}_t + e_i \quad (11)$$

A positive and statistically significant β_1 is expected, indicating that winning days are associated with higher abnormal volume, while β_2 is expected to be smaller in magnitude, negative or insignificant, consistent with investors' reluctance to realize losses.

3.6. Disposition Proxies and Conditional Volatility

To examine whether winning and losing days are also associated with shifts in return volatility, an ARMA (1,1) GARCH (1,1) model is used:

$$\sigma_t^2 = \omega + \alpha_1 \epsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \gamma_1 \text{Winning Day}_t + \gamma_2 \text{Losing Day}_t \quad (12)$$

3.7. Diagnostic Tests

Stationarity of returns, abnormal trading volume and the macroeconomic variables is tested using the Augmented Dickey-Fuller (ADF) test given their potential random-walk features:

$$\Delta y_t = \gamma_0 + \gamma_1 y_{t-1} + \gamma_2 t + \sum_{i=1}^p \beta_i \Delta y_{t-1} + e_t \quad (13)$$

3.8. Control Variables

In line with the Arbitrage Pricing Theory ([Ross, 1976](#)) which proposes that stock prices are driven by multiple macroeconomic factors ([Chinzara, 2010](#)) this study incorporates the inflation rate, exchange rate, interest rate and GDP growth rate alongside market capitalization, as control variables. Interest rate is proxied by the deposit rate which is expected to relate negatively to stock prices as capital shifts between bank deposits and equities ([Uddin & Alam, 2010](#)). Inflation is proxied by the Consumer Price Index where unexpected inflation is expected to depress stock prices through higher discount rates and reduced real consumption while

anticipated, demand-driven inflation can support corporate earnings and valuations (McConnell, Brue, & Flynn, 2012; Talla, 2013). Exchange rate is proxied by the national currency value per US dollar with depreciation affecting firms' cost structure and competitiveness and through the portfolio-adjustment channel, cross-border capital flows (Gunasekarage, Piseditasalai, & Power, 2004; Vejzagic & Zarafat, 2013). GDP growth, a broad indicator of economic activity is expected to relate positively to stock prices and market liquidity (Agarwal & Sharma, 2020; Dahal, 2022). Firm size is proxied by market capitalization; following standard asset-pricing methodology (Banz, 1981; Fama & French, 1992; Wakil, 2020) sample firms are sorted into equal market-capitalization terciles (small, medium and large) consistent with the approach used by Bharandev and Rao (2020) and Chen and Li (2025).

Table 1. Control variables and proxies.

Variables	Proxy
Interest Rate	Interest on Deposit
Exchange Rate	National Currency per USD
Inflation	Consumer Price Index (CPI)
Gross Domestic Product (GDP)	Annual GDP Growth Rate
Firm Size	Market Capitalization Categorization

3.9. Descriptive Statistics and Diagnostic Tests

Prior to the empirical tests, descriptive statistics: mean, standard deviation, minimum, maximum, skewness and kurtosis were calculated for all key variables used in the anchoring and disposition-effect models to provide an overview of each series' central tendency, dispersion, symmetry and tail behavior.

Table 2. Descriptive statistics for anchoring and disposition effect proxy variables and control variables.

	Count	Mean	Standard Deviation	Skewness	Kurtosis	Sum	Min.	Max.
Return	104,685	-0.0000775	0.0455138	-19.60186	3775.21	-8.108006	-4.238926	4.167526
Lagged Return	104,685	-0.0000788	0.045519	-19.60074	3774.565	-8.246495	-4.238926	4.167526
X52W	104,685	0.7240195	0.2116205	-1.040445	4.085661	75794.7	0.0068621	1
XHH	104,685	0.4465991	0.2739136	0.2059759	2.08555	46752.68	0.0014844	1
D	104,685	0.0061118	0.0779389	12.67379	161.6249	640	0	1
I	104,685	0.221523	0.4152736	1.34118	2.798764	23197	0	1
ABVOL	104,685	10.052941	10.171543	2.701567	11.93358	110227.1	0.0213938	7.029326
Win Day	104,685	0.0339208	0.1810262	5.149324	27.51554	3551	0	1
Lose Day	104,685	0.0275302	0.1636232	5.775123	34.35204	2882	0	1
Inflation	104,685	0.0097344	0.0196684	4.624328	45.53739	1019.058	-0.0855657	.2856783
Interest Rate	104,685	0.0981955	0.0984785	2.803257	17.72615	10279.69	0.0000298	1.216759
Exchange Rate	104,685	16.99018	22.61829	3.687799	24.82685	1778634	0.0030437	306.5356
GDP Growth	104,685	3.901336	4.616236	4.727847	49.29215	408415.2	0.0007717	82.60923
Market Capitalization	104,685	2.77e+09	1.14e+10	12.19524	193.8676	2.90e+14	364668.9	2.74e+11

Firm-day observations, 2010–2025. Instead of using raw Market Capitalization data, categorical size terciles are used in the regressions. Inflation, interest rate, exchange rate and GDP growth are common to both the anchoring and disposition-effect models and are therefore reported once.

Table 2 shows that average daily returns are close to zero with a standard deviation of 0.0455, indicating that daily equity returns are governed primarily by variance rather than trend where both return series exhibit negative skewness and very high kurtosis consistent with a heavy-tailed, leptokurtic distribution. Nearness to the 52-week high (X52W) averages 0.724 while nearness to the historical high (XHH) averages a lower 0.447, indicating that stocks generally trade further below their all-time high than their 52-week high. The dummy D (day the stock reaches its historical peak) has a mean of only 0.0061 confirming this is a rare event while I (52-week high equal to historical high) occur more frequently with a mean of 0.222. Average abnormal trading volume (ABVOL) has a mean of 1.053 and pronounced positive skewness (2.70) indicating that trading volume spikes above average far more often than it falls symmetrically below it. Win Day has a mean of 0.034, slightly higher than Lose Day's mean of 0.028 consistent with the generally upward drift of EGX prices over the sample; both are highly skewed binary indicators. Among the shared macroeconomic controls, inflation and interest rate both exhibit high kurtosis and positive skewness consistent with episodic spikes tied to the 2010–2013, 2016 devaluation and 2022–2025 sub-periods rather than a stable underlying trend, exchange rate shows the widest range (0.0030 to 306.54) and the highest kurtosis (24.83) of the control variables reflecting the extreme currency depreciation observed later in the sample. GDP growth shows moderate dispersion around a mean of 3.901 with kurtosis (49.29) driven by isolated high-growth and contraction years within the fifteen-year window.

Table 3. Panel unit root (ADF) test - anchoring model variables.

Variable	Z-Statistic	P-Value
Return	-44.51	0.0000
ABVOL	-44.46	0.0000
Exchange Rate	-44.51	0.0000
Interest Rate	-44.51	0.0000
GDP Growth	-44.51	0.0000
Inflation	-44.51	0.0000
Market Capitalization	-41.80	0.0000

Return is tested for the anchoring model and ABVOL for the disposition-effect model; the remaining variables are common to both models and are reported once. Identical statistics reflect that “p-values” of the firm level tests reach the numerical minimum so the null of a unit root is rejected for all series.

All series reject the null hypothesis of a unit root (Z-statistics ranging from -44.46 to -41.80, $p = 0.0000$), confirming stationarity across both models and ruling out spurious regression.

Table 4. Hausman specification test - anchoring model.

Period	χ^2	P-Value
Full Period	60.92	0.0000
2010–2013	55.92	0.0000
2014–2018	45.53	0.0000
2019–2021	57.63	0.0000
2022–2025	59.13	0.0000

Table 4 presents the results of the Hausman specification test for the anchoring model, estimated separately for the full sample and each of the four sub-periods. In every case, the test yields a highly significant chi-square statistic (ranging from 45.53 in 2014–2018 to 60.92 for the full period, all $p = 0.0000$) leading to a consistent rejection of the null hypothesis that the random-effects model provides estimates comparable to the fixed-effects alternative. This uniform rejection across the full sample and all four sub-periods confirms that unobserved time-invariant firm characteristics are systematically correlated with the model's explanatory variables rendering the random-effects approach biased regardless of the political or macroeconomic regime under consideration. Consequently, the fixed-effects model is used throughout the analysis as the appropriate estimator, as it eliminates firm-level heterogeneity by focusing on within-firm variation over time.

Table 5. Hausman test diagnostics - disposition effect model.

Period	Win-Day Model χ^2	P-Value	Lose-Day Model χ^2	P-Value
Full Period	-5.45	—	3.40	0.8456
2010–2013	0.45	0.9996	15.49	0.0302
2014–2018	7.21	0.4079	4.97	0.6633
2019–2021	-138.26	—	34.35	0.0000
2022–2025	16.66	0.0197	23.85	0.0012

Source: Negative χ^2 values reflect finite-sample properties in which the estimated Fixed Effects - Random Effects covariance difference fails positive semi-definiteness (Schreiber, 2008) rather than a valid test statistic.

Table 5 yields mixed conclusions across periods and specifications. Despite this variation, a firm fixed-effects panel estimator is applied across all specifications to ensure robust control for unobserved firm-level heterogeneity and analytical consistency across both models.

Table 6 exhibits the correlation analysis for anchoring proxy variables along with control variables reveals that stock returns exhibit a statistically significant but weak positive correlation with nearness to the 52-week high ($r = 0.015$) and a weak negative correlation with nearness to the historical high ($r = -0.007$), indicating that the two anchoring variables move in opposite directions relative to returns. The two anchoring proxies are moderately positively correlated with one another ($r = 0.500$) as expected given that both derive from the same price series though the magnitude remains low enough to avoid severe multicollinearity. Among macroeconomic controls, interest rate and exchange rate are strongly correlated ($r = 0.919$) while market capitalization shows weak correlations with all other variables where the regressions use categorical firm-size dummies rather than the raw market-capitalization variable.

Table 7 exhibits the disposition effect proxy variables correlation analysis showing that abnormal trading volume is positively and significantly correlated with the Win Day dummy ($r = 0.240$, $p < 0.001$) while its association with Lose Day is substantially weaker ($r = 0.024$, $p < 0.001$) which is initial bivariate evidence consistent with the disposition effect. Among macroeconomic controls, exchange rate and interest rate display high collinearity ($r = 0.919$) and GDP growth is positively correlated with both ($r = 0.572$ and $r = 0.707$, respectively).

Table 6. Correlation matrix – anchoring proxies and control variables.

	Return	Lagged Return	X52W	XHH	D	I	Inflation	Interest Rate	Exchange Rate	GDP Growth	Market Cap.
Return	1.0000										
Lagged Return	0.0313***	1.0000									
X52W	0.0105***	0.0847***	1.0000								
XHH	-0.0073**	0.0281***	0.5003***	1.0000							
D	0.0064**	0.0497***	0.0998***	0.1547***	1.0000						
I	-0.0122***	-0.0110***	0.0201***	0.5559***	0.1382***	1.0000					
Inflation	-0.0083***	0.0021	0.0950***	-0.0429***	-0.0096***	-0.0843***	1.0000				
Interest Rate	-0.0584***	-0.0055*	0.0611***	0.0048	-0.0026	0.0028	0.4455***	1.0000			
Exchange Rate	-0.0397***	0.0016	0.0872***	-0.0149***	0.0002	-0.0039	0.4214***	0.9192***	1.0000		
GDP Growth	-0.0997***	-0.0251***	-0.0349***	-0.0233***	0.0073**	0.0182***	0.4128***	0.7069***	0.5723***	1.0000	
Market Cap.	-0.0182***	-0.0087***	-0.0244***	0.0395***	-0.0001	0.1020***	0.0388***	0.1694***	0.1351***	0.0759***	1.0000

Note: Pearson correlation coefficients (diagonal = 1.0000, own-correlation, unstarred). ***, **, and * denote that the variable is significant at 1%, 5%, and 10%, respectively.

Table 7. Correlation matrix – disposition effect measures and control variables.

	ABVOL	Win Day	Lose Day	GDP Growth	Market Cap.	Exchange Rate	Inflation	Interest Rate
ABVOL	1.0000							
Win Day	0.2396***	1.0000						
Lose Day	0.0237***	-0.0315***	1.0000					
GDP Growth	0.0680***	-0.0024	0.1195***	1.0000				
Market Cap.	-0.0055*	-0.0027	-0.0007	0.0759***	1.0000			
Exchange Rate	0.0571***	0.0071**	-0.0030	0.5723***	0.1351***	1.0000		
Inflation	0.0849***	0.0294***	-0.0121***	0.4128***	0.0388***	0.4214***	1.0000	
Interest Rate	0.0689***	0.0038	0.0291***	0.7069***	0.1694***	0.9192***	0.4455***	1.0000

Note: Pearson correlation coefficients (diagonal = 1.0000, own-correlation, unstarred). ***, **, and * denote that the variable is significant at 1%, 5%, and 10%, respectively.

4. Results

4.1. Anchoring and Return Predictability

Table 8 presents the fixed-effects panel regression evaluating how the two anchoring proxies predict subsequent equity returns across the full sample and the four subperiods.

Table 8. Fixed-effects panel regression - return predictability (Underreaction/Overreaction).

Variable	Full Period	2010–2013	2014–2018	2019–2021	2022–2025
Lagged Return	0.028	0.088**	-0.019	0.036	0.032***
X52W	0.002*	0.002*	-0.002	0.002	-0.002
XHH	-0.006***	-0.010***	-0.008***	-0.030	-0.008*
D	0.005	0.009***	0.009***	-0.021	0.003
I	0.000	0.004***	-0.001	-0.001	-0.002**
Inflation	0.079***	0.312***	0.088*	0.010	0.023
Interest Rate	-0.003	-0.013	0.045	0.181	0.036
Exchange Rate	0.000	-0.000	-0.000	-0.001	-0.000
GDP Growth	-0.001***	-0.001**	-0.002**	-0.002***	-0.001**
Small Market Cap	-0.004***	-0.002*	-0.008***	-0.016***	-0.009***
Medium Market Cap	-0.002**	0.000	-0.004***	-0.005***	-0.003
Constant	0.007***	0.008***	0.012***	0.020***	0.013**
Observations	104,685	27,391	34,166	18,715	24,413
R ²	0.013	0.032	0.013	0.020	0.015

Note: ***, **, and * denote that the variable is significant at 1%, 5%, and 10%, respectively.

The lagged-return coefficient is positive and significant only in 2010–2013 ($\beta = 0.088$, $p < 0.05$) and 2022–2025 ($\beta = 0.032$, $p < 0.01$), becoming insignificant elsewhere indicating that short-term momentum in the Egyptian market is episodic rather than a pervasive structural feature that is consistent with Uddin et al. (2021) who note that past returns predict future performance at daily horizons only until anchoring metrics are included, as these proxies absorb explanatory power previously captured by simple autoregressive specifications. However, during 2022–2025, the 52-week-high proxy loses significance while the lagged-return variable retains predictive power, a divergence from Uddin et al. (2021) suggesting that investor underreaction contracted to a noticeably shorter horizon during this phase amid the compounding shocks of the Ukraine war, inflation and currency pressure.

Nearness to the 52-week high is positive and marginally significant in the full sample ($\beta = 0.002$, $p < 0.10$), aligning with Uddin et al. (2021) and Iqbal (2022) the cognitive framework of George and Hwang (2004) the relationship is restricted to the 2010–2013 period, becoming statistically insignificant thereafter. This temporal decay corresponds with Addoum, Delikouras, Ke, and Kumar (2019) who show that market participants face substantial information-processing constraints during political transitions suggesting the predictive power of the 52-week high in Egypt reflects a regime-specific cognitive friction rather than an enduring structural anomaly. By comparison, nearness to the historical high is a more reliable and persistent return predictor. Across the full sample, it is negative and highly significant ($\beta = -0.006$, $p < 0.01$) indicating that stocks trading closer to their historical high systematically yield lower subsequent returns consistent with the investor-correction hypothesis of Li and Yu (2012) and with Pakistani evidence in Uddin et al. (2021) and Iqbal (2022). The relationship remains significant in 2010–2013, 2014–2018 and 2022–2025 but loses significance in 2019–2021. Firm-size dummies show that small- and medium-capitalization firms underperform large-capitalization firms after controlling for anchoring, a pattern that contradicts the conventional size-premium literature (Banz, 1981; Fama & French, 1992, 1993). This can be explained by lower overall business quality among small firms unrelated to size (Asness, Frazzini, Israel, Moskowitz, & Pedersen, 2018) combined with severe illiquidity and limited analyst attention producing a persistent structural discount. Among macroeconomic controls, GDP growth is significant in all periods with a consistently negative coefficient pointing to a countercyclical, forward-looking equity-discounting mechanism, besides small capitalization dummy is significant in all periods, inflation is positive and significant in the full sample driven predominantly by the 2010–2013 revolutionary period ($\beta = 0.312$, $p < 0.01$) consistent with Larson and Madura (2001) on the outsized effect of major political shocks. Interest rate and exchange rate remain statistically insignificant throughout, reinforcing those behavioral anchors retain superior explanatory power over macroeconomic fundamentals for daily EGX returns (Uddin et al., 2021).

4.2. Anchoring and Conditional Volatility

Table 9. GARCH (1,1)-ARMA (1,1) - anchoring and conditional volatility.

	Full Period	2010–2013	2014–2018	2019–2021	2022–2025
Mean Equation					
Constant	-0.0004***	-0.0002*	-0.0005***	-0.0005***	-0.0005***
AR	-0.228***	-0.301***	-0.182***	-0.165***	-0.956***
MA	0.345***	0.444***	0.335***	0.330***	0.958***
Conditional Variance					
Underreaction (X52W)	-0.821***	-1.009***	-0.566***	-1.036***	1.299
Overreaction (XHH)	-0.272***	-0.717***	-0.340***	-0.533***	0.603
Constant	-8.941***	-8.531***	-8.742***	-8.661***	-11.236***
ARCH (α)	0.293***	0.251***	0.260***	0.380***	0.588***
GARCH (β)	0.690***	0.676***	0.626***	0.664***	0.760***
ARCH + GARCH	0.983	0.927	0.886	1.044	1.348
Observations	104,685	27,391	34,166	18,715	24,413

Note: ***, and * denote that the variable is significant at 1% and 10%, respectively.

Table 9 reports GARCH (1,1)-ARMA (1,1) estimates testing whether underreaction and overreaction proxies provide incremental explanatory power for conditional volatility. The AR and MA parameters are significant across all regimes, with coefficient magnitudes expanding markedly in 2022-2025, consistent with an equity market absorbing severe compounding shocks. In the conditional-variance equation, both underreaction and overreaction coefficients are negative and statistically significant in the full period and the first three subperiods indicating that proximity to a behavioral anchor systematically depresses conditional volatility rather than amplifying it which is a result supported by [Driessen et al. \(2013\)](#) who document variance suppression as prices approach 52-week extremes and grounded in [Tversky and Kahneman \(1974\)](#) anchoring heuristic under which salient price benchmarks dampen investor disagreement and trading activity. This volatility-dampening relationship undergoes a structural shift during 2022-2025 when both coefficients turn positive and lose statistical significance indicating an absence of a detectable anchoring-volatility relationship rather than confirmed evidence of a positive variance effect consistent with [Larson and Madura \(2001\)](#) on behavioral overreaction intensifying around high-uncertainty political events. Volatility persistence (ARCH + GARCH) rises progressively from 0.927 in 2010-2013 to 1.348 in 2022-2025 with the final two subperiods exceeding unity indicating that volatility shocks in the COVID-19 and geopolitical-risk periods do not rapidly decay but exert long-memory effects that behavioral anchors alone cannot absorb.

4.3. Disposition Effect and Abnormal Trading Volume

Table 10. Fixed-effects panel regression - win day and abnormal trading volume.

Variable	Full Period	2010–2013	2014–2018	2019–2021	2022–2025
Win Day	1.543***	1.175***	1.581***	1.435***	1.836***
GDP Growth	0.0049	0.0027	0.0154**	-0.0019	0.0005
Exchange Rate	-0.0020	-0.0976*	0.0052	0.0094	-0.0050*
Inflation	2.937***	6.577***	2.667***	-1.176	2.922***
Interest Rate	0.633*	9.196**	-0.723	-0.618	1.227*
Small Market Cap	0.013	-0.091	-0.164	-0.295	-0.371
Medium Market Cap	0.116	0.123	0.046	0.334**	-0.234
Constant	0.880***	0.838***	0.926***	1.016***	1.162***
Observations	104,685	27,391	34,166	18,715	24,413
R ²	0.067	0.057	0.087	0.047	0.098

Note: ***, **, and * denote that the variable is significant at 1%, 5%, and 10%, respectively.

Table 10 shows that the Win Day coefficient is positive and statistically significant ($p < 0.01$) in every specification, the full sample ($\beta = 1.543$) and all four subperiods (β ranging from 1.175 to 1.836) indicating that the association between abnormal trading volume and 52-week-high breakthroughs is stable across every macro-political regime from the 2011 revolutionary period through the 2022 geopolitical-risk phase.

Table 11. Fixed-effects panel regression – lose day and abnormal trading volume.

Variable	Full Period	2010–2013	2014–2018	2019–2021	2022–2025
Lose Day	0.151*	0.096	0.005	0.532***	0.316*
GDP Growth	0.0031	0.0061	0.0097	-0.0114	-0.0014
Exchange Rate	-0.0018	-0.104**	0.0053	0.0126	-0.0057**
Inflation	3.463***	6.927***	3.385***	-1.800	3.380***
Interest Rate	0.599*	9.534**	-0.561	-0.816	1.401**
Small Market Cap	-0.053	-0.155	-0.229	-0.434*	-0.513*
Medium Market Cap	0.103	0.130	0.021	0.295**	-0.265
Constant	0.956***	0.886***	1.017***	1.105***	1.295***
Observations	104,685	27,391	34,166	18,715	24,413
R ²	0.011	0.021	0.016	0.022	0.012

Note: ***, **, and * denote that the variable is significant at 1%, 5%, and 10%, respectively.

Table 11 shows that Lose Day is a weaker and less consistent predictor: significant at the 10 percent level in the full sample ($\beta = 0.151$), significant at 1 percent in 2019–2021 ($\beta = 0.532$) and at 10 percent in 2022–2025 ($\beta = 0.316$), but insignificant in 2010–2013 and 2014–2018. In every subperiod, the Win Day coefficient exceeds the corresponding Lose Day coefficient, so the asymmetry in which realized gains generate a stronger abnormal-volume response than realized losses holds without exception.

This asymmetry matches the pattern predicted by the disposition effect under Prospect Theory (Kahneman & Tversky, 1979) as applied by Hersh Shefrin and Statman (1985): investors are expected to realize gains more readily than losses, selling winning positions to lock in gains while holding losing positions rather than realizing the loss. This aligns with the stronger and more consistent Win Day coefficient relative to Lose Day and accords with the stock-level evidence reviewed by Bharandev and Rao (2020), Odean (1998), Lehenkari and Perttunen (2004) and Frazzini (2006). Among the macroeconomic controls, inflation and interest rate are positive and significant in the full period, 2010–2013, 2014–2018 and 2022–2025 (for inflation) consistent with a difference-of-opinion framework (Harris & Raviv, 1993) in which investors disagree about the implications of salient macro news, generating two-sided trading that raises volume regardless of price direction (Chen, Mohan, & Steiner, 1999; Schnorpfel, Weber, & Hackethal, 2025) while exchange rate is negative and significant specifically in 2010–2013 and 2022–2025, the two subperiods marked by sustained rather than one-off currency stress, consistent with Bernanke (1983) model of investment under irreversibility and with Forbes and Warnock (2012) on capital flight under sustained depreciation.

4.4. Disposition Effect and Conditional Volatility

Table 12 tests whether win-day and lose-day trading behavior explains conditional volatility in addition to the conditional mean. The 2022–2025 subperiod stands out with the AR coefficient turning positive (0.976) and MA turning negative (-1.001) that is a full sign reversal relative to the other periods pointing to markedly different short-run dynamics in the most recent, turbulent phase of the sample. In the conditional-variance equation, both Winning Day and Losing Day terms are positive and statistically significant in the full period and every subperiod without exception consistent with Driessen et al. (2013) who find that idiosyncratic return variance increases sharply once a reference point is crossed. The relative magnitude of the two effects is not stable across subperiods: Losing Day exceeds Winning Day in 2010–2013 and 2014–2018, but Winning Day exceeds Losing Day in 2019–2021 and 2022–2025, suggesting that the relative volatility impact of win- versus lose-breakthroughs is itself regime-dependent. Volatility persistence (ARCH + GARCH) is 0.539 in the full sample and 2010–2013, notably low at 0.161 in 2014–2018 and rises to 0.887 in 2019–2021 and 1.319 in 2022–2025 that is only the geopolitical-risk subperiod exceeds unity, indicating that volatility shocks in that regime do not fully decay but persist with long memory. In conclusion, both types of breakthrough events raise conditional volatility throughout the sample, consistent with the mechanism documented by Driessen et al. (2013).

Table 12. GARCH (1,1)-ARMA (1,1) - Disposition effect and conditional volatility.

	Full Period	2010–2013	2014–2018	2019–2021	2022–2025
Mean Equation					
Constant	-0.0005***	-0.0003***	-0.0003**	-0.0006***	-0.0010***
AR	-0.427***	-0.607***	-0.253***	-0.340***	0.976***
MA	0.508***	0.687***	0.394***	0.474***	-1.001***
Conditional Variance					
Constant	-8.121***	-8.481***	-7.850***	-8.616***	-7.723***
Winning Day	1.888***	1.109***	1.329***	2.500***	2.970***
Losing Day	2.022***	2.279***	1.479***	2.429***	2.176***
ARCH (α)	0.344***	0.287***	0.182***	0.504***	1.004***
GARCH (β)	0.196***	0.252***	-0.021*	0.383***	0.315***
ARCH + GARCH	0.539	0.539	0.161	0.887	1.319
Observations	104,685	27,391	34,166	18,715	24,413

Note: *** and * denote that the variable is significant at 1% and 10%, respectively.

5. Discussion

Overall, the results support H2 to H6 while H1 receives only weak support. The empirical evaluation of anchoring, measured through nearness to the historical high and nearness to the 52-week high (George & Hwang, 2004; Uddin et al., 2021) demonstrates that price-benchmark salience in the Egyptian Stock Exchange is dominated by overreaction rather than underreaction mechanisms. The fixed-effects panel model establishes nearness to the historical high as the primary and persistent return predictor exhibiting a negative and statistically significant coefficient across the full sample and three subperiods consistent with the overreaction and correction dynamic proposed by Li and Yu (2012). Conversely, nearness to the 52-week high predicts returns marginally in the full sample and exclusively during the 2010–2013 Revolution, after which its explanatory power disappears, indicating cognitive information-processing frictions under acute political uncertainty (Addoum et al., 2019) rather than a structural anchoring anomaly. GARCH conditional-variance estimations reinforce this interpretation: both anchoring proxies yield negative and statistically significant coefficients across the full sample and the first three subperiods, confirming that proximity to salient price benchmarks systematically compresses conditional volatility by narrowing investor disagreement (Driessen et al., 2013). This volatility dampening effect is disrupted during the 2022–2025 geopolitical risk regime where compounding macroeconomic shocks overwhelmed behavioral anchors, rendering both coefficients positive and statistically insignificant.

The empirical evaluation of the disposition effect, measured through the sensitivity of abnormal trading volume to Win Days and Lose Days following Bharandev and Rao (2020) provides the most consistent behavioral evidence of the two biases examined. The fixed-effects panel model establishes that the Win Day coefficient is positive, substantial in magnitude and statistically significant across the full sample and every subperiod without exception, with the trading-volume expansion on Win Days systematically exceeding that of Lose Days, whose coefficients are smaller, less stable and insignificant across two subperiods. This asymmetric volume response in which realized gains trigger significantly higher trading activity than realized losses directly aligns with the theoretical predictions of Prospect Theory (Kahneman & Tversky, 1979) and the behavioral framework of Hershey Shefrin and Statman (1985). Unlike anchoring, the disposition effect operates as a regime-invariant structural feature of the EGX, persisting uniformly from the 2010–2013 Revolution through the 2022–2025 geopolitical-risk regime. GARCH conditional-variance models complement these volume-based findings, showing that both Win Day and Lose Day breakthroughs exert positive and statistically significant effects on conditional volatility across all estimation windows, consistent with the idiosyncratic risk dynamics documented by Driessen et al. (2013) with the relative magnitude of the two effects reversing between earlier and more recent regimes where Losing Day breaches dominate conditional volatility in 2010–2013 and 2014–2018 whereas Winning Day breaches have the stronger impact in 2019–2021 and 2022–2025. Consequently, while the disposition effect is a persistent feature of investor trading behavior in the EGX, its transmission to conditional volatility is regime dependent.

5.1. Limitations

Several limitations should be noted when interpreting the findings.

- Anchoring and Disposition effect are psychological states that cannot be observed directly, so this study infers them from price, return and volume patterns. These proxies cannot fully separate behavioral motives from rational explanations such as time-varying risk premiums and liquidity effects. Bharandev and Rao (2020) raise the same concern for their disposition effect proxy.
- The four subperiods are defined by major political and economic events rather than by formal structural break tests. Results near each boundary may therefore be sensitive to the exact dates and alternative tests could suggest somewhat different regime windows.

- Hausman statistics for the disposition effect model (Table 5) are negative and fall outside the conventional chi-square framework, a known finite sample artifact. The fixed effects estimator was retained throughout for consistency but its choice could not be confirmed in every subperiod.
- The study uses a fixed panel of 30 firms that were EGX30 constituents in 2010 including firms later delisted to avoid survivorship bias, so comparisons with dynamically updated index-based samples should be made with caution.
- Uddin et al. (2021) derive their anchoring proxies from the aggregate index closing price that is at market level whereas the present study measures both biases at firm level using a panel of 30 stocks. The results are therefore not directly comparable with market level evidence.

5.2. Recommendations for Future Research

- Future research could extend the analysis of anchoring and the disposition effect to EGX30, EGX70 or EGX100 index thereby measuring each bias directly at the aggregate market level under the same ARMA (1,1) – GARCH (1,1) specification.
- Robust Hausman specification test should be applied to the disposition effect models, in order to resolve the negative test statistics reported here and to provide firmer basis for selecting between fixed effects and random effects estimators.
- Formal structural break tests could be used to determine the subperiod boundaries in order to assess whether regime dependent patterns documented here persist under data driven break dates.
- Comparative studies across MENA and other frontier markets that could adopt the same regime-based framework would clarify how these biases behave under each market's distinct political and macroeconomic condition.
- The interaction between anchoring and the disposition effect should be examined directly, for example whether anchoring moderates disposition driven trading rather than treating the two biases as independent phenomenon.

6. Conclusion

The empirical findings across both anchoring and the disposition effect converge on a central insight: behavioral dynamics exert a persistent and economically meaningful influence on price formation and volatility in the Egyptian Stock Exchange, yet their directional transmission, intensity and empirical detectability remain fundamentally conditioned by the prevailing political and macroeconomic regime. The disposition effect operates as the more regime-invariant of the two biases persisting uniformly across every subperiod and indicating that the psychological propensity to realize gains prematurely while retaining losing assets is a persistent characteristic of Egyptian investor behavior rather than a temporary crisis response. Anchoring, by contrast, is confirmed by the return predictability of the overreaction proxy (nearness to historical high) across all estimation windows except the 2019-2021 pandemic period, whereas the underreaction proxy (nearness to 52-week high) yields predictive power only during the 2010-2013 Revolution that is a more regime-sensitive pattern.

Regarding conditional volatility, the ARMA-GARCH estimations confirm that both behavioral proxies represent material and independently significant components of conditional variance. The anchoring overreaction proxy reduces volatility significantly across all subperiods except 2022-2025 that a regime distinct from the 2019-2021 window in which its return-based predictability disappears, reinforcing the empirical independence of bias presence from its impact on volatility. The disposition effect exhibits the most uniform volatility footprint of the two biases, with both Win Day and Lose Day breakthroughs maintaining statistically significant coefficients in the conditional-variance equation across all estimation windows without exception. These conditional-variance estimations confirm that behavioral biases constitute a material, independently significant component of equity risk in the Egyptian market that conventional autoregressive shock-persistence models fail to fully absorb, carrying distinct implications for investors, risk managers and regulators operating in emerging markets characterized by episodic political and macroeconomic instability.

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