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Analysis of the Anchoring Heuristic Effect in the Brazilian Stock Market

Análise do Efeito da Heurística Comportamental da Ancoragem no Mercado Acionário Brasileiro

Análisis del Efecto de la Heurística Conductual del Anclaje en el Mercado Accionario Brasileño

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Abstract

This study investigates the presence and effect of the anchoring heuristic on stock trading in the Brazilian stock market between 2017 and 2020. To this end, a panel data estimation model was applied to a sample of fifty stocks included in the Bovespa Index. Using two dummy variables representing breakouts above the highest prices and below the lowest prices recorded over the previous fifty-two weeks, we tested the hypothesis that past prices influence market participants' decision-making, leading to deviations in trading volume from expected levels. The findings indicate that, following breakouts above previous price highs, abnormal trading volume tended to decline, whereas breaches below previous price lows resulted in an increase in abnormal trading volume. These results support the assumptions of behavioral finance and the anchoring heuristic by demonstrating that investors use specific price levels as anchors when making buy and sell decisions. The presence of anchoring suggests that investors are influenced by factors that are not necessarily relevant to the accurate valuation of financial assets, making them susceptible to systematic errors that may ultimately lead to inferior investment outcomes relative to market performance over a given period.

Keywords: behavioral finance, heuristics, anchoring, financial markets.

Resumo

Este trabalho analisa a presença e o efeito da heurística comportamental da ancoragem na negociação de ações na bolsa brasileira, no período 2017-2020. Para isso, utilizou-se um modelo de estimação com dados em painel em um grupo de cinquenta ações do Índice Bovespa. A partir de duas variáveis dummy, representando a superação de níveis máximos e mínimos de preço das últimas cinquenta e duas semanas, foi testada a hipótese de que os preços passados influenciam a tomada de decisões de agentes, alterando o volume de negociação em relação ao esperado. Identificou-se que, após a superação dos níveis máximos de preço, o volume atípico tendeu a cair, enquanto a perda dos níveis mínimos levou a um aumento nessa variável. Dessa forma, os resultados validam as premissas da teoria das finanças comportamentais e da heurística da ancoragem, pois mostram que investidores utilizam certos níveis de preço como âncoras para tomar decisões de compra e para vender ativos. A presença da ancoragem demonstra que os investidores são motivados por fatores que não são, necessariamente, relevantes à correta avaliação do valor desses ativos, estando suscetíveis a erros, o que ocasiona resultados inferiores aos que o mercado oferece em determinado período.

Palavras-chave: *finanças comportamentais, heurísticas, ancoragem, mercado financeiro.*

Resumen

Este trabajo analiza la presencia y el efecto de la heurística conductual del anclaje en la negociación de acciones en la bolsa de valores brasileña durante el período 2017–2020. Para ello, se empleó un modelo de estimación con datos de panel aplicado a un *conjunto de cincuenta acciones que integran el Índice Bovespa. A partir de dos variables dicotómicas (dummy), que representan la superación de los niveles máximos y mínimos de precio registrados en las cincuenta y dos semanas previas, se puso a prueba la hipótesis de que los precios pasados influyen en la toma de decisiones de los agentes económicos, modificando el volumen de negociación con respecto al esperado. Se identificó que, tras la superación de los niveles máximos de precio, el volumen anómalo tendió a disminuir, mientras que la pérdida de los niveles mínimos condujo a un aumento de dicha variable. De este modo, los resultados validan los supuestos de la teoría de las finanzas conductuales y de la heurística del anclaje, al demostrar que los inversionistas utilizan determinados niveles de precios como anclas para tomar decisiones de compra y venta de activos. La presencia del anclaje evidencia que los inversionistas están motivados por factores que no son necesariamente relevantes para la correcta valoración de dichos activos, por lo que son susceptibles a cometer errores que pueden generar resultados inferiores a los que ofrece el mercado en un período determinado.*

Palabras clave: *finanzas conductuales, heurísticas, anclaje, mercado financiero.*

Introduction

The Brazilian capital market has undergone substantial structural changes in recent years. Combined with the reduction in the benchmark interest rate (SELIC) beginning in 2016 and growing public interest in and knowledge of equity investing, these developments have fueled the expansion of the market as a whole. According to Brasil, Bolsa, Balcão (B3), between 2017 and September 2020, the number of individual investors increased by 395%[1], surpassing three million registered taxpayers, while the total market capitalization of listed companies exceeded BRL 711 billion. Nevertheless, only 1.45% of the Brazilian population invests in the stock market, compared with approximately 52% in countries such as the United States.

As the market has evolved, investment decisions and trading activity have become increasingly prominent topics in both academic and professional discussions, particularly in the field of investment analysis. In response, several financial theories have been developed to explain investor behavior. Traditional models sought to understand investment decision-making and stock price dynamics. Their theoretical foundation rested on the principle of utility maximization proposed by Von Neumann and Morgenstern (1944), who argued that, under specific axioms of rational behavior, individuals facing uncertainty act to maximize the expected utility of available alternatives.

Building upon the concept of rational maximization, Fama (1970) introduced the Efficient Market Hypothesis (EMH), linking asset prices to investors' ability to incorporate available information. According to this framework, financial markets efficiently assimilate new information and immediately reflect it in asset prices. Consequently, for a given level of risk, no investor can consistently outperform the expected market return, regardless of their investment strategy or informational advantage. Fama proposed three forms of market efficiency — weak, semi-strong, and strong — depending on the type of information assumed to be fully incorporated into market prices.

Although these theories have played a fundamental role in the development of capital market research and have provided an essential foundation for subsequent studies, they have proven insufficient to fully explain observed market behavior. In this context, Kahneman and Tversky (1979), two Israeli psychologists, challenged the assumption that economic agents always behave rationally to maximize expected outcomes. Their work gave rise to Prospect Theory, which became the cornerstone of behavioral finance and introduced a new framework for understanding decision-making, particularly in economic contexts. Earlier, Simon (1959) had proposed the concept of bounded rationality, arguing that some problems are too complex to be fully solved within the limits of human cognitive capacity.

Based on experiments involving hypothetical decision-making under uncertainty, Kahneman and Tversky (1979) reached two primary conclusions: (i) individuals respond differently to gains and losses of equal magnitude, and (ii) errors in decision-making are systematic and predictable, arising from what they termed behavioral heuristics.

These heuristics are mental shortcuts that simplify decision-making when maximizing expected utility is impractical, such as choosing the combination of goods that provides the greatest satisfaction under a budget constraint. In themselves, heuristics are not inherently detrimental; however, they can give rise to behavioral biases, which are systematic errors in judgment and decision-making. Tversky and Kahneman (1974) originally identified three major heuristics: availability, representativeness, and anchoring.

The availability heuristic suggests that individuals estimate the likelihood or frequency of an event based on how easily similar instances come to mind. With the increasing availability of investment-related information through news outlets, digital influencers, and social media, this heuristic has become increasingly relevant in financial markets. The representativeness heuristic, in contrast, relies on commonly accepted patterns or stereotypes when making

[1] Data are calculated based on the taxpayer identification numbers registered with custody agents and may therefore count the same investor multiple times if they maintain accounts with more than one brokerage firm (Brasil, Bolsa e Balcão. Histórico Pessoas Físicas, 2020).

decisions under uncertainty. In financial markets, such stereotypes may stem from investors' perceptions of a company's reputation, its historical performance, or prevailing market sentiment.

The third heuristic, anchoring, occurs when individuals rely on a reference point — typically a numerical value, or anchor — to guide their decisions, even when that value has little or no relevance for predicting future outcomes. Its existence was demonstrated through an experiment in which two groups of participants were randomly assigned different numerical values before answering a quantitative question. Despite the numbers being entirely unrelated to the correct answers, participants consistently relied on them as anchors, thereby biasing their responses.

Kahneman and Tversky's findings have subsequently been expanded and corroborated by numerous researchers. De Bondt and Thaler (1985) documented several stock market inefficiencies associated with investors' overreaction to news and events. Likewise, Shiller (1981) compared the present value of expected corporate dividends with observed stock prices and concluded that stock prices exhibited substantially greater volatility than could be justified by changes in expected dividend values.

Against this background, the present study addresses the following research question: Is there evidence of the anchoring heuristic in the trading of securities on B3? Accordingly, the objective is to examine both the presence and the magnitude of the anchoring heuristic's effect on stock trading in the Brazilian stock market during the 2017–2020 period.

As argued by Thaler (1999), understanding human behavior enriches discussions of financial markets. Testing and validating behavioral finance theories deepens knowledge of finance, particularly regarding expected asset returns, market dynamics, investment risk, and portfolio selection. These contributions promote greater market efficiency and improve both quantitative and qualitative outcomes for market participants.

Despite its importance, behavioral finance remains relatively underexplored in the Brazilian context. Most domestic studies have followed approaches similar to that of Diniz and Brugugnoli (2015), who replicated the experiment conducted by Kahneman and Tversky (1979) and confirmed that decision-makers systematically commit judgment errors, consistent with the original findings. Vieira (2012) found that the greater an investor's risk tolerance, the more likely they are to rely on behavioral heuristics, a tendency attributed to the increased complexity of decision-making. Similarly, Silva and Lucena (2019) investigated the determinants of herd behavior among companies listed on B3 and found a positive association between herding, the release of favorable news, and the subprime crisis, suggesting that investors adjust their behavior in response to positive information.

Borges (2007) examined the determinants of stock trading volume by relating fifty-two-week price highs and lows to the anchoring heuristic. More recently, Gallo and Bertella (2016) replicated this analysis using different parameters and concluded that anchoring contributes to investor overreaction, thereby providing further empirical support for behavioral finance theory.

The present study follows the same line of inquiry as these two studies but applies the analysis to a more recent period. The anchoring heuristic was selected because price anchors play a particularly prominent role in the Brazilian market, where financial news outlets and digital influencers frequently highlight breakouts above or below specific price levels as significant events for investors. Furthermore, the numerical nature of price anchors lends itself to quantitative analysis, thereby enhancing the methodological rigor and robustness of the findings.

This study is particularly relevant because previous investigations were conducted using data from trading periods characterized by markedly different market conditions, including substantially fewer investors, more limited access to information, and less sophisticated regulatory mechanisms. Consequently, this research contributes by reassessing earlier evidence within a contemporary market environment using updated parameters, while also providing a foundation for future studies in behavioral finance.

Behavioral Finance, Heuristics, and Empirical Evidence

Behavioral Finance

Behavioral finance differs from traditional finance by recognizing that economic agents do not possess unlimited rationality — one of the fundamental axioms of conventional financial theory — and that, under certain circumstances, they systematically behave according to noneconomic considerations. According to Mussa et al. (2008), behavioral finance represents an effort to refine modern financial theory by incorporating concepts from psychology and sociology. These disciplines make it possible to identify the influence of emotions and cognitive errors on investors' decisions, which ultimately shape market prices.

The leading figures in behavioral finance are the Israeli psychologists Daniel Kahneman and Amos Tversky. In their 1971 paper, *Belief in the law of small numbers*, they introduced their initial ideas regarding the reliability of statistical inferences drawn from small samples. In 1974, they published *Judgment under Uncertainty: Heuristics and Biases*, in which they described behavioral heuristics and identified a series of cognitive biases arising from these mental shortcuts. Their ideas gained widespread acceptance because their experiments demonstrated that the errors made by decision-makers are intrinsic to human cognitive processes rather than isolated deviations from rational utility maximization.

Later, in 1979, they published *Prospect Theory: An Analysis of Decision under Risk*, introducing what became known as Prospect Theory. Their findings showed that individuals tend to be risk-averse when facing potential gains but become risk-seeking when confronted with potential losses. In other words, people are generally willing to accept greater risk to avoid losses, whereas they prefer to secure smaller gains rather than gamble for larger ones. These findings contradict classical microeconomic utility theory, which assumes that decision-making depends solely on changes in utility levels.

According to Prospect Theory, it is psychologically unrealistic to characterize decisions under uncertainty — where outcomes are unknown at the time of choice — solely in terms of final wealth states, as assumed by traditional expected utility models. Instead, individuals evaluate such situations by assigning substantially greater weight to changes in wealth, whether these involve gains, losses, or maintaining the status quo (Tversky & Kahneman, 1983). This perspective is further supported by the studies of Fishburn and Kochenberger (1979), Hershey and Schoemaker (1980), Payne et al. (1980), among others, all of which document greater risk-seeking behavior in the domain of losses across a variety of decision-making contexts.

Importantly, behavioral finance does not represent a complete rejection of the traditional principles of economics and finance but rather an extension and refinement of existing theoretical models. In this regard, Milanez (2003) argues that behavioral finance seeks to demonstrate the limitations of traditional economic axioms in explaining price movements in financial markets.

Behavioral Heuristics

Individuals systematically make errors in decision-making because they rely on heuristics — rules of thumb that simplify the decision-making process (Aldrighi & Milanez, 2005). These mental shortcuts arise from the limited human capacity to process all available information relevant to a given problem. Tversky and Kahneman (1974) identified three principal heuristics: availability, representativeness, and anchoring and adjustment. They also described several cognitive biases that emerge from the use of these heuristics.

Under the availability heuristic, individuals estimate the frequency or probability of an event based on how easily similar instances can be recalled. As noted by Aldrighi and Milanez (2005), events that are more salient or more recent are more likely to be remembered. According to Lima Filho (2010), additional factors unrelated to the actual frequency of an event may influence information retrieval and consequently produce systematic errors in decision-making. Because many investors rely heavily on information when making investment decisions, they are particularly susceptible to the effects of the availability heuristic.

Biases associated with the retrievability of instances occur when individuals estimate the size or frequency of a category based on the ease with which relevant examples can be recalled. In contrast, biases resulting from the effectiveness of a search set arise when examples from one category are easier to retrieve than those from another, even when the underlying probabilities are comparable. Furthermore, when relevant examples are absent from memory, individuals may exhibit biases of imaginability, evaluating the likelihood of events according to how easily they can mentally construct them. Finally, illusory correlation refers to the tendency to perceive and rely on nonexistent associations between two or more events or characteristics.

The representativeness heuristic involves relying on commonly accepted patterns or stereotypes when making decisions in situations where outcomes are difficult to estimate. In financial markets, such stereotypes may stem from an investor's opinion of a company, its historical performance, or prevailing market consensus. According to Tversky and Kahneman (1974), judgments are influenced by: (i) the degree to which an event resembles the population from which it originates, and (ii) the extent to which the event reflects the characteristics of the process that generated it.

Insensitivity to prior probabilities refers to the tendency to disregard base-rate probabilities when evaluating outcomes. Insensitivity to sample size illustrates how individuals incorrectly generalize from population characteristics when interpreting the results of specific samples. Similarly, misconceptions of chance occur when people expect short sequences of random events to display the same characteristics as the underlying random process.

Another related bias is insensitivity to predictability, whereby predictions are formed primarily through the representativeness heuristic. The illusion of validity, in turn, refers to unwarranted confidence arising from the apparent consistency between an initial piece of information and a predicted outcome, even when that information has little predictive value. Within this context, misconceptions of regression occur when individuals fail to develop accurate intuitions about the phenomenon of regression toward the mean. Such errors arise either because people fail to anticipate regression when it should occur or because they construct spurious causal explanations for its occurrence.

Anchoring is the heuristic whereby initial values or previously provided information serve as reference points that influence subsequent judgments. Tversky and Kahneman (1974) demonstrated this phenomenon by assigning different numerical values to two groups of participants before asking them to answer an unrelated quantitative question. The results showed that participants relied on the assigned numbers as reference points (ie, as anchors) thereby systematically biasing their responses.

The insufficient adjustment bias occurs when individuals use the result of an incomplete calculation as the anchor for their own estimates. Biases in the evaluation of conjunctive and disjunctive events show that people tend to overestimate the probability of conjunctive events while underestimating the probability of disjunctive events.

Finally, anchoring in the assessment of subjective probability distributions demonstrates that individuals make calibration errors when estimating probabilities. A classic illustration involves asking experts to express their beliefs about the future value of the Dow Jones Index as a probability distribution. Across most studies, the realized values fell outside the confidence intervals provided by participants more frequently than expected, indicating that these intervals were excessively narrow and reflected greater certainty than was warranted given the available information.

Methodology

Panel Data Model

Consistent with the approaches adopted by Huddart et al. (2006), Borges (2007), and Gallo and Bertella (2016), this study estimates the determinants of the trading volume of stocks listed on a stock exchange. To this end, a panel data modeling approach was employed, as it is well suited to the characteristics of the sample, which consists of observations for a selected group of stocks organized over time.

Panel data models can be estimated using either fixed-effects or random-effects specifications. The former is directly applicable to unbalanced panels and assumes that the individual effects, α_i, may be correlated with one or more regressors, X_{it}. Correct estimation therefore requires controlling for this correlation. Formally, the fixed-effects model is specified as Equation (1):

$$Y_{it} = \alpha_i + X_{it}\beta + \varepsilon_{it} \tag{1}$$

where α_i is a fixed component that captures unobserved heterogeneity across the units of analysis. The subscript i indicates that the intercept may differ across units; X_{it} denotes the set of explanatory variables; and ε_{it} is the error term [$\varepsilon_{it} \sim iid(0,\sigma_\varepsilon^2)$]. In random-effects models, by contrast, the unobserved individual effect (α_i) is assumed to be uncorrelated with the explanatory variables. Consequently, no relationship exists between α_i and X_{it}, and α_i is incorporated into the composite error term μ_{it}, as shown in Equation (2):

$$Y_{it} = \alpha_i + X_{it}\beta + \mu_{it} \tag{2}$$

em que $\mu_{it} = \alpha_{it} + \varepsilon_{it}$, com $\varepsilon_i \sim iid(0,\sigma_\varepsilon^2)$ e $u_{it} \sim iid(0,\sigma_u^2)$;

The choice between the two specifications is based on the Hausman test, which evaluates the null hypothesis that the difference between the fixed-effects and random-effects coefficient estimates is not systematic. The fixed-effects estimator is preferred when and are correlated; otherwise, the random-effects estimator is more appropriate. According to Wooldridge (2003), a statistically significant difference between the two estimators provides evidence in favor of the fixed-effects model, leading to rejection of the null hypothesis.

Before model estimation, the statistical properties of the panel series must be examined. To this end, the IPS (Im, Pesaran, and Shin) and LLC (Levin, Lin, and Chu) panel unit root tests were applied. The IPS test is based on the average of augmented Dickey–Fuller (ADF) statistics and allows for heterogeneous autoregressive parameters across cross-sectional units. Its null hypothesis assumes the presence of a unit root, whereas the alternative hypothesis states that at least one cross-sectional unit is stationary. The IPS test also accommodates both fixed and individual effects. Pesaran (2004) argues that when panel dimensions are large, conventional techniques for estimating cross-sectional dependence become inadequate, making more robust testing procedures necessary.

The LLC test in turn provides a more robust panel unit root test than conducting individual stationarity tests for each cross-sectional unit separately. Under the null hypothesis, the series contains a unit root, whereas the alternative hypothesis assumes stationarity. The test may include several deterministic components, including the absence of exogenous variables, fixed and individual effects, and deterministic trends, with lag length selected based on autocorrelation criteria.

To determine whether the panel variables are cointegrated, the Pedroni (1999, 2004) cointegration test was employed. This procedure comprises seven residual-based test statistics. Under the null hypothesis, the nonstationary panel variables are not cointegrated. Under the alternative hypothesis, the cross-sectional units exhibit sufficiently large test statistics to support the existence of cointegration. These seven statistics are divided into two categories: group-mean statistics, which rely on individual cross-sectional estimates, and panel statistics.

Subsequently, the Wooldridge, Pesaran, and Wald diagnostic tests were performed to assess serial autocorrelation, cross-sectional dependence, and heteroskedasticity, respectively. The Wooldridge test evaluates the null hypothesis of no serial autocorrelation against the alternative hypothesis that past information influences the current behavior of the error terms. The Wald test follows the same logic but focuses on detecting heteroskedasticity. The Pesaran cross-sectional dependence test measures the average correlation across panel units. Its null hypothesis assumes strict cross-sectional independence or weak cross-sectional dependence, whereas the alternative hypothesis assumes that the error terms are correlated across panels.

When these specification problems are detected, estimation is corrected using the Panel-Corrected Standard Errors (PCSE) estimator. This linear regression approach accounts for the presence of heteroskedasticity and autocorrelation in the error structure by correcting the standard errors during estimation. In addition, it allows the researcher to specify whether autocorrelation is constant over time or contemporaneous across panels. The model is expressed as Equation (3):

$$\gamma_{it} = x_{it}\beta + \varepsilon_{it} \tag{3}$$

where $i = 1,\ldots, m$ denotes the number of panels, $t = 1,\ldots,T_i$, Ti is the number of time periods observed for panel i and is the error term, which may exhibit serial autocorrelation over time or contemporaneous correlation across panel units.

When autocorrelation is explicitly modeled, the final estimation is performed using the Prais–Winsten transformation, with parameter estimates conditioned on the estimated autocorrelation coefficients. Under the assumed covariance structure of the error terms, the estimated variance–covariance matrix of the parameters is asymptotically efficient based on generalized least squares estimation (Kmenta, 1997).

Furthermore, Beck and Katz (1995) demonstrated that in panel time-series models, when the estimation errors produced by ordinary least squares cannot be assumed to be spherical, there is no guarantee that the estimated standard errors will be valid, potentially leading to incorrect inferences regarding the model's confidence intervals. Estimation errors may also exhibit contemporaneous correlation across panel units, heteroskedasticity across panels, whereby error variances differ among units, and serial autocorrelation within panels. Under these conditions, the PCSE estimator provides one of the most efficient approaches for estimating panel time-series models.

Data and Variables

The dataset consists of weekly observations for the stocks included in the Bovespa Index (IBOVESPA) portfolio during the first quarter of 2016, with the index composition held constant throughout the study period. The initial sample comprised sixty-one stocks. Five stocks were excluded because trading was discontinued during the study period, two were removed due to mergers with other companies, and four were excluded because they did not provide data suitable for analysis owing to liquidity constraints or temporary trading suspensions. Consequently, the final sample consisted of 50 stocks (Appendix A). The study period spans 2017 to 2020, comprising 181 weeks. This period is particularly relevant because it coincides with a substantial increase in the popularity of stock market investing in Brazil, resulting in record levels of both individual investors and trading activity.

The IBOVESPA was selected because it is the most representative benchmark of the Brazilian equity market. This choice was intended to minimize liquidity-related estimation issues while providing a broad assessment of the behavior of the Brazilian stock market. All data were obtained from the ProfitChart™ platform and were already adjusted for dividend distributions, stock splits, and reverse stock splits. Furthermore, except for the manually constructed variables, all variables were transformed using the natural logarithm.

Abnormal Trading Volume and the DMAX and DMIN Dummy Variables

Abnormal trading volume (VOLat) was used as the dependent variable. Consistent with Gallo and Bertella (2016), this variable was calculated as the difference between the observed weekly trading volume of a stock (VOL) and its expected trading volume, where expected volume was defined as the arithmetic mean of trading volume over the reference period, as follows:

$$\sum_{i=1}^{n} VOL_{ij} \tag{4}$$

$$E(VOL) = {}^{\sum VOL_{ij-1}}/_{n} \tag{5}$$

$$VOLat = \sum VOL_{ij} - E(VOL_{ij}) \tag{6}$$

where $i = 1,\ldots,50$; j = 07/10/2017,…, 12/21/2020; VOL_{ij} denotes the trading volume of stock i at time t; and $VOLat_{ij}$ represents the abnormal weekly trading volume of stock i at time j.

To test for the presence and effect of the anchoring heuristic on abnormal trading volume, two dummy variables, DMAX and DMIN, were constructed. DMAX was assigned a value of 1 whenever a stock's closing price exceeded its highest closing price recorded during the previous fifty-two weeks. Similarly, DMIN was assigned a value of 1 whenever the closing price fell below its lowest closing price recorded during the previous fifty-two weeks. These variables were calculated using a rolling window, whereby the fifty-two-week reference period was updated each week to reflect the most recent fifty-two weeks of trading.

Control Variables

To isolate the effect of anchoring, a set of control variables was included to account for other factors that could influence stock trading volume. Chart 1 presents these variables and their descriptions.

Chart 1

Control variables

Variable	Description
RET1	Weekly logarithmic stock return relative to the previous week.
RET2	Weekly logarithmic stock return relative to the previous two weeks.
RET3	Weekly logarithmic stock return relative to the previous three weeks.
RET4	Weekly logarithmic stock return relative to the previous four weeks.
STD	Stock volatility over the previous twenty-four weeks, measured as the standard deviation of closing prices over the same period.

Source: Prepared by the authors (2022).

The control variables are consistent with those examined by Borges (2007) and were selected because they are considered potentially relevant determinants of investors' trading decisions. The return variables capture the historical performance realized by shareholders, whereas volatility is commonly regarded as a measure of market risk and is also associated with the creation of trading opportunities arising from differences between market prices and a stock's intrinsic value.

The return variables measure the percentage gain earned by investors holding a given stock over the specified periods. They were calculated from weekly closing prices as the logarithmic ratio between the current closing price and the corresponding closing price one, two, three, and four weeks earlier.

Analytical Model

After incorporating the control variables, the empirical model used to identify the presence of the anchoring heuristic in stock trading was specified as follows:

$$VOLat_{ij} = \beta_0 + \beta_1 DMAX_{ij} + \beta_2 DMIN_{ij} + \beta_3 RET1_{ij} + \beta_4 RET2_{ij} + \beta_5 RET3_{ij} + \beta_6 RET4_{ij} + \beta_7 STD_{ij} + \mu_{IJ} \quad (7)$$

where i = 1,…,50 and j = 07/10/2017,…, 12/21/2020; VOL_{ij} denotes the abnormal weekly trading volume of stock i at time j.

Consistent with the behavioral finance framework and the anchoring heuristic, and in line with Borges (2007) and Gallo and Bertella (2016), DMAX and DMIN are expected to exhibit statistically significant effects on abnormal trading volume, regardless of the direction of those effects. Furthermore, under the assumptions of traditional finance and the Efficient Market Hypothesis (EMH), the control variables are not expected to be statistically significant, since they are derived from historical price information that should already be fully incorporated into current trading activity.

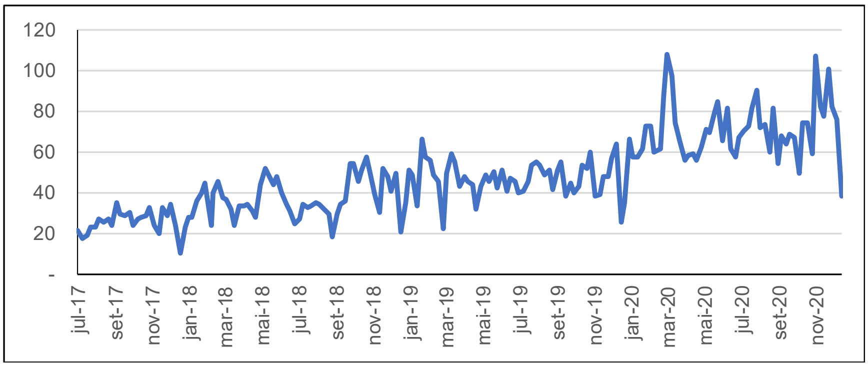
Results and Discussion

Descriptive Statistics and Specification and Diagnostic Tests

The descriptive analysis begins with an examination of weekly trading volume over the study period. As illustrated in Figure 1, the 2017–2020 period was characterized by substantial growth in trading activity, encompassing all transactions executed on the Brazilian stock exchange (B3).

Figure 1

IBOVESPA trading volume between 2017 and 2020 (BRL billions)



Source: B3 (2022).

The increase in trading volume likely contributed to making the assumptions of behavioral finance more evident, as a larger number of market participants and transactions increases the opportunities for behavioral effects to emerge. This expansion also highlights the relevance of studying investor behavior and reflects the continued development of the Brazilian financial market.

Regarding the dummy variables, a total of 349 occurrences were recorded during the study period (Table 1), comprising 191 observations for DMAX and 158 observations for DMIN.

Table 1

Descriptive statistics for the dummy variables

Statistic	DMAX	DMIN
Occurrences (dummy = 1)	191	158
Mean per stock	3.82	3.16
Stocks with at least one occurrence	16	10
Maximum occurrences per stock	50	95

Source: Research results (2022).

The IPS and LLC unit root tests indicated that all series were stationary in levels, with the exception of the volatility variable under the IPS test. However, volatility was found to be stationary when evaluated using the LLC test (Table 2). The LLC test could not be applied to the stock return series because these variables were constructed from unbalanced panel data.

Table 2

Results of the IPS and LLC unit root tests

Variable/Test	IPS[1]	LLC[2]
VOLat	-34.8710***	-20.9591***
RET1	-68.9095***	-
RET2	-43.6615***	-
RET3	-33.6059***	-
RET4	-28.6231***	-
STD	3.4453	-7.6640***

Source: Research results (2022).
[1]Assumes individual unit roots; [2]Assumes a common unit root.
***, **, and * indicate rejection of the null hypothesis of nonstationarity at the 1%, 5%, and 10% significance levels, respectively.

The Pedroni cointegration test subsequently indicated that the variables are cointegrated based on all three reported statistics, with rejection of the null hypothesis at the 1% significance level. When combined with evidence of serial correlation, this result suggests that the model should be estimated using time lags (Table 3).

Table 3

Results of the cointegration and diagnostic tests

Test statistic	Value
Modified Phillips-Perron t	-45.9967***
Phillips-Perron t	-46.2888***
Augmented Dickey-Fuller t	-46.1559***
Hausman	25.21***
Wooldridge	7.902***
Wald	1.3e+06***

Source: Research results (2022).
***, **, and * indicate rejection of the null hypothesis of no cointegration at the 1%, 5%, and 10% significance levels, respectively.

The Hausman test supported the use of a fixed-effects model, rejecting the null hypothesis that the differences between the fixed-effects and random-effects estimators are not systematic. The diagnostic tests performed on the initial specification also rejected the null hypotheses of no serial autocorrelation and homoskedasticity, indicating that these issues required correction.

Finally, the Pesaran test for cross-sectional dependence rejected the null hypothesis of cross-sectional independence for all variables (Table 4). Consequently, the final specification incorporates corrections for cross-sectional dependence.

Table 4

Results of the Pesaran cross-sectional dependence test

Variable	Value
VOLat	225.847***
RET1	197.051***
RET2	203.319***
RET3	219.109***
RET4	232.541***
STD	218.907***

Source: Research results (2022).
***, **, and * indicate rejection of the null hypothesis of cross-sectional independence at the 1%, 5%, and 10% significance levels, respectively.

In summary, the statistical tests indicate that the panel time series are stationary in levels (IPS and LLC), cointegrated (Pedroni), affected by both serial and cross-sectional dependence (Wooldridge and Pesaran), and heteroskedastic (Wald). Accordingly, the final model was estimated using the Panel-Corrected Standard Errors (PCSE) estimator with temporal lags, thereby addressing all identified specification issues.

Results of the Empirical Model

After evaluating the properties of the panel time series and confirming the suitability of the empirical specification, the model was estimated using the Panel-Corrected Standard Errors (PCSE) estimator (Table 5). Notably, this specification explicitly corrects for the serial autocorrelation and heteroskedasticity identified in the diagnostic tests. Furthermore, the return variables corresponding to the previous three and four weeks were not statistically significant, suggesting that investors placed greater emphasis on more recent stock returns while assigning less weight to older price information. From the perspective of these variables, the market may therefore be considered efficient in incorporating historical price information into current prices.

As originally proposed by Tversky and Kahneman (1974), the anchoring heuristic assumes that investors rely on historical price information when making buy and sell decisions, basing their judgments on the relative position of current prices with respect to a chosen anchor. Such reference points are not necessarily meaningful indicators of an asset’s intrinsic value, making their use inconsistent with the assumptions of traditional finance and market efficiency.

Table 5

PCSE regression results for VOLat (2017–2020)

Variables	**Coefficient**	**z-statistic**
DMAX	-0.0779	-7.37***
DMIN	0.0536	2.17**
RET1	0.0212	2.03**
RET2	0.0157	1.62*
RET3	-0.002	-0.23
RET4	-0.002	-0.19
STD	0.5506	2.43**
Intercept	22.1368	867.06***
R^2		0,9955
Wald χ^2		68,67

Source: Research results (2022).

***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Borges (2007) found evidence that investors use the lowest price observed during the previous fifty-two weeks as a reference point when making trading decisions, leading to an increase in trading volume. This finding was also confirmed in the present study, which additionally identified an effect associated with the fifty-two-week high. However, unlike Borges (2007), who reported no statistically significant relationship for this variable, the present analysis found that exceeding the fifty-two-week high was associated with a reduction in trading volume.

Both dummy variables were statistically significant in explaining changes in trading volume during periods when closing prices either exceeded the highest closing price or fell below the lowest closing price observed over the previous fifty-two weeks. Specifically, when a stock's closing price surpassed its fifty-two-week high, abnormal trading volume (VOLat) decreased. Conversely, when the closing price fell below its fifty-two-week low, abnormal trading volume increased, indicating more intense trading activity during those periods.

These findings indicate that investors rely on the anchoring heuristic when making decisions regarding the purchase and sale of assets in their portfolios. The negative relationship observed for DMAX differs from the findings reported by Huddart et al. (2006) and Borges (2007). Nevertheless, this result remains consistent with behavioral finance theory, as it suggests that investors modify their trading behavior when prices exceed previous highs, thereby demonstrating the influence of anchoring. By contrast, the positive coefficient estimated for DMIN is fully consistent with the existing literature and with the anchoring heuristic, indicating that investors tend to trade more actively after prices break below previous lows, increasing abnormal trading volume during such periods.

One possible explanation for the partially divergent result obtained for DMAX, relative to Borges (2007), is that investors already holding the stock chose to maintain their positions in anticipation of continued upward price movements. At the same time, potential investors who were not yet invested may have perceived these prices as exceeding the assets' intrinsic value and therefore refrained from entering the market. It is also important to note that previous studies were conducted during periods characterized by substantially different market conditions, particularly regarding the number and profile of investors, factors that may have contributed to the observed differences.

With respect to the control variables, all variables except the returns from the previous three and four weeks were statistically significant, indicating that both historical prices and past volatility influenced current trading activity. Under the assumptions of traditional market efficiency, such a result would not be expected, since historical information should already be fully reflected in current prices. Furthermore, the positive coefficients indicate that investors tend to trade more actively following positive stock returns. The return observed during the previous week exerted a stronger influence than returns from earlier weeks, a finding that is consistent with behavioral finance theory, according to which information that is more readily available to investors has a greater impact on decision-making. Specifically, a 1% increase in the previous week's return was associated with an approximately 0.02% increase in abnormal trading volume, whereas the corresponding effect for returns over the previous two weeks was approximately 0.01%.

Asset volatility (STD) also exerted a positive and comparatively large effect on abnormal trading volume. This finding is consistent with theoretical expectations, as heightened price volatility often signals unusual market movements and consequently stimulates trading activity. According to the estimated model, a 1% increase in volatility was associated with an approximately 0.55% increase in weekly abnormal trading volume. This positive relationship between trading volume and volatility is consistent with the findings of Medeiros and Doornik (2008), who documented both contemporaneous and dynamic relationships between these variables. One possible explanation is that periods of elevated volatility lead investors to perceive the market as riskier while simultaneously creating opportunities either to sell existing positions or to purchase assets at discounted prices.

Despite the substantial increase in both the number of investors and the amount of market information available, the anchoring heuristic continues to play a significant role in determining trading activity. This finding reinforces the validity of behavioral finance theory by demonstrating that, even under market conditions that are more conducive to efficiency, the influence of anchoring cannot be disregarded. Moreover, despite its remarkable growth in recent years, the Brazilian financial market remains comparatively more uncertain from both regulatory and institutional perspectives than more mature markets, such as those in the United States and Europe. In addition, Brazilian investors generally possess less market experience, factors that may have contributed to the observed results.

Conclusions

To contribute to the behavioral finance literature and expand the existing empirical evidence, this study investigated the presence and magnitude of the anchoring heuristic in stock trading on the Brazilian stock market between 2017 and 2020. To accomplish this objective, a panel data regression approach was employed.

The results provide evidence of the presence of the anchoring heuristic in stock trading through the statistical significance of the dummy variables representing breakouts above or below the highest and lowest prices recorded during the previous fifty-two weeks. These variables significantly explained abnormal trading volume in the market. Specifically, abnormal trading volume tended to decline after prices exceeded previous highs, whereas breaches below previous lows were associated with an increase in abnormal trading volume.

Returns observed over the previous two weeks, together with asset volatility, exerted positive effects on abnormal trading volume, indicating that investors consider these variables relevant when making trading decisions. In contrast, returns from the previous three and four weeks were not statistically significant, suggesting that investors assign greater importance to more recent information than to older price data. Accordingly, the evidence supports the weak-form market efficiency hypothesis for returns observed three and four weeks earlier, but not for returns from the two most recent weeks.

Overall, the findings reinforce the notion that, despite the growing number of market participants and the increasing availability of investment-related information—both of which should contribute to greater market efficiency—the predictions of behavioral finance continue to be observed, with investors not behaving in a fully rational or efficient manner. Furthermore, the statistical significance of the control variables is inconsistent with the Efficient Market Hypothesis and indicates that investors continue to rely on historical price information, particularly the most recent observations, when making current buy and sell decisions.

The presence of anchoring in asset trading suggests that investors are influenced by factors that are not necessarily relevant to the accurate valuation of financial assets, making them susceptible to systematic decision-making errors that may ultimately result in investment performance inferior to prevailing market returns. In this context, understanding behavioral heuristics and cognitive biases is essential for improving market efficiency and helping both novice and experienced investors achieve better investment outcomes.

This study was conducted using a limited number of control variables and empirical specifications. Consequently, further research is encouraged to expand the empirical evidence concerning anchoring and other behavioral heuristics. In particular, future studies should examine anchoring over shorter time horizons to identify how far into the past investors continue to regard price information as relevant. Additional research involving less actively traded stocks would also be valuable for assessing whether securities with lower analyst coverage and reduced market attention are more susceptible to anchoring effects than those included in IBOVESPA. Finally, given the relatively limited body of research on behavioral finance in the Brazilian context compared with the international literature, together with the growing investment culture in Brazil, further investigation into how behavioral biases influence investors and securities trading activity remains an important research agenda.

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Appendix A – Tickers of the Sampled Stocks

ABEV3, B3SA3, BBAS3, BBDC3, BBDC4, BBSE3, BRAP4, BRFS3, BRKM5, BRML3, CCRO3, CESP6, CIEL3, CMIG4, CPFE3, CPLE6, CSAN3, CSNA3, CYRE3, ECOR3, EMBR3, ENBR3, EQTL3, GGBR4, GOAU4, HGTX3, HYPE3, ITSA4, ITUB4, JBSS3, KLBN11, LAME4, LREN3, MRFG3, MRVE3, MULT3, NTCO3, OIBR3, PETR3, PETR4, QUAL3, RADL3, RENT3, SANB11, SBSP3, TIMS3, UGPA3, USIM5, VALE3, WEGE3.