ISSN 1808-057X
DOI: 10.1590/1808-057x20241894.en

ORIGINAL ARTICLE

Evaluating momentum in Brazil using quantile regressions

Rodrigo Abbade da Silva[1]
https://orcid.org/0000-0002-7312-4819
Email: rodrigoabbade@unipampa.edu.br

Newton da Costa Jr.[2,3]
https://orcid.org/0000-0001-7723-2676
Email: newton.costa@ufsc.br

Manuel J. da Rocha Armada[4]
https://orcid.org/0000-0002-2301-1752
Email: rarmada@eeg.uminho.pt

[1] Universidade Federal do Pampa, Departamento de Administração, Santana do Livramento, RS, Brazil
[2] Universidade Federal de Santa Catarina, Programa de Pós-Graduação em Administração, Florianópolis, SC, Brazil
[3] Pontifícia Universidade Católica do Paraná, Programa de Pós-Graduação em Administração, Curitiba, PR, Brazil
[4] Universidade do Minho, Escola de Economia e Gestão, Minho, Portugal

Received on 04/02/2023 – Desk acceptance on 06/15/2023 – 2nd version approved on 09/18/2023
Editor-in-Chief: Andson Braga de Aguiar
Associate Editor: Andrea Maria Accioly Fonseca Minardi

ABSTRACT

The purpose of this study was to measure the relationship between expected returns and capital gains overhang (CGO) (a proxy for the disposition effect) in the Brazilian financial market. It also investigated the ability of the disposition effect to induce momentum. Quantile regression allows the study of the importance of extreme values in the regression. In this way, it is possible to study the relationship between the disposition effect and the expected return between losing and winning stocks using data for the Brazilian financial market. This may help explain the conflicting results found in the literature when studying this relationship in other countries. This study contributes to the development of the topic of the relationship between the disposition effect and unrealized capital gains in the financial market. For this, we apply Fama-MacBeth regression and quantile regression models. Initially, we study the relationship between CGO and expected return. Subsequently, we investigate the ability of the disposition effect to generate the momentum effect at extreme quantiles of expected return (0.05th – losing stocks and 0.95th – winning stocks). We used a sample of 227 shares of companies listed on the Brazilian stock exchange (B3) and monthly historical series from January 2000 to October 2018. We found a significant and positive relationship between CGO and expected return across different levels of expected return, decreasing from the lowest to the highest quantile of expected return. This indicates that Brazilian investors, who are prone to the disposition effect, operate at the extreme quantiles of expected return.

Keywords: prospect theory, disposition effect, momentum, quantile regression, uninformed investors.

Correspondence address

Rodrigo Abbade da Silva
Universidade Federal do Pampa, Departamento de Administração
Rua Barão do Triunfo, 1048 – CEP: 97573-634
Centro – Santana do Livramento – RS – Brazil

This is a bilingual text. This article has also been translated into Portuguese and published under the DOI https://doi.org/10.1590/1808-057x20241894.pt

This article stems from a Ph.D. thesis submitted by the co-author Rodrigo Abbade da Silva, in 2020.

Study presented at the 21st Brazilian Finance Meeting, July 2021.

Avaliação do momentum no Brasil usando regressões quantílicas

RESUMO

O objetivo deste estudo foi medir a relação entre os retornos esperados e o excesso de ganhos de capital (CGO, do inglês capital gains overhang) (como proxy para o efeito disposição) no mercado financeiro brasileiro. Ele também investigou a capacidade do efeito disposição de induzir o momentum. A regressão quantílica permite o estudo da importância dos valores extremos na regressão. Dessa forma, é possível estudar a relação entre o efeito disposição e o retorno esperado entre ações vencedoras e perdedoras usando dados do mercado financeiro brasileiro. Isso pode ajudar a explicar os resultados conflitantes encontrados na literatura ao estudar essa relação em outros países. Este estudo contribui para o desenvolvimento do tema da relação entre o efeito disposição e os ganhos de capital não realizados no mercado financeiro. Para isso, aplicamos os modelos de regressão Fama-MacBeth e de regressão quantílica. Inicialmente, estudamos a relação entre o CGO e o retorno esperado. Posteriormente, investigamos a capacidade do efeito disposição de gerar o efeito momentum em quantis extremos do retorno esperado (0,05º – ações perdedoras e 0,95º – ações vencedoras). Usamos uma amostra de 227 ações de empresas listadas na bolsa de valores brasileira (B3) e séries históricas mensais de janeiro de 2000 a outubro de 2018. Encontramos uma relação significativa e positiva entre o CGO e o retorno esperado em diferentes níveis de retorno esperado, diminuindo do menor para o maior quantil de retorno esperado. Isso indica que os investidores brasileiros, que são propensos ao efeito disposição, operam nos quantis extremos do retorno esperado.

Palavras-chave: *teoria do prospecto, efeito disposição, momentum, regressão quantílica, investidores desinformados.*

1. INTRODUCTION

According to Grinblatt and Han (2002), momentum is an anomaly found in the financial market and can be defined as the persistence of stock returns over the three-month to one-year time horizon. The disposition effect can be understood as the greater propensity of investors to sell stocks that have increased in value (winning stocks) relative to their purchase price versus stocks that have decreased in value (losing stocks). The combination of these different understandings may indicate that the disposition effect induces momentum because, due to the release of good news in the market, winning stocks would be sold as soon as possible, slowing down the speed at which stock prices would adjust to the new fundamental price, which is higher than their previous price. Meanwhile, with the release of bad news in the market, losing stocks would tend to be held by investors, which would restrain the reduction of stock prices to their new fundamental price, which is lower than their previous price.

Furthermore, Grinblatt and Han (2002), by combining prospect theory and mental accounting (PT/MA), proposed the capital gains overhang (CGO) model of unrealized capital gains (losses), which has a positive correlation with expected stock returns, using past stock returns to predict future stock returns. CGO behaves according to PT/MA, i.e., it sets a cumulative reference price (aggregate cost of stocks to investors) or simply an aggregate reversion price, e.g., the point at which investors would come to believe that a winning stock has turned into a losing stock and thus change their behavior from selling winning stocks to holding losing stocks.

Jegadeesh and Titman (1993) analyzed the performance of an investment strategy based on forming portfolios by buying winning stocks and selling losing stocks in the U.S. financial market. They found that winning stocks tended to generate positive returns and outperform losing stocks over a time horizon of three months to one year. This persistence has been documented as the momentum effect. Moreover, it is more evident over intermediate and long time horizons. Also in the US financial market, Grundy and Martin (2001) analyzed the performance of the momentum strategy based on buying recent winning stocks and keeping only recent losers with small losses in a portfolio. They found that this momentum-based strategy was more profitable than strategies based on building a portfolio using total stock returns. Furthermore, they found that the momentum effect could not be explained by different industry sectors and cross-sectional differences.

Grinblatt and Han (2002) pioneered the analysis of the disposition and momentum effects using CGO, size and past returns as control variables for the US financial market. They found that the momentum effect can be driven by the correlation between past stock returns and CGO (as a proxy for the disposition effect). Similarly, Bhootra and Hur (2012), when studying the momentum effect in the US financial market over the period from

1980 to 2005, found a positive relationship between CGO and future stock returns.

Several studies in the international literature have found evidence of the momentum effect. Rouwenhorst (1998) found it in Austria, Belgium, Denmark, France, Germany, Italy, the Netherlands, Norway, Spain, Sweden, Switzerland, and the United Kingdom. Other studies that support the existence of the momentum effect in Europe include those of Hon and Tonks (2003) for the United Kingdom, Glaser and Weber (2003) for Germany, and Muga and Santamaria (2007) for Spain.

Rouwenhorst (1998) argued that the factors that contribute to the existence of the momentum effect in the US financial market are not present in the emerging financial markets of Asia. Indeed, when he assessed the possible existence of the momentum effect in the intermediate time horizon in 20 emerging markets, he found that the effect exists in 16 economies, including Brazil. Hameed and Kusnadi (2002), when performing the same analysis in Asian financial markets, found no momentum effect in the financial markets of South Korea, Hong Kong, Malaysia, Singapore, Taiwan, and Thailand. Wang et al. (2017), when examining China's financial market between 1994 and 2000, found no evidence of the momentum effect in the intermediate and long time horizons.

Muga and Santamaria (2007) tested the existence of the momentum effect in four Latin American countries (Argentina, Brazil, Chile, and Mexico) using data from 1994 to 2005. The results showed the presence of the momentum effect in the four countries in question. They emphasized that this is one of the few studies in which the momentum effect is more pronounced in Latin America than in European countries or developed economies. They pointed out that asset pricing models consistent with risk-averse investors failed to explain the persistence of stock returns and that both stock type and country influence the occurrence of the momentum effect, with the influence of stock type being more relevant.

As shown above, after Jegadeesh and Titman's (1993) study, which was the first to identify the momentum effect, several studies have been conducted on the momentum effect in different countries around the world, mainly in Europe, North America and Asia, including both developed and developing countries. However, the analysis of the momentum effect in Brazil with the more sophisticated quantile regression model controlled for CGO represents a gap in the behavioral finance literature. The relevance of the CGO variable is, first, that it allows the identification of the disposition effect and, second, that it allows the assessment of whether the disposition effect induces momentum. Quantile regression allows the identification, at the extreme quantiles (0.05th and 0.95th), of how investors behave in situations of greater losses and gains, respectively.

The only study identified with a framework similar to the one used in this paper is the research conducted by Ahmed and Doukas (2021) on the US financial market. These authors stressed the need to revisit the momentum effect with the quantile regression approach to test its robustness in greater depth, since most of the studies on this topic use ordinary least squares (OLS) models, and the main shortcoming of this method is that it does not accurately represent the influence of the extreme values of the sample in their results.

Thus, our main contribution addresses this gap in the literature by analyzing the momentum effect in a developing market using the quantile regression method, exploring its main impacts on the extreme quantiles (highest and lowest) of expected return and CGO. In addition, the relationship between the momentum effect and CGO is examined. Through this variable, it is possible to identify whether the disposition effect can induce the momentum effect, allowing us to determine whether there is a linear relationship between past returns and CGO as the quantiles of the dependent variable in the quantile regression vary. It also helps to identify, in light of PT/MA, winning stocks through CGO. Thus, attentive investors can design profitable strategies based on the momentum effect, taking into account the disposition effect.

This article is structured as follows. The next section reviews the empirical evidence and develops the research hypotheses, while Section 3 describes the data. Section 4 presents a summary of the quantile regression model and the empirical model used in the study, and Section 5 presents the results obtained. The conclusions are presented in Section 6.

2. LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

According to Grinblatt and Han (2002), momentum can be defined as the persistence of stock returns over a time horizon of three months to one year. Jegadeesh and Titman (1993) argued that buying winning stocks and selling losing stocks can provide investors with positive abnormal returns, more so over the intermediate time horizon.

Grinblatt and Han (2005) argued that stocks with positive CGO, when related to positive return momentum, are often stocks with positive expected return, i.e., winning stocks. However, if the opposite occurs, we have losing stocks. Thus, the disposition effect is associated with an underreaction in the market, a slowdown in the speed at which prices adjust to new fundamental values due to new information coming into the market.

Frazzini (2006) argued that there may be different patterns of investor reactions to good and bad news because there are different patterns of price persistence. Thus, it is believed that these non-uniform patterns could be better captured by the quantile regression model. Therefore, the following hypothesis is raised:

> Hypothesis 1: The relationship between past returns over the three time horizons and CGO is not uniform and varies across quantiles.

The second hypothesis, inspired by Grinblatt and Han (2005) and Leal et al. (2010), aims to test the conflict in the literature on the relationship between CGO and expected returns. Grinblatt and Han (2005) and Frazzini (2006) found a positive relationship between CGO and expected returns. However, studies such as those of Choe and Eom (2009), Goetzmann and Massa (2008), and Kong et al. (2015) found a negative relationship between CGO and expected returns. Furthermore, according to Leal et al. (2010), the disposition effect may react differently under different conditions, which would consequently affect the behavior of the momentum effect, as found by Kim and Nofsinger (2007) regarding the financial market in Japan due to its market trend.

Leal et al. (2010) found a difference in the intensity of the disposition effect as a function of firm size in the Portuguese financial market. Grinblatt and Keloharju (2000), for various types of investors (local, foreign, government, financial and non-financial institutions) in the Finnish financial market, perceived the opposite disposition effect only for local investors. In addition, studies have found a relationship between investor sentiment and risk-return, with the possibility that the former distorts investor behavior, possibly because uninformed investors or noise traders are more likely to act irrationally in the market during periods of optimism than institutional investors (Baker & Wurgler, 2006; Brown & Cliff, 2004; Long, Shleifer, Summers, & Waldmann, 1990); Piccoli, Costa, Silva, & Cruz, 2018). Thus, this may suggest that there is a non-linear relationship between CGO and expected return, which could not be verified by the OLS estimation technique applied in the aforementioned studies, but can be studied using the quantile regression model. This leads to the second hypothesis:

> Hypothesis 2: The relationship between expected return and CGO is non-linear.

3. DATA

Monthly closing prices of all stocks listed on the B3, the Brazilian stock exchange, were collected for the period from January 2000 to October 2018. The data source used was from the company Economatica. Also, similar to Marschner and Ceretta (2021) and Piccoli et al. (2018), we use the consumer confidence index as a proxy for investor sentiment, obtained through the Ipeadata 2020 database. This decision was made because the Brazilian market lacks the necessary information to generate the sentiment indices used by Baker and Wurgler (2006) and Yu and Yuan (2011). Furthermore, there is no consensus in the Brazilian literature about which index is more precise, but the index we use is the only one whose historical series encompasses the 2007 financial crisis. To minimize survivorship bias, the list of companies collected considered active and inactive stocks. Furthermore, all stocks with fewer than 36 observations were removed to avoid losing data for the CGO estimation. We also lost observations in the initial 36-month truncation of the data to calculate the reference price, leaving a final sample of 227 stocks and 46,360 observations. As a result of this procedure, the analysis period for this paper begins in January 2003 and ends in October 2018. Moreover, monthly rather than weekly periodicity was used to calculate CGO because the sample used included a large number of small stocks that would be affected by thin trading if weekly data were used, a procedure also used by Ahmed and Doukas (2021) for the US market. Table 1 reports the coefficients.

Table 1
Description of the variables

Variables	Definition
CGO_t	Capital gains overhang is calculated as the percentage difference between current prices and the reference price. $$CGO_t = \frac{P_t - RP_t}{P_t} \quad (1)$$ where P_t is the closing price at time *t* and RP_t is the reference price calculated according to Grinblatt & Han (2002).
r_t^i	Stock returns as measured by the change in monthly closing prices $$r_t^i = \frac{P_t^i - P_{t-1}^i}{P_{t-1}^i} \quad (2)$$ where P_t^i is the closing price in month t and P_{t-1}^i is the closing price in month *t-1*.
$r_{-3:-1}$	The cumulative past return over the short-term horizon of the last 3 months.
$r_{-12:-4}$	The intermediate-term horizon between the last 4 and 12 months.
$r_{-36:-13}$	The long-term horizon between the last 13 and 36 months.
$V_{-3:-1}$	The average turnover over the short-term horizon for the last 3 months.
$V_{-12:-4}$	The average turnover over the intermediate-term horizon between the last 4 and 12 months.
$V_{-36:-13}$	The average turnover over the long-term horizon between the last 13 and 36 months.
V	The proxy for the volume effect is the average monthly turnover ratio (share volume divided by the number of shares outstanding) over the last 12 months.
Institutional investors	The percentage of freely traded shares held by institutions relative to the number of outstanding shares. We employ the definition proposed by Baker & Nofsinger (2010), who argue that institutional investors can be understood as rational investors. This is because they have the required knowledge and are capable of initiating movements, generating mispricing and inefficiency in the market.
Leverage	The monthly ratio of equity to debt. A measure of a company's indebtedness.
Size	A proxy for monthly market capitalization expressed as a natural logarithm.
Investor sentiment	This indicator assesses the level of confidence of the population in the overall situation of the country and in the current and future conditions of their families.

Source: *Prepared by the authors.*

The variable CGO is a measure of unrealized capital gains (losses) relative to reference prices (RP_t). Therefore, to estimate it, it is first necessary to calculate RP_t, because the estimated CGO will be proportional to RP_t. According to Grinblatt and Han (2005), to calculate RP_t, it is necessary to truncate the data, which results in the loss of some observations. Furthermore, Grinblatt and Han (2005) used 60-month truncation to estimate their RP_t, but they found that RP_t is often robust to truncations of 36 to 84 months of data. Therefore, in our work, to avoid the loss of various data and increase the robustness of the tests, we chose to truncate RP_t at 36 months, according to Equation 3:

$$RP_t = \frac{1}{k}\sum_{n=1}^{36}\left(V_{t-n}\prod_{\tau=1}^{n-1}\left[1 - V_{t-n+\tau}\right]\right)P_{t-n} \quad (3)$$

where V_t is the turnover ratio at *t*; P_{t-n} is the closing price at *t*–*n*, also representing the probability that a stock bought at *t*–*n* has not yet been sold; *k* is the constant that makes the sum of the weights equal to one. In the parentheses, the mathematical term is a weight, and all the weights sum to one.

The CGO measure can also be understood as the percentage deviation between the aggregate base cost (RP_t) and the current stock prices (P_t), as suggested by Bhootra and Hur (2012) and Frazzini (2006). Thus, unrealized capital gains are the best estimate of the base cost of stocks represented to an investor. Similarly, CGO is the difference between current prices and the reference price, thereby serving as a proxy for the mispricing of stocks, according to Equation 1.

3.1 Summary Statistics

The descriptive statistics of the variables used in this study are presented in Table 2. There we can see that CGO has a negative mean (-0.3293) and a standard deviation equal to 1.724. However, the expected return has a positive mean (0.0176) and a standard deviation equal to 0.273. These results are in line with those found by Ahmed and Doukas (2021) for the US market.

Table 2
Descriptive statistics

Variables	Obs.	Mean	Median	Standard deviation	Min.	Max.	Skew	10th Pct.	90th Pct.
CGO	48,388	-0.3293	-0.0086	1.7240	-99.1295	1.0000	-16.9023	-1.0507	0.3608
r	46,467	0.0176	-0.0029	0.2730	-0.8813	29.7422	42.7456	-0.1386	0.1653
$r_{-3:-1}$	49,088	0.0525	0.0014	0.4632	-0.9306	38.4090	25.4855	-0.2374	0.3346
$r_{-12:-4}$	52,294	0.1673	0.0269	0.8778	-0.9850	38.4310	10.8194	-0.4014	0.7387
$r_{-36:-13}$	56,032	0.5033	0.0454	3.2379	-0.9936	136.9496	21.6197	-0.5814	1.4841
S	52,720	13.9008	14.1149	2.3386	4.0490	20.5704	-0.3176	10.6833	16.7241
V	45,073	0.0118	0.0022	0.0328	0.0000	1.5947	14.0023	0.0000	0.0294

Note: *This table presents the main descriptive statistics for the following variables: (1) capital gains overhang (CGO); monthly stock return (r); the cumulative returns over the three time horizons (*$(r_{-3:-1})$*,*$(r_{-12:-4})$*, and *$(r_{-36:-13})$*); the natural log of the monthly market capitalization as a proxy for size (S); and the average monthly turnover over the last 12 months as a proxy for liquidity (V).*
Source: *Prepared by the authors.*

4. EMPIRICAL MODEL

4.1 Quantile Regression Technique

First, the two main estimation techniques used in linear regression models are presented. They are then related to the development of the quantile regression model developed by Koenker and Bassett (1978).

4.1.1 Ordinary least squares (OLS) and least absolute deviations (LAD) methods

According to Ahmed and Doukas (2021) and Wooldridge (2015), quantile regression regresses multiple estimates determined by quantiles. Thus, different data intervals are generated as a function of the distribution of the dependent variable *y*, instead of focusing only on the conditional mean of the entire sample (Hendricks & Koenker, 1992). The basic regression model is expressed in Equation 4:

$$y_{it} = x_{it}^{'}.\beta + u_{it} \quad (4)$$

where *y* is the dependent variable; *x* is the independent variable; *u* is the error term; *β* is the slope coefficient; *i* = 1, 2, 3…, *N* is the sample units; and *t* = 1, 2, 3…., *t* is the time.

The OLS method is based on the central limit theorem, which is often used in the literature because of its ease of application and accuracy. This method aims to minimize the residual sum of squares. Also based on the central limit theorem, the method of least absolute deviations seeks to minimize the sum of the absolute values of the residuals, as seen in equations 5 and 6, respectively:

$$\min \sum_i (u_{it})^2 = \sum_i \left(y_{it} - x_{it}^{'}.\beta\right)^2 \quad (5)$$

$$\min \sum_i |u_{it}| = \sum_i \left|y_{it} - x_{it}^{'}.\beta\right| \quad (6)$$

Thus, OLS is more successful when the regression residuals are not highly dispersed, while LAD is more robust to asymmetric conditional distributions with wide tails (Wooldridge, 2015).

According to Koenker and Bassett (1978), the quantile regression model calculates the effect of the dependent variable on different parts of the distribution using LAD. In this regard, it aims to overcome the limitations of the OLS and LAD techniques.

4.1.2 Quantile regression model

Traditional linear regression models provide a specific view of the results, while the quantile regression model can provide a detailed understanding of the entire regression (Koenker & Bassett, 1978). The quantile regression model was developed as an extension of the conventional LAD technique. Unlike traditional regression models, quantile regression generates quantiles from the independent variables and then uses the LAD technique to solve the intervals of the quantiles, one by one, according to the objective of the study. It often verifies how the extreme values of the independent variables affect the dependent variable, which generates several linear regression models as a function of the quantiles.

According to Rodriguez and Yao (2017), the traditional linear regression model is estimated according to Equation 7:

$$E(y_i) = \beta_0 + \beta_1 x_{i1} + \ldots + \beta_p x_{ip},\ i = 1, \ldots, n \quad (7)$$

And β_j is estimated using the ordinary least squares technique:

$$min_{\beta_0,\ldots,\beta_p} \sum_{i=1}^{n} \left(y_i - \beta_0 - \sum_{j=1}^{p} x_{ij} \beta_j \right)^2 \quad (8)$$

In contrast, quantile regression solves it at the level of the quantiles (τ), using the least absolute deviations technique:

$$Q_\tau(y_i) = \beta_0(\tau) + \beta_1(\tau) x_{i1} + \ldots + \beta_p(\tau) x_{ip}, i = 1, \ldots, n \quad (9)$$

And β_j is estimated by means of the minimization problem:

$$min_{\beta_0(\tau),\ldots,\beta_p(\tau)} \sum_{i=1}^{n} \rho_\tau \left(y_i - \beta_0(\tau) - \sum_{j=1}^{\rho} x_{ij} \beta_j(\tau) \right) \quad (10)$$

where $\rho_\tau(r) = \tau \max(r, 0) + (1 - \tau) \max(-r, 0)$. The function $\rho_\tau(r)$ is referred to as check loss because its shape resembles a check mark. Thus, for each quantile level (τ), the LAD estimation technique is applied by designing the regression coefficients. Furthermore, the solution, when the quantile $\tau = 0.5$, corresponds to the solution of the regression without a quantile using the least absolute deviation technique and $2\rho_{0.5}(r)$ is the absolute value of the function.

In addition, quantile regression is robust to data with heteroscedasticity, skewness and heavy-tailed distributions, characteristics often found in financial data.

4.2 Model Specification

On the methodological side, similar to Ahmed and Doukas (2021) in their research for the U.S. financial market, we compared the Fama and MacBeth (1973) regression with the quantile regression for the Brazilian financial market. As a control regressor of the return effect, we use the cumulative return over short, intermediate and long time horizons. To control for the premium effect of size, we use the logarithm of market capitalization. To control for the volume effect, we use the average monthly turnover over the last 12 months. With this, a regression model can be developed as follows in Equation 11:

$$r_t = a_0 + a_1 r_{-3:-1} + a_2 r_{-12:-4} + a_3 r_{-36:-13} + a_4 V + a_5 S + a_6 CGO \quad (11)$$

where r_t is the monthly stock return; $r_{-t1:-t2}$ is the cumulative monthly return from $t - t1$ to $t - t2$; V is the average monthly turnover over the past 12 months; S is the log of monthly market capitalization; and CGO is the capital gains overhang.

This quantile regression model was implemented at the 0.05th; 0.10th; 0.25th; 0.50th; 0.75th; 0.90th; 0.95th quantiles of expected return. The bootstrapping resampling technique with 20 repetitions was performed to estimate the standard errors; according to Gould (1993), this number of replications is often sufficient to generate robust standard errors. This allows the development of a joint distribution and therefore the calculation of the F statistics to examine the significant differences in the coefficients between the conditional distribution quantiles. To examine the curve of the relationship between CGO and expected return and to test the heterogeneity of CGO at different levels of expected return, in the same way as Hendricks and Koenker (1992) and Koenker and Bassett (1982), we developed the following tests.

$$T_n = \left(\hat{\beta}_{T1} - \hat{\beta}_{T2} \right)' \left(H^{-1} J H^{-1} \right) \left(\hat{\beta}_{T1} - \hat{\beta}_{T2} \right) \quad (12)$$

in which T_n is the hypothesis test applied, a kind of t-test for quantile regression; the estimated $\hat{\beta}$ at the different quantiles are compared to understand if they are statistically the same or different; and the term $H^{-1}JH^{-1}$ is a set of formulas described in the text by Koenker and Bassett (1982) and Hendricks and Koenker (1992).

By means of Equation 12, it is possible to test the hypotheses H_0: $\hat{\beta}_{T1} = \hat{\beta}_{T2}$ against H_1: $\hat{\beta}_{T1} \neq \hat{\beta}_{T2}$. If the null hypothesis is rejected, we can confirm that there are significantly non-equal coefficients across multiple quantiles of the expected return distribution. Finally, we tested for differences between coefficients or slopes of θ versus $(1 - \theta)$ quantiles. For example, we compared the 0.05th quantile to the 0.95th, the 0.10th to the 0.90th, and the 0.25th to the 0.75th.

5. RESULTS

This section is divided into three parts. First, the determinants of CGO are presented; second, the relationship between CGO and expected return is measured; and third, the relationship between the disposition effect and momentum is investigated.

5.1 Unrealized Capital Gains Overhang: Cross-Sectional Determinants

This section examines the relationship between CGO and its determinants according to Grinblatt and Han (2005), represented by Equation 13:

$$CGO_t = a_0 + a_1 r_{-3:-1} + a_2 r_{-12:-4} + a_3 r_{-36:-13} + a_4 V_{-3:-1} + a_5 V_{-12:-4} + a_6 V_{-36:-13} + a_7 S \quad (13)$$

where CGO_t is capital gains overhang; $r_{-t1:-t2}$ is the monthly cumulative return from $t\text{-}t_1$ to $t\text{-}t_2$; $V_{-t1:-t2}$ is the average monthly turnover from $t\text{-}t_1$ to $t\text{-}t_2$; and S is the logarithm of monthly market capitalization as a proxy for firm size.

In Table 3 shows the correlation matrix of equations 13 and 11 in panels A and B, respectively.

Table 3
Correlation and heteroscedasticity matrix

Panel A: Correlation matrix for the determinants of capital gains overhang								
	CGO	$r_{-3:-1}$	$r_{-12:-4}$	$r_{-36:-13}$	$V_{-3:-1}$	$V_{-12:-4}$	$V_{-36:-13}$	***S***
CGO	1							
$r_{-3:-1}$	0.1453***	1						
$r_{-12:-4}$	0.1717***	0.0313***	1					
$r_{-36:-13}$	0.0474***	-0.0032	-0.0006	1				
$V_{-3:-1}$	0.0299***	0.1368***	0.0189***	-0.0017	1			
$V_{-12:-4}$	0.0389***	0.0209***	0.1240***	-0.0062	0.4312***	1		
$V_{-36:-13}$	0.0129***	0.0190***	0.0390***	0.0579***	0.1021***	0.4563***	1	
S	0.2295***	0.0026	0.0185***	-0.0015	0.0653***	0.0847***	0.0262***	1

Panel B: Correlation matrix for expected return, past return and capital gains overhang							
	r	$r_{-3:-1}$	$r_{-12:-4}$	$r_{-36:-13}$	***V***	***S***	***CGO***
r	1						
$r_{-3:-1}$	0.0136***	1					
$r_{-12:-4}$	0.0176***	0.0313***	1				
$r_{-36:-13}$	-0.0042	-0.0032	-0.0006	1			
V	0.0331***	0.0459***	0.0137***	-0.0006	1		
S	-0.0059	0.0026	0.0185***	-0.0015	0.0772***	1	
CGO	0.1015***	0.1453***	0.1717***	0.0474***	0.0273***	0.2295***	1

Panel C: Heteroscedasticity test (Breusch-Pagan test)				
Model	**Equation 13**	**Equation 14**	**Equation 15**	**Equation 11**
p-value	0.0000***	0.0000***	0.0000***	0.0000***

Note: *This table shows capital gains overhang (CGO), monthly stock return (r), cumulative return over the three time horizons* (($r_{-3:-1}$); ($r_{-12:-4}$); ($r_{-36:-13}$)), *average monthly turnover over the past 12 months as a proxy for liquidity (V), average monthly turnover over the three time horizons* (($V_{-3:-1}$); ($V_{-12:-4}$); ($V_{-36:-13}$)), *and logarithm of monthly market capitalization as a proxy for size (S). The Breusch-Pagan heteroscedasticity test at the 5% significance level indicates that all models used in this research exhibit heteroscedasticity.*
Significant at 1% (***), 5% (**), 10% (*).
Source: *Prepared by the authors.*

In Table 3, the results support the use of quantile regression to analyze these data, since quantile regression provides robust results when dealing with data where the variance of the residuals is not constant (Koenker & Bassett, 1982).

In Table 4, we compared the two-stage Fama-MacBeth (FM) regression estimated by ordinary least squares (OLS) and the quantile regression at quantiles 0.05; 0.10; 0.25; 0.50; 0.75; 0.90; 0.95, estimated using the least absolute deviations (LAD) technique. For the FM regression, a significant and positive relationship was found between CGO, cumulative past return over the three time horizons, and size. This suggests that higher past returns and larger company size tend to generate higher capital gains. There was also a significant negative association between CGO and average turnover over the short and long time horizons. This indicates that the higher the transaction volume, the lower the capital gains. The results show that past cumulative returns, turnover over the three time horizons, and size explain 36.94% of the cross-sectional variation in capital gains. These results are in line with the findings of Ahmed and Doukas (2021), Grinblatt and Han (2005), and Sadhwani and Bhayo (2021).

Table 4
Determinants of capital gains overhang based on the main sample

Panel A: Determinants of capital gains overhang: Fama-MacBeth and quantile regressions

Variables	Fama-MacBeth	0.05	0.10	0.25	0.50	0.75	0.90	0.95
a_1	0.5270	0.5784	0.6466	0.6522	0.6382	0.6029	0.5677	0.5270
	39.35***	9.95***	15.57***	32.16***	55.88***	62.47***	64.47***	39.35***
a_2	0.3045	0.2047	0.2401	0.2724	0.2885	0.2985	0.3068	0.3045
	41.05***	9.83***	14.01***	29.28***	37.33***	43.44***	41.18***	41.05***
a_3	0.0630	0.0199	0.0142	0.0115	0.0243	0.0392	0.0515	0.0630
	19.86***	5.40***	4.82***	7.03***	7.03***	12.92***	18.19***	19.86***
a_4	-0.1048	0.0149	-0.1703	-0.2109	-0.2043	-0.1823	-0.1367	-0.1048
	-5.10***	0.13	-2.49**	-4.66***	-6.04***	-5.81***	-5.58***	-5.10***
a_5	0.0110	0.2368	0.1864	0.1327	-0.0368	-0.0534	-0.0156	0.0110
	0.41	2.34**	2.56**	2.49**	-0.84	-1.16	-0.39	0.41
a_6	-0.0231	0.1115	0.1013	0.0258	-0.0007	-0.0214	-0.0079	-0.0231
	-1.69*	2.58***	3.19***	1.24	-0.04	-1.32	-0.38	-1.69*
a_7	0.0002	0.3289	0.2215	0.1187	0.0558	0.0250	0.0077	0.0002
	0.30	52.90***	65.73***	66.51***	61.27***	34.16***	10.74***	0.30
a_0	0.2011	-6.2949	-4.1118	-2.0967	-0.9061	-0.3147	0.0323	0.2011
	17.20***	-55.53***	-73.53***	-71.37***	-62.98***	-29.02***	2.86***	17.20***
R^2	0.3694	0.1662	0.1674	0.1536	0.1484	0.1669	0.1871	0.1890
observations	41,859	41,859	41,859	41,859	41,859	41,859	41,859	41,859

Panel B: Test of equality of the coefficients estimated using quantiles

Variables	Quantiles					
	0.05 vs 0.95		0.10 vs 0.90		0.25 vs 0.75	
	F-statistic	p-value	F-statistic	p-value	F-statistic	p-value
a_1	0.86	0.3546	4.01**	0.0451	8.96***	0.0028
a_2	31.17***	0.0000	20.74***	0.0000	20.88***	0.0000
a_3	124.69***	0.0000	174.97***	0.0000	167.62***	0.0000
a_4	1.06	0.3024	0.17	0.6782	0.34	0.5622
a_5	5.42**	0.0199	5.67**	0.0173	11.16***	0.0008
a_6	10.47***	0.0012	12.24***	0.0005	5.76**	0.0164
a_7	2,950.04***	0.0000	4,098.38***	0.0000	2,996.22***	0.0000

Note: *Capital gains overhang (CGO); cumulative return over the three time horizons (($r_{-3:-1}$); ($r_{-12:-4}$); ($r_{-36:-13}$)); average monthly turnover over the three time horizons (($V_{-3:-1}$); ($V_{-12:-4}$); ($V_{-36:-13}$)); natural logarithm of monthly market capitalization (S). Directly below each variable is its respective t-statistic. The standard error is corrected by bootstrapping in quantile regression (20 resamples) and corrected by the Newey-West method (1 lag) for Fama-MacBeth. R^2 for Fama-MacBeth is the average R^2. On the other hand, for quantile regression, it is the pseudo R^2.*
Significant at 1% (***), 5% (**), 10% (*).
Equation: $CGO_t = a_0 + a_1 r_{-3:-1} + a_2 r_{-12:-4} + a_3 r_{-36:-13} + a_4 V_{-3:-1} + a_5 V_{-12:-4} + a_6 V_{-36:-13} + a_7 S$ *(13)*
Source: *Prepared by the authors.*

Furthermore, as shown in Table 4, the quantile regression results are consistent with the first hypothesis of this study: past cumulative returns are not uniform and vary across different quantiles of CGO. This result suggests that investors react asymmetrically to good and bad news. In addition, we found that past short-term cumulative returns tend to increase from quantiles 0.05 to 0.25, and then tend to decrease until the highest quantile. This indicates that for the short-term return coefficient, there are higher capital gains in the 0.25th CGO quantile and lower capital gains in the highest CGO quantile. However, past intermediate-term cumulative returns tend to increase from the 0.05th quantile to the 0.90th quantile, and then decrease until the highest quantile. This indicates that past intermediate-term returns are more (less) profitable at the 0.90th (0.05th) CGO quantile. Finally, the past long-term cumulative return tends to decrease from the 0.05th quantile to the 0.25th quantile, and then tends to increase until the highest quantile. This suggests that for past long-term returns, it is more (less) profitable to be in the 0.95th (0.25th) CGO quantile.

This indicates that the ability of past winners (losers) to generate unrealized capital gains (losses) increases from the 0.05th to the 0.25th quantile, based on past short- and intermediate-term cumulative returns. However, for past long-term cumulative returns, this ability increases from the median (0.50th) to the 0.95th quantile. Thus, based on the past short-, intermediate- and long-term cumulative returns, momentum is strongest at the 0.25th, 0.90th and 0.95th quantiles, respectively. These results partially corroborate the findings of Ahmed and Doukas (2021), who identified heterogeneous and homogeneous behavior for long-term cumulative returns. In addition, they reported systematic decreasing behavior between past short- and intermediate-term cumulative returns as the CGO quantiles increase, which suggests that momentum is stronger at lower quantiles over the short and intermediate time horizons.

When studying the relationship between CGO and turnover, we expected to find a negative relationship. According to Ahmed and Doukas (2021), as the turnover increases, the reference prices should converge faster to the market price, that is, the CGO variable should tend to zero. If we pay attention to the extreme quantiles of the regression (0.05th and 0.95th), we can see that the relationship between CGO and average turnover is significant in the short and long time horizons and negative at the highest quantile (0.95th). However, contrary to what we expected, CGO and turnover have a significant positive relationship in the intermediate and long time horizons at the lowest quantile (0.05th). This indicates that at the lowest CGO quantile (0.05th), the higher the turnover, the slower the reference price will converge to the market price, thus generating unrealized capital gains. Focusing on the extreme values, our result differed from that reported by Ahmed and Doukas (2021) only for the 0.95th quantile. In summary, the quantile regression shows that there is a different behavior of the study variables depending on the different quantiles of the CGO distribution. This could explain the different results in the literature on the relationship between CGO and expected return, results that could not be identified using the OLS technique.

The quantile regression also indicated that firm size is significantly and positively related to CGO across the quantiles, except at the 0.95th quantile, which is not significant. This is in line with the theory that the larger the firm size, the higher the unrealized capital gains, since size reflects past performance, which is not fully captured by past cumulative returns. Furthermore, a decreasing trend in size was observed as the CGO quantiles increased. That is, the ability of large firms to generate higher unrealized capital gains and capture past performance decreased as the capital gains quantiles increased. These results corroborate the findings of Ahmed and Doukas (2021) for the U.S. financial market.

Panel B of Table 4 shows the results of the tests of equality of the coefficients. $r_{-3:-1}$ is significant and different only at quantiles 0.10 *versus* 0.25 and 0.75 versus 0.90; $r_{-12:-4}$, $r_{-36:-13}$, $V_{-12:-4}$, $V_{-36:-13}$, and S are significant and vary with the different CGO quantiles. On the other hand, the fact that $V_{-3:-1}$ is not significant indicates that the coefficient is the same as the quantiles vary. This supports our first hypothesis. This is because the quantile regression shows non-linear behavior for past returns over the short (except for the 0.05th versus the 0.95th quantile), intermediate and long time horizons.

5.2 Expected Return, Past Return, and Unrealized Capital Gains

In Table 5, the FM regression indicates that expected returns have a significant and positive cross-sectional relationship with CGO. This is consistent with the findings of Ahmed and Doukas (2021), Birru (2015), Grinblatt and Han (2005), and Sadhwani and Bhayo (2021). Furthermore, the quantile regression indicates that the relationship between expected return and CGO is positive and decreases as the quantile of expected return increases from the lowest (0.05th) to the highest (0.95th). This result is partially different from that found by Ahmed and Doukas (2021). Although they found the same trend, the results were significant and negative from the 0.75th to 0.95th quantiles.

Table 5
Expected return, past return and capital gains overhang based on the main sample

Panel A: Expected return, past return, and capital gains overhang: Fama-MacBeth and quantile regressions								
Variables	**Fama-MacBeth**	**0.05**	**0.10**	**0.25**	**0.50**	**0.75**	**0.90**	**0.95**
a_1	-0.0780	-0.0654	-0.0475	-0.0262	-0.0064	0.0065	0.0328	0.0469
	-11.32***	-7.19***	-8.50***	-10.61***	-3.42***	1.32	4.45***	3.21***
a_2	-0.0353	-0.0326	-0.0249	-0.0137	-0.0039	-0.0013	0.0019	0.0051
	-7.96***	-13.10***	-12.58***	-9.26***	-2.89***	-0.82	0.80	1.63
a_3	-0.0122	-0.0067	-0.0051	-0.0017	-0.0004	-0.0001	0.0002	0.0002
	-5.22***	-7.24***	-6.79***	-2.81***	-2.64***	-0.40	0.38	0.34
a_4	0.2538	-0.3203	-0.3065	-0.1344	0.1446	0.4373	0.9533	1.3007
	3.71***	-5.00***	-5.34***	-3.54***	4.94***	7.91***	5.35***	5.45***
a_5	-0.0062	0.0050	0.0036	0.0020	0.0017	-0.0016	-0.0137	-0.0279
	-4.84***	8.13***	9.36***	4.95***	4.82***	-3.09***	-14.63***	-17.53***
a_6	0.1138	0.1042	0.0816	0.0490	0.0194	0.0104	0.0070	0.0055
	7.01***	24.24***	26.48***	18.01***	12.36***	9.77***	7.62***	3.12***
a_0	0.1040	-0.1958	-0.1456	-0.0735	-0.0221	0.0880	0.3496	0.6318
	5.48***	-19.61***	-24.91***	-12.28***	-4.52***	11.66***	24.47***	24.09***
R^2	0.1698	0.1717	0.1212	0.0585	0.0197	0.0096	0.0211	0.0430
Observations	42,204	42,204	42,204	42,204	42,204	42,204	42,204	42,204

Panel B: Test of equality of the coefficients estimated with quantiles						
	Quantiles					
Variables	**0.05 vs. 0.95**		**0.10 vs. 0.90**		**0.25 vs. 0.75**	
	F-statistic	**p-value**	**F-statistic**	**p-value**	**F-statistic**	**p-value**
a_1	46.59***	0.0000	72.00***	0.0000	38.17***	0.0000
a_2	104.49***	0.0000	97.91***	0.0000	42.59***	0.0000
a_3	43.29***	0.0000	42.21***	0.0000	7.44***	0.0064
a_4	37.55***	0.0000	46.46***	0.0000	58.09***	0.0000
a_5	585.66***	0.0000	370.83***	0.0000	71.43***	0.0000
a_6	536.13***	0.0000	647.96***	0.0000	307.65***	0.0000

Note: *Monthly stock return (r); cumulative return over the three time horizons (($r_{-3:-1}$); ($r_{-12:-4}$); ($r_{-36:-13}$)); average monthly turnover over the past 12 months as a proxy for liquidity (V); natural logarithm of monthly market capitalization as a proxy for size (S); capital gains overhang (CGO). Directly below each variable is its respective t-statistic. The standard error is corrected by bootstrapping in quantile regression (20 resamples) and corrected by Newey-West (1 lag) for Fama-MacBeth. R^2 for Fama-MacBeth is the mean R^2. On the other hand, for quantile regression it is the pseudo R^2.*
Significant at 1% (***), 5% (**), 10% (*).
Equation: $r_t = a_0 + a_1 r_{-3:-1} + a_2 r_{-12:-4} + a_3 r_{-36:-13} + a_4 V + a_5 S + a_6 CGO$ *(11)*
Source: *Prepared by the authors.*

Table 5 shows that the cumulative past returns over the three time horizons (short, intermediate, and long) often increase systematically from the lowest quantile (0.05th) to the highest quantile (0.95th). However, it should be noted that the short-, intermediate- and long-term past returns are negative up to the 0.50th, 0.75th and 0.75th quantiles, respectively, after which they become positive. These results partially match those of Ahmed and Doukas (2021), as they found an upward trend for both short- and long-term past returns, as expected, with increasing return quantiles. However, for intermediate-term past return, there is an upward trend from the lowest quantile (0.05th) to the median (0.50th) and then a downward trend to the highest quantile (0.95th).

Panel B of Table 5 shows the results of the tests of equality of the coefficients. They indicate that CGO varies according to the quantiles of expected return. This confirms our second hypothesis that the relationship between expected return and CGO is not uniform. It also suggests that the relationship between CGO and expected return depends on the quantile of the expected return distribution. This may explain the conflicting results in the literature on this subject when the OLS technique is employed, as sometimes the relationship between

CGO and expected return is positive and sometimes it is negative.

In summary, the results indicate that investors are prone to the disposition effect across all quantiles of expected return. Moreover, because CGO is significant and positive in all quantiles, this confirms the momentum pattern only in the 0.90th and 0.95th quantiles of expected return. It also suggests that in the other quantiles and in the FM regression there is a reversal effect, but it is not induced by the disposition effect, because $r_{-12:-4}$ is significant and positive with CGO included in the function as an independent variable. We delve into this analysis in the next section. This result for the two highest quantiles of expected return is consistent with Grinblatt and Han (2005) and partially in line with Ahmed and Doukas (2021), who found a reversal effect for the quantiles above the median expected return. It is also possible to observe that CGO is higher (lower) in the lowest (highest) quantile of expected return. This supports the V-shaped pattern reported by An (2016) and Ahmed and Doukas (2021).

Finally, the results indicate that investors in the Brazilian financial market should pay more attention to stocks with higher CGO, which are in the lowest quantile of expected return, in order to achieve higher gains. A profitable strategy would be based solely on the disposition effect and not on the momentum effect. According to Ahmed and Doukas (2021), good news stocks undervalue stock prices at this point because investors realize gains quickly, while creating excess supply in the market. This lowers stock prices. On the other hand, stocks with bad news overvalue prices because investors tend to hold on to losing stocks, limiting their supply in the market, which forces prices to remain high.

5.3 The Disposition Effect and Momentum

Grinblatt and Han (2002, 2005), Jegadeesh and Titman (1993), and Li and Yang (2013) found that, as investors' risk aversion shifts from less risk averse to more risk averse, the disposition effect and the momentum effect increase for the US financial market for low- and high-tech stocks. Jegadeesh and Titman (1993) argued that the disposition effect alone may be able to induce momentum in intermediate past returns. This is because intermediate momentum disappears when CGO is included in the regression as an independent variable. However, the ability of the disposition effect to generate momentum is controversial in the literature.

Birru (2015) and Muga and Santamaria (2007) argued that the disposition effect alone cannot generate momentum. On the other hand, Hur, Pritamani, and Sharma (2010) and Shumway and Wu (2011) argued that the disposition effect has a great influence on the generation of momentum, although they did not determine the disposition effect as a necessary and sufficient condition for this. Furthermore, Hur and Singh (2019), for the US financial market, found that the anchoring effect and/or the disposition effect together or alone can generate momentum. In addition, Sadhwani and Bhayo (2021) found that only the disposition effect induces momentum, but the reverse does not occur. Moreover, its influence varies over time in the U.S. financial market.

In this respect, this section analyzes the extreme values of the quantiles (0.05th and 0.95th), areas where the greatest losses and gains are found, respectively, and thus may be of fundamental interest to investors, both individual and institutional (Ahmed & Doukas, 2021; Nath & Brooks, 2015). For this purpose, we followed the same procedures as Ahmed and Doukas (2021) and Grinblatt and Han (2005), adapted for Brazil. This consisted of examining three equations (14, 15, 11) to determine the ability of the disposition effect to generate momentum. We used the Fama and MacBeth (1973) regression, a two-stage procedure, and quantile regression, controlled and uncontrolled by the CGO variable.

$$r_t = a_0 + a_1 r_{-3:-1} + a_2 r_{-12:-4} + a_3 r_{-36:-13} + a_4 V \tag{14}$$

$$r_t = a_0 + a_1 r_{-3:-1} + a_2 r_{-12:-4} + a_3 r_{-36:-13} + a_4 V + a_5 S \tag{15}$$

$$r_t = a_0 + a_1 r_{-3:-1} + a_2 r_{-12:-4} + a_3 r_{-36:-13} + a_4 V + a_5 S + a_6 CGO \tag{16}$$

where r_t is the monthly stock return; $r_{-t1:-t2}$ is the monthly cumulative return from t-t_1 to t-t_2; V is the average monthly turnover for the last 12 months; S is the logarithm of the monthly market capitalization; and CGO is the capital gains overhang.

More specifically, the ability of the disposition effect represented by the CGO proxy to induce intermediate momentum was examined. According to Grinblatt and Han (2005), for the disposition effect to generate intermediate momentum, the past return over the intermediate time horizon must be positive and significantly related to the expected return in equations 14 and 15 without CGO. However, once the effect of CGO is controlled for in Equation 11, the return over the intermediate time horizon should no longer be significant.

To facilitate the analysis, Table 6 summarizes the behavior of the variable of interest, cumulative past return over the intermediate time horizon ($r_{-12:-4}$), in the three equations.

Table 6
Cumulative return over the intermediate time horizon – $r_{-12:-4}$ across the three models

Quantiles		Fama-MacBeth			5%			95%		
Model		**Model 14**	**Model 15**	**Model 11**	**Model 14**	**Model 15**	**Model 11**	**Model 14**	**Model 15**	**Model 11**
Whole sample		0.0012	-0.0007	-0.0353	0.0001	0.0003	-0.0326	0.0046	0.0066	0.0051
		0.30	-0.17	-7.96***	0.07	0.27	-13.10***	1.15	2.05**	1.63
Institutional	Above the median	0.0017	-0.0004	-0.0346	-0.0005	-0.0001	-0.0358	0.0056	0.0066	0.0049
		0.42	-0.09	-7.97***	-0.29	-0.08	-11.58***	1.51	2.55**	1.68*
	Below the median	-0.0094	-0.0169	-0.1374	0.0831	0.0545	-0.005	-0.0536	-0.0148	-0.0241
		-0.59	-1.02	-3.03***	5.53***	3.47***	-0.33	-2.00**	-0.66	-0.77
Leverage	Above the median	0.0039	0.0016	-0.0335	0.0001	0.0002	-0.0331	0.0047	0.0065	0.0049
		0.88	0.38	-7.50***	0.07	0.18	-11.25***	0.87	2.18**	1.24
	Below the median	-0.0124	-0.0145	-0.0483	0.0093	0.0008	-0.0289	0.0084	0.008	0.0047
		-1.65*	-1.97**	-6.06***	1.33	0.13	-4.89***	0.64	0.49	0.29
Size	Above the median	0.0004	-0.0001	-0.0634	0.0008	0.001	-0.0843	0.0001	0.0021	-0.0062
		0.08	-0.03	-9.57***	0.23	0.30	-18.15***	0.01	0.39	-0.92
	Below the median	0.0029	0.002	-0.0419	-0.0006	0.0016	-0.0234	0.009	0.0053	0.0047
		0.61	0.42	-8.39***	-0.32	1.07	-7.76***	1.68*	0.95	0.87
Trend	High	0.0021	0.0022	-0.0226	-0.0067	-0.0062	0.0106	0.0138	0.0139	-0.0767
		0.64	0.66	-6.06***	-2.29**	-2.91***	1.90*	2.98***	2.22**	-13.62***
	Low	-0.0002	-0.0053	-0.0312	0.0254	0.0108	-0.0551	-0.0752	-0.0764	-0.0773
		-0.02	-0.59	-11.46***	1.88*	1.37	-6.32***	-7.15***	-8.09***	-8.19***
Investor sentiment	Above the median	0.0070	0.0059	-0.0355	-0.0034	-0.0008	-0.0403	0.0121	0.0094	0.0061
		1.39	1.16	-5.93***	-1.42	-0.48	-10.55***	2.09**	2.19**	1.05
	Below the median	-0.0046	-0.0074	-0.0351	0.0034	0.0032	-0.0286	-0.0050	0.0047	-0.0006
		-0.73	-1.15	-5.39***	1.58	1.28	-5.67***	-0.58	0.73	-0.09

Note: *This table focuses on the ability of the disposition effect to generate momentum at the lowest (0.05) and highest (0.95) quantiles. Therefore, we present only the results for the cumulative return over the intermediate time horizon ($r_{-12:-4}$). Directly below the variable is its respective t-value. Regressions are compared before the effect size, after the effect size, and after the capital gains overhang are added.*

$r_t = a_0 + a_1 r_{-3:-1} + a_2 r_{-12:-4} + a_3 r_{-36:-13} + a_4 V \ (14)$

$r_t = a_0 + a_1 r_{-3:-1} + a_2 r_{-12:-4} + a_3 r_{-36:-13} + a_4 V + a_5 S \ (15)$

$r_t = a_0 + a_1 r_{-3:-1} + a_2 r_{-12:-4} + a_3 r_{-36:-13} + a_4 V + a_5 S + a_6 CGO \ (11)$

where: monthly stock return (r); cumulative return over the three time horizons (($r_{-3:-1}$); ($r_{-12:-4}$); ($r_{-36:-13}$)); average monthly turnover over the past 12 months as a proxy for liquidity (V); natural logarithm of monthly market capitalization as a proxy for size (S); capital gains overhang (CGO). Directly below each variable is its respective t-statistic. The standard error is corrected by bootstrapping in quantile regression (20 resamples) and corrected by Newey-West (1 lag) for Fama-MacBeth.
Significant at 1% (***), 5% (**), 10% (*).

Source: *Prepared by the authors.*

As can be seen in Table 6, the intermediate cumulative return at the lowest quantile (0.05) in the robustness tests is often significant and negative in Equation 11, where the effect is controlled for CGO. This could suggest a reversal effect instead of momentum, and also that the disposition effect is not a good proxy for the generation of momentum at the lower quantiles of expected return. This corroborates the findings of Ahmed and Doukas (2021) and Kong et al. (2015) for the U.S. and Chinese financial markets, respectively. They found that at the extreme quantile of expected return, the limited ability of the disposition effect to induce momentum stems from the lack of relationship between news and extreme returns. This indicates that finding a variable that significantly induces momentum remains a major puzzle in behavioral finance.

For the highest quantiles of expected return (0.95th), considering the whole sample, $r_{-12:-4}$ is significant and positive only in Equation 15, while in Equation 11, where the effect is controlled for CGO, $r_{-12:-4}$ is often insignificant. Thus, according to Grinblatt and Han (2002, 2005) and Sadhwani and Bhayo (2021), there is a spread between the fundamental value and the equilibrium price, leading to an underreaction of prices. This is different from Ahmed and Doukas (2021). This is weak evidence because this finding is robust for some of our subsamples, such as in Equation 14 in the subsamples of size (below the median) and investor sentiment (above the median), as well as in Equation 15 in leverage (above the median) and investor sentiment (above the median). Therefore, at the highest quantile of expected returns, an investment strategy based on intermediate momentum as proposed by Jegadeesh and Titman (1993) can be profitable.

In this regard, an investor intending to implement a strategy based on momentum should pay close attention to stocks with high past cumulative returns over an intermediate time horizon. It should be understood that the profitability of a momentum-based strategy may change due to the disposition effect when leverage, size, trend, investor sentiment, and the quantile of expected return vary. Since the disposition effect induces momentum in the highest quantile of expected return, it is expected that in the financial market, the disposition effect (selling stocks when prices rise and holding stocks when prices fall) will act as a model of underreaction to news. In this scenario, the current stock prices in the financial market are lower than their fundamental value. This induces the momentum effect, leading to persistence in the returns of winning (and losing) stocks. These results are partially consistent with those of Hur and Singh (2019), who, for the US financial market, by comparing CGO with the George and Hwang ratio, found that there is a disposition effect capable of generating momentum in portfolios composed of 10th percentile and 90th percentile stocks.

Interestingly, even in the highest quantiles of expected return (0.95th), $r_{-12:-4}$ in Equation 14 is significant and negative in the institutional subsample, but only for those below the median. This finding, when combined with the non-significant result for $r_{-12:-4}$ in Equation 11, points to a specific behavior in this subsample. Unlike the disposition effect, which induces momentum, the observed behavior here appears to induce a reversal effect. Investors in this category seem to prefer selling winning stocks and buying losing stocks in anticipation of a stock price reversal. This behavior is consistent with the findings of Ahmed and Doukas (2021) for the U.S. market in most of their robustness tests, suggesting a contrarian effect rather than a disposition effect.

The results of the robustness tests for the institutional subsample (above the median) and the trend (both high and low), where $r_{-12:-4}$ is significant in at least one of equations 14 and 15, and remains significant in Equation 11, provide evidence that the disposition effect does not induce either a momentum or a reversal effect in these subsamples. According to Ahmed and Doukas (2021) and Hur et al. (2010), the observed result for institutional investors (above the median) may be due to institutional investors being less prone to the disposition effect than individual investors. For a high trend, there is momentum, possibly due to the persistence of a stock price increase. This could also be a function of overreaction, as reported by Abinzano, Muga, and Santamaría (2010) for the Brazilian and Chilean financial markets. For a low trend, there is a reversal effect due to the persistence of a stock price decrease. This result is consistent with the findings of Cooper, Gutierrez, and Hameed (2004) for the US financial market. Furthermore, according to Lee, Yen, and Chan (2011), in a bear market, the disposition effect reverses its pattern of behavior, meaning that investors are more likely to redeem their stocks in a bear market than in a bull market. In this situation, we can hypothesize that a downward trend is similar to a financial crisis or a period of depression. In this sense, we can partially compare our result with the findings of Sadhwani and Bhayo (2021), who investigated the disposition effect in the US financial market during financial crises. They reported a frequent presence of the disposition effect and an absence of momentum, leading to the conclusion that the disposition effect does not generate momentum in times of crisis.

6. CONCLUSION

The purpose of this study was to measure the relationship between expected returns and CGO (a proxy for the disposition effect) in the Brazilian financial market. It also investigated the ability of the disposition effect to induce momentum, as proposed by Grinblatt and Han (2002). To this end, we applied the Fama-MacBeth regression and quantile regression models. This allowed us to study the behavior of the extreme values of the distribution of the dependent variable.

The results indicated that there is a non-uniform relationship between CGO and expected return as expected return quantiles vary. This may help explain the conflicting results found in the literature when studying this relationship in other countries. Moreover, there is a disposition effect at all quantiles of expected return, but its intensity varies. Furthermore, at the lowest quantile (0.05th) of expected return, the disposition effect (CGO) may not be a good proxy for providing intermediate momentum.

However, at the highest quantile (0.95th) of expected return, the disposition effect induces a profitable intermediate momentum. Therefore, in the Brazilian financial market, a momentum-based investment strategy can be profitable if investors pay more attention to stocks with higher CGO at the highest quantile of expected returns.

Our result partially corroborates those of Ahmed and Doukas (2021) for the US, finding that in the lowest quantile (0.05th) of expected return, the disposition effect is also not a good proxy for generating intermediate momentum, while in the highest quantile (0.95th) of expected return, there is a reversal effect instead of a momentum effect. With this, it is clear that a strategy based on intermediate momentum in the highest quantile of expected return would be profitable in Brazil, while generating losses in the US.

Limitations of this study include the use of monthly data instead of a shorter time period, which could increase the degree of freedom of the study and allow for a more complete identification of the relationships between dependent and independent variables. It also lacks other techniques for measuring risk factors to determine how prospect theory can influence investor behavior, as investor preferences vary from risk loving to risk averse, and/or the ability of other biases to induce momentum. Thus, we suggest that future studies examine other economies, such as those of the BRICS countries, to determine whether the momentum effect can be explained by different industry sectors and cross-sectional differences. Also, this study could be continued by investigating our subsamples to determine which one has the most influence on the induction of momentum.

REFERENCES

Abinzano, I., Muga, L., & Santamaría, R. (2010). The role of over-reaction and the disposition effect in explaining momentum in Latin American emerging markets. *Investigación Económica*, *69*(273), 151–186.

Ahmed, M. S., & Doukas, J. A. (2021). Revisiting disposition effec and momentum: a quantile regression perspective. *Review of Quantitative Finance and Accounting*, *56*(3), 1087–1128. https://doi.org/10.1007/s11156-020-00919-4

An, L. (2016). Asset Pricing When Traders Sell Extreme Winners and Losers. *Review of Financial Studies*, *29*(3), 823–861.

Baker, H. K., & Nofsinger, J. R. (2010). Behavioral finance: an overview. *Behavioral Finance: Investors, Corporations, and Markets*, 1–21.

Baker, M., & Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. *The Journal of Finance*, *61*(4), 1645–1680.

Bhootra, A., & Hur, J. (2012). On the relationship between concentration of prospect theory/mental accounting investors, cointegration, and momentum. *Journal of Banking and Finance*, *36*(5), 1266–1275.

Birru, J. (2015). Confusion of confusions: a test of the disposition effect and momentum. *The Review of Financial Studies*, *28*(7), 1849–1873.

Brown, G. W., & Cliff, M. T. (2004). Investor sentiment and the near-term stock market. *Journal of Empirical Finance*, *11*(1), 1–27.

Choe, H., & Eom, Y. (2009). The disposition effect and investment performance in the futures market. *Journal of Futures Markets: Futures, Options, and Other Derivative Products*, *29*(6), 496–522.

Cooper, M. J., Gutierrez, R. C., & Hameed, A. (2004). Market states and momentum. *Journal of Finance*.

Fama, E. F., & MacBeth, J. D. (1973). Risk, Return, and Equilibrium: Empirical Tests. *Journal of Political Economy*, *81*, 607–636.

Frazzini, A. (2006a). The disposition effect and underreaction to news. *The Journal of Finance*, *61*(4), 2017–2046.

Frazzini, A. (2006b). The disposition effect and underreaction to news. *The Journal of Finance*, *61*(4), 2017–2046.

Glaser, M., & Weber, M. (2003). Momentum and Turnover: Evidence from the German Stock Market. *Schmalenbach Business Review*, *55*(2), 108–135.

Goetzmann, W. N., & Massa, M. (2008). Disposition matters: Volume, volatility and price impact of a behavioral bias. *The Journal of Portfolio Management*, *34*(2), 193–125.

Gould, W. (1993). Quantile regression with bootstrapped standard errors. *Stata Technical Bulletin*, *2*(9).

Grinblatt, M., & Han, B. (2002). The disposition effect and momentum. *National Bureau of Economic Research Working Paper Series*, *8734*(January 2002), 1–45.

Grinblatt, M., & Han, B. (2005). Prospect theory, mental accounting, and momentum. *Journal of Financial Economics*, *78*(2), 311–339.

Grinblatt, M., & Keloharju, M. (2000). The investment behavior and performance of various investor types: a study of Finland's unique data set. *Journal of Financial Economics*, *55*(1), 43–67.

Hameed, A., & Kusnadi, Y. (2002). Momentum strategies: Evidence from Pacific Basin stock markets. *Journal of Financial Research*, *25*(3), 383–397.

Hendricks, W., & Koenker, R. (1992). Hierarchical Spline Models for Conditional Quantiles and the Demand for Electricity. *Journal of the American Statistical Association*, *87*(417), 58.

Hon, M. T., & Tonks, I. (2003). Momentum in the UK stock market. *Journal of Multinational Financial Management*, *13*(1), 43–70.

Hur, J., Pritamani, M., & Sharma, V. (2010). Momentum and the Disposition Effect: The Role of Individual Investors. *Financial Management*, *39*(3), 1155–1176.

Hur, J., & Singh, V. (2019). How do disposition effect and anchoring bias interact to impact momentum in stock returns? *Journal of Empirical Finance*, *53*, 238–256. https://doi.org/10.1016/j.jempfin.2019.07.007

Ipeadata. (2020). *Base de dados [online]*. Rio de Janeiro: IPEA. Retrieved from http://www.ipeadata.gov.br

Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of Finance*, *48*(1), 65–91.

Kim, K. A., & Nofsinger, J. R. (2007). The Behavior of Japanese Individual Investors During Bull and Bear Markets. *Journal of Behavioral Finance*, *8*(3), 138–153.

Koenker, R., & Bassett, G. (1978). Regression Quantiles. *Econometrica*, *46*(1), 33.

Koenker, R., & Bassett, G. (1982). Robust Tests for Heteroscedasticity Based on Regression Quantiles. *Econometrica*, 43–61.

Kong, L. L., Bai, M., & Wang, P. (2015). Is disposition related to momentum in Chinese market? *Managerial Finance*, *41*(6), 600–614.

Leal, C. C., Rocha Armada, M. J., & Duque, J. C. (2010). Are all individual investors equally prone to the disposition effect all the time? New evidence from a small market. *Frontiers in Finance and Economics*, *7*(2), 38–68.

Lee, J. S., Yen, P. H., & Chan, K. C. (2011). Market states and disposition effect: evidence from Taiwan mutual fund investors

Li, Y., & Yang, L. (2013). Prospect theory, the disposition effect, and asset prices. *Journal of Financial Economics*, *107*(3), 715–739.

Long, J. B. De, Shleifer, A., Summers, L. H., & Waldmann, R. J. (1990). Noise Trader Risk in Financial Markets. *Journal of Political Economy*, *98*, 703–738.

Marschner, P. F., & Ceretta, P. S. (2021). Sentimento do investidor, incerteza econômica e política monetária no Brasil. *Revista Contabilidade & Finanças*, *32*(87), 528–540. https://doi.org/10.1590/1808-057x202113220

Muga, L., & Santamaria, R. (2007). The momentum effect in Latin American emerging markets. *Emerging Markets Finance and Trade*, *43*(4), 24–45.

Piccoli, P., Costa, N. C. A., Silva, W. V., & Cruz, J. A. W. (2018). Investor sentiment and the risk–return tradeoff in the Brazilian market. *Accounting and Finance*, *58*, 599–618. https://doi.org/10.1111/acfi.12342

Rodriguez, R. N., & Yao, Y. (2017). *Five Things You Should Know about Quantile Regression* (SAS Institute Inc., Ed.). Cary, NC: Proceedings of the SAS Global Forum 2017 Conference.

Rouwenhorst, K. G. (1998). International momentum strategies. *The Journal of Finance*, *53*(1), 267–284.

Sadhwani, R., & Bhayo, M. U. R. (2021). Momentum and disposition effect in the US stock market. *Cogent Economics and Finance*, *9*(1). https://doi.org/10.1080/23322039.2021.1999004

Shumway, T., & Wu, G. (2011). Does Disposition Drive Momentum? *SSRN Electronic Journal*.

Wang, H., Yan, J., & Yu, J. (2017). Reference-dependent preferences and the risk–return trade-off. *Journal of Financial Economics*, *123*(2), 395–414.

Wooldridge, J. M. (2015). *Introductory econometrics: A modern approach*. Cengage Learning.

Yu, J., & Yuan, Y. (2011). Investor sentiment and the mean-variance relation. *Journal of Financial Economics*, *100*(2), 367–381.

FUNDING

This study was partially funded by the Coordination for the Improvement of Higher Education Personnel (Capes) – Finance Code 001.