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**How The Disposition Effect May Explain Momentum:
The Relationship Between Investment Behavior Biases and Brazilian
Market Movements**

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Abstract

Momentum is one of the most robust anomalies in financial markets, there are two main recent explanations for this phenomenon, a behavioral-based explanation through disposition-effect (i.e., the willingness to sell “winners” too quickly and to hold “losers” for a long time) and a fund-flow based explanation. The disposition-effect explanation is centered in the convergence of the spread between the fundamental value and the observed market price (disposition-effect causes an underreaction to news that generates this spread), and the fund flows-based explanation is due to the persistence of the performance of mutual-funds (which usually keep buying winning positions and selling the losses). This master thesis compares those theories using Brazilian data (which is suitable for the strong presence of momentum). Our empirical analysis was done using Fama-MacBeth regressions with results pointing the disposition-effect explanation as the most significant, with our robustness analysis contributing positively to the main findings.

Keywords: disposition-effect, momentum, behavioral finance, investment behavior bias, investment strategies, fund flows, asset pricing.

JEL Classification: G11; G12; G14

Resumo

Uma das anomalias mais robustas presente nos mercados financeiros é a existência de *momentum* nos preços de ações, existem duas principais explicações recentes para este fenômeno: explicação comportamental através do efeito-disposição (i.e. disposição de vender ativos “vencedores” rapidamente e de segurar ativos “perdedores” por muito tempo) e explicações de fluxos de fundos de investimento. A explicação através do efeito-disposição é centrada na convergência do *spread* entre o valor fundamental de um ativo e o preço de mercado observado (o efeito-disposição causa uma reação branda a notícias que gera esse spread), e a explicação baseada em fluxos de fundos que se deve pela persistência da performance de fundos (que usualmente continuam comprando posições vencedoras e vendendo as perdedoras). O objetivo desta dissertação é comparar essas teorias utilizando dados brasileiros (que é adequado pela forte presença de momentum). Nossa análise empírica foi feita através de regressões de Fama-MacBeth com resultados apontando a explicação centrada no efeito-disposição como a mais significativa, com nossa análise de robustez contribuindo positivamente para nossos resultados principais.

Palavras-chave: efeito-disposição, *momentum*, finanças comportamentais, viés de comportamento de investimento, estratégias de investimento, fluxos de fundos, apreçamento de ativos.

Classificação JEL: G11; G12; G14.

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1 Introduction

Momentum is arguably the strongest anomaly in financial markets¹. Jegadeesh and Titman (1993) were the first to document this phenomenon and show that a strategy – of buying winning stocks (stocks that have performed well in the past) and selling losing stocks (stocks that have performed poorly in the past) – generate significant returns. Even after Jegadeesh and Titman (1993) documented the existence of momentum, the anomaly still persists and has also been documented in international markets and other asset classes. In the Brazilian stock market, momentum is particularly strong. Given its empirical relevance, many theoretical explanations for the existence of momentum have been proposed. The two main competing explanations are: (i) through disposition-effect and (ii) through mutual fund flows. In this thesis, we evaluate empirically both explanations of momentum.

A more behavioral explanation of momentum is based on the disposition-effect. The disposition-effect refers to the investor's willingness to sell "winners" too quickly and to hold "losers" stocks for too long. According to this explanation, investors who suffer from disposition-effect will tend to underreact to news. Grinblatt and Han (2005) argue that investors who are subject to the disposition-effect are eager to make profits, selling their assets too soon (in case of good news), thus pushing the market price below its fundamental value² and generating a spread. In following periods this movement will continue (with investors subject to the disposition-effect that are less eager to make quick profits than those of the first period continuing to sell), keeping the spread until the fundamental value is reached. The convergence of this spread is interpreted as momentum and would happen in the opposite direction face to bad news.

In turn, the explanations based on the fund-flow hypothesis provide a learning interpretation for the momentum anomaly. According to Lou (2012), mutual funds that outperform others are expected to attract growing flows of investments. As a result of the increased inflow, these outperforming mutual funds reinvest in their past winning positions. In turn, funds with bad performance are likely to suffer capital outflows; losing investments the

¹ Momentum in finance can be defined as the trend of increasing prices continuing to grow and decreasing prices continuing to decrease. By comparison, in physics, the conservation of *momentum* requires that the amount of movement of a body remains unchanged in closed systems (i.e. no external forces), with an application of Newton's laws (1833). The analogy is straightforward: stocks with recurring positive (or negative) returns are said to be *momentum-dominated* by this tendency for returns to remain positive (or negative).

² True value of the asset, that would prevail in the market in the absence of market or behavioral disturbances.

managers of those funds usually close past losing positions. Combining the effects of both inflow and outflows, this simple reasoning can produce momentum in stock prices.

The main objective of this thesis is to compare both momentum explanation theories using the same empirical framework. We focus on the Brazilian financial market, which is suitable for the strong presence of momentum. We find that the behavioral-based explanation of disposition-effect was sufficient to explain momentum significantly. The same wasn't true for the fund-flows based explanation, that didn't manage to show significant results.

Our results contribute to the empirical literature on momentum. Grinblatt and Han (2005) used aggregated data from the US financial market to show the significance of the spread between the fundamental value and the market price, in both a theoretical and empirical analysis. Other studies include Shumway and Wu (2005), which found a significant spread that generates momentum for a large Chinese brokerage firm, and Hur, Pritmani and Sharma (2010), that pointed out that in assets with a larger presence of individual investors the momentum generated by disposition-effect is stronger. In the fund-flow based explanation literature, the two main studies comes from Lou (2012), that had a more empirical approach to the persistent performance of mutual-funds, showing a significant explanation for momentum, and the work from Vayanos and Woolley (2013), with a theoretical approach that besides momentum also pointed out the presence of reversal in the occurrence of extreme outflows or inflows. Our main results are closely related with previous outcomes from the behavioral literature, contributing with more significant results for the disposition-effect explanation, which wasn't in accordance with the literature of fund-flow based explanations.

Despite the strong presence of momentum in Brazil, this is the first empirical paper that compares both explanations of momentum using Brazilian data. There are, however, other works that study the disposition-effect phenomenon itself, studied by Arruda (2006) and Boguea and Barros (2008).

Our main analysis uses Fama and MacBeth (1973) regressions with consistent Newey-West (1987) HAC estimators for heteroscedasticity and autocorrelation. Our dependent variable was monthly returns of assets presented in the Brazilian financial market. To test for momentum, we included among our covariates the intermediate horizon past returns, in which the momentum is stronger and usually significant (in markets with momentum), accordingly to Jegadeesh and Titman (1993). An explanation for momentum is found when it's both significant and able to make this intermediate portfolio lost its significance. The main independent variables were unrealized gains, related to the disposition-effect explanation

(considers the average reference price which investors that suffer this anomaly use to make decisions), and the flux-induced-trading variable, related to the fund-flow explanation for momentum (measures the part of the capital variation from funds which is due to investments inflow and outflow). The performed analysis verify if the inclusion of one (or both) of these variables is enough to explain momentum. Our main results found that only the disposition-effect variable was both significant and enough to explain momentum. Other covariates from the analysis are past returns (of short and long-term horizons, besides the intermediate one), the logarithm of market capitalization and the average yearly turnover of shares of each company. Our database was composed of Brazilian market data coming from Economatica.

Our robustness analysis focused on: (i) possible additional explanations and (ii) subperiod analysis. The problem (i) focused on the volume effect that may explain momentum, since our main disposition-effect variable depends partially on the volume and time-series variation of the turnover. It was tested by isolating the volume-effect from our variable (disconsidering its time-series variation) for the tests. The issue (ii) is to check the strength of our results in different scenarios. We addressed this issue by subdividing our analysis into two periods, pre-2008 and after-2008 (which correspond to half of our sample and to different investment strategies and scenarios in international markets). The results from our robustness tests contribute positively to our main findings, which kept the significance of momentum for the disposition-effect.

This thesis is subdivided into six chapters. Chapter 2 focus on the literature review of both competing theories, also showing additional behavioral motivations for agents. Chapter 3 shows in-depth our dataset and our methodology, including summary statistics, graphs, a theoretical model and the empirical analysis methodology. Our main results are presented in chapter 4, with the robustness analysis in chapter 5. Finally, chapter 6 points our concluding remarks.

2 Main Explanations for Momentum

Momentum is one of the most robust anomalies in financial markets with recurrent examples in the literature. An overview is presented by Hur, Pritmani and Sharma (2010). As an example, we have: Haugen and Baker (1996) and Rouwenhorst (1998), which documented the recurrence of momentum in several international markets; Fama and French (2008), that reported the profitability of strategies that exploit this phenomenon as the recent central anomaly in financial markets; in addition, we also have Jegadeesh and Titman (2001), which provide more robust evidences for the findings of Jegadeesh and Titman (1993).

Since it's been one of the most important anomalies in Financial Economics, an expressive movement in the literature with the objective to explain momentum has been formed. Among the most important ones, we can highlight the explanations through behavioral biases, specially the explanation using the disposition-effect, and explanations by capital-fund flow investment movements.

2.1 Behavioral Explanations

The existence of the phenomenon of momentum contradicts one of the central paradigms of financial theory: the market efficiency hypothesis (MEH), as seen in Malkiel and Fama (1970). The paper of Malkiel (2003) summarizes the thought: by MEH, new information would be incorporated into prices instantly (prices would be "right", there would be no investment strategy that could systematically exceed the average risk-adjusted returns in the market).

However, a strong prior hypothesis within this framework of market efficiency is that individuals are rational. From Barberis and Thaler (2003), rationality means two things in this scope: (i) under the arrival of new information, individuals update their beliefs correctly (i.e., in the manner described by Bayes' law); (ii) their choices are accepted in a normative way, that is, they are consistent with subjective expected utilities (SEU), according to Savage (1954). Thus, from MEH, prices would be "right", there being a non existence of investment strategies that could intermittently surpass the average risk-adjusted returns of the market.

As persistent profits above the market average are found via momentum strategies, breaking the MEH precepts, an attempt is made to find an explanation for such anomaly. Again, as Hur, Pritmaniand Sharma (2010) have found, literature is divided into two groups for this explanation: (i) via a risk-compensation approach (macroeconomic or business cycles) as in Liew and Vassalou (2000), Griffin, Ji and Martin (2003) and Liu and Zhang (2008), that is, momentum would be broadly related to the welfare of the companies and the economy itself, being subject to their depressions, the momentum profits would be a compensation for this risk; and (ii) from the existence of an investment behavior bias, affecting the rationality of part of the market (being one of the branches of behavioral finance), this group is subdivided as to the updating of beliefs (overreaction and underreaction, face to recent news). Among the subgroup of overreaction are: Daniel, Hirshleifer and Subrahmanyam (1998) and Lewellen (2002), in which overconfidence, self-attribution and betting on trends behavior causes investors to exaggerate their reaction face to new information (thus causing an upward/downward trend as more and more investor keep repeating this behavior); from the underreaction group, Chan, Jegadeesh and Lakonishok (1996) and Barberis, Shleifer and Vishny (1998), in which investors would make decisions based on past returns, causing a convergence of the price until past returns are weak enough to stop attracting new investments.

Thus, we note that there was no consensus, whereas the explanations by risk appear to be insufficient, see Liu and Zhang (2008), and that the previous behavioral-based literature didn't manage to directly explain momentum (usually cite several types of behavioral bias, with no single or closed explanation). The recent literature on the subject suggests a new approach to the group of explanations by investment behavior bias, the explanation through the disposition-effect (DE)³, from contributions by Grinblatt and Han (2005), Shumway and Wu (2005), Frazzini (2006), Hur, Pritmaniand Sharma (2010) and Birru (2015). The disposition-effect, was first presented in Shefrin and Statman (1985), which is defined as the willingness to sell winning shares too early and hold losers for a long time (as is suggested by the title of the mentioned paper), legitimizing a possible explanation for the underreaction to news. The DE itself is also a well-documented behavior bias, as seen in Odean (1998), being relevant to highlight its elements before going into this literature that seeks to explain the momentum.

³One example of DE for the Brazilian market is the case of investors who bought OGXP3 shares of the group EBX (then controlled by Eike Batista). Faced with the fall in value from 2012, considerable part of the investors held the paper for a long time, eventually realizing gigantic losses.

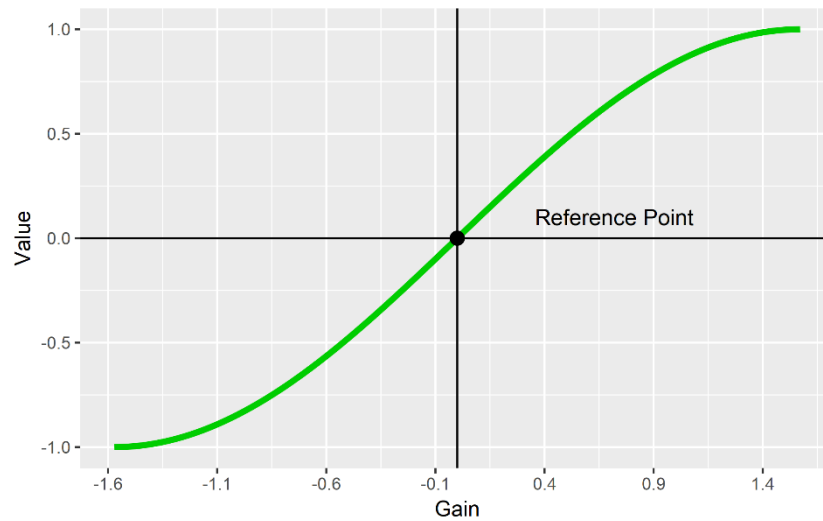
The positive theory of DE has four main elements: (i) Prospect Theory (PT) by Kahneman and Tversky (1979), with significant advances in Tversky and Kahneman (1992), which was set up against the paradoxes of Allais (1953), finds that bets are not evaluated (from the value function) in terms of final wealth, but rather of gains and losses (such as the reference value, e.g. returns on purchase value), assigning greater weights to small probabilities (argument for lotteries and insurance); although in PT utility functions are concave everywhere depending on the final wealth, the value function, in the face of moderate probabilities, has an "S" shape (as shown in figure 2) - concave (risk aversion) for gains and convex (risk seeking) for losses⁴, with preferences that violate the axioms of the expected utility theory of Neumann and Morgenstern (1944), which is central to subject expected utilities; (ii) Mental Accounting (MA) by Thaler (1980) states that investors tend to separate bets on different "mental accounts" and, from them, apply PT's decision rules to each account, ignoring interaction effects (e.g. "mental accounts" that are opened from the purchase of an asset *j*, are only closed under the total settlement of the same asset), being a good argument for the aversion of some investors in carrying out tax-swap operations, even in the case of shares that follow similar distributions⁵; (iii) "Seeking Pride and Avoiding Regret", regret the feeling associated with ex-post knowledge that previous decisions would produce better results and pride to its positive counterpart, noting that pride can turn in regret (e.g. asset *j* sold with gains generates pride, but if the price of *j* continue to rise the pride will turn into regret); (iv) "Self Control" has the most straightforward example in the reluctance to perform losses, the most central issue here is to control these losses, as set in Glick (1957), holding down losing stocks postpones the feeling of regret, and quickly selling winning stocks anticipates the feeling of pride⁶. Having defined the phenomenon, we can conclude that a disturbance face to the rational behavior of the traditional theory is observed in investors subject to the disposition-effect.

⁴One example for this risk aversion occurs in bets with an expected value greater than zero and with equal chances for gains and losses, e.g. in experiments people do not usually accept bets with equal chances to win R\$ 110.00 and to lose R\$ 100.00, see Kahneman and Tversky (1979) and Barberis and Xiong (2009).

⁵ PT alone does not explain this reluctance. Gross (1982) points out that in order to "treat" this "*get-evenitis disease*" one way would be to shift the thinking from closing "mental accounts" to asset-relocation thinking.

⁶ If the myopic agent does not have its own self-control, it is necessary to have devices to limit the losses (e.g. rational planner realizes a sale when reaching a given percentage of losses).

Figure 1 – Value Function accordingly to Prospect Theory.



Source: Own Elaboration.

In a seminal paper, Grinblatt and Han (2005) demonstrated, using US data, that the main elements of DE, PT⁷ and MA, create a spread between the fundamental value of a stock and its equilibrium price from the underreaction to news, and that the convergence of this spread would generate predictable equilibrium prices (momentum). This spread occurs since new information of an asset i would have a mitigated effect, because investors who suffer from the disposition-effect would lower the impact of both good news (they would sell their shares quickly to make small profits, increasing the price at a lower level) and bad news (they wouldn't sell their losses, making the price fall at a lower rate). Since rational investors would still follow the fundamental value, this spread would keep reducing until it reached an equilibrium price.

With data from a large brokerage firm in Shanghai in China, Shumway and Wu (2005) ordered stocks with higher gains / losses not realized by investors under the DE, they found a spread creation, which generates momentum. Frazzini (2006), on the other hand, deals specifically with the effect of investors subject to DE in underreaction to news with data from an American mutual fund holding. Hur, Pritmani and Sharma (2010) attest that the momentum generated by DE tends to be stronger in stocks with a large presence of individual investors. In the work of Birru (2015), the occurrence of DE before stock splits is pointed out, but this incidence does not occur after the split takes place, even when

⁷ Barberis and Xiong (2009) show that PT is sufficient to explain the DE in realized gains and losses (Hens and Vleck (2011) show that it is sufficient only in the case of agents who have entered the risky asset market, i.e., an *ex-post* and not one *ex-ante* explanation).

momentum still happens (apparent failure of explanation in the case of splits). Although there is documentation of DE in the Brazilian market, such as in Arruda (2006), Boguea and Barros (2008), Da Costa Jr., Mineto and Da Silva (2008) and Da Costa Jr. et al. (2013), literature has not yet looked at the relationship of DE with momentum in the Brazilian market.

From the aggregate data, Grinblatt and Han (2005) use in the application of their model the reference value of the entire market, being only the reference value of the investors subject to the DE that directly affects the momentum. In Shumway and Wu (2005), although DE is estimated individually, the sample is too small to be able to infer momentum in the entire market. Frazzini (2006) contributes to the relationship between DE and underreaction to news, but does not directly address the explanation of momentum. In addition to using aggregate data, Hur, Pritmani and Sharma (2010) neglect the presence of type 1 and type 2 errors, i.e., including some individual investors that are not subject to the DE and excluding institutional investors who are subject to the effect. Birru (2015) uses similar methodology to Grinblatt and Han (2005), but concentrates mostly in the specific case of stock splits. By all that, even with fundamental inputs, the literature still needs important contributions with more robust results, also considering different markets and financial scenarios.

2.2 Capital-Fund Flow Explanations

Going in the opposite direction of behavioral motivations, there has recently been a movement in the literature of explaining momentum through investment capital-flows of mutual funds. The empirical documentation that motivates this new literature begins with Lakonishok and Smidt (1986), which demonstrates that winning stocks have high turnover which leads to the conclusion of a greater prevalence of momentum strategies, especially in funds. In addition, Dasgupta, Prat and Verardo (2011) document that the "herd effect" provides momentum of intermediate terms, such as in Jegadeesh and Titman (1993), and long-term reversal. In a speech on the behavior of fund managers, former President of the European Central Bank, Jean-Claude Trichet (2001), commented that managers tend to follow trends by fear of the risk of being wrong on their own.

The first exponent of this literature was Lou (2012), in which he initially notes that: (i) the performance of mutual funds is persistent in horizons of one year; (ii) capital flows predict the performance of the fund in the next quarter ("smart-money" effect); and (iii) individual

stocks exhibit medium-term momentum. He argues that these three empirical patterns are explained (at least partially) by predictable price pressure caused by mutual funds capital flow. The author's motivation is that institutional capital flows can affect contemporary stock returns and that mutual fund flows are predictable from past performance and flows.

Lou (2012) argues that there is a persistence of fund performance, as winning funds attract more capital flows, generally reinvesting in past positions, maintaining or even increasing expected returns. The explanation for the smart-money effect comes from the very persistence of fund performance, attracting more and more new capital. The generation of momentum from the capital flows of funds comes from the reinvestment in past winning positions in funds that have achieved good past performance (and thus receive larger capital flows of new investments), the opposite occurring for funds with poor performance (when capital outflows occur, mutual funds are forced to liquidate their losing positions).

In their results, Lou (2012) verifies that funds liquidate 100% of their positions after a poor performance (with capital outflows) and reinvest 62% of capital inflows in existing positions. From its measure of Flux-Induced-Trading, it attests that explanations based on capital-fund flows can explain greater fraction of momentum profits in shorter and intermediate formation period (funds are constantly transferring their positions). This explanation is stronger in recent years (increasing the share of funds) and for stocks with higher market value.

Vayanos and Woolley (2013) come with a theoretical model on the explanation of momentum from capital flows of funds, having as empirical motivation the work of Lou (2012), showing that the explanation can work even in markets where investors and managers of funds are rational. As an explanation, the authors suppose a negative shock on an asset i , funds that control this asset report lower returns, triggering investor outflows that update negatively on the efficiency of the managers directing those funds. As a consequence, managers sell asset i , further pressing down the price. Momentum is generated if outflows are gradual and generate gradual price declines and diminish expected returns, in the other hand, reversal is generated by outflows that push prices below the fundamental value, thus expected returns eventually increase (going back to its fundamental value).

Although the argument used by Vayanos and Woolley (2013) for the conception of his theory is made considering agents (investors or fund managers) who may be rational, the literature on behavioral finance shows that even savvy and experienced investors are still susceptible to some types behavioral bias. According to Shefrin (2008), the core of all disturbances comes from problems of representativeness, an example from Kahneman and

Tversky (1972), in which agents make bets based in pocket rules (heuristics) and personal biases, contrary to the law of bayes. The author states that other types of bias, such as Overconfidence (bias related to the establishment of small confidence intervals for forecasts with a greater weight of probability), serve to broaden the representation problems.

De Bondt (1993) shows that most people make predictions in stock price betting on trends (on 62% of their sample bets where made on increasing trends; 40% on decreasing trends), showing an extrapolation bias. Grinblatt, Titman and Wermers (1995) provide evidence that 77% of mutual funds follow momentum strategies, but do not always sell their losing positions.

The phenomenon of Self-Attribution, with evidence from the literature of psychology as in Langer (1975), Miller and Ross (1975), Taylor and Brown (1988), shows that people tend to attribute success from talent and failures from external conditions, increasing confidence as market results and public information are in agreement with predictions, but not diminishing confidence otherwise. Self-Attribution can be related to the idea that "heads I win (by my own effort and talent), tails it's chance".

Overconfidence and especially Self-Attribution may be linked to momentum, given contributions by Daniel, Hirshleifer and Subrahmanyam (1998). The article shows that these types of behavioral disturbances are also associated with institutional investors, implying that investors make overreaction in the face of private information signs and underreact in the face of public information signs.

In Odean's article (1998), Overconfidence appears as the major determinant of the large volume of financial transactions, partly explaining the popularity of trend-setting and momentum strategies. With evidence from the work of Graham and Harvey (2002), financial executives appear to have both trend bias and individual investor biases, thus being prone to overconfidence.

The explanation of momentum in both cases (by the disposition-effect and the investment capital-flow of mutual funds) was not verified in Brazil. Given the need for contributions in this literature, since: (i) momentum is a significantly documented anomaly in the literature, both in Brazil and in the world, but that it still lacks a closed explanation that is globally accepted; and since (ii) in the Brazilian market that was not yet explored, this project is justified.

3 Data and Methodology

3.1 Data

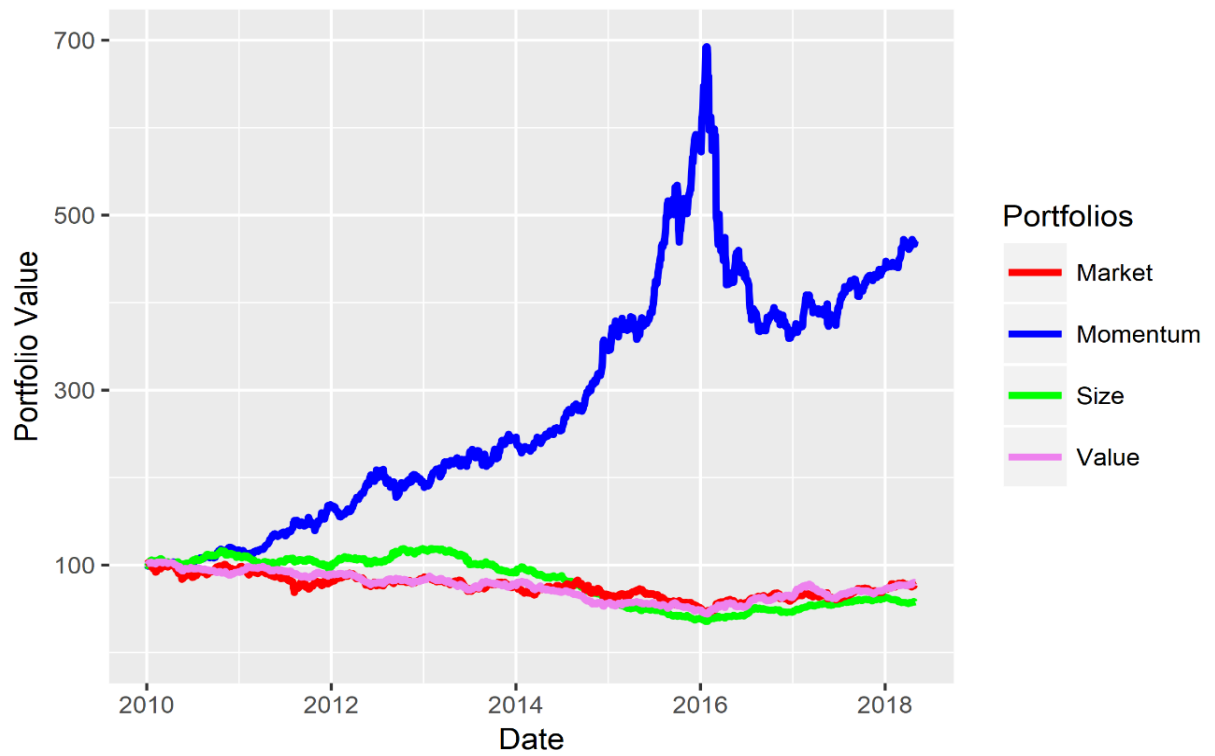
We've collected data of average and closing daily price (with and without adjustment), volumes and quantities traded, market value of each paper, turnover of each paper, daily value and market size indexes of stocks presented in Bovespa, besides, we've also collected total value invested in shares of each fund, total equity of each fund, monthly positions of each fund in each market share.

Our analysis is monthly with data from January 1994 to November 2017, contemplating 286 months. Three years were used to estimate the reference value for investors subject to the disposition-effect. Assets with no volume or with less than three years of observation were disconsidered. Outliers' quartile with an extreme variance of turnover was excluded from our analysis. Considering greater liquidity, only the most traded papers and funds were considered (237 assets and 1000 funds by market value and liquidity).

Considering the momentum phenomenon, we obtained financial factor measures from Brazil (from NEFIN's website) and United States (from French's website) to make a profitability comparison of momentum-based investment strategies. For both markets, we made a comparison with multiple strategies from the financial economics literature, which can be seen below in Figure 2 (Brazil) and Figure 3 (USA). In January 2010, R\$ 100.00 was theoretically invested in four portfolios following four long-short strategies: momentum (long in winners and short in losers), Size (long in high market value and short in low market value), Market (long in the market portfolio and short in the risk-free asset) and Value (long in high book-to-market ratio and short in low book-to-market ratio).

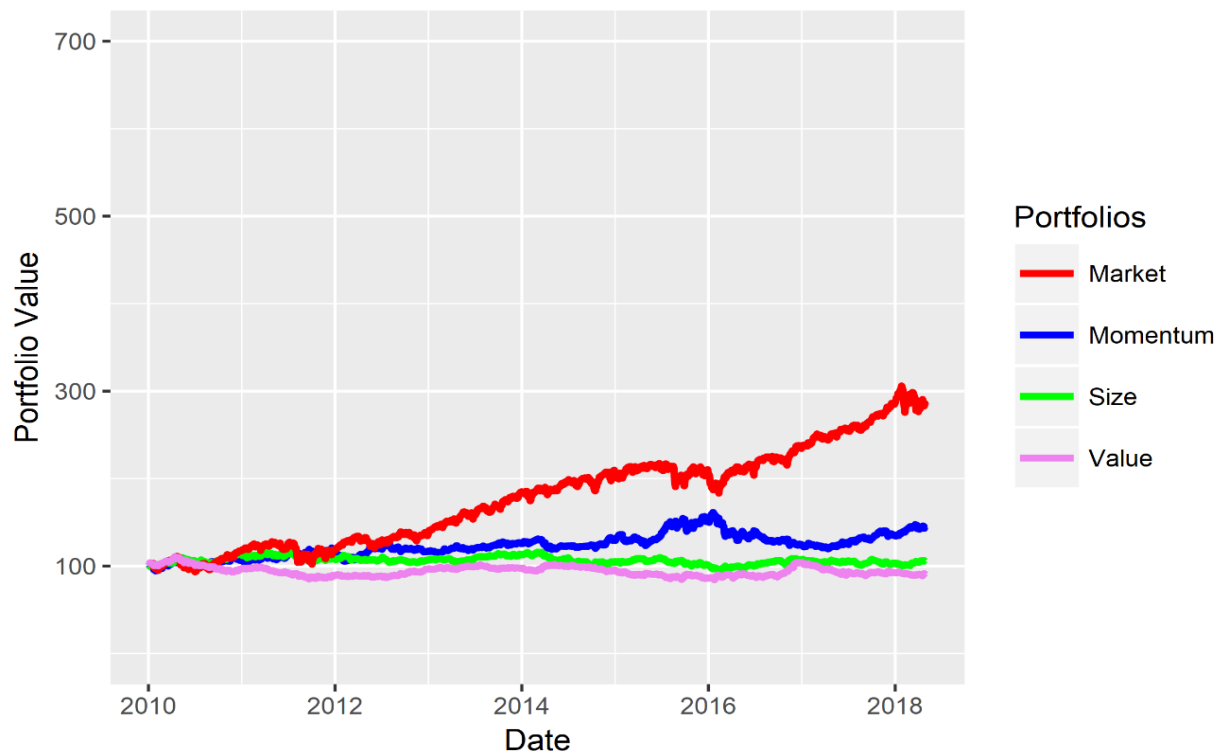
Figure 2 shows that momentum strategies (blue in the figure) have average yields much higher than the other strategies in Brazil: an investment of R\$ 100.00 in January 2010 for a portfolio following this strategy would have a value of R\$ 690.00 in January 2016. Considering the period between January 2010 and February 2016, there was an appreciation of 589.00% of the amount invested in 2010 through this strategy, being 373% from January 2010 to April 2018.

Figure 2 – Momentum investment strategy in the Brazilian financial market.



Source: Own Elaboration.

Figure 3 – Momentum investment strategy in the American financial market.



Source: Own Elaboration.

On the other hand, Figure 3 shows that, for the American market, Momentum strategies are not as near profitable when compared with Brazil. The most profitable strategy for the period was to follow the Market portfolio: an investment of R\$ 100.00 in January 2010 would have a value of R\$ 283.64 in April 2018, by comparison, the same investment for the same period following a momentum strategy would generate only R\$ 145.16.

3.2 Methodology

3.2.1 Theoretical Model

In the article by Grinblatt and Han (2005) a theoretical model based on a partial equilibrium scope of the supply and demand for a risky asset i was built. Since we're in the Mental Accounting framework, the partial equilibrium model ignores interactions among assets. In this model it was proposed a division of the aggregate demand for this risky asset i into two: the demand for this same asset by "disposition investors" (DI), $D_{d,t}$ (share μ of investors under the DE⁸); and the demand of "rational investors" (RI), $D_{r,t}$ (share $(1 - \mu)$ of investors without the DE):

$$\text{Rational Demand: } D_{r,t} = 1 + b_t(F_t - P_t)$$

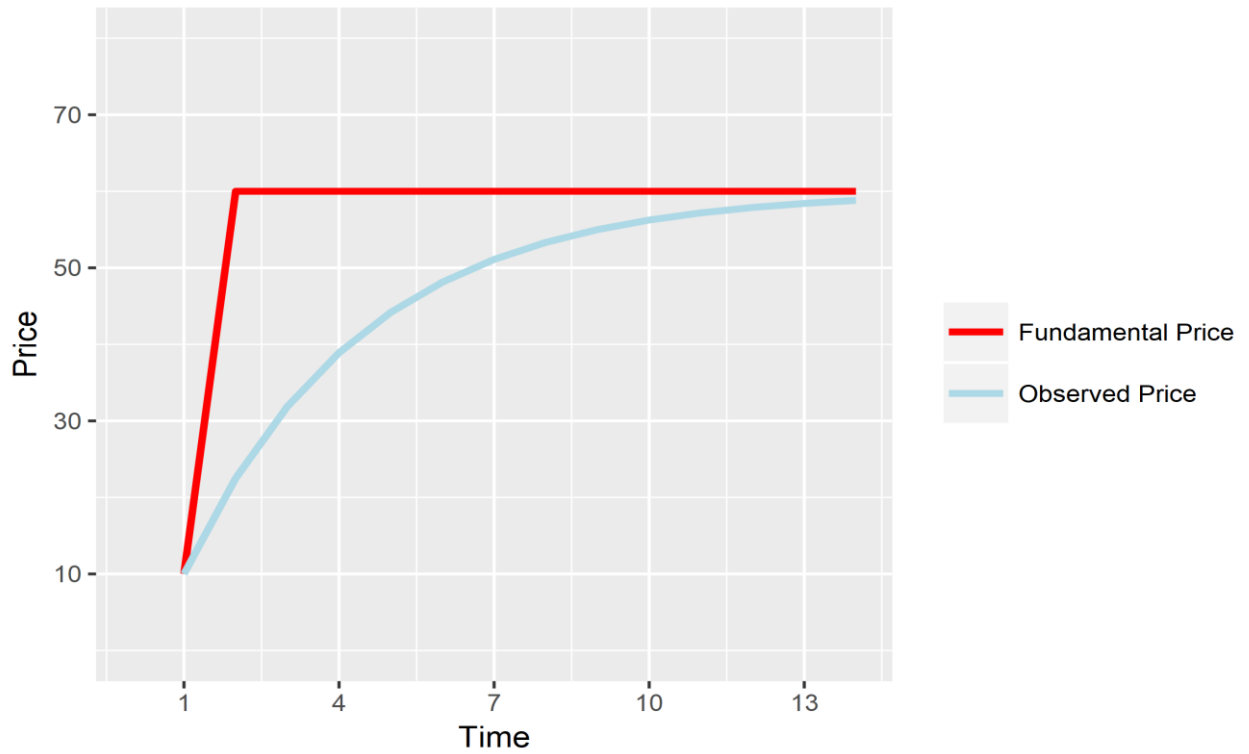
$$\text{DE Demand: } D_{d,t} = 1 + b_t[(F_t - P_t) + \lambda(R_t - P_t)]$$

Such that the supply of asset i is fixed in one unit; that F_t is the fundamental value of the asset i in t (the true price of the asset, that would prevail without the presence of DE) following a random walk; P_t is the market price of asset i observed in t ; R_t is the reference price (used by the disposition investors to measure gains and losses, it can be thought as the average price which DI bought the asset); λ is a constant that measures the relative importance of capital gain (i.e. reference price minus market price) in the demand for DI; and b_t is the slope of the rational component of the demand functions. That is, we have that the demand for DI depends not only on the deviations of the fundamental value, but also on deviations from its reference value (the capital gain).

⁸ Although the paper use the term PT / MA, since the model was strictly assembled only with the main elements of the DE, the term DE is used here since it is the most recurrent in the literature, besides, PT and MA are enough to explain the DE itself in most scenarios.

As shown in figure 3, at $t = 1$ take $F_t = P_t = R_t = R\$ 10,00$ for all investors: under good news, F_t goes to $R\$ 60.00$ in $t = 2$. In the absence of DE, P_t would also be equal to $R\$ 60.00$, but as DIs are risk averse in the part of gains, part of them carries out a sale operation, which causes the price to not increase as much; without further information the process continues until the price reaches equilibrium (rational investors would keep buying asset i until $F_t = P_t$).

Figure 2 – Dynamic of prices in the presence of investors subject to the disposition-effect.



Source: Own Elaboration

A From the aggregation of the demands and the satisfaction of the market clearing conditions, equilibrium is reached:

$$1 + b_t(F_t - P_t) + \mu\lambda b_t(R_t - P_t) = 1$$

or in an equivalent way (equilibrium price):

$$P_t = wF_t + (1 - w)R_t, \text{ s.t. } w = \frac{1}{1 + \mu\lambda}$$

which depends of F_t and the reference value R_t of DI.

Since in the model R_t is a function of both R_{t-1} and P_{t-1} (whereas the reference price is an average of past prices and reference values), the expected price variation will be (noting that $E_t(F_t) = E_t(F_{t+1})$, since we have as assumption that the fundamental price follows a Random Walk):

$$E_t\left(\frac{P_{t+1} - P_t}{P_t}\right) = (1 - w)V_t\left(\frac{P_t - R_t}{P_t}\right)$$

given that V_t is the share of the reference price update that is due to the past market prices.

Hence, Grinblatt and Han (2005) show from their model that the expected returns are a growing function of unrealized gains (note that w and V_t are numbers between 0 and 1).

3.2.2 Estimation

Grinblatt and Han (2005) propose a calculation of the reference value R_t in function of past prices and turnovers. In the authors' estimation, R_t was estimated over a five-year horizon. In the present work, a reference value with a horizon of three years was used:

$$R_{t-1} = \frac{1}{k} \sum_{n=1}^{156} \left(V_{t-1-n} \prod_{\tau=1}^{n-1} [1 - V_{t-1-n+\tau}] \right) P_{t-1-n}$$

With that, we can also define our proxy measure for unrealized gain, following the methodology of Grinblatt and Han (2005), that's going to be later used as the main independent variable to test momentum in the disposition-effect case⁹:

$$g_t = \frac{P_{t-1} - R_t}{P_{t-1}}$$

In order to evaluate the effect of behavioral biases in Brazil, it was estimated the disposition-effect following the methodology of Odean (1998), using the share of gains (losses) realized as a share of total holdings, i.e., share of realized and unrealized gains (losses) to obtain the measures of Proportion of Gains Realized (PGR) and Proportion of Losses Realized (PLR). Odean's (1998) calculation was made with disaggregated data from a large brokerage house, therefore our estimation for the aggregate case was modified, the definition of a gain or a loss was made using the reference value (i.e. if asset i had an unrealized gain greater than zero at t , all volume traded was interpreted as a gain). Since all volume traded of a given asset i was interpreted as either a gain or a loss (depending if unrealized gains was greater or smaller than zero), the total number of outstanding shares of assets with positive (negative) unrealized gain was considered as the total number of assets with a gain (loss). Thus, it was estimated the PGR:

⁹ Grinblatt and Han (2005) appoint that the reason for lagging P_t for P_{t-1} was to avoid confounding market microstructure effects, such as bid-ask bounce.

$$PGR_t = \frac{\text{quantity of shares of assets with } g_t > 0}{\text{total of outstanding shares of assets with } g_t > 0}$$

With PLR estimated in an analogous manner. In order to estimate the disposition-effect itself, here noted as disposition-effect index (DEI), one measure is subtracted from the other:

$$DEI = PGR - PLR$$

To follow the capital-fund flow based explanation, first we estimate the capital flow for each fund i , according to Sirri and Tufano (1998) methodology, discounting the Total Net Assets (TNA) of each fund the return in the period:

$$flow_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1} \times (1 + r_{i,t})}{TNA_{i,t-1}}$$

To take the expected value of $flow_{i,t+1}$, we take :

$$E_t[flow_{i,t+1}] = \beta_0 + \beta_1 alpha_{i,t} + \beta_2 flow_{i,t} + \beta_3 flow_{i,t-1} + \beta_4 flow_{i,t-2}$$

Where $alpha_{i,t}$ is the constant in Carhart (1997) four-factor asset pricing model:

$$E[r_{i,t} - rf_t] = alpha_{i,t} + \beta_{1,i}(rm_t - rf_t) + \beta_{2,i}(SMB_t) + \beta_{3,i}(HML_t) + \beta_{4,i}(UMD_t)$$

From this, it is estimated the Flux-Induced-Trading (FIT) for each asset j (adding up for the position of each fund i), which is going to be the main variable to test momentum for the capital-fund flow based explanation, according to Lou's methodology (2012):

$$E_t[FIT_{j,t+1}] = \frac{\sum_i shares_{i,j,t} \times E_t[flow_{i,t+1}] \times PSF_{i,t}}{\sum_i shares_{i,j,t}}$$

Where $PSF_{i,t}$ stands for a partial scaling factor used as a weight for each fund i based on its total net assets.

As it is standard in the literature, like Grinblatt and Han (2005) and Birru (2015), the estimation of the impact of the disposition-effect in momentum uses monthly cross-sectional regressions, according to Fama and MacBeth (1973). The same regression (with the proper testing variables), will be used for the capital-fund flow based explanation. Consistent Newey-West (1987) HAC estimators were used for heteroscedasticity and autocorrelation. The optimal number of lags was obtained according to Newey and West (1994) methodology. We have as dependent variable the monthly returns of the assets j in each cross-section:

$$r_t = a_0 + a_1 r_{-4:-1} + a_2 r_{-52:-5} + a_3 r_{-156:-53} + a_4 V_{avg} + a_5 s_{t-1} + a_6 g_{t-1} + a_7 FIT_{t-1}$$

As covariates we have: $r_{-4:-1}$, the previous month return with respect to the last week; $r_{-52,-5}$, the return of the past year with respect to the past month; $r_{-156:-53}$ the 3-year long run

return with respect to the previous year; V_{avg} , the average yearly turnover of the share of each company; and s , the logarithm of the market capitalization of each company in $t-1$. As explanatory variables we have the unrealized gains g and the measure of Flux-Induced-Trading, FIT . Additional variables may be tested in further interactions of this work.

4 Results

4.1 Summary statistics

We begin this section by showing summary statistics and visual informations about our covariates and our main explainable variables. Table 1 reports the time-series averages of summary statistics for the regressors, these include the mean, the standard deviation along with the 10th (p10), the 50th (p50) and the 90th (p90) percentile:

Table 1: Summary statistics of the regressors.

Table 1 shows time-series averages of summary statistics from each of our covariates and explainable variables.

Table 1: $r_t = a_0 + a_1 r_{-4:-1} + a_2 r_{-52:-5} + a_3 r_{-156:-53} + a_4 V_{avg} + a_5 s_{t-1} + a_6 g_{t-1} + a_7 FIT_{t-1}$					
Variable	Mean	p50	Standard Deviation	p10	p90
$r_{-4,-1}$	0.00	0.00	0.10	-0.11	0.11
$r_{-52,-5}$	0.05	0.07	0.45	-0.45	0.55
$r_{-156,-53}$	-0.02	0.03	0.70	-0.81	0.72
V_{avg}	0.02	0.01	0.02	0.00	0.03
s_{t-1}	10,600.00	2,550.00	27,800.00	385.00	23,500.00
g_{t-1}	-0.09	0.04	0.89	-0.49	0.29
FIT_{t-1}	-0.71	-0.66	5.10	-5.77	4.49

Source: Own Elaboration.

With the intention of obtaining additional insights into what explains our main independent variables (the unrealized gains g_t and the flux induced trading FIT_t) we regress them by our covariates.

Table 2 shows that unrealized gains are positively correlated with past returns and negatively related with average turnover, in agreement with the literature. The market capitalization coefficient being positive may indicate that large firms that had grown considerably in a horizon not captured by our returns tend to have greater capital gains. The regression also appoints that unrealized gains have a negative correlation with flux induced trading.

Table 2: Fama-Macbeth cross-sectional regression estimates of the independent variables.

Table show one of our main explanatory variable, unrealized gains g_t (related to the explanation of momentum by disposition-effect), regressed against our covariates.

Table 2: $g_t = a_0 + a_1 r_{-4:-1} + a_2 r_{-52:-5} + a_3 r_{-156:-53} + a_4 V_m + a_5 V_a + a_6 V_{lr} + a_7 s + a_7 FIT$						
Variable	Coef.	Std. Err.	t	P>t	[95%Conf.	Interval]
$r_{-4,-1}$	1.104	0.089	12.400	0.000	0.928	1.280
$r_{-52,-5}$	1.000	0.000	20.550	0.000	1.000	1.000
$r_{-156,-53}$	0.000	0.000	18.130	0.000	0.000	0.000
V_{avg}	-27.214	11.048	-2.460	0.015	-48.993	-5.000
$V_{-52,-5}$	25.658	11.166	2.300	0.023	3.647	47.669
$V_{-156,-53}$	0.682	0.717	0.950	0.343	-0.733	2.096
s_{t-1}	0.010	0.002	4.170	0.000	0.005	0.015
FIT_{t-1}	-0.010	0.004	-2.290	0.023	-0.018	-0.001
a_0	-0.188	0.039	-4.750	0.000	-0.266	-0.110

Source: Own Elaboration.

In a similar way, Table 3 shows that flux induced trading is positively correlated with past returns of intermediate and long term horizons, being stronger for intermediate returns (which is directly related to momentum portfolios). Likewise to unrealised gains, it's also negatively related with average turnovers. Such as the regression of capital gains shows that it is negatively correlated with flux induced trading, when we regress FIT_t we get the same conclusion: they are negatively related.

Table 3: Fama-Macbeth cross-sectional regression estimates of the independent variables.

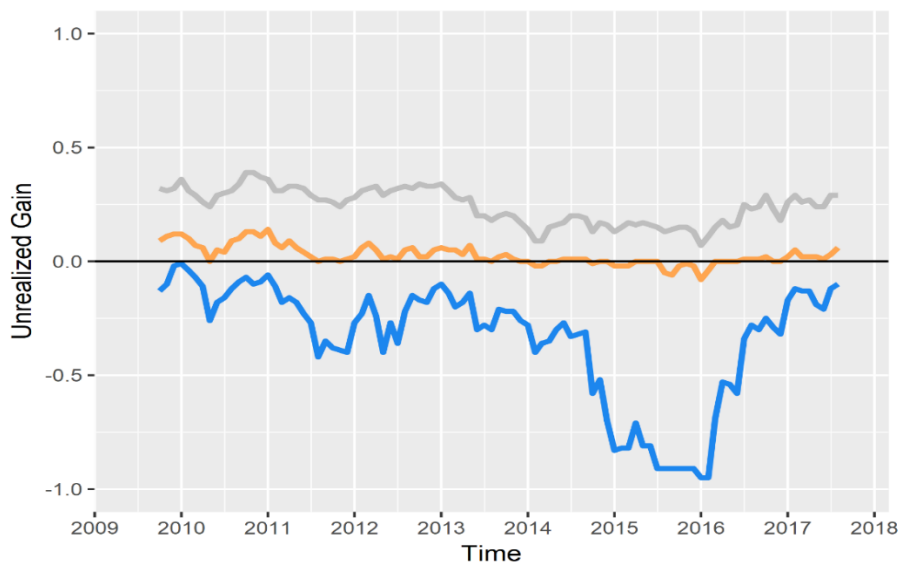
Table show one of our main explanatory variable, flux-induced-trading FIT_t (related to the fund flow-based explanation for momentum), regressed against our covariates.

Variable	Coef.	Std. Err.	t	P>t	[95% Conf. Interval]
$r_{-4,-1}$	-0.289	0.173	-1.680	0.095	-0.629 0.051
$r_{-52,-5}$	0.179	0.072	2.480	0.014	0.037 0.320
$r_{-156,-53}$	0.050	0.028	1.790	0.076	-0.005 0.106
V_{avg}	-77.708	28.210	-2.750	0.006	-133.318 -22.098
$V_{-52,-5}$	76.125	27.910	2.730	0.007	21.106 131.144
$V_{-156,-53}$	2.794	1.350	2.070	0.040	0.132 5.455
s_{t-1}	-0.041	0.016	-2.580	0.011	-0.071 -0.010
g_{t-1}	-0.137	0.045	-3.060	0.002	-0.226 -0.049
a_0	0.397	0.245	1.620	0.107	-0.086 0.881

Source: Own Elaboration.

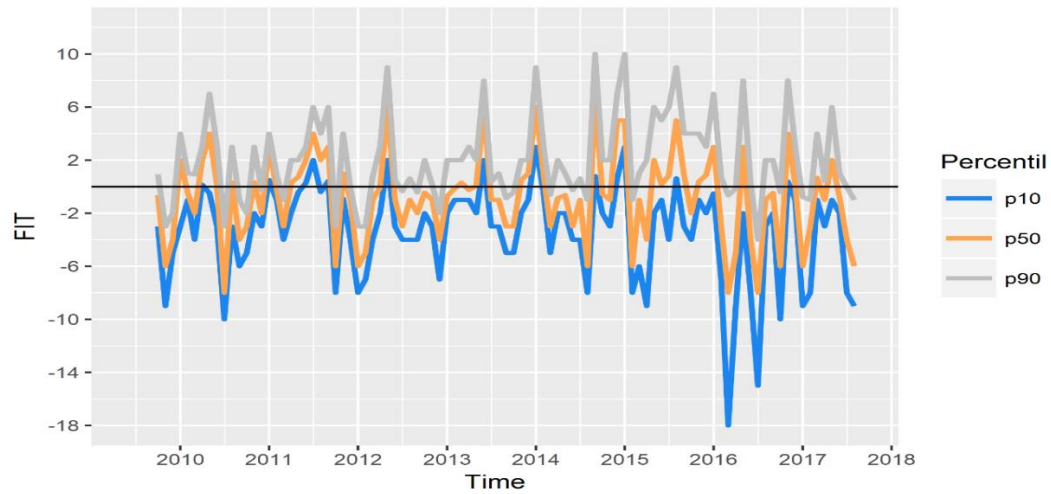
Figure 4 plots the time-series of the 10th, 50th and 90th percentile of the unrealized gains variable g_t , responsible to account for the behavioral-based explanation of momentum in our tests. It shows a considerable cross-sectional and time-series dispersion.

Figure 4 – Time-series of unrealized gains percentiles.



Source: Own Elaboration.

Figure 5 – Time-series of flux-induced-trading percentiles.



Source: Own Elaboration.

In the same direction, Figure 5 plots the same time-series statistics (10th, 50th and 90th percentile) for the Flux-Induced-Trading (FIT) variable, accountable for the capital-fund flow explanation. Here it's observable an even greater dispersion, both in the time-series and cross-sectional levels.

Another way to better visualize our main independent variables and their impact in returns is through double sorts. First, we sort our sample in quintiles; G1 till G5 for unrealized gains, i.e. from the low value quintile (G1) of g_t through the high value quintile (G5), and in a similar way F1 till F5 for the flux-induced-trading variable. Then we take the average one year return of this portfolio, comparing the results between portfolios and sorts.

Table 4: Double sorts – Mean portfolio return by first sorting on unrealized gains.

Table 4 illustrates the mean average return of each portfolio using double sorts with our main explanatory variables, first sorting on unrealized gains.

	G1	G2	G3	G4	G5
F1	-1.570	-0.653	-0.235	0.000	0.104
F2	-0.644	-0.066	0.264	0.445	0.633
F3	-0.213	0.252	0.491	0.662	0.903
F4	0.186	0.515	0.671	0.862	1.157
F5	0.585	0.995	1.120	1.307	2.297
F5-F1	0.021	0.016	0.014	0.013	0.021
t-test	(9.972)	(10.494)	(10.093)	(8.042)	(7.769)

Source: Own Elaboration.

Taking our double sorts by first sorting on unrealized gains (i.e. we first subdivide our sample in five quintiles of unrealized gains, and then, by fixing one quintile of g_t , we make another sort based on flux-induced-trading), as given in Table 4, we can see that by either moving right (i.e. increasing the unrealized gains quintile) or down (increasing the flux-induced-trading quintile) in the table, the average return is increasing. By taking the difference from the highest to the lowest FIT_t , we still manage to observe a significantly different from zero average return.

Table 5: Double sorts – Mean portfolio return by first sorting on flux-induced-trading.

Table 5 illustrates the mean average return of each portfolio using double sorts with our main explanatory variables, first sorting on flux-induced-trading.

	F1	F2	F3	F4	F5
G1	-0.973	0.137	0.440	0.715	1.303
G2	-0.919	0.131	0.458	0.729	1.249
G3	-0.600	0.116	0.461	0.734	1.155
G4	-0.619	0.188	0.493	0.766	1.267
G5	-0.554	0.170	0.473	0.769	1.761
G5-G1	0.012	0.014	0.015	0.011	0.015
t-test	(6.822)	(7.158)	(7.774)	(7.420)	(8.125)

Source: Own Elaboration.

In the same manner, Table 5 shows the double sorts by first sorting on flux-induced-trading. Here it's still observable the increase in the average return when we go for higher FIT_t quintiles, which isn't always observable when we go for higher unrealized gains quintiles. Nevertheless, the difference between the highest and lowest g_t quintiles is still significantly different from zero in all FIT_t quintiles.

4.2 Disposition-Effect Estimation

After calculating the reference values for each asset and each time period, the Proportion of Gains Realized (PGR) and the Proportion of Losses Realized (PLR) were estimated to then test the disposition-effect index. From Odean (1998), t- statistics test the null that the difference in proportions is equal to zero, assuming that all realized gains and losses are independent decisions:

Table 6: Disposition-effect index test.

Table 6 represents our results for the presence of disposition-effect in Brazil, following methodology of Odean (1998). We're checking if the difference between Proportion of Gains Realized and the Proportion of Losses Realized is significantly different from zero (which is interpreted as a presence of disposition-effect).

Variable	Mean	P>t	Standard Deviation
DEI_t	0.004	0.000	0.000

Source: Own Elaboration.

From the results presented in Table 6, it is verified that the disposition-effect index is significantly different from zero to 5% of significance. Taking the medians of both proportions, PGR was 50% higher than PLR, which is in agreement with the rest of the literature, as in Odean (1998), Seru, Shumway and Stoffman (2006) and Barber et al. Kumar (2009).

4.3 Main Results

In view of the indications of the disposition-effect in the Brazilian market, the main results are presented, omitting some regressors when noted. The Fama-Macbeth equation (1973) was estimated using Newey-West estimators (1987). Using the methodology of Newey and West (1994) it was found that the optimal number of lags was twenty-five. Tables 7-11 present the average coefficients and time-series t-statistics for the Fama-Macbeth regressions.

Table 7 was estimated excluding the unrealized gain, Flux-Induced-Trading (FIT) and market capitalization variables. In the case of Table 8, the unrealized gain and the FIT variables were excluded. From the results in both Tables, only with the covariates, it is observed a reversal of the short-term returns, but a persistence in the case of intermediate and long-term returns. We can also see that momentum is very strong, since the return of the intermediate portfolios ($r_{-52,-5}$) is quite significant. The volume effect (related to market capitalization) is not very significant.

Table 7: Fama-Macbeth cross-sectional regression estimates.

Table 7-11 bring us our main results. As dependent variable we have the monthly past returns and as independent variables we have last month's return, intermediate horizon return (last year), long horizon returns (last three years), average turnover, logarithmic of market capitalization, unrealized gains and flux-induced-trading. The tables differ by included/excluded variables. Our main objective here is to check if the inclusion of one (or more) of our main explanatory variables (unrealized gains g_t and flux-induced-trading FIT_t) is enough to explain momentum (by making the intermediate returns loose its significance). In the case of table 7, market capitalization, unrealized gains and flux-induced-trading were excluded.

Table 7: $r_t = a_0 + a_1 r_{-4:-1} + a_2 r_{-52:-5} + a_3 r_{-156:-53} + a_4 V_{avg}$

Variable	Coef.	Std. Err.	t	P>t	[95% Conf. Interval]
$r_{-4,-1}$	-0.007	0.009	-0.870	0.383	-0.024 0.009
$r_{-52,-5}$	0.003	0.002	1.860	0.064	0.000 0.007
$r_{-156,-53}$	0.001	0.001	0.690	0.494	-0.001 0.002
V_{avg}	-0.001	0.019	-0.040	0.971	-0.037 0.036
a_0	0.002	0.001	1.440	0.151	-0.001 0.004

Table 8: Fama-Macbeth cross-sectional regression estimates.

Table 7-11 bring us our main results. As dependent variable we have the monthly past returns and as independent variables we have last month's return, intermediate horizon return (last year), long horizon returns (last three years), average turnover, logarithmic of market capitalization, unrealized gains and flux-induced-trading. The tables differ by included/excluded variables. Our main objective here is to check if the inclusion of one (or more) of our main explanatory variables (unrealized gains g_t and flux-induced-trading FIT_t) is enough to explain momentum (by making the intermediate returns loose its significance). In the case of table 8, unrealized gains and flux-induced-trading were excluded.

Table 8: $r_t = a_0 + a_1 r_{-4:-1} + a_2 r_{-52:-5} + a_3 r_{-156:-53} + a_4 V_{avg} + a_5 s_t$

Variable	Coef.	Std. Err.	t	P>t	[95% Conf. Interval]
$r_{-4,-1}$	-0.007	0.008	-0.780	0.437	-0.023 0.010
$r_{-52,-5}$	0.004	0.002	2.060	0.041	0.000 0.008
$r_{-156,-53}$	0.001	0.001	1.420	0.156	0.000 0.002
V_{avg}	-0.004	0.019	-0.220	0.824	-0.042 0.033
s_{t-1}	-0.001	0.000	-1.160	0.249	-0.001 0.000
a_0	0.008	0.006	1.320	0.187	-0.004 0.021

Source: Own Elaboration.

Table 9: Fama-Macbeth cross-sectional regression estimates.

Table 7-11 bring us our main results. As dependent variable we have the monthly past returns and as independent variables we have last month's return, intermediate horizon return (last year), long horizon returns (last three years), average turnover, logarithmic of market capitalization, unrealized gains and flux-induced-trading. The tables differ by included/excluded variables. Our main objective here is to check if the inclusion of one (or more) of our main explanatory variables (unrealized gains g_t and flux-induced-trading FIT_t) is enough to explain momentum (by making the intermediate returns loose its significance). In the case of Table 9, flux-induced-trading was excluded.

Table 9: $r_t = a_0 + a_1 r_{-4:-1} + a_2 r_{-52:-5} + a_3 r_{-156:-53} + a_4 V_{avg} + a_5 s + a_6 g$						
Variable	Coef.	Std. Err.	t	P>t	[95% Conf. Interval]	
$r_{-4,-1}$	-0.010	0.008	-1.260	0.208	-0.027	0.006
$r_{-52,-5}$	0.001	0.001	0.400	0.686	-0.002	0.003
$r_{-156,-53}$	0.000	0.001	0.380	0.703	-0.001	0.002
V_{avg}	-0.002	0.020	-0.110	0.912	-0.041	0.037
s_{t-1}	-0.001	0.000	-1.420	0.156	-0.001	0.000
g_{t-1}	0.005	0.002	2.690	0.008	0.001	0.009
a_0	0.010	0.006	1.540	0.125	-0.003	0.022

Source: Own Elaboration.

Table 9 was estimated excluding the variable FIT. With the inclusion of the main independent variable for the explanation of the disposition-effect, the unrealized gain, it was verified that g_t was significant at 1% degree of significance. Besides, g_t also presented a positive coefficient, which is in accordance with the literature and the presented partial equilibrium model. The inclusion of the unrealized gains variable lead to the loss of significance of the intermediate portfolios return, in which the momentum is the strongest, as noted in Jegadeesh and Titman (1993). This loss of significance is interpreted as an explanation for momentum. By taking its coefficient and considering the summary statistics (given that the 90th percentile is on average 80% greater than the 10th percentile) we can see that winners out perform losers by 0.4% a month (4.8% a year).

Table 10: Fama-Macbeth cross-sectional regression estimates.

Table 7-11 bring us our main results. As dependent variable we have the monthly past returns and as independent variables we have last month's return, intermediate horizon return (last year), long horizon returns (last three years), average turnover, logarithmic of market capitalization, unrealized gains and flux-induced-trading. The tables differ by included/excluded variables. Our main objective here is to check if the inclusion of one (or more) of our main explanatory variables (unrealized gains g_t and flux-induced-trading FIT_t) is enough to explain momentum (by making the intermediate returns loose its significance). In the case of Table 10, unrealized gains was excluded.

Table 10: $r_t = a_0 + a_1 r_{-4:-1} + a_2 r_{-52:-5} + a_3 r_{-156:-53} + a_4 V_{avg} + a_5 s + a_7 FIT$						
Variable	Coef.	Std. Err.	t	P>t	[95% Conf. Interval]	
$r_{-4,-1}$	0.000	0.008	-0.030	0.979	-0.016	0.016
$r_{-52,-5}$	0.007	0.003	2.420	0.017	0.001	0.013
$r_{-156,-53}$	0.002	0.001	2.230	0.028	0.000	0.004
V_{avg}	-0.053	0.045	-1.160	0.247	-0.143	0.037
s_{t-1}	-0.001	0.001	-0.980	0.328	-0.002	0.001
FIT_{t-1}	0.001	0.001	0.100	0.922	-0.001	0.001
a_0	0.008	0.008	1.030	0.307	-0.008	0.024

Source: Own Elaboration.

Table 10 was estimated excluding the unrealized gain variable, but including the Flux-Induced-Trading (FIT) in its place. The main variable from the capital-fund flow based explanation of momentum, FIT , wasn't significant in the estimation. Its inclusion was not enough to make the significance of the momentum portfolios disappear, i.e., it failed to explain momentum.

Table 11: Fama-Macbeth cross-sectional regression estimates.

Table 7-11 bring us our main results. As dependent variable we have the monthly past returns and as independent variables we have last month's return, intermediate horizon return (last year), long horizon returns (last three years), average turnover, logarithmic of market capitalization, unrealized gains and flux-induced-trading. The tables differ by included/excluded variables. Our main objective here is to check if the inclusion of one (or more) of our main explanatory variables (unrealized gains g_t and flux-induced-trading FIT_t) is enough to explain momentum (by making the intermediate returns loose its significance). In the case of Table 11, all variables were included.

Table 11: $r_t = a_0 + a_1 r_{-4:-1} + a_2 r_{-52:-5} + a_3 r_{-156:-53} + a_4 V_{avrg} + a_5 s + a_6 g + a_7 FIT$

Variable	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
$r_{-4,-1}$	-0.010	0.008	-1.260	0.210	-0.024	0.005
$r_{-52,-5}$	-0.001	0.001	-0.390	0.699	-0.003	0.002
$r_{-156,-53}$	0.002	0.001	1.460	0.147	-0.001	0.004
V_{avrg}	-0.060	0.038	-1.610	0.112	-0.135	0.014
s_{t-1}	-0.001	0.001	-1.180	0.243	-0.002	0.000
g_{t-1}	0.007	0.003	2.080	0.040	0.000	0.014
FIT_{t-1}	0.002	0.001	0.160	0.875	-0.001	0.001
a_0	0.011	0.009	1.270	0.205	-0.006	0.028

Source: Own Elaboration.

Table 11 was estimated including all independent variables and all controls. when we include the two independent variables, we can see that only the unrealized gains was significant at 5%. In addition, the momentum portfolios also lost their significance (as in Table 9).

5 Robustness Analysis

Since our main variable from the behavioral-based explanation of momentum appears to have a strong effect, we make further investigation upon its legitimacy. Grinblatt and Han (2005) make the provocation of whether the significance of the explanation of unrealized gains could be due to some alternative reasons. Since the unrealized capital gains depends of the reference value, which was estimated by an average of past prices weighted by turnovers, it is indirectly related to volumes. The relationship between volume and prices is a well-known research subject, such as in Gervais, Kaniel and Mingelgrin (2001), hence, could the explanation of momentum be motivated by this volume effect? By our unrealized gains variable, high returns occur when in a distant horizon we had a considerable volume and a sudden spike in the price when it had no volume¹⁰. Thus, it's considered in the paper that if both the explanation of momentum and the coefficient of the unrealized gains variables comes entirely from the turnover part (i.e. the “volume-effect”), it would be an indication that extra explanations could arise.

For instance, if the reference value was estimated by an average of turnovers, it could still deliver the volume effect, but it would fail to deliver the time-series effect of our unrealized gains variable (that uses, in the weighting process, one turnover for each week). Thus, we inspect this matter by regressing our main equation, but changing g_t for a variable that captures only the volume-effect, $\overline{g}_t$, that would take the reference value by taking the average yearly turnover, instead of weekly turnovers.

Regarding our results from Table 12, by the inclusion of the unrealized gains variable with the average of turnovers as the weighting-base for the reference price, $\overline{g}_t$, the returns of the momentum portfolio (i.e. intermediate horizon) has lost its significance (just like Table 9). However, $\overline{g}_t$ failed to have a significant coefficient as explainable variable. Thus, despite its inclusion making the momentum disappear, since it didn't manage to be significant, it couldn't replace unrealized gains as the main explainable variable.

¹⁰ Like is noted in Grinblatt and Han (2005), volume is considerably persistent, consequently is the stocks with low volume that present the most extreme gains.

Table 12: Robustness check – Alternative explanations

Tables 12-20 bring us the robustness checks for our main results in the last section. Table 12 shows the test of a possible additional explanation for the significance of unrealized gains that's based on average volume (without taking into consideration time-series variance to obtain the reference value, only taking average volume instead).

Table 12: $r_t = a_0 + a_1 r_{-4:-1} + a_2 r_{-52:-5} + a_3 r_{-156:-53} + a_4 V_{avg} + a_5 s + a_6 \overline{g}_{t-1}$

Variable	Coef.	Std. Err.	t	P>t	[95% Conf. Interval]
$r_{-4,-1}$	-0.008	0.013	-0.630	0.528	-0.035 0.018
$r_{-52,-5}$	0.001	0.003	0.280	0.784	-0.005 0.007
$r_{-156,-53}$	0.001	0.002	0.600	0.550	-0.003 0.005
V_{avg}	0.020	0.023	0.890	0.374	-0.025 0.065
s_{t-1}	0.000	0.000	-0.290	0.774	-0.001 0.001
$\overline{g}_t$	0.001	0.002	0.500	0.617	-0.003 0.005
a_0	0.001	0.006	0.170	0.865	-0.012 0.014

Source: Own Elaboration.

Table 13: Robustness check – First Sub-sample

Tables 12-20 bring us the robustness checks for our main results in the last section. Tables 13-20 retest our main results from Tables 7-11 but for sub-samples (pre-2008 and post-2008). Tables 13-16 represent the test for the first half of our sample and Tables 17-20 represent the second half. Table 13 is comparable with Table 8, excluding unrealized gains and flux-induced-trading from our analysis.

Table 13: $r_t = a_0 + a_1 r_{-4:-1} + a_2 r_{-52:-5} + a_3 r_{-156:-53} + a_4 V_{avg} + a_5 s$

Variable	Coef.	Std. Err.	t	P>t	[95% Conf. Interval]
$r_{-4,-1}$	-0.031	0.015	-2.070	0.039	-0.061 -0.002
$r_{-52,-5}$	0.004	0.002	1.830	0.069	0.000 0.008
$r_{-156,-53}$	0.001	0.001	1.750	0.082	0.000 0.003
V_{avg}	0.010	0.020	0.510	0.613	-0.030 0.050
s_{t-1}	0.000	0.000	-0.670	0.505	-0.001 0.001
a_0	0.005	0.006	0.740	0.459	-0.008 0.017

Source: Own Elaboration.

Another common inquiry in empirical works is that a given explanation could work only for a specified period, i.e., that subperiods of a given sample could present an altered representation of the market. With the purpose of accounting this, primarily we split our data in half, the first half being from January 1997¹¹ until October 2008, the second half from October 2008 to August 2017, then we repeat the procedures presented in Tables 7-11 for each half, the comparison with Table 7 was omitted, since the main issue is compare the results with and without our main independent variables. By this, it's possible to analyze two different scenarios, taking into account the time before and the time after the 2008 sub-prime crisis, which had a considerable impact in turnover and market movements (from a bullish to bearish). Following Grinblatt and Han (2005), if we consider the rational versus disposition-effect investors approach to equilibrium prices as part of the core of equilibrium, the main effect on momentum's explanation should be the same, regardless of the period.

Tables 13 and 17 can be compared with Table 8, here we do not include our main explanatory variables. In both cases the returns of the momentum portfolio (of intermediate horizon) were significant at 10%, which is equivalent to the whole sample.

Table 14: Robustness check – First Sub-sample

Tables 12-20 bring us the robustness checks for our main results in the last section. Tables 13-20 retest our main results from Tables 7-11 but for sub-samples (pre-2008 and post-2008). Tables 13-16 represent the test for the first half of our sample and Tables 17-20 represent the second half. Table 14 is comparable with Table 9, excluding flux-induced-trading from our analysis.

Table 14: $r_t = a_0 + a_1 r_{-4;-1} + a_2 r_{-52;-5} + a_3 r_{-156;-53} + a_4 V_{avrg} + a_5 s + a_6 g$						
Variabel	Coef.	Std. Err.	t	P>t	[95% Conf.	Interval]
$r_{-4,-1}$	-0.040	0.015	-2.630	0.009	-0.071	-0.010
$r_{-52,-5}$	-0.003	0.003	-0.980	0.329	-0.008	0.003
$r_{-156,-53}$	0.000	0.001	-0.120	0.905	-0.002	0.002
V_{avrg}	0.014	0.023	0.610	0.542	-0.031	0.059
s_{t-1}	0.000	0.000	-1.070	0.287	-0.001	0.000
g_{t-1}	0.012	0.003	4.170	0.000	0.006	0.018
a_0	0.006	0.006	1.030	0.304	-0.006	0.019

Source: Own Elaboration.

¹¹ The period 1994 to 1997 was used to estimate the reference value.

Table 15: Robustness check – First Sub-sample

Tables 12-20 bring us the robustness checks for our main results in the last section. Tables 13-20 retest our main results from Tables 7-11 but for sub-samples (pre-2008 and post-2008). Tables 13-16 represent the test for the first half of our sample and Tables 17-20 represent the second half. Table 15 is comparable with Table 10, excluding unrealized gains from our analysis.

Table 15: $r_t = a_0 + a_1r_{-4:-1} + a_2r_{-52:-5} + a_3r_{-156:-53} + a_4V_{avg} + a_5s + a_7FIT$						
Variable	Coef.	Std. Err.	t	P>t	[95% Conf. Interval]	
$r_{-4,-1}$	-0.013	0.009	-1.420	0.161	-0.030	0.005
$r_{-52,-5}$	0.008	0.004	2.290	0.026	0.001	0.015
$r_{-156,-53}$	0.003	0.001	2.800	0.007	0.001	0.004
V_{avg}	-0.126	0.032	-3.910	0.000	-0.191	-0.061
s_{t-1}	-0.001	0.001	-1.680	0.100	-0.002	0.000
FIT_{t-1}	-0.001	0.001	-1.180	0.242	-0.002	0.001
a_0	0.014	0.009	1.520	0.135	-0.005	0.032

Source: Own Elaboration.

Table 16: Robustness check – First Sub-sample

Tables 12-20 bring us the robustness checks for our main results in the last section. Tables 13-20 retest our main results from Tables 7-11 but for sub-samples (pre-2008 and post-2008). Tables 13-16 represent the test for the first half of our sample and Tables 17-20 represent the second half. Table 16 is comparable with Table 11, including all variables analyzed.

Table 16: $r_t = a_0 + a_1r_{-4:-1} + a_2r_{-52:-5} + a_3r_{-156:-53} + a_4V_{avg} + a_5s + a_6g + a_7FIT$						
Variable	Coef.	Std. Err.	t	P>t	[95% Conf. Interval]	
$r_{-4,-1}$	-0.026	0.009	-3.010	0.004	-0.043	-0.009
$r_{-52,-5}$	-0.002	0.002	-1.010	0.318	-0.007	0.002
$r_{-156,-53}$	0.000	0.001	0.240	0.812	-0.001	0.002
V_{avg}	-0.125	0.033	-3.830	0.000	-0.190	-0.059
s_{t-1}	-0.001	0.001	-1.810	0.076	-0.002	0.000
g_{t-1}	0.013	0.003	3.960	0.000	0.006	0.019
FIT_{t-1}	-0.001	0.001	-1.090	0.279	-0.002	0.001
a_0	0.017	0.010	1.640	0.107	-0.004	0.037

Source: Own Elaboration.

Table 17: Robustness check – Second Sub-sample

Tables 12-20 bring us the robustness checks for our main results in the last section. Tables 13-20 retest our main results from Tables 7-11 but for sub-samples (pre-2008 and post-2008). Tables 13-16 represent the test for the first half of our sample and Tables 17-20 represent the second half. Table 17 is comparable with Table 8, excluding unrealized gains and flux-induced-trading from our analysis.

Table 17: $r_t = a_0 + a_1 r_{-4:-1} + a_2 r_{-52:-5} + a_3 r_{-156:-53} + a_4 V_{avg} + a_5 s$						
Variable	Coef.	Std. Err.	t	P>t	[95% Conf. Interval]	
$r_{-4,-1}$	0.003	0.006	0.450	0.655	-0.009	0.015
$r_{-52,-5}$	0.006	0.003	1.640	0.100	-0.001	0.012
$r_{-156,-53}$	0.002	0.001	2.020	0.046	0.000	0.004
V_{avg}	-0.003	0.012	-0.260	0.798	-0.026	0.020
s_{t-1}	0.000	0.001	0.320	0.747	-0.001	0.002
a_0	-0.003	0.009	-0.290	0.771	-0.022	0.016

Source: Own Elaboration.

In the same manner, we compare Tables 14 and 18 with Table 9, in this case we include the unrealized gains variable. Similarly, for the entire sample size, both sub-samples had a significant coefficient for g_t , with its inclusion making the significance of the returns of intermediate horizon disappear.

Comparing Table 10 with Tables 15 and 19, we observe the still lack of significance of our Flux Induced Trading variable in both sub-samples. Table 15 had a negative FIT_t coefficient, different from the results presented in Lou (2012), but is in accordance when we take into consideration the reversal effect of funds, like it's seen in Vayanos and Woolley (2013). Besides its non significance, it didn't manage to get rid of the significance of the intermediate portfolio returns, failing to explain momentum in both cases.

Table 18: Robustness check – Second Sub-sample

Tables 12-20 bring us the robustness checks for our main results in the last section. Tables 13-20 retest our main results from Tables 7-11 but for sub-samples (pre-2008 and post-2008). Tables 13-16 represent the test for the first half of our sample and Tables 17-20 represent the second half. Table 18 is comparable with Table 9, excluding flux-induced-trading from our analysis.

Table 18: $r_t = a_0 + a_1 r_{-4:-1} + a_2 r_{-52:-5} + a_3 r_{-156:-53} + a_4 V_{avg} + a_5 s + a_6 g$						
Variable	Coef.	Std. Err.	t	P>t	[95% Conf. Interval]	
$r_{-4,-1}$	-0.003	0.005	-0.660	0.509	-0.013	0.007
$r_{-52,-5}$	0.000	0.002	0.180	0.861	-0.004	0.004
$r_{-156,-53}$	0.001	0.001	1.080	0.280	-0.001	0.003
V_{avg}	-0.003	0.012	-0.220	0.822	-0.027	0.021
s_{t-1}	0.000	0.001	0.180	0.858	-0.001	0.001
g_{t-1}	0.007	0.003	2.240	0.027	0.001	0.013
a_0	-0.001	0.009	-0.120	0.906	-0.019	0.017

Source: Own Elaboration.

Table 19: Robustness check – Second Sub-sample

Tables 12-20 bring us the robustness checks for our main results in the last section. Tables 13-20 retest our main results from Tables 7-11 but for sub-samples (pre-2008 and post-2008). Tables 13-16 represent the test for the first half of our sample and Tables 17-20 represent the second half. Table 19 is comparable with Table 10, excluding unrealized gains from our analysis.

Table 19: $r_t = a_0 + a_1 r_{-4:-1} + a_2 r_{-52:-5} + a_3 r_{-156:-53} + a_4 V_{avg} + a_5 s + a_7 FIT$						
Variable	Coef.	Std. Err.	t	P>t	[95% Conf. Interval]	
$r_{-4,-1}$	0.001	0.008	0.100	0.922	-0.015	0.017
$r_{-52,-5}$	0.007	0.003	2.630	0.010	0.002	0.013
$r_{-156,-53}$	0.002	0.001	2.410	0.018	0.000	0.004
V_{avg}	-0.047	0.044	-1.050	0.295	-0.135	0.041
s_{t-1}	-0.001	0.001	-1.350	0.181	-0.002	0.000
FIT_{t-1}	0.000	0.001	0.140	0.892	-0.001	0.001
a_0	0.011	0.008	1.380	0.171	-0.005	0.026

Source: Own Elaboration.

Table 20: Robustness check – Second Sub-sample

Tables 12-20 bring us the robustness checks for our main results in the last section. Tables 13-20 retest our main results from Tables 7-11 but for sub-samples (pre-2008 and post-2008). Tables 13-16 represent the test for the first half of our sample and Tables 17-20 represent the second half. Table 20 is comparable with Table 11, including all variables analyzed.

Table 20: $r_t = a_0 + a_1 r_{-4:-1} + a_2 r_{-52:-5} + a_3 r_{-156:-53} + a_4 V_{avg} + a_5 s + a_6 g + a_7 FIT$						
Variable	Coef.	Std. Err.	t	P>t	[95% Conf. Interval]	
$r_{-4,-1}$	-0.009	0.008	-1.130	0.261	-0.024	0.007
$r_{-52,-5}$	0.000	0.001	-0.320	0.753	-0.003	0.002
$r_{-156,-53}$	0.002	0.001	1.680	0.095	0.000	0.004
V_{avg}	-0.046	0.034	-1.370	0.176	-0.113	0.021
s_{t-1}	-0.001	0.001	-1.490	0.140	-0.002	0.000
g_{t-1}	0.008	0.003	2.320	0.022	0.001	0.014
FIT_{t-1}	0.000	0.001	0.160	0.876	-0.001	0.001
a_0	0.013	0.008	1.550	0.124	-0.004	0.029

Source: Own Elaboration.

Finally, we include all covariates and the main explanatory variables, making a comparison of Table 11 with Tables 16 and 20. In agreement with the literature, both subperiods had a significant g_t , which made the momentum disappear from the intermediate horizon returns. Likewise to the previous comparison, it was observed a non significant FIT_t with a negative coefficient for it in Table 16.

Considering that similar results were obtained in both sub-samples and that alternative explanations were not sufficient, we present evidence that unrealized gains is a strong explanation for momentum, being a great contender against fund flow-based explanations. Further empirical investigation is required with the aim of supporting this results.

6 Concluding Remarks

Through the literature and the presented results, we have evidence to confirm the importance of the phenomenon of momentum in prices, considering that it is an anomaly that still has no closed explanation and continues to have a wide repercussion in both the academy and the market. The present work aimed to compare two of the most recent and important explanations for this phenomenon.

In addition to being a phenomenon widely documented and discussed in the literature in the case of developed countries, momentum is also observed very frequently in emerging markets. From Figure 2, we see how expressive this anomaly is, given that in the last few years it has been very strong in Brazil, which is the focus of this work. When in comparison with the American market, from Figure 3, it's evident that the presence of momentum in Brazil is stronger.

Two important explanations for momentum have been brought to be compared empirically for the case of the Brazilian financial market: the behavioral explanation through disposition-effect, such as in Grinblatt and Han (2005); and the capital-fund flow based explanation, from papers such as Lou (2012), when it was first presented.

Following the arguments of Grinblatt and Han (2005) and presenting results for the Brazilian case in Tables 7-11, we contribute to increase the range of evidences of behavioral effects to explain momentum, an anomaly that is of extreme importance for Financial Economics.

Applying Lou's (2012) methodology to the Brazilian market, a statistically significant explanation for momentum through fund-flow investments was not obtained. Further studies must still be done to corroborate this kind of explanation in the case of Brazil and other developing countries.

By Table 11, with the inclusion of all controls and explanatory variables, the momentum was explained significantly, with only the unrealized gains variable being significant. When comparing the results of Tables 8, 9 and 10, it is possible to observe that our evidence appoints the main inductor of the momentum explanation as the variable of unrealized gains, referring to the explanation through the behavior bias of disposition-effect. It's observed that future studies are still needed to verify additional explanations for momentum, also in view

of different markets and scenarios. Our results are robust taking into consideration additional explanation to our proxy variable for disposition-effect and robustness checks of subperiods.

The importance and recognition of behavioral phenomena is growing in both the market and academy, as evidenced by the Nobel laureate in 2017 Richard Thaler, and the increasing use of behavioral-based models in the financial market. It is shown here that even an anomaly with the robustness of momentum can have an explanation within the behavioral framework. The frequent use of non-rational investment strategies for individual investors and even institutional investors in developed and emerging markets contributes for this.

The traditional economic and financial theory, of rational agents and maximizing a usual value function, needs adaptations in the case of applications to the real world, in order to bear in mind the phenomena that escape the general case, as is the case of momentum. The tools from the behavioral literature have much to help with these adaptations.

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