Pontifícia Universidade Católica do Rio de Janeiro

Augusto Ferreira da Costa Neto

Essays on Financial Innovations: Feedback Trading, Tracking Efficiency and Innovation Index

Tese de Doutorado

Thesis presented to the Programa de Pós-Graduação em Administração de Empresas of PUC-Rio as a partial fulfillment of the requirements for the degree of Doutor em Ciências - Administração de Empresas.

Advisor: Prof. Marcelo Cabús Klötzle

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Abstract

Costa Neto, Augusto Ferreira da; Klötzle, Marcelo Cabús (Advisor). **Essays on Financial Innovations: Feedback Trading, Tracking Efficiency and Innovation Index .** Rio de Janeiro, 2021. 91p. Tese de Doutorado - Departamento de Administração, Pontifícia Universidade Católica do Rio de Janeiro.

Since the seminal work conducted by Schumpeter (1934), several researchers have studied the relationship between Research, Development & Innovation (R, D & I) expenditures and firms' performance, with mixed outputs among sectors, firms' sizes, geography, and markets degrees of development. This thesis aims to propose, through three essays, the creation of an index that captures a set of shares of companies listed in Brasil, Bolsa, Balcão (B3) that invest and declare to invest in R, D & I, as well as financial products, notably Exchange-traded funds (ETFs), which, linked to this index, can contribute to increase the volume of transactions of said shares, and thus contribute to more companies engaging in R, D & I activities, as well as, for those that already do, that commit themselves to divulge these actions to the market. The results indicate that it is possible to form a portfolio of companies that declare investment in R, D & I in such a way that their performance exceeds the main benchmark of the Brazilian market. For products linked to this theoretical portfolio, the evidence points to the need to observe the behavior of investors in these assets in emerging markets such as Brazil, as well as to develop mechanisms that guarantee the adherence of the product to the index, minimizing tracking errors.

Keywords

R, D & I Investments; Innovation Index; ETF; Investor Behavior; Tracking Efficiency.

Resumo

Costa Neto, Augusto Ferreira da; Klötzle, Marcelo Cabús. **Ensaios sobre Inovações Financeiras: *Feedback Trading, Tracking Efficiency* e Índice de Inovação.** Rio de Janeiro, 2021. 91p. Tese de Doutorado - Departamento de Administração, Pontifícia Universidade Católica do Rio de Janeiro.

Desde o trabalho seminal conduzido por Schumpeter (1934), vários pesquisadores estudaram a relação entre os gastos com Pesquisa, Desenvolvimento & Inovação (P, D & I) e o desempenho das empresas, obtendo evidências contraditórias entre setores, tamanhos das empresas, geografia e graus de desenvolvimento dos mercados. Esta tese tem como objetivo propor, por meio de três ensaios, a criação de um índice que capture um conjunto de ações de empresas listadas na Brasil, Bolsa, Balcão (B3) que investem e declaram investir em P, D & I, bem como produtos financeiros, notadamente Exchange-traded Funds (ETFs), que, atrelados a este índice, possam contribuir para aumentar o volume de negócios das referidas ações, e assim encorajar mais empresas a se envolverem em atividades de P, D & I, bem como, para as que já o fazem, se comprometerem a divulgar essas ações ao mercado. Os resultados indicam ser possível formar uma carteira de empresas que declaram investimento em P, D & I de tal sorte que o desempenho dessas supere o principal benchmark do mercado brasileiro. Para o caso de produtos atrelados a essa carteira teórica, as evidências apontam para a necessidade de se observar o comportamento dos investidores nestes ativos em mercados emergentes como o brasileiro, bem como desenvolver mecanismos que garantam a aderência do produto ao índice, minimizando erros de precificação.

Palavras-chave

Investimentos em P, D & I; Índice de Inovação; ETF; Comportamento do Investidor; *Tracking Efficiency*.

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The most refined ignorance is the ignorance of ignorance itself.

St. Augustine

1
Introduction

The analysis of the recent history of the international economy has demonstrated the growing importance of innovation in influencing the competitive strategies of companies and national development policies. As the so-called knowledge economy is consolidated, the world is increasingly witnessing the potential of innovation to produce small “revolutions” that have been changing the economic and business landscape, stimulating the growth and development of nations, and thus providing benefits to firms, communities, and individuals.

The growth of China and India in recent years (where India has doubled and China has tripled its relative share of world GDP) has been achieved, to a large extent, by incorporating, in an increasingly central way, technological innovation into development efforts.

Brazil has been seeking to advance innovation in national development policy over the past few years. Therefore, it is necessary to increase the share of private investment in research, development, and innovation (R, D & I) in companies. OECD data (2020) reveal that, although the total investment in R, D & I in Brazil has being reasonably aligned with the average of the OECD countries (about 1.4% of GDP), private participation in this investment is still around 40% of the total, while in countries like the United States, South Korea, and Japan, this participation is over 70%.

This reality leads us to seek alternatives to public funding for R, D & I activities, key success factors for a continental, poor and unequal country like Brazil, and therefore private participation in sharing the risks of technological development is essential in a scenario of increasing public resource constraints.

To address this disorder, this thesis aims to propose, through three essays, the creation of an index that captures a set of shares of companies listed in Brasil, Bolsa, Balcão (B3) that invest and declare to invest in R, D & I, as well as financial products, notably Exchange-traded funds (ETFs), which, linked to this index, can contribute to increase the volume of transactions of said shares, and thus contribute to more companies engaging in R, D & I activities, as well as, for those that already do, that commit themselves to divulge these actions to the market.

The first essay presents the results of a study on investor behavior in ETFs markets. According to DeLong et al. (1990), investors who generate the effect of feedback trading, also known as feedback traders, attempt to identify past stock price trends and make their investment decisions based on the expectation that these trends will persist. The standard feedback trading model of Sentana and Wadhwani (1992) was used in a sample of fifteen ETFs contracts in Brazil, South Africa, Korea, Mexico, and India, as well as three ETFs contracts in the U.S. market. Our empirical analysis suggests that there is evidence of feedback trading in emerging markets such as Brazil, South Korea, Mexico, and India, while there is no such evidence for the U.S. market. The results are consistent with the view that developed market investors are prone to pursue fundamental driven investment strategies while emerging market investors appear to have informational guided behavior.

The second essay examines the tracking efficiency of a sample of ETFs from seven different emerging and developed markets, in bullish and bearish market conditions, using daily closing prices data. It seeks to address two major questions. First, have ETFs from both developed and emerging markets the same behavior regarding tracking their underlying indexes? Second, is ETFs tracking ability affected by events that could change market conditions from a bullish to a bearish pattern, and vice-versa? Our findings suggest that tracking error appears to be higher in emerging markets when compared to developed ones. Furthermore, tracking error was found to be relatively higher in bearish conditions for developed markets, while in emerging markets this was quite the opposite.

Finally, the third essay investigates portfolios formed by companies that declare investments in R, D & I in the Brazilian stock market using different estimation models of the covariance matrix, from the simple sample covariance matrix to the matrix with shrinkage factor proposed by Ledoit & Wolf (2004a), comparing the results of these portfolios with the IBOVESPA index. The results show that it is possible to form a portfolio only with long positions and with a ceiling of 15% participation per asset that has a higher return and lower volatility than the benchmark. The suggested portfolio, having a small number of assets, is easy to replicate by individual or institutional investors, contributing to stimulate the creation of financial innovations, such as ETFs, and fostering the investment of companies in the Brazilian stock market in research, development, and innovation activities.

2
Feedback Trading in ETF Markets

2.1
Introduction

Exchange-traded funds (ETFs, hereafter) are investment vehicles similar to mutual funds. More specifically, ETFs are open-ended investment funds of a diversified portfolio of securities, acquired in the form of shares, which differ from mutual funds by being traded on the stock exchange for a fixed price established by the market. In other words, the share value is determined by the supply and demand and follows the exchange trading rules on which they are listed. ETFs are composed of a basket of assets and strictly follow a benchmark-index, providing investors, in general, with exposure to the stocks that make up this index.

The first known ETF emerged in Canada in 1989 with the purpose of replicating the hypothetical portfolio of the Toronto 35 Index, which tracks daily returns of the most traded companies in the TSE (Toronto Stock Exchange), responsible for 35% of their market value (Charteris, Chau, Gavriilidis & Kallinterakis, 2014). However, from 1993 onwards, with their launch in the United States, ETFs gained popularity as an investment vehicle to track the S&P 500 Index (ticker: SPY).

The maturity of ETFs as an industry, with participants from different specializations, and asset class is reflected in the high level of sophistication and diversification of products available. The objective of most of these funds is to simply replicate the performance of a certain benchmark-index. However, nowadays, there are ETFs that allow exposure to all markets (variable income, fixed income, commodities, currencies and volatility), geographies (countries or regions), sectors (from traditional to more exotic) and various forms (active or passive management, leveraged, reverse, etc.) (WFE, 2016).

The success of ETFs caused its basic concept – of listing structured products on the stock exchange – to be replicated with other asset types such as bank debt instruments (Exchange-Traded Notes – ETNs) and commodities (Exchange-Traded Commodities – ETCs). This set of structured products traded on the stock Exchange is generically named Exchange-Traded Products (ETPs), which is made up largely of ETFs, and are, as a result, increasingly attracting the interest of researchers.

As a result, ETFs became a popular investment vehicle, surpassing the hedge-fund industry in size, accumulating over 10 thousand ETFs globally and over US$ 3trillion in assets (WFE, 2016).

In an efficient market, free of arbitrage opportunities, the ETF value traded in the market must be equal to its Net Asset Value (NAV) after adjusting for transaction costs. The existence of arbitrators and a liquid market of shares and assets should result in small and temporary price differences between the share and its assets. However, in the context of ETFs, Chau, Deesomsak and Lau (2011) extended Sentana and Wadhwani's (1992) seminal model of feedback trading in an empirical analysis of the three largest ETFs in the U.S and found evidence of positive feedback trading, i.e., the existence of traders whose demand is based on the history of past returns rather than the expectation of future fundamentals, and that the intensity of the feedback trading was related to investor sentiment. However, these observations were made from data obtained in the already matured U.S market. This raises the question if the trend of feedback trading is equivalent in emerging markets and consequently if investors tend to behave similarly in these markets.

To answer these questions, this study expands on the analysis by Charteris et al. (2014) who found that ETFs are particularly susceptible to feedback trading. This is associated with investment strategies based on historical prices, implying that investment decisions are influenced by the past performance of the asset. Three ETFs from Brazil, China, Mexico, South Africa, Korea and India, respectively, were compared against three ETFs from the U.S market, highlighting the effects of feedback trading on investor behavior in these markets.

This study is structured into sections as follows: Section 2.2 briefly reviews the most recent literature. Section 2.3 describes the study’s methodology and data. Section 2.4 presents the results and discussion of the main findings. Section 2.5 presents Global Financial Crisis effects in our sample. Lastly, the conclusion is presented in section 2.6.

2.2

Literature Review

2.2.1

Financialization

The concept of financialization is described by Epstein (2001) as the increasing importance of financial markets, financial motives, financial institutions, and financial elites in the operation of the economy and its governing institutions, both at the national and international level. It refers to the increase in size and importance of a country's financial sector relative to its overall economy, and has gained importance in social sciences since the end of the twentieth century (Engelen, 2008). Although having become popular, Lagoarde-Segot (2016) argues that financialization concept is still excluded from the discourse of financial economists, and his study aims to provide the basis for its incorporation in academic finance, by connecting financialization with the concomitant development of cyberspace, global deregulation of financial markets, and the rise of shareholder governance.

With regard to ETFs market, Shank and Vianna (2016) argue that this market could be a good example of financialization, due to the importance that investors put on it, responsible for its recent growth. Therefore, the need to examine how investors trade ETFs has gained importance and relevance in academic studies.

2.2.2

Previous Studies on ETFs

One of the core tenets of modern finance theory is the Efficient Markets Hypothesis (EMH), proposed by Malkiel and Fama (1970) and systematically discussed ever since. The classic definition of EMH states that an efficient market is one in which the price of traded assets always fully reflects the market information available on the assets. More specifically, it would be impossible to obtain abnormal profits by using information, in an efficient market, since prices already reflect such information.

However, previous research regarding investor behavior in ETFs have reported evidence that this market is prone to investment strategies based on past performance, and the emergence of ETFs has enabled the development of several studies on EMH seeking evidence of arbitrage opportunities in these markets.

Avellaneda and Lee (2010) studied arbitrage strategies in the U.S market by conducting a Principal Component Analysis (PCA) and regression analysis of sector ETFs. Results showed that PCA-based arbitration strategies presented a Sharpe ratio of 1.44 from 1997 to 2007, while ETF-based arbitrage strategies showed a Sharpe ratio of 1.10 in the same period. However, by introducing a method that accounts for daily transacted volumes, a 1.51 Sharpe ratio increase was observed for ETFs, confirming arbitrage opportunities. A similar effect was observed by Hsu et al. (2010), when analyzing three indices in the U.S market (S&P Small Cap 600, Russell 2000 and NASDAQ Composite), three ETFs (Small Cap 600 Growth Index Fund, Russell 2000 Index Fund and NASDAQ Composite Index Tracking Fund), and an index and ETF from the emerging markets of Brazil, South Korea, Malaysia, Mexico and Taiwan, finding evidence of arbitrage opportunities in these emerging markets.

Charupat and Miu (2011) studied the performance of leveraged ETFs, financial innovations aimed at producing multiple positive or negative results of a benchmark index. The authors found by examining a sample of three leveraged ETFs in the Canadian market that these assets were generally traded by retail investors that hold their position for a noticeably short period, and that the deviations between ETF stock prices and its NAVs are small on average, but prone to increase.

Ivanov (2013) expanded on the work by DeFusco, Ivanov and Karels (2011), and examined ultrahigh-frequency (one-minute intervals) price data from three major ETFs in the U.S market (DIA, SPY and QQQQ). The author found evidence of negative price deviation (discount) in the DIA and QQQQ prices in compared to the NAV, and of positive price deviation (premium) of SPY prices compared to the NAV of underlying assets, therefore, indicating arbitrage opportunities in the market.

Maluf and Albuquerque (2013) investigated the efficiency of the iShare Ibovespa fund's share assessment process with respect to its NAV, through a high-frequency time series analysis. The results did not show excess returns after bootstrapping, suggesting unfeasibility for investors to obtain abnormal returns based on divergences between the values of the ETF shares and its respective index. These findings contrast with that of DeFusco et al. (2011), Chau et al. (2011), Ivanov (2013), Milani and Ceretta (2013), and Charteris et al. (2014).

The study by Charteris et al. (2014), expanded in this article, found evidence of feedback trading characteristics given deviations between prices and NAV of ETFs in the emerging markets of Brazil, India, South Africa and South Korea, with significance related to premiums, more specifically, when the price of ETF shares is higher than the NAV of the assets that make up the benchmark tracked by the ETF the day before. Through the analysis of an ETFs' sample in these four markets, Charteris et al. (2014) argue that the feedback trading characteristics found in their sample become clearer as premiums increase in magnitude, as well as after a shock such as the 2008 financial crisis.

Kallinterakis, Liu and Pantelous (2016) analyzed a sample of 19 ETFs in the U.S market between 2000 and 2016, and found evidence of feedback trading in several ETFs, particularly those related to the Asian market indices, varying in signal (premium and discount), level, and nature (observed / predicted) of the deviations, as well as in relation to the periods before and after the 2008 global financial crisis.

Ivanov (2016) analyzed the 100 largest ETFs in the U.S market, and found evidence suggesting that uninformed investors prefer to invest in ETFs rather than stocks or other investment funds. This, because by investing in an ETF, the investor becomes exposed to the asset portfolios that make up the underlying index tracked by the ETF, which may promote the rapid growth and popularity of this type of investment in the U.S market.

Using a panel VAR approach (Hasbrouck, 1991), Shank and Vianna (2016) examined the behavior of U.S. listed currency hedged ETF investors towards changes in the underlying benchmark and foreign exchange rate from July 2011 to November 2015.Their findings suggest that investors can anticipate changes in future exchange rates, and invest in currency hedged ETFs prior to changes. Furthermore, the use of financial instruments, such as ETFs, to hedge against exchange rate volatility, may have itself become a source of volatility, which have implications for the further financialization of the ETF industry.

2.2.3

Investor Behavior and Feedback Trading Models

Sentana and Wadhwani (1992) developed a model of investor behavior that provides a testable implication regarding the existence of feedback trading, the seminal and most used empirical model since then. The authors used daily U.S stock market indices data from 1885 to 1988 and found positive evidence of feedback trading to be more pronounced in pessimistic rather than in optimistic markets. The Sentana and Wadhwani (1992) model used in this study incorporates the innovations brought by Bollerslev (1986) in the proposal of the GARCH (Generalized Autoregressive Conditional Heteroskedasticity) models.

Madura and Richie (2004) studied overreaction effects in ETF markets which should not be as prone to overreaction effects as individual shares to having stock portfolios. Nonetheless, evidence suggests that the marketability characteristics of ETFs allow an unusual pressure on its prices, creating arbitrage opportunities for feedback traders.

Bohl and Siklos (2008) investigated the hypotheses that some participants in mature and emerging capital markets engage in feedback trading, based on the Shiller-Sentana-Wadhwani model. Their empirical results suggest that positive and negative feedback trading strategies do exist in both markets, although this kind of non-fundamental trading strategy is more likely to affect emerging markets.

Kalinterakis and Khurana (2009) investigated the behavior of ETF NIFTY BeES investors, the oldest ETF in the Indian market, seeking to identify characteristics of rational investors, who base their investment decisions based on fundamental analysis, and noise traders who fundamentally base investment decisions on market news, either good or bad, and with possible overreaction behavior due to past results. The authors found no significant evidence of noise traders in this market when applying Sentana and Wadhwani (1992) model, suggesting that ETF investors are long-term fundamentalist investors.

Koutmos (2014) conducted an extensive review of literature relating to positive feedback trading models and its application in bond, foreign exchange, index futures and individual stock markets, and highlighted the need to generalize these models used to investigate investor behavior in individual asset markets, to aggregate asset markets.

According to Chau et al. (2011), investor sentiment explains, at least in part, anomalies in the pricing of assets in general, and particularly ETFs.

Chiang, Li, Tan and Nelling (2015) examined investor herding behavior for ten Pacific-Basin markets, as well as the United States. By applying a constant coefficient regression model using daily data for individual firm stock returns, they found significant evidence of herding in each national market, including the US, suggesting that an increase in stock returns leads to an increase in the herding measure, showing that herding behavior reacts not only to the occurrence of large swings in market prices, but also to the state of market return and volatility conditions.

Charteris and Rupande (2017) found evidence of feedback trading on the South African stock market in about 23% of the transactions, of which 9% were positive and 14% negative. They used the Sentana and Wadhwani (1992) model, demonstrating the model's capacity to explain the behavior of investors towards individual assets as proposed by Koutmos (2014).

Positive feedback trading strategies, combined with a measure of investors' sentiment, was examined by Dai and Yang (2018). By modifying the classical Sentana and Wadhwani's (1992) model adding a sentiment factor, they analyzed the daily closing total return of CSI 300 index, as well as its individual returns of stocks. Their results suggest that positive feedback traders are more likely to trade when the prices of most securities move forward together, and when the sentiment of feedback traders is at an intermediate level, the feedback trading behavior is insignificant.

This study seeks evidence of feedback trading in the emerging markets of six emerging countries (Brazil, China, Mexico, South Africa, India, and Korea), and evaluates whether investors in these markets exhibit behaviors like those of the US market, as described by Chau et al. (2011). The methodology used to achieve this objective is explained in the following section.

2.3

Data and Methodology

Table 1 contains information regarding our sample and includes data on daily closing prices and net asset values (NAV) for three ETFs from each of the emerging markets of Brazil, China, South Africa, Mexico, Korea and India, as well as on three ETFs from the U.S market. Daily closing prices and NAVs of all ETFs are displayed in the local currency. We used the earliest start date available (inception) in the Thomson Reuters database pertaining to the three ETFs with highest transaction volume, aiming to obtain a representative sample of each market. All series ended on 05/05/2017.

Although many studies have applied the VAR approach described by Hasbrouck (1991) in his seminal work, we applied the well-established Sentana and Wadhwani (1992) model to evaluate evidence of feedback trading in the sample, assuming that this model is more likely to adjust in a non-high frequency data series. The model accounts for two types of investors: rational investors and feedback traders. The rational investor seeks to maximize their expected mean-variance utility according to the following demand function:

$$Q_t = \frac{E_{t-1}(r_t) - \alpha}{\theta \sigma_t^2} \tag{1}$$

where Q_t is the fraction of shares demanded, $E_{t-1}(r_t)$ measures the expected return of shares for the period t based on information from period t-1, α is the risk-free return, θ is the risk aversion coefficient and σ_t^2 is the conditional variance in t. The demand for feedback trader shares is a function of past return, given by:

$$Y_t = \gamma r_{t-1} \tag{2}$$

where Y_t is the fraction of shares demanded by the feedback trader and r_{t-1} is the share's return in the previous period (Sentana and Wadhwani, 1992). For positive feedback trading, γ is greater than zero, and for negative it is less than zero.

In an equilibrium market, all shares are demanded, and the general market equation is:

$$Q_t + Y_t = 1 \tag{3}$$

Substituting equations (1) and (2) into (3), we have:

$$E_{t-1}(r_t) = \alpha - \gamma r_{t-1}\theta\sigma_t^2 + \theta\sigma_t^2 \quad (4)$$

Assuming the realized returns are equal to the expected returns added to the stochastic error r_t = $E_{t-1}(r_t)$ + ε_t, we have:

$$r_t = \alpha - \gamma r_{t-1}\theta\sigma_t^2 + \theta\sigma_t^2 + \varepsilon_t \quad (5)$$

Equation (5) shows that the first-order autocorrelation of returns varies according to market risk σ_t^2, as shown by the term $\gamma r_{t-1}\theta\sigma_t^2$, while its signal will depend on the signal of the feedback trading term γ, wherein positive feedback trading will have a negative autocorrelation, and vice-versa. Positive feedback traders buy after a price rise and sell after a price fall (γ > 0), while negative feedback traders buy when the price is low and sell when the price is high (γ < 0) which is consistent with the behavior of those investors following ‘buy low/sell high’ strategies.

To address the issue that the observed autocorrelation may stem from both feedback trading and market frictions, Sentana and Wadwhani (1992) proposed the following model:

$$r_t = \alpha + \theta\sigma_t^2 + (\phi_0 + \phi_1\sigma_t^2)r_{t-1} + \varepsilon_t \quad (6)$$

Equation (6) measures the effect of existing market frictions through the coefficient ϕ_0, whereas ϕ_1 measures the presence of feedback trading. Given ϕ_1= -θγ, if ϕ_1< 0 and statistically significant, positive feedback traders will be dominant in the market and vice versa.

Equation (6) indicates that the volatility of the return time-series varies over time. The GARCH model proposed by Bollerslev (1986), is commonly applied as it captures not only heterogeneity of variance but also the leptokurtic distribution followed by most daily financial series. The model also captures volatility clusters where large changes in an asset’s price tend to cause large increases in volatility, while small changes tend to cause small increases.

Other models documented by Bollerslev (2008), such as the TGARCH (Threshold GARCH) and EGARCH (Exponential GARCH) may be more appropriate to capture another quite common phenomenon in financial series known as the leverage effect: negative shocks tend to cause more volatility than positive ones. Sentana and Wadhwani (1992), corroborated by Shi, Chiang and Liang (2012), argue that the choice of less parsimonious models would have little influence in detecting feedback trading, the main object of our study. We therefore tested this by running the specification test for the conditional variance equation in order to check whether the asymmetric GARCH (1,1) framework employed here captures adequately the volatility asymmetries present in our sample; to that end, we used the sign-bias test proposed by Engle and Ng (1993). The sign bias test examines whether there exist asymmetries following positive versus negative shocks not accounted for by the GARCH-model utilized. According to this test, the squared standardized residuals are regressed against a constant and a dummy that assumes the value of unity in case the residual one period back was negative, and the value of zero otherwise; if the dummy's coefficient is found to be statistically significant, this would imply an asymmetric impact on behalf of positive versus negative innovations over volatility. Results are shown in Table 2 (A and B), and since dummies' coefficients θ were found statistically significant at least at 10%, allow us to conclude that the asymmetric GARCH (1,1) framework employed here successfully captures the volatility asymmetries in our sample.

To analyze the influences of premiums and discounts on feedback trading behavior in our sample, we expanded the empirical version of Sentana and Wadhwani's (1992) model, proposed by Chau et al. (2011), thus, allowing feedback traders' demand to be affected by premiums and discounts as follows:

$$Y_t = [\gamma D_t + \lambda(1 - D_t)]r_{t-1} \tag{7}$$

In equation (7), D_t is a dummy variable that assumes the value of unity when premium or discount occurs in period t-1, and the value of zero otherwise. Equation (7) assumes that the effect of feedback trading varies in this case with the observed premium or discount, indicating that the price of the ETF in the previous period and its deviation from its NAV in this period, are used interactively by feedback traders. Therefore, equation (5) can then be rewritten as:

$$r_t = \alpha + \theta\sigma\theta\sigma_t^2 r_t^2 - [\gamma D_t + \lambda(1 - D_t)]_{t-1} + \varepsilon_t \tag{8}$$

Equation (6) can then be modified to:

$$r_t = \alpha + \theta\sigma_t^2 + D_t\big(\varphi_{0,0} + \varphi_{1,0}\sigma_t^2\big)r_{t-1} + (1 - D_t)\big(\varphi_{0,1} + \varphi_{1,1}\sigma_t^2\big)r_{t-1} + \varepsilon_t \tag{9}$$

In order to empirically estimate equation (6), we define the conditional variance as an asymmetric GARCH process (Glosten, Jagannathan, and Runkle, 1993):

$$\sigma_t^2 = \omega + \beta\varepsilon_{t-1}^2 + \lambda\sigma_{t-1}^2 + \delta S_{t-1}\varepsilon_{t-1}^2 \tag{10}$$

In equation (10), δ captures the volatility asymmetry after positive or negative shocks. S_{t-1} is a binary variable that takes the value of 1 if the shock at time t-1 is negative, and otherwise the value of zero. A significantly positive δ value indicates that a negative shock increases the volatility more strongly than a positive shock.

2.4

Results and Discussion

The descriptive statistics (mean, standard deviation, asymmetry and kurtosis) for the daily log-returns of the sample are found in Panel A of Table 3 (A and B). All sampled ETFs displayed a leptokurtic distribution at 1% significance, and thirteen of the twenty-one sampled ETFs displayed negative asymmetry, corroborating with Charteris et al. (2014). Symmetry and kurtosis measures suggest non-normal distributions. Rejection of normality can be partially attributed to temporal dependencies in the time series, which were investigated by applying L-Jung Box tests. L-Jung Box tests were significant at 1% for fourteen of the twenty-one ETFs and at 5% for two of them (except for SMAL11, 226490, 233740, GOMS, and NBES, all from emerging markets) suggesting temporal dependencies in the beginning of the time series due to, for instance, market inefficiencies.

We attempted to detect signs of reversal in autocorrelations due to positive and/or negative feedback trading effects by performing L-Jung Box tests on the log-return squares of the sample. Our results were significant at 1% for all ETFS, with much higher values than the tests applied to the log-returns, suggesting that the existence of high autocorrelation may be related to the presence of feedback trading effects in the sample.

Panel B on Table 3 (A and B) shows summary of the positive (premiums) and negative (discounts) distributions of the price deviation of ETFs in relation to its NAVs, whereas Panel C shows the data regarding the behavior of these deviations day-to-day. In most cases of price deviation (52%), ETFs are sold at a discount in relation to its NAVs, except in the Mexican, South African and Chinese markets, and in most cases this discount is above 0.5%.

Table 4 (A and B) shows the estimation of equations (6) and (10), that is, the original Sentana and Wadhwani (1992) model.

The coefficients relative to the conditional variance, ω, β, λ and δ were statistically significant at 1% for most samples, and because δ is positive in most cases, it appears that negative shocks tend to increase volatility at greater intensity than positive shocks, corroborating with Glosten et al. (1993). In addition, we could reach similar conclusions by calculating the ratio (β+δ)/β. This ratio was positive and above unit for 14 of the 21 ETFs evaluated in the sample, indicating that volatility increases in periods when the market shrinks in greater proportions than is observed during market growth. The significance of β and λ suggests high autocorrelation and persistence, respectively, indicating that the current volatility is affected by shocks and past volatility.

The coefficient ϕ_0 from the main equation was significant for 16 of the 21 sampled ETFs, indicating first-order autocorrelation. The $\phi_1$feedback trading coefficient (the main object this study), was statistically significant at 1% for the ETFs of the emerging markets, except for South Africa, and negative for 13 ETFs, suggesting the presence of positive feedback traders in these markets. Furthermore, the coefficient ϕ_1 was not statistically significant for the U.S market, in contrast with the reported by Chau et al. (2011), suggesting the presence of positive feedback traders in emerging markets and absence in the U.S market. This could indicate greater efficiency in more developed markets, where investors appear to be more attracted to fundamentalist aspects of their investments, as shown in Bohl and Siklos (2008), whereas emerging market investors appear to have their behavior influenced by arbitrage opportunities arising from price differences between ETF shares and their respective NAVs.

In order to verify the effect of premiums and discounts on feedback trading, we used the percentage of daily deviation of each sampled ETF and its respective NAV to define the dummy variable of equation (9). We defined the variable $D_t = 1$ when the ETF was traded at a discount the previous day and $D_t = 0$ when negotiated at a premium. The results are shown in Table 5. We found evidence indicating a relationship between feedback trading and the occurrence of discounts in the 3 ETFs of the Brazilian and South African markets, 2 ETFs in the Chinese, Indian and Mexican markets and 1 ETF in the U.S market, which is contrary to the findings of Charteris et al. (2014). Additionally, evidence of first-order autocorrelation was found for ETFs in Brazil, South Africa, India, Mexico, China and the United States, of which $\varphi_{0,0}$ and $\varphi_{0,1}$ were significant at 1% for 14 ETFs of the sample.

By formally testing the hypothesis that $\varphi_{0,0} = \varphi_{0,1}$ and $\varphi_{1,0} = \varphi_{1,1}$ we rejected the null hypothesis, at 1% significance for 14 of the 21 ETFs, noting that $\varphi_{1,0} < \varphi_{1,1}$ for 8 of these ETFs, suggesting the effect of feedback trading was more significant in the presence of premiums.

2.5

Global Financial Crisis (GFC) Effects

The recent Global Financial Crisis (hereafter GFC) has some unique characteristics, such as the length, breadth and crisis sources. Compared to other financial crises (e.g., 1997 Asian crisis and 2001 internet bubble crisis), many researchers determine the crisis length and source ad-hoc based on major economic and financial events. It is worth to mention that, in order to correctly define the crisis period, studies on financial contagion are in some degree arbitrary.

We specified the length of GFC and its phases following both an economic and a statistical approach as follows. Firstly, we defined a relatively long crisis period based on all major international financial and economic news events representing the GFC. The choice of the crisis period was based on official timelines provided by Federal Reserve Board of St. Louis (2009) and the Bank for International Settlements (Filardo et al., 2009). These studies separate the timeline of GFC in four phases. Phase 1 described as "initial financial turmoil" spans from 1st August 2007 to 15th September 2008. Phase 2 is defined as "sharp financial market deterioration" (16th September 2008 until 31st December 2008), phase 3 described as "macroeconomic deterioration" (1st January 2009 until 31st March 2009) and phase 4 is a phase of "stabilization and tentative signs of recovery" (post-crisis period) including a financial market rally (1st April 2009 onwards, until the end of the sample period).

In order to simplify our analysis, we divided our sample into three time periods: Pre-crisis, before 03/31/2007; Crisis, from 08/01/2007 to 03/31/2009; and Post-Crisis, from 04/01/2009/ onwards. Since ETFs of our sample have different inception dates, we considered only those ones that were launched before Crisis period. Results are shown in Table 6 (A and B), and suggest that Post-Crisis effects seem to be more persistent in our sample. In the case of US market, for instance, results show positive feedback trading evidence in Pre-Crisis period, in line with what was found by Chau et al. (2011) for SPY. Nevertheless, after Crisis period, investors seem to assume a fundamental driven behavior, and feedback trading effects cannot be observed.

2.6

Conclusions and Implications

Exchange Traded Funds (ETFs) are the latest innovation in the global financial market, seeking to attract investors through benefits such as risk diversification and cost rationalization, as well as high liquidity (Ben-David, Franzoni and Moussawi, 2017). Although the introduction of ETFs may result in more complete and efficient markets, as it provides access to a diversified portfolio of assets, the presence of feedback traders in the market may affect its efficiency. Koutmos and Saidi (2010) state that, if many market participants engage in positive feedback trading strategies, asset prices may deviate substantially and persistently from fundamental values. It is, therefore, extremely important for policy makers to understand the behavior of investors, especially in emerging markets, due to informational asymmetry or even to a lack of investors' experience.

The behavior of investors was investigated by analyzing a sample of eighteen ETFs from the emerging markets of Brazil, China, South Africa, Korea, India and Mexico, as well as three ETFs from the U.S market. Despite of being investigated separately both emerging (Charteris et al., 2014) and developed markets (Chau et al., 2011), our innovation consists in comparing those markets in a single study, pursuing to explain potential reasons for the differences observed between developed and emerging markets. We extended the work done by Charteris et al. (2014) by expanding their database with the three ETFs presenting the highest trading volume for each analyzed market, as well as including Mexico, due to its importance in Latin American markets, and China, due to its importance to global markets. Our results indicated the presence of feedback traders in the Brazilian, Korean, Indian and Mexican markets, suggesting that investors are influenced by the verification of arbitrage opportunities in the event of deviations between ETFs' shares and the NAV of its underlying assets, while there is no such evidence for the American market, in contrast with the reported by Chau et al. (2011).

In order to capture all possible effects during ETFs lifetime, we use the largest time series available at Thomson Reuters database, since their inception up to May 2017. Nevertheless, our results seem to be more consistent with the view that developed markets investors are prone to pursue fundamental driven investment strategies, while emerging markets investors appear to have informational guided behavior, corroborating with the findings of Bohl and Siklos (2008).

Although Chinese market does not appear to reflect feedback trading effects, as expected, many previous studies have reported behavioral biases in Chinese investors, like disposition effect, overconfidence and representativeness bias (Chen, Kim, Nofsinger & Rui, 2007), leading them to make poor trade decisions and the assets they purchase to underperform those ones they sell. According to these authors, Chinese investors seem to be even more overconfident than U.S. investors, their disposition effect appears stronger, and their sophistication does not appear to mitigate behavioral biases, nor even improve trading performance.

Emerging markets still make up an exceedingly small part of the global ETF market, led by the United States. Despite of this, it is extremely important that studies of this nature be gradually expanded as these markets grow, in order to verify how emerging markets, compare to their developed counterparts in terms of efficiency of information sharing and rationalization of its operations.

These results also provide valuable implications for the financialization of the ETF industry. As investors increase the trading volume in ETFs due to increasing arbitrage opportunities derived from ETFs price deviations, they are likely to increase the volatility of their funds, even though the ETF is designed to prevent volatility. Therefore, as the financialization of the ETF industry continues to grow, it is possible that trading volume and volatility will increase impacting both domestic and international financial markets, as stated by Shank and Vianna (2015).

As a suggestion for future research, one could use high-frequency data and Hasbrouck's (1991) vector autoregressive (VAR) model. This model was originally applied to high-frequency data per second, where the direction of causality is explicitly from the flow of orders to the returns of asset prices. By introducing a shock in the trading process, accounting for private information, Hasbrouck (1991) calculated the cumulative effect on asset returns. The greater the cumulative effect, or impulse response, the greater the transaction information. By using VAR modeling, one could verify if feedback trading effects persist on a high-frequency data basis.

Finally, emerging markets policy makers could benefit from these findings by stimulating the creation of specific sectors indexes, as well as their corresponding ETFs, aiming to encourage investors to access a more complete asset portfolio and contributing to the capital market development and liquidity, whereas developing new mechanisms that could minimize informational asymmetry and the persistence of so called noise traders, a phenomenon observed recently in studies regarding ETF markets (Brown, Davies and Ringgenberg, 2018).

Table 1
Selected ETFs by market and series launch-date

ETF	Launch-date	Market
BOVA11 - IShares Ibovespa	2008-12-02	Brazil
PIBB11 - It Now PIBB IBrX-50	2004-07-27	
SMAL11 - iShares BM&FBOVESPA Small Cap	2008-12-02	
GLDJ - NewGold	2004-11-02	South Africa
STX40J - Satrix 40	2004-06-01	
STXSWXJ - Satrix Swix Top 40	2007-09-03	
226490 - Samsung KODEX KOSPI 200 Securities	2015-08-24	Korea
233740 - Samsung KODEX Leverage	2015-12-17	
251340 - Samsung KODEX Inverse	2016-08-10	
159915 - E Fund ChiNext	2011-12-09	China
510050 - ChinaAMC China 50	2006-10-16	
510900 - E Fund Hang Seng China Enterprises QDII	2012-10-22	
GOMS - Goldman Sachs CPSE	2014-05-20	India
BIRN - BIRLA Sun Life Nifty	2011-07-27	
NBES - Goldman Sachs Nifty BeE	2009-11-09	
ANGELD10 - Smartshares-ANGELD	2010-10-27	Mexico
DIABLOI10 - Smartshares-DIABLOI	2010-10-27	
NAFTRAC - iShares NAFTRAC	2002-04-30	
XLF - Financial Select Sector SPDR	1998-12-16	United States
IWM - iShares Russell 2000	2000-05-26	
SPY - SPDR S&P 500	1993-01-29	

Table 2 - A
Sign Bias test for GARCH (1,1) Model

Sign Bias Test Equation: $(\varepsilon_t/\sigma_t)^2 = \alpha + \theta s_{t-1} + u_t$

Conditional Variance Specification: $\sigma_t^2 = \omega + \beta\varepsilon_{t-1}^2 + \lambda\sigma_{t-1}^2 + \delta s_{t-1}\varepsilon_{t-1}^2$

	Brazil			South Africa			Korea			China		
Parameters	**BOVA11**	**PIBB11**	**SMAL11**	**GLDJ**	**STX40J**	**STXSWXJ**	**226490**	**233740**	**251340**	**159915**	**510050**	**510900**
α	27.66154	1.481944	5.892602	3.616366	367.8860	823.4568	5.07E-05	0.000185	9.69E-05	44,085.67	44,868.01	1,093.232
	(0.0000)	(0.0000)	(0.0000)	(0.9182)	(0.8262)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0051)
θ	118.0022	-0.752409	7.847923	80.21342	-244.9615	86.27070	-1.26E-05	-0.000173	-3.27E-05	9,067.269	3,179.083	22,154.52
	(0.0000)	(0.0000)	(0.0000)	(0.0152)	(0.0603)	(0.0000)	(0.0999)	(0.0088)	(0.0622)	(0.0386)	(0.0372)	(0.0000)
ω	17,270.29	-0.026773	18.72387	9,662.627	33.346415	-615,362.2	2.46E-08	1.42E-07	2.05E-08	6.80E+09	7.09E+09	4,961,218
	(0.0000)	(0.0000)	(0.1193)	(0.0000)	(0.3092)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0005)
β	-0.000606	0.738930	-0.000510	-0.000398	-0.000307	0.004491	-0.017127	-0.082922	-0.015355	-0.001909	-0.002067	-0.003693
	(0.7223)	(0.0000)	(0.0063)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.11811)	(0.1851)	(0.0074)	(0.0000)
λ	9.187828	-0.204647	83.31036	-1.562934	0.050666	1.738544	-0.099468	-0.081965	-2.466374	0.044540	0.048399	4.958160
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.9977)	(0.0000)	(0.7853)	(0.7317)	(0.0055)	(0.7571)	(0.5845)	(0.0000)
δ	0.120314	0.879740	0.270115	0.866365	0.565691	0.990807	-0.754763	0.917185	0.502458	0.589972	0.591810	0.833421
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.1860)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Parentheses include the p-values

Table 2 - B
Sign Bias test for GARCH (1,1) Model

Sign Bias Test equation $(\varepsilon_t/\sigma_t)^2 = \alpha + \theta s_{t-1} + u_t$

Conditional Variance Specification: $\sigma_t^2 = \omega + \beta\varepsilon_{t-1}^2 + \lambda\sigma_{t-1}^2 + \delta s_{t-1}\varepsilon_{t-1}^2$

	India			Mexico			United States		
Parameters	**GOMS**	**BIRN**	**NBES**	**ANGELD10**	**NAFTRAC**	**DIABLOI10**	**XLF**	**IWM**	**SPY**
α	8.739840	0.005042	0.328509	47.09958	930.7429	71.14013	3,560.252	102.8816	81.79973
	(0.94480)	(0.0000)	(0.0000)	(0.0000)	(0.7311)	(0.0000)	(0.0002)	(0.0000)	(0.0000)
θ	481.8409	0.173846	-0.063446	-7.934416	-340.9086	-54.02036	-744.1128	-1.095636	-59.56190
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0481)	(0.0000)	(0.0871)	(0.1034)	(0.0000)
ω	908,645.1	0.000140	0.561414	1,355.050	1.78E+08	77,275.25	1.78E+08	29,992.77	484,422.7
	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.2239)	(0.0000)	(0.3335)	(0.0000)	(0.0000)
β	-0.007028	-0.003417	-0.001317	-0.000471	-0.000977	-0.000875	-0.000450	-0.003591	0.128508
	(0.0419)	(0.0000)	(0.7073)	(0.0575)	(0.0000)	(0.1889)	(0.0005)	(0.0000)	(0.0000)
λ	1.804473	8.484552	-3.482355	146.7887	0.049982	412.6880	0.010583	2.790282	-72.19645
	(0.0226)	(0.0000)	(0.0000)	(0.0000)	(0.9968)	(0.0000)	(0.9274)	(0.0000)	(0.0000)
δ	0.554487	0.817894	0.061507	0.201486	0.587702	0.365673	0.594255	0.863641	0.091507
	(0.0000)	(0.0000)	(0.0846)	(0.0000)	(0.0831)	(0.0000)	(0.1565)	(0.0000)	(0.0000)

Parentheses include the p-values

Table 3 - A
Descriptive Statistcs

	Brazil			South Africa			Korea			China		
	BOVA11	**PIBB11**	**SMAL11**	**GLDJ**	**STX40J**	**STXSWXJ**	**226490**	**233740**	**251340**	**159915**	**510050**	**510900**
Panel A: statistical properties of the return-series												
μ (%)	0.0267	0.0429	0.0488	0.0549	0.0477	0.0263	0.0458	-0.0354	0.0163	0.0551	0.0247	0.0001
σ (%)	1.5311	1.7635	1.3278	1.3416	1.3211	1.4667	0.7205	2.1248	1.0108	2.3760	1.8675	1.6159
S	0.1100***	-0.1070***	0.0266***	0.0271***	-0.0828***	0.2928***	-0.3979***	-1.3794***	-0.2710***	-0.4478***	-0.2134***	0.0064***
E (K)	5.1992***	7.3908***	5.7716***	3.7139***	3.2991***	15.3555***	2.4662***	11.0320***	1.9886***	7.1290***	7.4566***	9.5623***
Jarque-Bera	447.39***	7592.20***	3,051.00***	1,875.60***	1,533.50***	24,833.00***	124.24***	1,945.10***	33.98***	1,048.74***	2,300.02***	2,124.51***
LB (10)	18.18**	28.50***	11.57	33.09***	34.61***	78.31***	5.74	9.03	22.12**	27.04***	24.39***	27.59***
LB^2 (10)	243.75***	2,308.20***	130.03***	1,098.30***	2,167.00***	496.04***	28.62***	37.16***	21.38**	1,113.20***	434.78***	302.50***
Panel B: properties of percentage price deviations												
Average price deviation (%)	0.06	-0.59	-0.04	0.25	-0.03	-0.01	0.00	-0.27	-0.05	-0.10	-0.10	0.14
# days with a premium	1,160	768	1,153	1,701	1,082	1,273	216	154	88	582	963	503
# days with a discount	1,006	2,566	986	1,058	1,320	1,093	229	208	105	813	158	672
Average premium (%)	0.25	0.24	0.35	0.91	0.21	0.39	0.44	1.48	0.8	0.31	0.21	1.11
Average discount (%)	-0.16	-0.84	-0.49	-0.69	-0.26	-0.02	-0.51	-1.56	-0.77	-0.39	-0.30	-0.59
# days when premium > 0.25%	398	199	448	1308	233	619	144	129	72	261	258	364
# days when premium > 0.50%	165	97	238	992	83	295	88	110	52	94	59	259
# days when premium > 0.75%	61	64	138	749	38	156	53	95	38	38	27	198
# days when premium > 1.00%	32	41	85	558	23	88	28	80	26	19	14	160
# days when discount < - 0.25%	168	1,753	374	679	383	588	135	183	79	418	624	505
# days when discount < - 0.50%	34	1,443	210	462	154	359	80	162	62	174	181	334
# days when discount < - 0.75%	12	1,151	148	321	75	215	47	143	39	79	120	190
# days when discount < - 1.00%	7	881	114	236	36	115	31	123	32	39	92	85
Panel C: properties of daily changes in percentage price deviations												
# days when change > 0.25%	335	763	511	1,056	470	650	153	142	83	375	518	402
# days when change > 0.50%	95	451	286	821	205	393	113	126	70	192	142	254
# days when change > 0.75%	48	265	190	634	102	271	81	115	55	101	47	169
# days when change > 1.00%	24	167	133	491	62	185	62	105	44	65	26	103
# days when change < -0.25%	312	764	524	1,043	466	681	169	169	71	380	525	398
# days when change < -0.50%	98	467	308	806	202	417	121	154	57	201	121	271
# days when change < -0.75%	50	279	199	628	102	274	85	137	52	95	43	170
# days when change < -1.00%	28	165	137	506	66	170	67	122	47	54	19	104

*** denotes significance at 1% level, ** denotes significance at 5% level and * denotes significance at 10% level; μ = mean; σ = standard deviation; S = skewness; E(K) = excess kurtosis;
LB (10) e LB^2 (10) = The Ljung-Box test-statistics for returns and square returns for 10 lags.

Table 3 - B
Descriptive Statistcs

	India			Mexico			United States		
	GOMS	**BIRN**	**NBES**	**ANGELD10**	**NAFTRAC**	**DIABLOI10**	**XLF**	**IWM**	**SPY**
Panel A: statistical properties of the return-series									
μ (%)	0.0240	0.0343	0.0335	0.0053	0.0485	-0.0448	0.0017	0.0283	0.0255
σ (%)	1.1968	2.6112	0.9426	1.7246	1.1906	0.9384	1.9521	1.5053	1.1215
S	-0.3595***	-0.1864***	-0.07261***	-0.3410***	0.0634***	0.1969***	-0.2543***	0.1909***	-0.1033***
E (K)	3.9068***	3.5640***	1.7539***	2.9888***	6.7258***	2.9845***	18.1433***	10.3210***	11.3201***
Jarque-Bera	508.24***	806.31***	252.16***	666.47***	7,387.50***	642.67***	44,414.00***	19,938.00***	35,550.00***
LB (10)	14.36	162.30***	9.28	51.28***	57.33***	30.24***	69.32***	34.47***	60.91***
LB^2 (10)	27.39***	108.76***	75.78***	228.60***	1,863.80***	210.58***	2,733.70***	1,096.80***	4,084.30***
Panel B: properties of percentage price deviations									
Average price deviation (%)	-0.19	0.78	-0.07	0.09	-0.01	0.26	0	-0.04	-0.01
# days with a premium	123	664	812	1,084	762	1,187	2,287	1,918	3,239
# days with a discount	651	844	1,143	606	1,269	491	2,357	2,404	3,403
Average premium (%)	0.23	8.67	0.29	0.33	0.13	0.47	0.13	0.12	0.1
Average discount (%)	-0.27	-5.43	-0.33	-0.34	-0.11	-0.24	-0.13	-0.17	-0.12
# days when premium > 0.25%	45	650	370	549	50	708	325	228	302
# days when premium > 0.50%	8	634	166	229	17	438	68	28	46
# days when premium > 0.75%	4	618	27	80	12	253	27	4	21
# days when premium > 1.00%	1	601	9	37	10	128	14	3	6
# days when discount < - 0.25%	387	823	533	230	78	174	302	394	423
# days when discount < - 0.50%	22	801	297	103	28	55	76	95	89
# days when discount < - 0.75%	3	778	127	68	17	21	26	35	29
# days when discount < - 1.00%	2	759	17	46	15	10	17	15	12
Panel C: properties of daily changes in percentage price deviations									
# days when change > 0.25%	81	607	877	409	107	414	435	486	541
# days when change > 0.50%	24	543	480	203	38	205	177	137	126
# days when change > 0.75%	9	484	310	111	22	110	69	37	43
# days when change > 1.00%	2	416	199	67	16	62	33	15	21
# days when change < -0.25%	77	630	1,022	395	114	405	415	469	533
# days when change < -0.50%	25	557	556	195	35	215	175	140	148
# days when change < -0.75%	9	480	326	106	20	108	73	47	45
# days when change < -1.00%	3	420	187	69	15	62	32	16	14

*** denotes significance at 1% level, ** denotes significance at 5% level and * denotes significance at 10% level; μ = mean; σ = standard deviation; S = skewness; E(K) = excess kurtosis;
LB (10) e LB^2 (10) = The Ljung-Box test-statistics for returns and square returns for 10 lags.

Table 4 - A

Maximum Likelihood Estimates of the Sentana and Wadhwani (1992) Model: ETF daily returns

Conditional Mean Equation: $r_t = \alpha + \theta\sigma_t^2 + (\phi_0 + \phi_1\sigma_t^2)r_{t-1} + \varepsilon_t$

Conditional Variance Specification: $\sigma_t^2 = \omega + \beta\varepsilon_{t-1}^2 + \lambda\sigma_{t-1}^2 + \delta s_{t-1}\varepsilon_{t-1}^2$

	Brazil			South Africa			Korea			China		
Parameters	**BOVA11**	**PIBB11**	**SMAL11**	**GLDJ**	**STX40J**	**STXSWXJ**	**226490**	**233740**	**251340**	**159915**	**510050**	**510900**
α	-0.0366	-0.0158	0.0233	0.0316	-0.0062	0.0038	-40.5865	-22.0473	-7.2750	-0.0007	0.0008	-0.0013
	(0.0000)	(0.0000)	(0.0135)	(0.0000)	(0.0029)	(0.0057)	(0.9998)	(1.0000)	(0.9996)	(0.0000)	(0.0000)	(0.0000)
θ	2.3448	-0.4991	-0.1588	0.0638	-0.1304	-2.0390	-49.2578	-1,086.4530	-0.9516	-0.0748	-10.3130	6.2728
	(0.0000)	(0.0000)	(0.0689)	(0.0006)	(0.5186)	(0.0498)	(0.0000)	(0.0351)	(0.2714)	(0.9748)	(0.0000)	(0.0000)
ϕ0	0.2419	0.4912	0.3624	0.2460	0.0256	0.2524	0.0366	0.0374	0.2781	0.2223	0.1591	0.4656
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.1684)	(0.0000)	(1.0000)	(1.0000)	(0.9983)	(0.0000)	(0.0000)	(0.0000)
ϕ1	-1.4066	-0.1382	-0.0828	-0.0159	0.0924	-9.3421	-0.1981	-0.7822	0.0747	18.7386	1,168.2010	-15.3640
	(0.0077)	(0.0000)	(0.2808)	(0.0634)	(0.8873)	(0.3181)	(0.0000)	(0.0235)	(0.0000)	(0.6354)	(0.0000)	(0.1113)
ω	0.0001	0.0004	0.0082	0.0015	0.0002	0.0004	3.66E+11	6.55E+14	2.06E+09	1.3545	1.33E-07	9.10E-07
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.5454)	(0.0000)	(0.17560)	(0.0007)	(0.0000)
β	0.0282	0.0988	0.0915	0.0741	0.4318	0.3031	0.0238	0.1238	0.1341	0.2027	0.0616	0.1206
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.4653)	(0.3521)	(0.2700)	(0.0000)	(0.0000)	(0.0000)
λ	0.9707	0.8869	0.8046	0.8966	0.8443	0.5266	0.5366	0.5139	0.5456	-0.0912	-0.0090	-0.0780
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.1748)	(0.0000)	(0.0000)	(0.0422)	(0.0000)
δ	-0.0128	0.0540	0.1021	0.1011	-0.3234	-0.0411	8.6018	68.9105	0.2413	0.8731	0.9419	0.9033
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0610)	(0.1336)	(0.7715)	(0.1976)	(0.0000)	(0.0000)	(0.0000)
(β + δ)/β	0.54	1.55	2.12	2.36	0.25	0.86	362.74	557.65	2.80	5.31	16.29	8.49

Parentheses include the p-values

Table 4 - B

Maximum Likelihood Estimates of the Sentana and Wadhwani (1992) Model: ETF daily returns

Conditional Mean Equation: $r_t = \alpha + \theta\sigma_t^2 + (\phi_0 + \phi_1\sigma_t^2)r_{t-1} + \varepsilon_t$

Conditional Variance Specification: $\sigma_t^2 = \omega + \beta\varepsilon_{t-1}^2 + \lambda\sigma_{t-1}^2 + \delta s_{t-1}\varepsilon_{t-1}^2$

	India			Mexico			United States		
Parameters	**GOMS**	**BIRN**	**NBES**	**ANGELD10**	**NAFTRAC**	**DIABLOI10**	**XLF**	**IWM**	**SPY**
α	-0.0231	-0.2525	0.1504	0.0192	-0.0043	0.0150	-0.0009	-0.0080	-0.0057
	(0.0000)	(0.0001)	(0.0126)	(0.0004)	(0.0000)	(0.0000)	(0.0003)	(0.0000)	(0.0000)
θ	0.2645	0.0115	-0.0546	-0.0168	0.9246	1.9335	0.1058	-0.0056	-0.1219
	(0.0000)	(0.0000)	(0.0000)	(0.9595)	(0.0000)	(0.0000)	(0.6859)	(0.9626)	(0.0003)
ϕ0	-0.4957	0.9639	0.7484	0.2669	0.1974	0.4044	0.0198	0.1078	0.1357
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.3535)	(0.0000)	(0.0000)
ϕ1	0.1791	-0.0009	-0.0023	-0.5473	-0.8414	-4.3667	-0.0667	0.0181	0.0079
	(0.0000)	(0.0000)	(0.3914)	(0.6055)	(0.0051)	(0.0000)	(0.9729)	(0.3023)	(0.7494)
ω	0.0108	0.0284	0.5802	0.0052	0.0003	0.0001	0.0000	0.0001	0.0003
	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0180)	(0.0000)	(0.0000)
β	-0.0318	0.0994	0.1806	0.3855	0.2236	0.0863	0.2125	0.0588	0.2490
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
λ	0.5764	0.9251	0.6581	0.4536	0.6196	0.9049	0.8614	0.9249	0.7336
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
δ	-0.0633	-0.0584	-0.0521	-0.1865	0.2716	0.0154	0.0107	0.0297	0.3650
	(0.0000)	(0.0006)	(0.1592)	(0.0000)	(0.1236)	(0.1236)	(0.3644)	(0.0000)	(0.0000)
(β + δ)/β	2.99	0.41	0.71	0.52	2.21	1.18	1.05	1.51	2.47

Parentheses include the p-values

Table 5 - A

Maximum Likelihood of the Sentana and Wadhwani (1992) Model: the effect of feedback trading when the ETF exhibits a lagged discount

Conditional Mean Equation: $r_t = \alpha + \theta\sigma_t^2 + D_t\left(\varphi_{0,0} + \varphi_{1,0}\sigma_t^2\right)r_{t-1} + (1 - D_t)\left(\varphi_{0,1} + \varphi_{1,1}\sigma_t^2\right)r_{t-1} + \varepsilon_t$

Conditional Variance Specification: $\sigma_t^2 = \omega + \beta\varepsilon_{t-1}^2 + \lambda\sigma_{t-1}^2 + \delta s_{t-1}\varepsilon_{t-1}^2$

	Brazil			South Africa			Korea			China		
Parameters	**BOVA11**	**PIBB11**	**SMAL11**	**GLDJ**	**STX40J**	**STXSWXJ**	**226490**	**233740**	**251340**	**159915**	**510050**	**510900**
α	-0.0351	-0.0053	0.0214	0.0262	-0.0031	0.0049	-29.3442	-35.1149	-28.6284	-0.0006	-0.0009	-0.0023
	(0.0000)	(0.1591)	(0.0706)	(0.0015)	(0.1891)	(0.0028)	(1.0000)	(1.0000)	(1.0000)	(0.0009)	(0.0000)	(0.0000)
θ	2.1596	-0.5752	-0.1379	0.0193	0.0886	-2.1931	-167.2952	200.3941	-11.4630	2.2124	-8.1822	4.2232
	(0.0000)	(0.0000)	(0.3508)	(0.4661)	(0.6989)	(0.1452)	(0.0001)	(0.0366)	(0.9049)	(0.4920)	(0.02290)	(0.0069)
$\varphi_{0,0}$	0.2593	0.5151	0.3606	0.0372	0.2454	0.3028	0.0697	-0.0063	-0.0957	0.2641	0.1488	0.2692
	(0.0000)	(0.0000)	(0.0000)	(0.4426)	(0.0000)	(0.0000)	(1.0000)	(1.0000)	(1.0000)	(0.0000)	(0.0000)	(0.0000)
$\varphi_{0,1}$	-3.6347	-0.2035	-0.0677	0.0063	-0.5335	-11.0444	-0.4957	0.3686	-0.0306	31.5842	1,286.7120	180.1623
	(0.0120)	(0.0000)	(0.5611)	(0.7483)	(0.4639)	(0.2777)	(0.0001)	(0.0000)	(0.9861)	(0.6621)	(0.0000)	(0.5033)
$\varphi_{1,0}$	0.2554	0.1794	0.3740	0.3220	-0.2775	0.1677	-0.9288	0.3915	-0.7105	0.1701	0.1756	0.7320
	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0098)	(0.9998)	(1.0000)	(1.0000)	(0.0171)	(0.0001)	(0.0000)
$\varphi_{1,1}$	-1.0491	0.4838	-0.1526	-0.0141	1.0086	15.4690	0.0000	-2.4390	0.0000	-74.5677	1,002.5910	-21.3315
	(0.0968)	(0.0000)	(0.3841)	(0.1358)	(0.4386)	(0.2584)	(1.0000)	(0.0000)	(0.9999)	(0.7761)	(0.0000)	(0.0330)
ω	0.0001	0.0003	0.0081	0.0015	0.0002	0.0004	3.00E+12	3.96E+13	5.15E+11	1.36E-07	1.29E-07	7.24E-07
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0042)	(0.0004)	(0.5238)	(0.2173)	(0.0009)	(0.0000)
β	0.0293	0.0903	0.0910	0.0724	0.3922	0.3106	0.0308	0.3577	0.1190	0.1965	0.0610	0.1146
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.5994)	(0.0000)	(0.9862)	(0.0000)	(0.0000)	(0.0000)
λ	0.9697	0.8925	0.8061	0.8963	0.8425	0.5109	0.5373	0.5478	0.5537	-0.0906	-0.0087	-0.0774
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0029)	(0.0000)	(0.4065)	(0.0000)	(0.0497)	(0.0000)
δ	-0.0135	0.0592	0.1012	0.0998	-0.2971	-0.0368	8.5735	0.0822	-216.2897	0.8780	0.9425	0.9137
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.1444)	(0.3737)	(0.8627)	(0.9970)	(0.0000)	(0.0000)	(0.0000)
$\varphi_{0,0} = \varphi_{0,1}$	0.5263	0.3357	-0.0134	-0.2848	0.5229	0.1351	0.9985	-0.3978	0.9985	0.0940	-0.0268	-0.4628
	(0.0000)	(0.0000)	(0.9372)	(0.0000)	(0.0000)	(0.1954)	(0.0001)	(0.0000)	(0.0001)	(0.5157)	(0.6784)	(0.0000)
$\varphi_{1,0} = \varphi_{1,1}$	-1.4101	-0.6873	0.0849	0.0205	-1.5421	-26.5134	-0.4957	2.8075	-0.4957	106.1519	284.1215	201.4938
	(0.0000)	(0.0000)	(0.9372)	(0.0000)	(0.0000)	(0.1952)	(0.0000)	(0.0000)	(0.0000)	(0.5155)	(0.6784)	(0.0000)
(β + δ)/β	0.54	1.66	2.11	2.38	0.24	0.88	279.69	1.23	-1,816.48	5.47	16,46	8.98

Parentheses include the p-value $\varphi_{0,0} = \varphi_{0,1}$ and $\varphi_{1,0} = \varphi_{1,1}$ hypotheses-estimates are generated by Wald's test.

Table 5 - B
Maximum Likelihood of the Sentana and Wadhwani (1992) Model: the effect of feedback trading when the ETF exhibits a lagged discount

Conditional Mean Equation: $r_t = \alpha + \theta\sigma_t^2 + D_t\left(\varphi_{0,0} + \varphi_{1,0}\sigma_t^2\right)r_{t-1} + (1 - D_t)\left(\varphi_{0,1} + \varphi_{1,1}\sigma_t^2\right)r_{t-1} + \varepsilon_t$

Conditional Variance Specification: $\sigma_t^2 = \omega + \beta\varepsilon_{t-1}^2 + \lambda\sigma_{t-1}^2 + \delta s_{t-1}\varepsilon_{t-1}^2$

	India			Mexico			United States		
Parameters	**GOMS**	**BIRN**	**NBES**	**ANGELD10**	**NAFTRAC**	**DIABLOI10**	**XLF**	**IWM**	**SPY**
α	-0.0133	-0.1443	0.0839	0.0184	-0.0022	0.0132	-0.0025	-0.0033	-0.0013
	(0.6220)	(0.1423)	(0.3905)	(0.0435)	(0.0000)	(0.0000)	(0.0000)	(0.0638)	(0.1883)
θ	0.2342	0.0448	-0.0168	-0.4761	0.1990	0.8472	-0.5442	-0.0038	-0.0646
	(0.8949)	(0.0000)	(0.5489)	(0.5532)	(0.3313)	(0.0240)	(0.1541)	(0.9790)	(0.2307)
$\varphi_{0,0}$	0.0088	1.0228	0.7686	0.1253	0.3470	0.1229	-0.1920	0.1850	0.2931
	(0.9784)	(0.0000)	(0.0000)	(0.2156)	(0.0000)	(0.2299)	(0.0000)	(0.0000)	(0.0000)
$\varphi_{0,1}$	9.3579	0.0032	0.0034	-0.4282	-4.3615	-7.7110	0.8702	0.0164	0.0006
	(0.4788)	(0.0057)	(0.5090)	(0.8083)	(0.0000)	(0.0602)	(0.7977)	(0.4331)	(0.9880)
$\varphi_{1,0}$	0.0827	0.6449	0.6937	0.3621	0.0559	0.5273	0.2421	0.0046	0.0333
	(0.8872)	(0.0000)	(0.0000)	(0.0000)	(0.0985)	(0.0000)	(0.0000)	(0.9116)	(0.1460)
$\varphi_{1,1}$	-0.3260	-0.0019	-0.0067	-0.3271	-0.2142	-3.0060	-1.3380	0.0065	0.0090
	(0.9775)	(0.0000)	(0.3588)	(0.8988)	(0.9573)	(0.0017)	(0.6721)	(0.9972)	(0.8914)
ω	0.0074	0.0311	0.6052	0.0051	0.0004	0.0001	0.0000	0.0001	0.0002
	(0.6527)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0010)	(0.0000)	(0.0000)
β	-0.0215	0.1031	0.1772	0.3783	0.2658	0.0776	0.1883	0.0571	0.2321
	(0.8257)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
λ	0.5563	0.9221	0.6481	0.4583	0.5549	0.9120	0.8640	0.9268	0.7387
	(0.5823)	(0.0000)	(0.3588)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
δ	-0.0842	-0.0625	-0.0408	-0.1761	0.3893	0.0160	0.0295	0.0306	0.4005
	(0.5766)	(0.0000)	(0.2860)	(0.0000)	(0.0000)	(0.0816)	(0.0118)	(0.0000)	(0.0000)
$\varphi_{0,0} = \varphi_{0,1}$	-0.1828	0.3779	0.0749	-0.2368	0.2910	-0.4044	-0.4341	0.1804	0.2598
	(0.3906)	(0.0000)	(0.3854)	(0.1957)	(0.0000)	(0.0000)	(0.0000)	(0.0009)	(0.0000)
$\varphi_{1,0} = \varphi_{1,1}$	9.4828	0.0050	0.0101	-0.1011	-4.1473	-4.7050	2.2082	0.0099	-0.0084
	(0.3902)	(0.0000)	(0.3852)	(0.1914)	(0.0000)	(0.0000)	(0.0000)	(0.0009)	(0.0000)
(β + δ)/β	4.92	0.39	0.77	0.53	2.46	1.21	1.16	1.54	2.73

Parentheses include the p-value $\varphi_{0,0} = \varphi_{0,1}$ and $\varphi_{1,0} = \varphi_{1,1}$ hypotheses-estimates are generated by Wald's test.

Table 6 - A

Maximum Likelihood Estimates of the Sentana and Wadhwani (1992) Model: ETF daily returns before, during and after GFC's outbreak.

Conditional Mean Equation: $r_t = \alpha + \theta\sigma_t^2 + (\phi_0 + \phi_1\sigma_t^2)r_{t-1} + \varepsilon_t$

Conditional Variance Specification: $\sigma_t^2 = \omega + \beta\varepsilon_{t-1}^2 + \lambda\sigma_{t-1}^2 + \delta s_{t-1}\varepsilon_{t-1}^2$

	Brazil (PIBB11)			South Africa (GLDJ)			South Africa (STX40J)			China (510050)		
Parameters	**Pre-Crisis**	**Crisis**	**Post-Crisis**	**Pre-Crisis**	**Crisis**	**Post-Crisis**	**Pre-Crisis**	**Crisis**	**Post-Crisis**	**Pre-Crisis**	**Crisis**	**Post-Crisis**
α	-0.0951	-0.3018	-0.0081	0.1170	0.3136	0.0207	0.0003	-0.0001	0.0038	-0.0001	-0.0002	-0.0009
	(0.0000)	(0.0000)	(0.0075)	(0.0000)	(0.0000)	(0.7773)	(0.6785)	(0.8511)	(0.8108)	(0.8828)	(0.7941)	(0.0000)
θ	-0.7849	0.0976	-0.5909	0.2300	-0.0609	0.0107	-3.6584	-0.7968	-0.9020	11.7568	-14.7905	-9.7683
	(0.0000)	(0.0771)	(0.0000)	(0.1290)	(0.0352)	(0.7728)	(0.0000)	(0.0115)	(0.5186)	(0.4334)	(0.0001)	(0.1511)
ϕ0	0.5838	0.3939	0.4068	0.1855	0.1761	0.1254	0.6783	0.1536	0.1148	0.0286	0.6181	0.0741
	(0.0000)	(0.0000)	(0.0000)	(0.0026)	(0.0088)	(0.0000)	(0.0000)	(0.0596)	(0.0026)	(0.8118)	(0.0000)	(0.0094)
ϕ1	-0.2278	0.0786	-0.1722	0.2061	-0.0258	-0.0108	-5.4221	-0.6787	-0.2388	206.9045	7.8941	3,712.814
	(0.0273)	(0.0879)	(0.0000)	(0.3646)	(0.1698)	(0.2159)	(0.0000)	(0.6627)	(0.8115)	(0.7397)	(0.9659)	(0.0000)
ω	0.0354	0.0211	0.0004	0.0005	0.0094	0.8216	3.37E-05	5.56E-06	0.0120	4.40E-06	1.86E-06	1.25E-07
	(0.0000)	(0.0721)	(0.0000)	(0.1969)	(0.0274)	(0.0079)	(0.0000)	(0.0000)	(0.0000)	(0.0632)	(0.0004)	(0.0022)
β	0.1371	0.1590	0.1294	0.0197	-0.0348	0.0629	-0.4937	0.4635	0.0663	0.2680	0.0442	0.0402
	(0.0196)	(0.0027)	(0.0000)	(0.0452)	(0.0154)	(0.0001)	(0.0018)	(0.0000)	(0.0001)	(0.0101)	(0.0015)	(0.0000)
λ	0.3025	0.7956	0.8568	0.9632	0.9548	0.5538	0.9960	0.7178	-0.0736	0.7845	0.9329	0.9596
	(0.0146)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0011)	(0.0000)	(0.0000)	(0.4186)	(0.0000)	(0.0000)	(0.0000)
δ	0.1255	0.0085	0.0762	0.0323	0.1714	-0.1280	0.5993	0.0705	0.0073	-0.1391	0.0058	-0.0120
	(0.1746)	(0.8652)	(0.0000)	(0.0021)	(0.0000)	(0.0000)	(0.0019)	(0.5331)	(0.7440)	(0.2033)	(0.8370)	(0.0047)
(β + δ)/β	1.92	1.05	1.59	2.64	-3.93	-1.04	-0.21	1.15	1.11	0.48	1.13	0.70

Parentheses include the p-values

Table 6 - B

Maximum Likelihood Estimates of the Sentana and Wadhwani (1992) Model: ETF daily returns before, during and after GFC's outbreak.

Conditional Mean Equation: $r_t = \alpha + \theta\sigma_t^2 + (\phi_0 + \phi_1\sigma_t^2)r_{t-1} + \varepsilon_t$

Conditional Variance Specification: $\sigma_t^2 = \omega + \beta\varepsilon_{t-1}^2 + \lambda\sigma_{t-1}^2 + \delta s_{t-1}\varepsilon_{t-1}^2$

	Mexico (NAFTRAC)			United States (SPY)			United States (XLF)			United States (IWM)		
Parameters	**Pre-Crisis**	**Crisis**	**Post-Crisis**	**Pre-Crisis**	**Crisis**	**Post-Crisis**	**Pre-Crisis**	**Crisis**	**Post-Crisis**	**Pre-Crisis**	**Crisis**	**Post-Crisis**
α	0.0093	4.98E-05	-0.0089	-0.0052	-0.2410	0.0106	-0.0039	0.0026	-0.0009	-0.0154	-0.0761	0.0038
	(0.5742)	(1.0000)	(0.0000)	(0.0074)	(0.0408)	(0.0000)	(0.0014)	(0.7718)	(0.0216)	(0.0074)	(0.1052)	(0.4380)
θ	-19.8378	-1.1774	0.9425	-0.0686	0.0063	-2.4641	0.6107	8.20E-05	3.0867	-0.2599	2.0541	-2.5360
	(0.5532)	(0.9995)	(0.0000)	(0.2094)	(0.9747)	(0.0000)	(0.1030)	(0.9999)	(0.1066)	(0.4078)	(0.1707)	(0.0415)
ϕ0	-0.1225	-0.0003	0.2066	0.1924	0.0470	-0.0034	0.0313	0.1554	0.0475	0.1274	0.0118	0.1020
	(0.2931)	(0.9999)	(0.0000)	(0.0000)	(0.4930)	(0.8952)	(0.3417)	(0.1392)	(0.1346)	(0.0000)	(0.9093)	(0.0790)
ϕ1	440.4494	11.0970	-0.8823	-0.0914	0.1686	0.6032	-0.0543	-2.7837	-68.0829	-0.0127	3.6320	-8.8075
	(0.0323)	(0.9993)	(0.0336)	(0.0247)	(0.0000)	(0.6583)	(0.9644)	(0.6387)	(0.4285)	(0.7869)	(0.2383)	(0.4760)
ω	0.0001	0.0005	0.0005	2.52E-05	0.0011	0.0023	0.0002	0.0008	1.69E-06	0.0079	0.0068	6.35E-05
	(0.0000)	(0.7671)	(0.0000)	(0.06070)	(0.0745)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0025)
β	0.0119	0.0443	0.1643	0.0753	0.2321	1.2968	0.6977	0.1558	0.1207	0.0639	-0.0491	0.0338
	(0.1449)	(0.8888)	(0.0000)	(0.0000)	(0.0002)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0017)	(0.0000)	(0.0000)
λ	0.7726	0.5617	0.6419	0.9420	0.8043	0.0171	0.6105	0.83139	0.9395	0.3973	0.7577	0.9573
	(0.0000)	(0.7041)	(0.0000)	(0.0000)	(0.0000)	(0.1844)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0000)
δ	-0.0287	-0.0467	0.3354	-0.0206	-0.0810	-0.9123	-0.2942	-0.1279	-0.1185	0.1509	0.1860	-0.0158
	(0.0131)	(0.8830)	(0.0000)	(0.0010)	(0.2303)	(0.0000)	(0.0000)	(0.0010)	(0.0000)	(0.0000)	(0.0000)	(0.0320)
(β + δ)/β	-1,41	-0.05	3.04	0.73	0.65	0.30	0.58	0.18	0.02	-1.36	-2,79	0.53

Parentheses include the p-values

Appendix A
Variable Definition Table

Equation (1)	$Q_t = \frac{E_{t-1}(r_t) - \alpha}{\theta \sigma_t^2}$
Parameters	**Definition**
Q_t	Fraction of Shares demanded
$E_{t-1}(r_t)$	Expected return of shares for the period t based on information from period t-1
α	Risk Free return
θ	Risk aversion coefficient
σ_t^2	Conditional variance in t
Equation (2)	$Y_t = \gamma r_{t-1}$
Parameters	**Definition**
Y_t	Quantity of shares demanded by the feedback trader
r_{t-1}	Share's return in the previous period
γ	Feedback trading term
Equation (6)	$r_t = \alpha + \theta \sigma_t^2 + (\phi_0 + \phi_1 \sigma_t^2) r_{t-1} + \varepsilon_t$
Parameters	**Definition**
rt	Return of shares for the period t
α	Risk Free return
θ	Risk aversion coefficient
ϕ0	Market Frictions Coefficient
ϕ1	Feedback trading Coefficient
Equation (9)	$r_t = \alpha + \theta \sigma_t^2 + D_t(\varphi_{0,0} + \varphi_{1,0}\sigma_t^2) r_{t-1} + (1 - D_t)(\varphi_{0,1} + \varphi_{1,1}\sigma_t^2) r_{t-1} + \varepsilon_t$
Parameters	**Definition**
rt	Return of shares for the period t
α	Risk Free return
θ	Risk aversion coefficient
$\varphi_{0,0}$	Market Frictions Coefficient
$\varphi_{0,1}$	Feedback trading Coefficient
$\varphi_{1,0}$	Market Frictions Coefficient
$\varphi_{1,1}$	Feedback trading Coefficient
Dt	Dummy variable
Equation (10)	$\sigma_t^2 = \omega + \beta \varepsilon_{t-1}^2 + \lambda \sigma_{t-1}^2 + \delta s_{t-1} \varepsilon_{t-1}^2$
Parameters	**Definition**
δ	Volatility asymmetry after positive or negative shocks
St-1	Binary variable that takes the value of 1 if the shock at time t-1 is negative, and otherwise the value of zero
Sign Bias Test	$(\varepsilon_t / \sigma_t)^2 = \alpha + \theta s_{t-1} + u_t$
Parameters	**Definition**
θ	Dummy variable
St-1	Binary variable that takes the value of 1 if the shock at time t-1 is negative, and otherwise the value of zero

3

Tracking Efficiency in ETF Markets

3.1

Introduction

Exchange-traded funds (ETFs, hereafter) are essentially Index Funds that are listed and traded on exchanges like stocks, which was not possible until their development in the late 1980s in Canada, gaining popularity since the inception of SPY in the USA in 1993. It surpassed the hedge-fund industry in size by 2016 (da Costa Neto, Klotzle, & Figueiredo Pinto, 2019). Globally, ETFs have opened a whole new panorama of investment opportunities to retail as well as institutional investors and managers. They enable investors to gain broad exposure to entire stock markets in different countries and specific sectors with relative ease, on a real-time basis and at a lower cost than many other forms of investing.

Although nowadays it is relatively easy to find ETFs that allow exposure to a variety of markets, sectors, geographies, or forms, an ETF is mostly a basket of stocks that pursue to reflect the performance of a specific benchmark index, like S&P 500 or Russell 200 Index. An ETF trading value is based on the net asset value of the underlying stocks that it represents. ETFs are just like mutual funds that can be bought and sold in real-time at a price that changes throughout the day, due, among others, to supply-demand effects (Shanmugham & Zabiulla, 2012) or arbitrage bounds that arise from their creation/redemption processes, commonly referred to as pricing efficiency (Charupat & Miu, 2013).

When investing in an ETF, one wants it to track its underlying index as close as possible, and so evaluate the tracking performance of such a vehicle, besides its pricing efficiency, turns out to be crucial. But have ETFs from both developed and emerging markets the same behavior regarding tracking their underlying indexes? Furthermore, is ETFs tracking ability affected by events that could change market conditions from a bearish to a bullish pattern and vice-versa, such as 2008's Global Financial Crisis or even 2020's novel coronavirus (SARS-CoV-2) pandemic?

In an attempt to address these issues, we have updated the sample used in da Costa Neto et al. (2019), including data on daily closing prices for three ETFs from each of the emerging markets of Brazil, China, South Africa, Mexico, Korea, and India, as well as on three ETFs from the US market, with their correspondent underlying indexes. According to the authors, those were the highest transaction volume ETFs for each market available in the Thomson Reuters database, aiming to be a representative sample of those markets. All series started at the inception date of each ETF and ended on April 30, 2020.

To the best of our knowledge, this article is the first study that comprehensively and explicitly investigates the association of ETF tracking efficiency with bullish and bearish market conditions in emerging as well as in developed markets, using a Discrete Threshold Regression model (Tsay, 1989).

This article is structured into sections as follows: Section 3.2 briefly reviews the literature related to the subject. Section 3.3 describes the study's methodology and data. Section 3.4 presents the results and discussion of the main findings. Finally, the conclusion is presented in Section 3.5.

3.2

Literature Review

The efficiency of passive index funds on tracking their benchmarks has been drawing the attention of researchers and managers over the years. Roll (1992) suggests that the level of tracking error is one of the most important criteria concerning ETF performance, while Charupat and Miu (2013) highlighted management fees, transaction costs, dividends, and cash holding, replicating strategy and the compounding effect of leveraged and inverse ETFs as the key factors that dictate tracking error and performance of ETFs.

Gruber (1996) was the first one to study the performance of index funds by using the Jensen Alpha and document that a sample of US S&P 500 index funds underperformed the benchmark index by approximately 0.2 % per annum on an after-cost basis from 1990 to 1994.

Frino and Gallagher (2001) studied the tracking error of 42 S&P 500 index mutual funds from December 1993 up to February 1999 and pointed out that tracking error is unavoidable in index fund performance due to the presence of market frictions. They explained that, because of this inevitability, index managers face a trade-off between the minimization of tracking error and transaction costs.

Gastineau (2002) enhanced that index funds that attempted to track Russell 200 index were highly affected by their index composition, and the requirements of portfolio rebalancing incurred in transaction costs to the fund, affecting their tracking ability.

Elton, Gruber, Comer, and Li (2002) compared the tracking ability of SPDR and conventional S&P 500 index funds. They suggested that SPDR underperforms the S&P 500 by 28.4 basis points per year and the conventional index funds by 18 basis points per year due to management fees and the loss of return from dividend reinvestment.

Frino, Gallagher, Neubert, and Oetomo (2004) stated that the number of share issuances/repurchases and constituents companies spin-offs on the S&P 500 index value, give rise to the tracking errors of its index funds.

Gallagher and Segara (2006) analyzed the capacity of the Australian index ETF to follow the performance of its underlying index. They realized that tracking error is inevitable on performance, and that tracking error of ETF is considerably smaller than conventional index funds due to some issues such as liquidity costs, higher costs, and dividend policies.

Milonas and Rompotis (2006) studied trading and performance features of 36 Swiss ETFs during 2001-2006 and concluded that Swiss ETFs underperform their benchmarks. They also reported that Swiss ETFs expose investors to a higher risk than the standard deviation of indexes, and that tracking error is positively related to the risk of ETFs and management fees.

Wong and Shun (2010) were the first to investigate the performance of ETFs across bearish and bullish markets. They studied 15 ETFs from 1999 to 2007 and showed by Sharpe’s ratio that ETFs returns are not positive, proportional to the market volatility and that even ETFs that track the same underlying index do not perform the same.

Charupat and Miu (2011) analyzed pricing and performance of leveraged ETFs and found evidence that tracking errors were small for holding periods up to a week, becoming increasingly larger for longer horizons, and therefore could be regarded as being time-dependent.

Chu (2011) examined the tracking error of 18 ETFs traded in the Hong Kong stock market during 2004-2008 and found it higher than those in Australia and the US. He pointed out that this situation is due to the higher cost of trading stocks in

Honk Kong and/or to the use of synthetic investment tools instead of holding the underlying stocks. He also referred that tracking error is positively related to the expense ratio of ETF and negatively related to its size.

Rompotis (2011) applied regression to determine the tracking errors between ETFs and their stated benchmarks and found persistence in tracking errors over time.

Buetow and Henderson (2012) analyzed ETFs returns in the US market and found that, on average, ETFs closely track their benchmark index, although ETFs that track indexes composed of less liquid securities are prone to exhibit a larger tracking error.

Blitz and Huij (2012) examined the performance of emerging markets ETFs, finding evidence that those funds tracking errors were substantially higher than previously reported levels of tracking errors for developed markets funds.

Elia (2012) compared the tracking ability of 48 European ETFs that track 20 different benchmarks and found ETFs in Europe to have a substantial tracking error. He concluded that synthetic replication ETFs have a smaller tracking error and higher tax efficiency than physical replication ETFs and that synthetic ETFs underperform their benchmark and physical ETFs competitors. Additionally, he argued that synthetic ETFs are more efficient in tracking emerging market benchmarks.

Shanmugham and Zabiulla (2012), in a study on Indian ETF Nifty BeES using high-frequency data, found tracking ability to vary across the two market regimes, observing tracking error to be higher during the bearish market conditions.

Sarkar, Dutta and Dutta (2013) pointed several advantages of investing in an index fund, e.g., exposure to a diversified portfolio, minimization of company-specific risks and high liquidity. They claim that, especially for an investor with a long investment horizon, along with low tracking error, cointegration is a desirable property that a good index fund is expected to exhibit, and found that only 4 out of 23 Indian index funds considered in their study satisfied both these criteria (Nifty BeES, Kotak Nifty ETF, UTI Master Index Fund and HDFC Index Fund Sensex Plan).

Milonas and Rompotis (2015) studied tracking error of 38 German bonds ETFs, finding evidence that a statistically significant tracking error of 0.06% was persistent every quarter.

Leung and Ward (2015) studied tracking performance of leveraged ETFs on gold, and their price relationships with gold spot and futures, finding that leveraged gold ETFs tend to underperform their corresponding benchmark, becoming worse over a longer holding period.

Strydom, Charteris, and McCullough (2015) employed several measures of tracking error to test the relative tracking ability of index funds and ETFs which track the FTSE/JSE Top 40 index. They found that the tracking errors associated with both forms of passive investment in South Africa are similar to those estimates obtained in international research for European, Australian, and other emerging markets based on the majority of the tracking error methods employed, but are not as efficient as the US market.

Osterhoff and Kaserer (2016) studied eight fully replicating German ETFs, finding that daily tracking errors are significantly dependent on the liquidity of underlying stocks.

Chen, Chen, and Frijns (2017) examined tracking performance and tracking error of New Zealand ETFs, finding evidence that those ETFs do not replicate their underlying indexes perfectly. By cointegration analysis, they showed that such ETFs have substantially different exposures to their underlying indexes from what they should be. Although performance improves at a monthly basis, regression analysis showed that both characteristics of the ETFs and the constituents of the underlying indexes, as well as their volatilities are determinants of the tracking error of the ETFs.

Chu (2017) examined the tracking performance of two Hong Kong ETFs: Tracker Fund and X iShares A50. They reported that the time series regression model of pricing deviation is significantly influenced by market value, dividend yield, trading volume, bid-ask spread, and market risk. Furthermore, they argued that the size of the regression coefficients indicates that synthetic ETFs have a relatively poor ability to track the market during market fluctuations.

Kaur and Singh (2018) examined the performance characteristics of 12 gold ETFs in India across bearish and bullish markets, finding that tracking error is higher in the bearish market regime. Furthermore, they found evidence that trading volume has a positive impact on ETFs' tracking ability, whereas volatility and pricing deviation, on the contrary, harm it.

Piccotti (2018) showed that ETFs with larger NAV (Net Asset Value) tracking error standard deviations (TESDs) tend to trade at higher premiums, and claims that TESD has the desirable properties as a liquidity segmentation measure.

Mallika and Sulphey (2018) aimed to examine the price discovery process and the performance of Gold Exchange Traded Funds, employing Johansen cointegration and Johansen's Vector Error Correction Model (VECM) for price discovery analysis. Tracking Error analysis showed that Gold ETFs had neither outperformed nor underperformed the spot price.

Saunders (2018), analyzing ninety-three country-specific exchange-traded funds from 47 different countries, found evidence that the ETF expense ratio is a significant explanatory variable for tracking error.

More recently, Rakowski and Shirley (2020) shed light on Exchange-Traded Notes (ETNs), that are similar to ETF, except for the absence of underlying portfolio holdings, offering investors different advantages in terms of lower tracking errors when compared to ETFs.

Forthcoming studies suggest tracking error as a determinant for ETFs likelihood of closure (Akhigbe, Balasubramnian, & Newman, 2020) and attempt to address tracking error under different stock market trends, although with limited sample (Zhang & Zhang, 2020).

3.3
Data and Research Methodology

3.3.1
Data

Table 1 shows information regarding the ETFs and corresponding underlying indexes. Daily price data were obtained from the Thomson Reuters database. All series started at the inception date of each ETF and ended on April 30, 2020. Missing data on ETFs or underlying indexes daily closing prices have been disregarded. Returns were calculated by the difference between price natural log in the day (t) and in the day (t-1) for both ETFs and underlying indexes series. This sample was considered because of the relevance of those markets in the global industry. In addition to pioneers, the United States are also the largest ETF market in the world, with nearly two-thirds of the industry's global equity, that reached in 2020 almost US$ 7.7 trillion of assets under management worldwide. Brazil and Mexico are amongst the biggest emerging markets in Latin America. India, South Africa and Korea are important global emerging markets, and China, as the second biggest economy in the world, plays an important role in foreign investments.

3.3.2
Measures of Tracking Errors

Several methods have been used to evaluate passive portfolio management. The first method of tracking error (Roll, 1992; Frino and Gallagher, 2001, Gallagher and Segara, 2006; and Rompotis, 2009) is the mean of the absolute daily return difference between ETF and its benchmark, as in:

$$TE_1 = \frac{\sum_{t=1}^{n} \left| R_{i,t}^{ETF} - R_{j,t}^{Bench} \right|}{n} \qquad (1)$$

where $R_{\mathrm{i},t}^{ETF}$ and $R_{j,t}^{Bench}$ are, respectively, the return of the ETF and the underlying index on day t, and n is the period under consideration.

The second method (Roll, 1992; Frino and Gallagher, 2001; and Aber, Li & Can, 2009) consists in the standard deviation of the difference between ETFs and benchmark's returns over time, as in:

$$TE_2 = \sqrt{\frac{\sum_{t=1}^{n} \left(R_{i,t}^{ETF} - R_{j,t}^{Bench} \right)2}{n-1}} \qquad (2)$$

where $R_{\mathrm{i},t}^{ETF}$, and $R_{j,t}^{Bench}$have the same meaning as in equation (1).

Frino and Gallagher (2001), Rompotis (2009) and Milonas and Rompotis (2010) proposed that tracking error is the standard error of the following regression:

$$R_{i,t}^{ETF} = \alpha_i + \beta_i R_{j,t}^{Bench} + \varepsilon_t \qquad (3)$$

A positive (negative) estimated value of the intercept (α) will suggest the ETF outperforms (underperforms) the underlying index.

Finally, since investors normally do not understand risk as to the returns above the minimum set as target for investment, Milonas, and Rompotis (2010) suggested a method known as semi-standard deviation, which is only applied for the days when ETF does not beat the benchmark index:

$$TE_4 = \sqrt{\frac{\sum_{t=1}^{n} Min[\left(R_{i,t}^{ETF} - R_{j,t}^{Bench}\right);0]^2}{n}} \tag{4}$$

Note that TE2 will be identical to TE4 if the estimated values of the intercept (α) and the slope coefficient (β) are equal to zero and unity, respectively, and the sample size is large enough such that (n-1) is n in the limit of large n.

Milani and Ceretta (2016) claim that, despite conceptual improvements brought by Charupat and Miu (2013), there is still some divergencies concerning performance and tracking ability measures in ETF markets, and suggest equation (3), used in this study, as a candidate to evaluate ETFs tracking ability, pursuing to standardize future studies regarding this subject.

3.3.3
Identification of Markets Regimes and Regression Model Selection

Several previous studies attempted to address financial series behavior across market regime changes. Dual Beta Model (DBM) (Fabozzi & Francis, 1977, 1979; Wiggins, 1992; Cinebell, Squires, & Stevens, 1993; Howton & Peterson, 1998; Chawla, 2003; and Badhuri & Durai, 2006), Jensen's model (Wong & Shum, 2010; Shanmugham & Zabiulla, 2012) and Logistic Regression Transition Models (Bhaduri & Durai, 2006; Woodward & Anderson, 2009), among others, appear to be the most applied, with regards to analyzing alpha and beta variations across bearish and bullish markets conditions.

Pagan and Sossounov (2003) proposed a framework for analyzing bullish and bearish markets, following Bry and Boschan (1971) seminal work in detecting turning points in the market. This technique was used in Kaur and Singh (2018) to identify peaks and troughs when testing the tracking efficiency of gold ETFs across bearish and bullish market regimes in India.

In this study, we have used a Discrete Threshold Regression (TR) model (Hansen 1999, 2011; Potter, 1999), a simple form of nonlinear regression featuring piecewise linear specifications and regime-switching that occurs when an observed variable crosses an unknown threshold. This model specification is easy to estimate and interpret and can be suited for a time series that possess regime-switching behavior, like ETFs and their underlying indexes.

The general form of a multiple linear regression model with t observations and m thresholds, producing m + 1 regimes, could be written as:

$$Y_t = X_t'\beta + z_t'\delta_j + \varepsilon_t \quad (5)$$

The regressors are divided into two groups: the X variables are those which parameters do not change across regimes, while Z variables have coefficients that are regime-specific.

There is an observable threshold variable q_t that strictly increases threshold values ($\gamma_1 < \gamma_2 < \ldots < \gamma_m$), such we are in regime j if and only

$$\gamma_j \leq q_t < \gamma_{j+1} \quad (6)$$

where we set $\gamma_0 = -\infty$ and $\gamma_{m+1} = \infty$. Thus, we are in regime j if the value of the threshold variable is at least as large as the j-th threshold value, but not as large as the (j + 1) -th threshold.

In this study, for a single threshold, two-regime (bearish and bullish) model, we have:

$$R_{i,t}^{ETF} = \alpha_1 + \beta_1 R_{j,t}^{Bench} + \varepsilon_{1t} \qquad \text{if } -\infty < q_t < R_{j,t}^{Bench} \quad (7)$$

$$R_{i,t}^{ETF} = \alpha_2 + \beta_2 R_{j,t}^{Bench} + \varepsilon_{2t} \qquad \text{if } R_{j,t}^{Bench} \leq q_t < \infty \quad (8)$$

Equation (7) refers to the bearish market and equation (8) refers to the bullish market. If coefficients of the regression are statistically significant, ε_{1t} and ε_{2t} are the estimated tracking errors for the correspondent regimes.

3.4
Results and Discussion
3.4.1
Preliminary Analysis

Table 2 (A and B) presents the summary statistics of daily returns of ETFs considered in our sample, as well as their underlying indexes. The average daily returns are positive for the majority of funds (exceptions were 23370 and 251340, in Korea; GOMS, in India; and ANGELI10 and DIABLOI10, in Mexico) and benchmarks (exceptions were KOSDAQ 150 Index, in Korea; GEM Index, in China; IPC in Mexico and IXM, in the US), implying the fact that, generally, price series have increased over the period.

The statistics show that both returns series exhibit standard deviation greater than unity and are negatively skewed (exceptions regarding ETFs were GLDJ in South Africa and DIABLOI10, in Mexico, and regarding benchmarks, Gold in South Africa, Inverse KOSDAQ in Korea, GEM Index in China and IPC Inverse, in Mexico). The value of kurtosis is greater than 3 in all series, meaning that they have a heavier tail than the standard normal distribution. The significant Jarque-Bera statistics indicate a departure from normality through rejecting the hypothesis of symmetric distribution.

Tracking errors were found to be positive, which may be natural due to transaction costs. Results suggest that ETFs returns are higher than underlying indexes returns not only because of transaction costs but also due to their particular performance and replicating strategies.

In time series econometrics, it is usual to check the stationarity of a series before using it in an ordinary least square (OLS), or regression results may be spurious. To test the stationarity of data, the Augmented Dickey-Fuller (ADF) test was employed. The results of the unit root test are exhibited in Table 3 (A and B) for both the ETFs and benchmarks return series.

Unit root test for stationarity is performed on levels and first difference. Based on Schwarz’s information criteria, the optimal lag length chosen for the ADF test is 1. Test statistics reject the null hypothesis of a unit root at a 1 percent level of significance, implying the fact that both ETFs and underlying indexes series are stationary.

3.4.2
Tracking Errors Estimations

Table 4 summarizes the estimation results of tracking error across different market conditions.

The vast majority of ETFs presented statistically and significant overall, bearish and bullish tracking errors at 1 % level (exceptions were 159915 in China, significant at 10% level, and BIRN in India, significant at 5% level, both emerging markets). The coefficients significance suggests that the choice of a parsimonious model (Discrete Threshold Regression) rather than more sophisticated ones (Dual beta model, Logistic Smoothed Threshold Model) appropriated captured tracking errors in the sample, the main object of this study.

Generally speaking, we can say that BIRN, from India, presented the highest overall TE (5,1%), bearish TE (7,70%), and bullish TE (1,33%). The lowest overall TE (0,28%) and bullish TE (0,44%) were presented by SPY, from the US. It is worth noting that the lowest bearish TE (0,52%) was presented by 510050, from China, an emerging market, which could be understood as inappropriate, at first glance. Overall, the TE of bullish markets appears to be higher in emerging markets (11 out of 18 funds of the sample) than in developed markets, which presented a higher TE in the bearish market for all three funds of the sample. Thresholds were found to be different from zero for 17 funds, as well as positive for 13 out of them.

We found 20,492 observations (45%) in bearish market conditions in all the emerging markets, while in bullish market conditions there were 25,296 observations (55%), i.e., these are the numbers of occurrences that were below or above the threshold, respectively. In the US market, there were 5,288 observations (24%) in bearish market conditions, while in bullish market conditions there were 16,318 observations (76%). This could partially explain why overall TE appears to be higher in emerging markets since the bullish market conditions in the US market are more persistent.

Several previous studies showed that volume was found to bear a significantly positive impact on the tracking efficiency of ETFs (Rompotis, 2011; Kaur & Singh, 2018). This could explain why the three US funds showed the lowest tracking error of the sample. Furthermore, the high volume could be viewed as an indicator of the reduced bid-ask spread, as well as reduced transaction costs, which could imply that actively traded funds tend to follow their underlying indexes more accurately.

Moreover, volatility is also commonly named as influent when it comes to increasing tracking errors (Kaur & Singh, 2018). This characteristic could partially explain the lower TE level in the US market when compared to emerging markets in our sample.

Other characteristics such as fund size, replication strategy, expense ratio, premium, and bid-ask spread were reported as having an important relationship with tracking efficiency of ETFs (Khan, Bacha, & Masih, 2015), and are likely to explain the differences between emerging markets and the US market tracking errors.

Regarding emerging markets indexes, if an investor wants to buy an ETF from different emerging markets, he should be aware that, generally speaking, the number of observations in bullish market conditions were higher than in bearish market conditions, and tracking ability of ETFs during both conditions are poorer.

3.5
Summary and Conclusions

We have studied the efficiency of Exchange-Traded Funds in tracking their benchmark indexes. By updating the sample used in da Costa Neto et al. (2019), we analyzed tracking errors related to 21 ETFs from six emerging markets as well as in the US market, using a Discrete Threshold Autoregressive model (Tsay, 1989) to evaluate tracking errors on bearish and bullish market conditions. The results suggest that tracking error is higher in emerging markets when compared to a developed market, meaning that they do not fully replicate their benchmarks. Moreover, following Chu (2011) and Blitz et al. (2012), we also conclude that those that track developed markets indexes present better tracking ability. Regarding market conditions, TE appears to be relatively higher in a bearish market for a developed market, while in emerging markets it appears to be higher in bullish market conditions.

This study gave rise to two outstanding contributions to ETFs knowledge base and literature: first, to the best of our knowledge, this is perhaps the first empirical research on ETFs tracking errors using Discrete Threshold

Autoregressive model to allow data determine changes in market conditions. The model seems to adequately allow data series itself to estimate thresholds that best determine market conditions changes, instead of an algorithm or even period based data splitting. Second, this article comprehensively and explicitly investigates the association of ETF tracking efficiency with bullish and bearish market conditions, both in emerging and in developed markets as well.

As a remark, the sample period of data used is different for all ETFs which is justified by different inceptions dates and also by the fact that some funds started to track their current benchmarks after their inception. This has limited our study in terms of homogeneity since our conclusions could be different if we had the same lifetime for each ETF. With this in mind, we suggest a future study about this topic, but using the same sample period for all funds, with a higher number of observations if possible.

Managers could benefit from these findings if they attempt to evaluate the replication strategies when making ETFs portfolios, trying to minimize tracking errors, for instance, by adopting full replication practices and approximating ETFs performances from their underlying indexes.

Investors could get the most from these findings by selecting managers and ETFs that follow investment processes that guarantee suitable compliance with their strategies and expectations regarding diversification, tax efficiency, or underlying indexes tracking ability.

Finally, policymakers could develop indexes and ETFs that closely track them, to stimulate the creation/fostering of specific economic sectors or asset classes, like innovative companies, ESG (Environment, Social and Governance) intensive companies, and so on.

Table 1
Selected ETFs by market and series launch-date

ETF	Launch-date	Market	Underlying Index
BOVA11 - IShares Ibovespa	2008-12-02		Ibovespa
PIBB11 - It Now PIBB IBrX-50	2004-07-27	Brazil	IBrX-50
SMAL11 - iShares BM&FBOVESPA Small Cap	2008-12-02		BM&FBovespa Small Cap Index (SMLL)
GLDJ - NewGold	2004-11-02		Gold
STX40J - Satrix 40	2004-06-01	South Africa	ALSI 40 Index
STXSWXJ - Satrix Swix Top 40	2007-09-03		FTSE/JSE Swix Top 40 index
226490 - Samsung KODEX KOSPI 200 Securities	2015-08-24		KOSPI Index
233740 - Samsung KODEX Leverage	2015-12-17	Korea	2 x KOSDAQ 150 Index
251340 - Samsung KODEX Inverse	2016-08-10		Inverse KOSDAQ 150 Index
159915 - E Fund ChiNext	2011-12-09		GEM Index
510050 - ChinaAMC China 50	2006-10-16	China	SSE50 Index
510900 - E Fund Hang Seng China Enterprises QDII	2012-10-22		Hang Seng China Enterprise (HSE) Index
GOMS - Goldman Sachs CPSE	2014-05-20		Nifty CPSE Index
BIRN - BIRLA Sun Life Nifty	2011-07-27	India	Nifty 50
NBES - Goldman Sachs Nifty BeE	2009-11-09		Nifty 50
ANGELD10 - Smartshares-ANGELD	2010-10-27		2 x IPC (Mexbol Index)
DIABLOI10 - Smartshares-DIABLOI	2010-10-27	Mexico	-1 x IPC (Mexbol Index)
NAFTRAC - iShares NAFTRAC	2002-04-30		IPC Index
XLF - Financial Select Sector SPDR	1998-12-16		Financial Select Sector (IXM)
IWM - iShares Russell 2000	2000-05-26	United States	Russell 2000 Index
SPY - SPDR S&P 500	1993-01-29		S&P 500 Index

Table 2 A
Descriptive Statistcs

	Brazil			South Africa			Korea			China		
	BOVA11	**PIBB11**	**SMAL11**	**GLDJ**	**STX40J**	**STXSWXJ**	**226490**	**233740**	**251340**	**159915**	**510050**	**510900**
Panel A: statistical properties of ETFs return-series												
Mean	0.000284	0.000364	0.000357	0.000631	0.000397	0.000178	5.86E-05	-0.000386	-0.000336	0.000450	0.000270	8.13E-05
Median	0.000450	0.000650	0.000867	0.000349	0.000966	0.000000	0.000656	0.000469	0.000000	0.000000	0.000000	0.000000
Maximum	0.125708	0.167158	0.109357	0.075715	0.077567	0.177548	0.080422	0.178075	0.083033	0.095389	0.095521	0.095489
Minimum	-0.157528	-0.156629	-0.191595	-0.078067	-0.097141	-0.179071	-0.087318	-0.199757	-0.105470	-0.105560	-0.105190	-0.104560
Standard Deviation	0.016681	0.018305	0.015525	0.013240	0.013495	0.015708	0.010043	0.032958	0.017784	0.022068	0.017969	0.014575
Skewness	-0.607947	-0.451113	-1.901051	0.104025	-0.158927	-0.220829	-0.394940	-0.477794	-0.184382	-0.464007	-0.231386	-0.101356
Kurtosis	12.78339	12.84483	26.63344	6.54814	6.97361	18.51319	16.28032	7.55108	6.87898	7.25586	7.60552	10.29264
Jarque-Bera	11,412.10	15,682.35	64,414.21	2,032.79	2,633.21	31,722.51	8,473.44	956.93	576.30	1,611.96	2,940.58	4,056.09
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Number of Observations	2,818	3,851	2,698	3,862	3,977	3,161	1,149	1,062	911	2,039	3,294	1,829
	Ibovespa	**IBrX-50**	**BM&F Bovespa Small Cap Index (SMLL)**	**Gold**	**ALSI 40 Index**	**FTSE/JSE Swix Top 40 index**	**KOSPI Index**	**2 x KOSDAQ 150 Index**	**Inverse KOSDAQ 150 Index**	**GEM Index**	**SSE50 Index**	**Hang Seng China Enterprise (HSE) Index**
Panel B: statistical properties of Underlying Indexes return-series												
Mean	0.000189	0.000223	0.000195	0.000250	0.000399	0.000197	1.10E-05	-0.000317	0.000166	-0.000375	0.000159	-0.000131
Median	0.000000	0.000000	3.25E-05	0.000000	0.000362	0.000121	0.000136	0.000000	0.000000	0.000000	0.000000	0.000000
Maximum	0.130228	0.138407	0.103693	0.190375	0.090570	0.090570	0.082513	0.196977	0.101188	0.425466	0.092332	0.047120
Minimum	-0.159938	-0.162451	-0.182201	-0.162244	-0.104504	-0.104504	-0.087670	-0.202375	-0.098488	-0.257829	-0.099497	-0.057837
Standard Deviation	0.016207	0.017539	0.014292	0.026266	0.013073	0.013390	0.010002	0.033646	0.017381	0.044960	0.017698	0.010603
Skewness	-0.680887	-0.457802	-2,146846	0.283964	-0.251847	-0.186643	-0.360713	-0.283699	0.172737	2.064340	-0.356488	-0.344665
Kurtosis	14.49684	13.78127	29.92686	7.65828	8.97509	9.27986	17.59456	7.77390	7.35648	20.25070	7.00706	6.19289
Jarque-Bera	15,737.58	18,785.50	83,580.82	3,543.72	5,958.11	5,212.49	10,222.35	1,022,71	724.94	26,730.68	2,273.53	813.12
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Number of Observations	2,818	3,851	2,698	3,862	3,977	3161	1149	1,062	911	2,039	3,294	1,829

Table 2 B
Descriptive Statistcs

	India			Mexico			United States		
	GOMS	**BIRN**	**NBES**	**ANGELD10**	**DIABLOI10**	**NAFTRAC**	**XLF**	**IWM**	**SPY**
Panel A: statistical properties of ETFs return-series									
Mean	-0.000251	0.000380	0.000290	-0.000382	-0.000248	0.000368	4.00E-05	0.000222	0.000280
Median	0.000000	0.000000	0.000613	0.000000	0.000000	0.000562	0.000301	0.000811	0.000527
Maximum	0.093107	0.124494	0.065051	0.088698	0.062394	0.069190	0.151867	0.087545	0.135577
Minimum	-0.111977	-0.149662	-0.107191	-0.125521	-0.063626	-0.081960	-0.182322	-0.142335	-0.115887
Standard Deviation	0.013616	0.024909	0.010089	0.018746	0.010013	0.010777	0.019012	0.015180	0.011898
Skewness	-0.70711	-0.22279	-0.66548	-0.69673	0.23012	-0.32664	-0.13655	-0.53371	-0.28202
Kurtosis	12.81061	6.60681	12.45846	8.05756	7.29979	6.89821	17.21776	10.04484	15.03506
Jarque-Bera	5,984.95	1,094.03	9,819.04	2,723.39	1,837.28	2,845.30	45,238.11	10,593.84	41,479.72
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Number of Observations	1,462	1,988	2,583	2,375	2,358	4,371	5,369	5,008	6,858
	Nifty CPSE Index	**Nifty 50**	**Nifty 50**	**2 x IPC (Mexbol Index)**	**-1 x IPC (Mexbol Index)**	**IPC Index**	**Financial Select Sector (IXM)**	**Russell 2000 Index**	**S&P 500 Index**
Panel B: statistical properties of Underlying Indexes return-series									
Mean	0.000107	0.000200	0.000199	-9.11E-05	4.17E-05	0.000364	-2.64E-05	0.000157	0.000256
Median	0.000897	0.000000	0.000000	0.000000	0.000000	0.000331	0.000000	0.000279	0.000270
Maximum	0.062407	0.084003	0.084003	0.094879	0.066381	0.065101	0.172031	0.089759	0.109572
Minimum	-0.161268	-0.139038	-0.139038	-0.132762	-0.047439	-0.066381	-0.186378	-0.153437	-0.127652
Standard Deviation	0.014348	0.010880	0.010707	0.018754	0.009385	0.010643	0.018978	0.015230	0.011630
Skewness	-1.77504	-1.20975	-0.99382	-0.650192	0.64718	-0.34453	-0.25940	-0.58882	-0.41175
Kurtosis	18.94431	23.75765	20.14351	8.32883	8.35516	6.75773	19.29484	11.37092	15.17436
Jarque-Bera	16,254.03	36,176.14	32,056.18	2,977.41	2,982.19	2,658.18	59,459.69	14,911.15	42,546.20
Probability	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
Number of Observations	1,462	1,988	2,583	2,375	2,358	4,371	5,369	5,008	6,858

Table 3 A
Results of Unit Root Test

	Brazil			South Africa			Korea			China		
	BOVA11	**PIBB11**	**SMAL11**	**GLDJ**	**STX40J**	**STXSWXJ**	**226490**	**233740**	**251340**	**159915**	**510050**	**510900**
Panel A: ADF t-stat for ETFs returns series												
Level	-57.96892	-65.86615	-18.55696	-46.73517	-65.21861	-68.14899	-16.35344	-33.88307	-32.83883	-44.43340	-57.88794	-43.34291
	(0.0001)	(0.0001)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)
First Difference	-23.80981	-28.71134	-23.01143	-27.71716	-20.44280	-22.29153	-17.10173	-15.48383	-14.46242	-20.40461	-22.28675	-20.31612
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)))	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	Ibovespa	**IBrX-50**	**BM&F Bovespa Small Cap Index (SMLL)**	**Gold**	**ALSI 40 Index**	**FTSE/JSE Swix Top 40 index**	**KOSPI Index**	**2 x KOSDAQ 150 Index**	**Inverse KOSDAQ 150 Index**	**GEM Index**	**SSE50 Index**	**Hang Seng China Enterprise (HSE) Index**
Panel B:ADF t-stat for Underlying Indexes returns series												
Level	-57.89839	-65.00120	-18.29233	-59.87171	64.66079	-57.39544	-16.58056	-34.56479	-32.44040	-45.21942	57.56976	-41,68303
	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0000)
First Difference	-23.69719	-28.45514	-23.11494	-24.83806	-22.06946	-20.01808	17.10274	-15.79175	-14.553,34	-20.92469	-22.15959	-17.88758
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)))	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Parentheses indicate the p-values.

Table 3 B
Results of Unit Root Test

	India			Mexico			United States		
	GOMS	**BIRN**	**NBES**	**ANGELD10**	**DIABLOI10**	**NAFTRAC**	**XLF**	**IWM**	**SPY**
Panel A: ADF t-stat for ETFs returns series									
Level	-36.37287	-33.85528	-49.70127	-35.22253	-46.57861	-62.03495	-81.66165	-79.90183	-90.28009
	(0.0000)	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
First Difference	-23.06992	-18.94887	-22.82327	-18.92220	-21.54505	-24.90942	-21.73019	-24.08126	-27.45485
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
	Nifty CPSE Index	**Nifty 50**	**Nifty 50**	**2 x IPC (Mexbol Index)**	**-1 x IPC (Mexbol Index)**	**IPC Index**	**Financial Select Sector (IXM)**	**Russell 2000 Index**	**S&P 500 Index**
Panel B:ADF t-stat for Underlying Indexes returns series									
Level	-37.93524	-15.51107	-50.74746	-45.14784	-47.07083	-61.78892	-83.04870	-78.64479	-91.19391
	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
First Difference	-20.86215	-19.35519	-20.00904	-22.77000	-20.62637	-24.69238	-22,45506	-23.24214	-28.00387
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Parentheses indicate the p-values.

Table 4
Tracking Error of ETFs across bullish and bearish merkets

		Brazil			South Africa			Korea			China	
	BOVA11	**PIBB11**	**SMAL11**	**GLDJ**	**STX40J**	**STXSWXJ**	**226490**	**233740**	**251340**	**159915**	**510050**	**510900**
TE (Overall)	0.00518***	0.00600***	0.01013***	0.00711***	0.00744***	0.01483***	0.00851***	0.00737***	0.00838***	0.01085***	0.00378***	0.02249***
Number of observations	2,818	3,851	2,698	3,862	3,977	3,161	1,149	1,062	911	2,039	3,294	1,829
TE (Bearish)	0.01328***	0.01120***	0.01664***	0.02276***	0.01456***	0.02251***	0.01418***	0.01310***	0.01274***	0.04093***	0.00522***	0.05594***
Number of observations	536	1,763	1,223	824	1,786	2,375	586	572	728	309	2,784	500
TE (Bullish)	0.00792***	0.01180***	0.02189***	0.01038***	0.01466***	0.03977***	0.01713***	0.01568***	0.02336***	0.01375*	0.01386***	0.03894***
Number of observations	2,282	2,088	1,475	3,038	2,191	786	563	490	183	1,730	510	1,329
Threshold	-0.01066	0.00000	0.00000	-0.01608	0.00000	0.00684	0.00030	0.00144	0.01071	-0.03046	0.01430	-0.00436

		India			Mexico			United States	
	GOMS	**BIRN**	**NBES**	**ANGELD10**	**DIABLOI10**	**NAFTRAC**	**XLF**	**IWM**	**SPY**
TE (Overall)	0.01766***	0.05102***	0.00690***	0.00701***	0.00973***	0.00436***	0.00319***	0.00305***	0.00284***
Number of observations	1,462	1,988	2,583	2,375	2,358	4,371	5,369	5,008	6,858
TE (Bearish)	0.03043***	0.07698***	0.01762***	0.00934***	0.01967***	0.01415***	0.00570***	0.00758***	0.00715***
Number of observations	603	1,427	439	2,019	1,363	655	2,355	1,110	1,168
TE (Bullish)	0.04056***	0.13333**	0.01038***	0.02861***	0.01911***	0.00642***	0.00562***	0.00494***	0.00435***
Number of observations	859	561	2,144	356	995	3,716	3,014	3,898	5,690
Threshold	0.00000	0.00447	0.00789	0.01671	0.00097	0.00885	0.00095	-0.00818	0.00722

*** denotes significance at 1% level, ** denotes significance at 5% level and * denotes significance at 10% level

4

Innovation Index for the Brazilian Market: A Proposal

4.1

Introduction

Research, Development, and Innovation (R, D & I, hereafter) is a key factor for the development of firms and countries. The analysis of the recent history of the international economy has demonstrated the growing importance of innovation in influencing the competitive strategies of companies and national development policies. As the so-called knowledge economy is consolidated, the world is increasingly witnessing the potential of innovation to produce small "revolutions" that have been changing the economic and business landscape, stimulating the growth and development of nations, and thus providing benefits to firms, communities, and individuals.

The growth of China and India in recent years (where India has doubled and China has tripled its relative share of world GDP) has been achieved, to a large extent, by incorporating, in an increasingly central way, technological innovation into development efforts (OECD, 2020).

Brazil has been seeking to advance innovation in national development policy over the past few years. Therefore, it is necessary to seek to increase the share of private investment in research, development, and innovation (R, D & I) in companies. OECD data (2018) reveal that, in Brazil, although the total investment in R, D & I is reasonably aligned with the average of the countries that make up the bloc (about 1.4% of GDP), private participation in this investment is still around 40% of the total, while in countries like the United States, South Korea, and Japan, this participation is over 70%.

This reality leads us to the following problem:

How to help increase the private appetite for investment in R, D & I activities in Brazilian companies?

To address this disorder, we investigate portfolios formed by companies that declare investments in research, development, and innovation in the stock market using different estimation models of the covariance matrix, from the simple sample covariance matrix to the matrix with shrinkage factor proposed by Ledoit & Wolf (2004a), comparing the results of these portfolios with the IBOVESPA index.

Our findings suggest that a portfolio formed by assets with a cap proportion of fifteen percent and with short sales restrictions outperforms the benchmark (IBOVESPA Index), as well as the Global Minimum Variance Portfolio (GMVP), the Market-Value and the Equally-weighted portfolios, both in and out-of-sample.

The main contributions of this study are twofold: first, it extends the literature regarding R, D & I investments and financial performance, by showing that it is possible, at least for the Brazilian market, to form an R, D & I intensive firms' portfolio that outperforms the market benchmark. And second, it corroborates with the view that even simple optimization techniques can obtain portfolios with better risk-return ratios, since market-value indexes, which are common in benchmarks, are by construction inefficient in Markowitz's sense (Gohout & Specht, 2007).

From this point on, the paper is organized as follows. Section 4.2 reviews the literature on the relationship between R, D & I investment and firm performance, as well as on portfolio management. Section 4.3 presents our method of portfolio formation, the sample composition, and the statistical summary. Section 4.4 presents the main results, and finally, Section 4.5 concludes the paper.

4.2 Literature Review

4.2.1 R, D & I Expenditures and Firm Performance

Since the seminal work conducted by Schumpeter (1934), several researchers have studied the relationship between R, D & I expenditures and firms' performance, with mixed outputs among sectors, firms' sizes, geography, and markets degrees of development.

The first studies on the relationship between investment in R, D & I and the future performance of firms emerged in association with the assessment of the impact of another intangible investment: the expenditure on Marketing. This association arose from the need to capitalize on the investments made in these two items and depreciate them over time since they generate value for several years after their realization.

Ben-Zion (1978), Griliches (1981), Hirschey (1982), Bublitz and Ettredge (1989), as well as Chauvin and Hirschey (1993), evaluated the effect of investment in Marketing and R, D & I on the value of the company, finding a positive relationship between them.

Sougiannis (1994) evaluated the relationship between investment in R, D & I and the firm's value and found evidence that indicates that the increase in investment in R, D & I promotes a five-fold increase in the company's market value.

Chan, Lakonishok, and Sougiannis (2001), however, found no evidence of an association between future return and intensity of R, D & I, when the latter is measured by investment in R, D & I on sales.

Eberhart, Maxwell, and Siddique (2004) analyzed the market reaction to the significant and unexpected increase in investment in R, D & I of North American companies between 1951 and 2001, reporting that both investors experience significant abnormal returns in the five years after the unexpected increase investment in R, D & I, as companies see a significant positive abnormal operating performance in the same period.

Lev, Radhakrishnan, and Ciftci (2006), in turn, when comparing the performance of leading and follower companies, the first being those that have a higher intensity of R, D & I to the industry, identified that the leading companies sustain better performance for at least four subsequent years, despite presenting worse profitability in the current year.

Nguyen, Nivoix, and Noma (2010) found no evidence of poor pricing of investment in R, D & I. Using both R, D & I / Sales and R, D & I / Market Equity the authors conclude that, at least in the Japanese market, investors adequately price the benefits of those expenditures.

Pandit, Wasley, and Zach. (2011) evaluated the relationship between innovation inputs and outputs and the future operational performance of companies. Using expenditure on R, D & I as a proxy for innovation inputs and patent citations for outputs, the authors also found a positive relationship between the quantity and quality of patents with the firm's future operating performance.

Hirshleifer, Hsu, and Li (2013) showed that the firm's innovative efficiency, measured by the number of patents or patent citations divided by the investment in

R, D & I, is strongly and positively associated with the presence of excess future returns.

Songur and Heavilin (2017) investigate the relationship between abnormal research and development investment change and expected stock returns. Considering all domestic stocks listed on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and NASDAQ over the 1975–2015 period, they provide evidence that firms that abnormally increase their R, D & I investments earn higher returns in comparison to the market portfolio.

Paula and Silva (2018) investigated the complementarity of internal and external R, D & I for innovation development and the effect of innovation on the financial performance of European manufacturing firms. Using multigroup structural equation modeling, they found evidence that partially supported that internal and external R, D & I are complementary in firms from high-technology industries, whereas they are not in firms from low-technology industries. However, the empirical analysis indicated that innovation performance did not influence short-term financial performance for the whole sample, although in countries strangled by the 2008 financial innovation seems to have helped firms to recover faster. This effect is in line with those shown in Lome, Heggeseth, and Moen (2016). Using binary logistic regression on a sample of 247 Norwegian manufacturers, they found that firms who devoted considerable resources to R, D & I activities performed significantly better than other firms through the late 2000s financial crisis.

Paula and Silva Rocha (2020) investigated the influence of internal R, D & I and patent applications by Latin American firms on firm performance. A sample of 751 firms from six Latin American countries showed that, when performance is measured by turnover growth, internal R, D & I has a positive influence and patents have a negative influence, and that internal R, D & I also affects patents, showing a negative indirect influence on performance.

Seo and Kim (2020), collecting data from 173 small and medium enterprises in Korea and employing hierarchical regression methodology, found that investment in intangible assets is not a waste of money, but on the contrary, has a positive effect on firms' profitability and value.

In Brazil, Hungarato, and Sanches (2006) carried out a study of events and identified a positive and significant variation in the abnormal returns of high-tech companies, after analyzing the price variation between 30 and 60 days after the disclosure of expenses with R, D & I.

Alves, Silva, Macedo, and Marques (2011), in turn, evaluated the relationship between spending on R, D & I and the share price for electricity distribution companies and, after controlling the impact of investment in R, D & I by Profit and Stockholders' Equity (PL), the variable was not significant.

Hungarato and Teixeira (2012) evaluated the relationship between spending on R, D & I and the share price and did not find a positive and significant relationship between these variables.

Fernandes, Gonçalves, and Perobelli (2013) assessed the impact of the number of patents generated and the investment in R, D & I on the value of firms between 2007 and 2009. Patent information was not significant and the investment in R, D & I was significant, but negative, suggesting that the market interprets R, D & I expenses exclusively as costs, and not as investments that will generate long-term benefits.

Da Silva, Klötzle Figueiredo, and da Motta (2015) studied the relationship between innovative intensity measured by investment in R, D & I and future return, evaluating the impact of these expenditures within three years after the year of their occurrence, for the period between 2005 and 2013, and did not find evidence of an association between investment in R, D & I and future returns. However, companies engaged in R, D & I had a positive and significant relationship with future operating performance as measured by profitability on the asset.

Further on, da Silva, da Motta, Klötzle, Pinto, and da Gama Silva (2018) studied the ability of Brazilian companies to appropriate the benefits associated with R, D & I investments, and analyzed 48 firms between 2009 and 2014, finding evidence that the capital market seems to ignore the ability of firms to efficiently allocate their R, D & I budgets, suggesting that innovations associated with sales increase produce future returns greater than those associated with cost reduction.

Carmona, Tomelin, Dani, and Hein (2017) investigate the relationship between investment in innovation, technological intensity, and performance of industrial sectors. Using secondary sources that consolidate data from more than 46,000 Brazilian industrial enterprises, the authors found, through a linear regression technique a positive interrelation between R & D expenditures with performance, represented by net sales, with a statistically significant explanatory power model.

On the other hand, Espíndola, Santos, and Vasconcelos (2018) analyzed the value relevance of disclosing R, D & I expenditures in Brazil's capital market between 2011 and 2015, examining a population of 440 public companies listed in B3. The authors claim that R, D & I expenditures disclosure and the value applied in R, D & I activities do not indicate a greater probability to gain a competitive advantage in the context of the Brazilian capital market.

Oliveira, Magnani, Tortoli, Figari, and Ambrozini (2019) analyzed Brazilian public firms, from 2009 to 2016, by panel data regressions, in a sample composed of 1,597 firm-year observations. The results show a negative and statistically significant relationship between current R, D & I expenses and current abnormal return, suggesting that R, D & I expenses tend to produce returns just in longer periods.

De Almeida Adriano, Medeiros, de Vasconcelos, and De Luca (2020) investigated the relationship between disclosure of spending on R, D & I and the level of innovation in Brazilian firms traded on B3, the relationship between corporate governance and this disclosure, and the relation of this disclosure and the market value, finding that sampled firms disclosing spending on R, D & I filed more patents and had higher market value than non-disclosing ones.

Almendra, de Vasconcelos, Aragão, and Cysne (2017) were, to the best of our knowledge, the first to investigate the influence of the capital structure in the investments in innovation of 120 industries in the Brazilian Market. From 2015 to 2015, considering short-term, long-term, and total debt as proxies for capital structure, and the number of registered patents and the percentage of expenditure in R, D & I to sales as proxies to investments in innovation, they found evidence that only the long-term and total debts have a positive influence on innovation investments through patents, suggesting that own resources may be insufficient to investments in innovation.

Due to ambiguous findings, and aiming to contribute to foster private investments in innovative activities at the firms' level, we investigate if it is possible to form a theoretical portfolio to the Brazilian market that captures listed companies that invest and declare to invest in innovation activities, aiming to analyze if that portfolio can overperform market benchmarks.

4.2.2

Portfolio Management

The usage of mean-variance approaches to perform portfolio selection is universally accepted by researchers and financial analysts. Markowitz (1952) was a pioneer in applying the concept of the efficient frontier to form diversified portfolios of risky assets, aiming to address the risk-return puzzle that emerged from the utility function of investors.

Formally, given a universe with N risky assets with average returns $\mu = (\mu_1, \mu_2, \ldots, \mu_N)'$ and the variance-covariance matrix Σ, Markowitz's problem consists in finding a weight vector $w = (w_1, w_2, \ldots, w_N)'$ that solves the following equation, given an expected average return r:

$$\min w'\Sigma w \text{ subject to } \Sigma_i \, wi = 1 \text{ and } w'\mu = r \qquad (1)$$

By solving this problem for several expected return levels, the efficient frontier is derived. In practice, to implement an efficient portfolio one has to estimate de variance-covariance matrix, besides assets expected returns.

Nevertheless, Merton (1980) advises that an estimation error, mainly in expected returns, could lead to poor results out-of-the-sample (Michaud, 1989; Best & Grauer, 1991). Thus, if an investor does not have a robust method to estimate expected asset returns, it could be advisable to ignore those returns and focus on the variance-covariance matrix (Jagannathan & Ma, 2003). In this case, the only achievable portfolio in the efficient frontier would be the Global Minimum Variance Portfolio (GMVP), which "is the portfolio with the smallest possible variation for any mean return" (Constantinides & Malliaris, 1995).

To address the expected returns estimation problem, Black and Litterman (1992) made an extraordinary contribution to the portfolio management theory, by incorporating a Bayesian interpretation where investors or portfolio managers have a prior belief on portfolio weights or assets expected returns, allowing them to control how strongly a particular view influences portfolios weights in accordance with the degree of confidence with which they hold their views, thus attenuating the common badly-behaved portfolios generated by Markowitz's problem-solving process.

Several empirical studies claim that GMVP produces, out-of-the-sample, risk-adjusted returns greater than other mean-variance based portfolios (Jorion, 1985, 1991; Jagannathan & Ma, 2003; Clark, De Silva & Thorley, 2006).

DeMiguel, Garlappi, Nogales, and Uppal (2007), by extending the work of Jagannathan and Ma (2003) and Ledoit and Wolf (2004a), provided a general framework for identifying portfolios that perform well out-of-sample even in the presence of estimation error, finding that the norm-constrained portfolios they proposed have lower variance and a higher Sharpe ratio than other strategies.

Disatnik and Benninga (2007) dealt with the construction of the covariance matrix for portfolio optimization and showed that, in terms of the ex-post standard deviation of the global minimum variance portfolio, there is no statistically significant gain from using more sophisticated shrinkage estimators instead of simpler portfolios of estimators. They claim this to be true both when short-sale constraints that prevent the portfolio weights from being negative are imposed as well as when they are not imposed.

Further on, DeMiguel, Garlappi, and Uppal (2009) evaluated the out-of-sample performance of the sample-based mean-variance model, and its extensions designed to reduce estimation error, relative to the equal-weighted, finding that none of the studied models was consistently better than the equal-weighted portfolio in terms of Sharpe ratio, certainty-equivalent return, or turnover, which indicates that, out-of-the-sample, the gain from optimal diversification is more than offset by estimation error.

Levy and Levy (2014) proposed two substantial extents to the constrained optimization approach: the Variance-Based Constraints (VBC), and the Global Variance-Based Constraints (GVBC) methods. By the VBC method the constraint imposed on the weight of a given stock is inversely proportional to its standard deviation: the higher a stock's sample standard deviation, the higher the potential estimation error of its parameters, and therefore the tighter the constraint imposed on its weight. GVBC employs a similar idea, but instead of imposing a sharp boundary constraint on each stock, a quadratic ''cost'' is assigned to deviations from the equally-weighted rule, and a single global constraint is imposed on the total cost of all deviations. They claim that those two new approaches are superior to ten other evaluated optimization tests.

Mainik, Mitov, and Rüschendorf (2015) performed a backtesting study of the portfolio optimization strategy based on the Extreme Risk Index (ERI). The performance of this strategy was benchmarked against the minimum variance portfolio and the equally weighted portfolio, two important benchmarks for large-scale applications. Their results showed that the ERI strategy significantly outperformed both the minimum-variance portfolio and the equally weighted portfolio on assets with heavy tails.

Bessler, Opfer, and Wolff (2017) proposed a sample-based version of the Black–Litterman model and implemented it on a multi-asset portfolio consisting of global stocks, bonds, and commodity indices, covering the period from January 1993 to December 2011. By testing its out-of-sample performance relative to other asset allocation models, they found that Black–Litterman optimized portfolios significantly outperform equal-weighted portfolios and consistently perform better than mean-variance and minimum-variance strategies in terms of out-of-sample Sharpe ratios, even after controlling for different levels of risk aversion, investment constraints, and transaction costs.

Hwang, Xu, and In (2018) showed that, for portfolios containing a relatively small number of stocks, equally-weighted portfolios outperform optimal mean-variance diversification and are less exposed to tail risk. However, for a relatively large number of stocks in the portfolio, equal-weighted portfolios maintain their superior performance but increase tail risk and result in more concave portfolio returns, implying that the outperformance of naive diversification acts as compensation for the increase in tail risk and concavity.

Xiong and Akansu (2019) compared the performance of the minimum variance, the market and eigen portfolios returns of US equities from 1999 to 2018, showing that the eigen portfolios (i.e., portfolios which returns are perfectly decorrelated and covariance matrices are diagonal) overperformed all other considered in the study, concluding that eigen portfolios provide a promising method to build new market indices for sectors and sub-sectors of interest.

Yan and Yan (2020) empirically investigated the out-of-sample performance of the equally-weighted portfolio rule and the Markowitz mean-variance strategies in the largest emerging market (i.e., China's A-shares market) and showed that some mean-variance optimization strategies can outperform the equally-weighted portfolio rule in China's A-shares market, while minimum-variance strategies cannot. Furthermore, they found an obvious advantage of mean-variance optimization when the number of assets is large and the estimation window is short (about 60 months), claiming that the results provide support for the use of optimal diversification strategies in emerging markets.

Çela, Hafner, Mestel, and Pferschy (2021) proposed a new approach to integrate qualitative views, in particular ordering relations among expected asset returns, in the well-known Black-Litterman (BL) framework, assuming investor views to be stochastic and adapt the BL-formula for the posterior expectation of asset returns, conditioned on ordering information. They found that this approach achieves the highest predictive power, irrespective of the dataset, the assumed level of accuracy of the ordering information, and mostly irrespective of the investor's confidence in the qualitative view, even though the improvement resulting from this approach is moderate, observing a similar behavior in the context of portfolio performance analysis.

In Brazil, Caldeira and Portugal (2010) claim that the covariance matrices used to optimize portfolios based on mean-variance analysis are difficult to estimate, and so ad hoc methods often need to be applied to limit or smooth the efficient allocations recommended by the model. Using a cointegration methodology to devise two quantitative strategies (index tracking and long-short) aiming to design optimal portfolios acquiring the asset prices co-movements, they found that index-tracking portfolios replicated the benchmarks return and volatility, while the long-short strategy generated stable returns under several market circumstances, presenting low volatility.

Thomé Neto, Leal, and Almeida (2011) developed an index of global minimum variance portfolio (MVP) for the most liquid stocks in Brazil, finding that the imposition of a ten percent ceiling on the MVP weights for each asset made it possible to beat the IBOVESPA Index.

Santos and Tessari (2012) assessed the out-of-sample performance of two alternative quantitative portfolio optimization techniques – mean-variance and minimum variance optimization – and compared their performance concerning an equally-weighted portfolio and also to IBOVESPA Index. Focusing on short-selling-constrained portfolios and considering alternative estimators for the covariance matrices, they claim that the quantitative approaches delivered improved results in terms of lower portfolio volatility and better risk-adjusted returns.

Rubesam and Beltrame (2013) also investigated minimum variance portfolios in the Brazilian equity market using different methods to estimate the covariance matrix, comparing their performance to the IBOVESPA Index and other three benchmarks, finding evidence that the minimum variance portfolios have higher returns with lower risk compared to all of the benchmarks.

In recent research, Fernandes, Street, Fernandes, and Valladão (2018) proposed an investment strategy based on the Black-Litterman model (Black and Litterman, 1992) with conditional information using Brazilian data and showed that the resulting optimal portfolios outperformed traditional mean-variance portfolios even in an emerging market with one of the highest nominal interest rates.

By this literature review, it is worth to notice that several techniques could improve the results of the classic Markowitz's mean-variance optimization process, either by adopting different methods for estimating variance-covariance matrices or by adopting different techniques for estimating the expected returns on assets, in order to improve the performance of the out-of-the-sample portfolio.

4.3
Research Methodology and Data

There are commonly three types of indexes: 1. Price-weighted, 2. Equally-weighted, and 3. Value-weighted. Since there are flaws in the interpretation of returns with price-weighted stock indexes, we decided not to consider it as a plausible option to construct the innovation index portfolio (INVX, hereafter).

Equally-weighted would be where one calculated the daily returns for each stock in his/her index, i.e., (Price today + Dividend - Price yesterday)/(Price yesterday). This is in decimal form. Then one sum the returns for that day for all the stocks that comprise his/her stock index. Then one divides that sum by the number of stocks in his/her stock index. By repeating that calculation for each day of the period of the study. If the considered periodicity is other than daily, e.g., weekly, monthly, quarterly, annual, then one should do the same procedure with the different period.

Market value-weighted takes each daily return of each stock in the index and multiplies it by the market value weight of that stock in the index. First, one should compute the market value of the stock (Stock price multiplied by the number of common shares). Then sum all the market values of all the stock in the index. Then calculate the market value weight of each stock by dividing its market value by the market value of the stock index.

This should be done for each day, for as long as the period of the study. Again, one can switch to other periods (weekly, monthly, etc.) as needed.

The sample consists of all stocks listed on the Brasil Bolsa, Balcão, (B3) on December 31st , 2019, excluding financial firms and those that did not have the following attributes:

1. Consecutive monthly quotes for a period of 12 months before the portfolios were formed;
2. Equity market value higher than R$ 10 Billion (Ten billion reais);
3. Positive book value, with a tolerance of five days; and
4. Positive ratio (Investment in R, D &I / Net Revenues) on the fiscal year ended on December 31st, 2019.

The monthly closing values of IBOVESPA, the average monthly quotes and closing of shares, with adjustment of earnings and dividends in the period from 2015 to 2019 were obtained from the Thomson-Reuters database, i.e., sixty observations for each asset. The information about investment in R, D & I was obtained in the annual financial statements available in the Securities and Exchange Commission of Brazil website in 2020. The portfolios were formed with a three-month delay from the publication of data on investment in R, D & I; in Brazil, companies have until March 31st of the following year to publish their financial statements. Thus, the classification of the “innovative firms” comprising a portfolio formed in July 2020, for example, considers the investment in R, D & I in 2019, the notification of which may be made until March 31st , 2020. This delay is to ensure that all investors have access to information and sufficient time to incorporate it into their pricing processes. Observing these criteria, we obtained a sample of 349 firms for the period analyzed, of which, 94 reported investment in R, D & I. Nevertheless, only 13 firms had equity market value higher than R$ 10 Billion, and those firms were considered to form the INVX theoretical portfolio. This number is close to what is considered ideal by Ceretta and Costa Jr. (2000).

Our main goal in this study was to consider another approach to forming the INVX theoretical portfolio, since both equally-weighted and value-weighted portfolios are commonly inefficient (Gohout & Specht, 2007). Focusing on it, we formed four different portfolios:

1. Equally-weighted portfolio (EW);
2. Market-valued portfolio (MV);
3. The Global Minimum Variance portfolio (GMVP);
4. Optimized portfolio, with the restriction of non-short-sales and a ceiling of 15% maximum weight of each asset (NSS-15).

Although this number is arbitrary, it finds support in the literature. Thomé Neto et al. (2011) claim that best results are obtained with maximum weights of 10% per share, with worse performances as this value increases. Our main results, obtained with a maximum weight of 15% per share, were better than results with a maximum weight of 10%, and we observed that results with higher values, although better in performance, caused an important concentration in few assets, what could drive to a lack of diversification.

We considered four methods to estimate the variance-covariance matrix:

1. Historical Data (Markowitz, 1952);
2. Single Index Model (Sharpe, 1963);
3. Constant Correlation Model (Elton & Gruber, 1973); and
4. Shrinkage Model (Ledoit & Wolf, 2004a).

The simplest model for estimating the covariance matrix consists of use the sample covariance matrix (Historical data). A criticism common to this method is the low efficiency in estimating, especially when the number of assets is large, since the total number of parameters to be estimated grows exponentially. The traditional statistical method is based on the hypothesis of independent returns and identically distributed (i.i.d.), and consists of calculating the sample covariance matrix using a sample of time series of asset returns in a recent period. The covariance between assets i and j is estimated by:

$$\hat{\sigma}_{ij} = \frac{1}{T}\sum_{t=1}^{T}\left(r_{i,t} - \bar{r}_i\right)\left(r_{j,t} - \bar{r}_j\right) \tag{2}$$

Where $r_{i,t}$ is the return of asset i in day t and $\bar{r}_i$ is the sample mean of returns.

The Single-Index model (SIM) began as an attempt to simplify some of the computational complexities of calculating the variance-covariance matrix (Sharpe, 1963). The basic assumption of the SIM is that the returns of each asset can be linearly regressed on a market index x:

$$\widetilde{r_i} = \alpha_i + \beta\widetilde{r_x} + \tilde{\varepsilon}_t \tag{3}$$

where the correlation between εi and εj is zero. Given this assumption, it is easy to establish the following two facts:

$$E = (\widetilde{r_\iota}) = \alpha_i + \beta\widetilde{r_x} + \tilde{\varepsilon}_t \tag{4}$$

$$\sigma_{i,j} = \begin{cases} \beta_i\beta_j\sigma_x^2 & \mathrm{i} \neq j \\ \sigma_i^2 & \mathrm{i} = j \end{cases} \tag{5}$$

Essentially the SIM assumes involves changes in the estimates of the covariances, but not the sample variance. In our case, we regressed returns of each asset on the IBOVESPA Index, getting the betas.

The Constant Correlation model (Elton & Gruber, 1973) computes the variance-covariance matrix by assuming that the variances of the asset returns are the sample variances, but that the covariances are all related by the same correlation coefficient, which is generally taken to be the average correlation coefficient of the assets in question. Since $\mathrm{cov}\left(r_i, r_j\right) = \sigma_{ij} = \rho_{ij}\sigma_i\sigma_j$, this assumption means that in the constant-correlation model:

$$\sigma_{i,j} = \begin{cases} \sigma_{ii} = \sigma_i^2 & \mathrm{i} = j \\ \sigma_{ij} = \rho\sigma_i\sigma_j & \mathrm{i} \neq j \end{cases} \tag{6}$$

The Shrinkage model (Ledoit & Wolf, 2004a) has recently achieved popularity. This method assumes that the variance-covariance matrix is a convex combination of the sample covariance matrix and some other matrix:

$$\text{Shrinkage Var-Cov matrix} = \lambda * \text{Sample Var-Cov} + (1 - \lambda) * \text{Other matrix} \tag{7}$$

In our case, the other matrix is the identity matrix, with variances in the diagonal and 0 otherwise. There is still a little theory on how to proper choose the shrinkage operator λ, and following Ledoit & Wolf (2004a), we selected a λ that generated a wholly positive GMVP.

4.4

Results and Discussion

To compare the different portfolio allocation strategies, a data set comprising the monthly observations of N = 13 assets that were selected following the criteria shown in section 3, as well as the IBOVESPA Index over the period between December 2014 to December 2019, making a total of L = 60 monthly returns. The returns were calculated as the difference in price logarithms and the risk-free rate used to calculate excess returns was the monthly CDI. The data were obtained from the Thomson-Reuters database. Table 1 shows the 13 shares traded on B3 that were used in this study, as well as the main descriptive statistics obtained from the sample of the monthly returns of each asset.

Table 1
Descriptive statistics of the returns on assets used in the optimization process

Code	Mean	Std-dev	Min	Max	Skewness	Kurtosis
VALE3	0.017705	0.128693	-0.325462	0.265747	-0.254796	3,2333
PETR4	0.019796	0.141786	-0.325193	0.480406	0.369741	4,0712
WEGE3	0.020539	0.068040	-0.151488	0.176422	-0.218643	2,8670
SUZB3	0.012566	0.091495	-0.239235	0.427744	1217482	1,0320
NTCO3	0.003234	0.135037	-0.667117	0.266879	-1908847	1,1437
CPFE3	0.011742	0.072680	-0.270140	0.178822	-1074239	6,5206
EGIE3	0.017229	0.060629	-0.100565	0.250874	0.843117	5,1768
CMIG4	0.006629	0.125577	-0.228219	0.432104	0.731804	4,4351
EQTL3	0.028898	0.064548	-0.157365	0.168272	-0.387935	3,4787
BRKM5	0.014672	0.121871	-0.340480	0.267381	-0.201691	3,0811
BRFS3	-0.009070	0.103131	-0.270452	0.315439	0.439860	3,9882
CIEL3	-0.013005	0.100733	-0.326822	0.294967	-0.133107	4,2074
EMBR3	-0.002960	0.086250	-0.234321	0.249792	-0.100530	4,4671

Table 2 presents a statistical summary of the performance of the portfolios in the whole period. Since the constant correlation model presented the variance-covariance matrix with the best performance for the sample considered, the four portfolios were formed using this matrix in the optimization process (complete data available with the authors by request).

The non-parametric Wilcoxon order sum test was used to evaluate the statistical difference between the series of returns. Fay and Proschan (2010) ensure that this test is widely used and is probably more effective than the t-test when the data cannot be said to present normal distribution.

$$W = \Sigma_{i=1}^{n}\left[\mathrm{sgn}\left(x_{2,i} - x_{1,i}\right) x\, R_i\right] \tag{8}$$

Hawke and Kossowski (2011) state that it is necessary to assume that the sample analyzed has normal distribution to use Pearson’s correlation coefficient. Spearman's correlation coefficient is a non-parametric statistic that does not require assumptions about data distribution and that allows the detection of non-linear relations and was therefore used as the correlation measure in this study.

$$\rho = \frac{\left(1-6\sum_{i=1}^{n} d_i^2\right)}{n^3-n} \tag{9}$$

Except for the Market-value portfolio (MV), all the others presented a standard deviation smaller than the IBOVESPA, as expected. In this study, Equally-weighted (EW) portfolio was the only one to underperformed IBOVESPA, while all the others outperformed it. This goes against the findings in previous studies in the Brazilian market (Thomé Neto et al., 2011; Santos & Tessari, 2012; Rubesam & Beltrame, 2013). When applying a fifteen percent ceiling in the non-short-sales portfolio, the number of assets in the portfolio decreases to nine and could be an attention point when it comes to diversification. As in the IBOVESPA, portfolios were not balanced on monthly basis, since the goal of INVX is to be an index annually reviewed, and its portfolio will last from July of a year to June the next.

Table 2
Summary statistics of the returns on INVX portfolios and IBOVESPA Index

	IBOVESPA	INVX - EW	INVX - GMVP	INVX - MV	INVX- NSS-15
Mean	0.014100	0.009844	0.015157	0.016590	0.017874
Median	0.008175	0.005556	0.012382	0.020296	0.017453
Maximum	0.156724	0.105723	0.141803	0.242704	0.126948
Minimum	-0.115078	-0.099852	-0.070267	-0.203662	-0.092667
Std. Dev.	0.057604	0.045316	0.039044	0.082426	0.045574
Skewness	0.086097	6.93E-05	0.296673	-0.018119	0.028247
Kurtosis	2,6836	2,7570	4,0450	3,8477	2,8061
Jarque-Bera	0.324351	0.147563	3.610	1.799	0.101973
Probability	0.850292	0.928875	0.164450	0.406615	0.950291
Sum	0.846020	0.590652	0.909448	0.995420	1.072435
Sum Sq. Dev.	0.195778	0.121158	0.089940	0.400845	0.122540
Wilcoxon	n/a	0.375278	0.223067	0.070857	0.532737
(p-value)	n/a	(0.7075)	(0.8235)	(0.9435)	(0.5942)
Spearman	n/a	0.898194	0.764601	0.859961	0.843512
(p-value)	n/a	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Observations	60	60	60	60	60

All portfolios show a high, positive, and significant at the one percent level correlation with the IBOVESPA.

The Wilcoxon test results reject the null hypothesis that the difference between the returns of IBOVESPA and the returns of all portfolios follows a symmetric distribution around zero.

Figure 1 shows the accumulated monthly return (in-the-sample) of IBOVESPA and the four INVX portfolios for the period from December 2014 to December 2019. It is possible to notice that, as expected, all the portfolios have a similar behavior, starting to distance themselves from IBOVESPA from July 2015. Highlight INVX MV and INVX NSS-15, whose cumulative performances in-the-sample were superior to the IBOVESPA. The INVX NSS-15 theoretical portfolio had, in-the-sample, an average return of 1.79%, a standard deviation of 4.56%, and a Sharpe Ratio of 35.49%, while the IBOVESPA index presented an average return of 1.41%, standard deviation of 5.76%, and a Sharpe Ratio of 21.53%.

We used the Sharpe Ratio (Sharpe, 1994) as a measure of the performance of an investment (e.g., a security or portfolio) compared to a risk-free asset, after adjusting for its risk. It is defined as the difference between the returns of the investment and the risk-free return, divided by the standard deviation of the investment (i.e., its volatility). It represents the additional amount of return that an investor receives per unit of increase in risk. In our case, we use the monthly CDI as a proxy of the risk-free rate.

$$Is = \frac{E(r_i - r_f)}{\sigma_i} \tag{10}$$

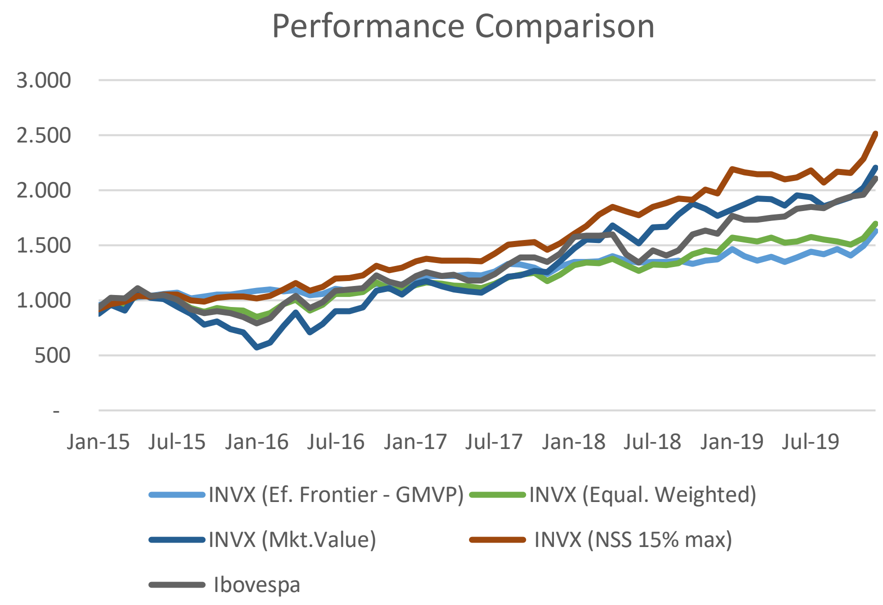

Figure 1 – Accumulated performance comparison among IBOVESPA and INVX portfolios.

Figure 2 exhibits the “out-of-sample” performance comparison between IBOVESPA and INVX – NSS 15, which was the best performer portfolio in-the-sample. We use the term “out-of-sample” to indicate that a result is obtained in a period after the formation of the portfolio, i.e., using data after those used in estimation. For example, if a portfolio is formed using the series of returns historical data for the year 2000 and the portfolio's performance is calculated for the year 2001, this result is out-of-sample. If we evaluate the result in the year 2000, this result will be “in-the-sample”. The distinction is essential; the results obtained outside the sample are relevant to guide investment choices in practice, as they represent which, in principle, could have been produced in reality. In our case, we ran the test “out-of-sample” as a robustness check in 2020, and even in an extreme event such as the Sars-Cov-2 pandemic, the results hold. The INVX NSS-15 theoretical portfolio had, out-of-sample, an average return of 1.20%, a standard deviation of 9.51%, and a Sharpe Ratio of 10.81%, while the IBOVESPA index presented an average return of 0.20%, standard deviation of 12.92%, and a Sharpe Ratio of 0.20%.

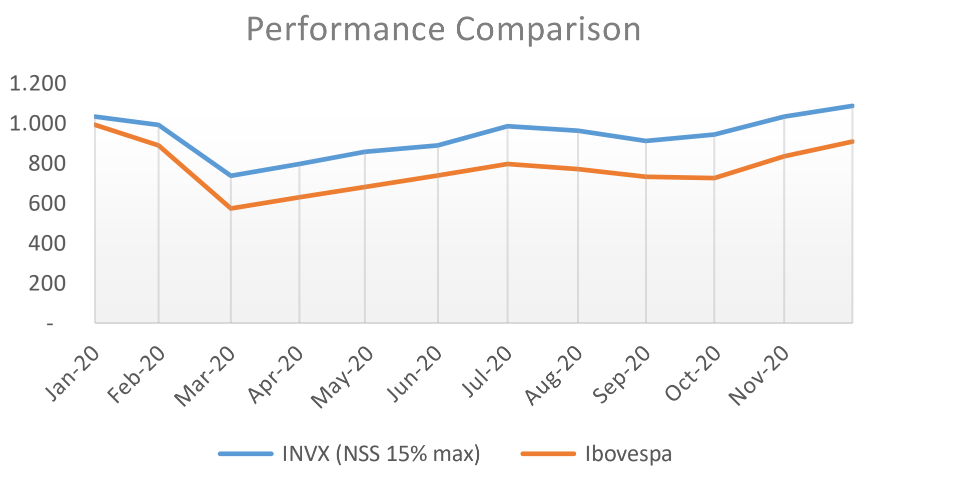

Figure 2 – Accumulated performance comparison between IBOVESPA and INVX NSS-15 portfolio.

4.5

Conclusions

We investigated whether is possible or not to obtain portfolios formed by companies that declare investments in research, development, and innovation in the Brazilian stock market using different estimation models of the covariance matrix, from the simple sample covariance matrix to the matrix with shrinkage factor proposed by Ledoit & Wolf (2004a), comparing the results of these portfolios with the IBOVESPA index. The results showed that it is possible to form a portfolio only with long positions and with a maximum of 15% participation of each asset that has a higher return and lower volatility than the benchmark (INVX).

The index is an instrument that serves to measure the return of applications in a theoretical portfolio of innovative companies. This instrument can be used by the market as a beacon for investment policies and can be replicated by any investor. The product is expected to encourage agents to invest in companies participating in the index, providing greater liquidity and volume could be an alternative index to capture companies in the Brazilian market that invest and declare to invest in innovation activities, considering the restrictions assumptions in the study.

Our main contributions with this study are twofold: first, it extends the literature regarding R, D & I investments and financial performance, by showing that it is possible, at least for the Brazilian market, to form an R, D & I intensive firms' portfolio that outperforms the market benchmark. And second, it corroborates with the view that even simple optimization techniques can obtain portfolios with better risk-return ratios, since market value indexes, which are common in benchmarks, are by construction inefficient in Markowitz's sense (Gohout & Specht, 2007).

The out-of-the sample performance of the INVX suggests that even in a highly turbulent period as we faced with the novel Sars-Cov-2 pandemic in 2020, it is possible to form an innovative intensive companies' portfolio that could outperform the most important benchmark for the Brazilian market, the IBOVESPA index.

Our results suggest that creating an exchange-traded fund (ETF) based on the INVX portfolio with limited weights can generate an attractive financial product since it seems to overperforms the IBOVESPA Index. The strategy can also be easily replicated by investment clubs and even by individual investors who are willing to do the calculation of weights every year, an easily solved problem with an Excel® spreadsheet. The INVX could also be developed and used as a benchmark for innovative companies' performance, in alternative to the IBOVESPA index. This product may encourage other firms to increase their R, D & I investments, or even properly disclose them, aiming to be part of the INVX theoretical portfolio and take advantage of the increase in negotiation volumes of their shares, as well as contributing to improving informational guide to the financial market.

As a suggestion for future research, new approaches to portfolio optimization could be implemented, like Black-Litterman, Bayes-Stein, and Bayes diffuse prior (Platanakis, Sutcliffe, & Ye, 2021). The sample could also be extended, and high-frequency data could be considered to check if results hold.

5
Conclusion

This thesis attempted to address an important issue concerning fostering innovation investments in an emerging market: How to stimulate private investors to increase their participation in Research, Development and Innovation (R, D & I) activities.

The first essay studied the investor behavior in exchange-traded fund (ETF) markets. By applying the standard feedback trading model of Sentana and Wadhwani (1992) in a sample of 18 ETFs contracts in Brazil, China, South Africa, Korea, Mexico and India, as well as three ETFs contracts in the US market, it was possible to identify evidence of feedback trading in emerging markets such as Brazil, Korea, Mexico and India, while there is no such evidence for the US market. The results are consistent with the view that developed markets investors are prone to pursue fundamental-driven investment strategies, while emerging markets investors appear to have informational guided behavior. Emerging markets policy makers could benefit from these findings by stimulating new mechanisms that could minimize informational asymmetry and the persistence of noise traders.

The second essay expanded the first one's database to investigate another important characteristic of this important financial innovation: the tracking efficiency. It was found that emerging markets ETFs are prone to exhibit higher tracking errors than developed markets ETFs, and this effect appears to be even higher when in a bearish market.

The third essay attempted to verify if it were possible to propose an Innovation Index for the Brazilian market, that could serve to measure the return of applications in a theoretical portfolio of innovative companies. This instrument can be used by the market as a beacon for investment policies and can be replicated by any investor. The product is expected to encourage agents to invest in companies participating in the index, providing greater liquidity and volume.

The main objective of the Innovation Index is for the market to recognize which public companies are the ones that most invest in innovation and be able to assess whether the innovation effort of these companies is reflected in greater value for its shareholders. The good performance of this index will stimulate greater demand for papers from these companies, increasing its value and stimulating investment in innovation in other companies and even the IPO of other innovative companies in Brasil, Bolsa, Balcão (B3).

In Brazil, the financial market and the instruments at its disposal are still extremely limited, and the creation of an Innovation Index and Exchange-Traded Fund (ETF) that replicates it could contribute to dynamize this industry.

ETFs are investment vehicles similar to mutual funds, but whose shares are traded on the stock exchange at a price established in the market, that is, the value of the quota is determined by conditions supply and demand and according to the trading rules of the exchange on which they are listed.

Since their appearance in the United States in the early 1990s, ETFs have become quite popular investment vehicles, to the point that in 2015 they exceeded the size of the hedge fund industry, accumulating more than US$ 7.7 trillion of assets under management worldwide. According to the SEC (Securities and Exchange Commission), in the United States alone there were almost 2,200 funds listed at the end of 2020.

In addition to pioneers, the United States is also the largest ETF market in the world, with nearly two-thirds of the industry's global equity, followed by United Kingdom, Germany, Japan, and France as the five largest markets by total assets under management.

According to a survey by the ETFGI consultancy, there are approximately 12,5 thousand ETFs listed, in more than 60 exchanges, in 51 countries. In Brazil, the numbers are still modest. There are currently 24 ETFs listed on B3 referenced to stock indexes, two of which are foreign (referenced to the S&P 500). These funds reached, in December 2020, total equity of R$ 37.5 billion, with a daily turnover above R$ 1.4 billion.

This research fills an important gap in the field of Business Administration, by proposing the creation of the Innovation Index (INVX) for the Brazilian market, as well as the launch of financial products, such as ETFs, related to this index, seeking to understand the main obstacles and driving factors of the capital market in the country.

In this way, this research aims to foster the creation of financial innovations that allow better planning and development of companies in Brazil, thus contributing to the country's growth.

6

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