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Investor behavior in ETF markets: a comparative study between the US and emerging markets

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Abstract

Purpose – The purpose of this paper is to present the results of a study on investor behavior in exchange-traded fund (ETF) markets. The standard feedback trading model of Sentana and Wadhwani (1992) is used 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.

Design/methodology/approach – The sample includes data on daily closing prices and net asset values (NAVs) for three ETFs from each of the emerging markets of Brazil, China, Mexico, Korea and India, as well as on three ETFs from the US market. The authors used the earliest start date available in the Thomson Reuters database pertaining to all of the ETFs, and all series ended on May 5, 2017, and applied the well-established Santana and Wadhwani (1992) seminal model to evaluate evidence of feedback trading in the sample.

Findings – The empirical analysis suggests that there is 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.

Research limitations/implications – Emerging markets still make up a very small part of the global ETF market, led by the USA. Nevertheless, 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 the efficiency of information sharing and rationalization of its operations.

Practical implications – Emerging markets policy makers could benefit from these findings by stimulating 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).

Originality/value – The behavior of investors was investigated by analyzing a sample of 18 ETFs from the emerging markets of Brazil, China, South Africa, Korea, India and Mexico, as well as three ETFs from the US market. Despite of being investigated separately both emerging (Charteris *et al.*, 2014) and developed markets (Chau *et al.*, 2011), the innovation consists in comparing those markets in a single study, pursuing to explain potential reasons for the differences observed between developed and emerging markets.

Keywords Financialization, Investor behaviour, ETF, Feedback trading

Paper type Research paper

1. Introduction

Exchange-traded funds (ETFs) 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.

JEL Classification — G10, G15, G23

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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 percent of their market value (Charteris *et al.*, 2014). However, from 1993 onwards, with its launch in the USA, 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.) (World Federation of Exchanges Monthly Statistics, 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) and commodities (exchange-traded commodities). This set of structured products traded on the stock Exchange is generically named exchange-traded products, which are 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 10,000 ETFs globally and over US$13 trillion in assets (World Federation of Exchanges Monthly Statistics, 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 *et al.* (2011) extended Sentana and Wadhwani's (1992) seminal model of feedback trading in an empirical analysis of the three largest ETFs in the USA 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 US 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 US market, highlighting the effects of feedback trading on investor behavior in these markets.

This study is structured into sections as follows: Section 2 briefly reviews the most recent literature. Section 3 describes the study's methodology and data. Section 4 presents the results and discussion of the main findings. Section 5 presents the global financial crisis (GFC) effects in our sample. Lastly, the conclusion is presented in Section 6.

2. Literature review

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 (2017) argues that the 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 Previous studies on ETFs

One of the core tenets of the 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 US 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 US 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 very 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 *et al.* (2011), and examined the ultrahigh-frequency (1-min intervals) price data from three major ETFs in the US market (DIA, SPY and QQQQ). The author found evidence of negative price deviation (discount) in the DIA and QQQQ prices 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 paper, 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 are higher than the NAV of the assets that make up the benchmark tracked by the ETF the day before. Through the analysis of an ETF 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 *et al.* (2016) analyzed a sample of 19 ETFs in the US 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 GFC.

Ivanov (2016) analyzed the 100 largest ETFs in the US market, and found evidence suggesting that uninformed investors prefer to invest in ETFs rather than stocks or other investment funds 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 US market.

Using a panel VAR approach (Hasbrouck, 1991), Shank and Vianna (2016) examined the behavior of US-listed currency-hedged ETF investors toward 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 has implications for the further financialization of the ETF industry.

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 US 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. Sentana and Wadhwani's (1992) model used in this study incorporates the innovations brought by Bollerslev (1986) in the proposal of the generalized autoregressive conditional heteroskedasticity (GARCH) 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.

Kallinterakis 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's (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 *et al.* (2015) examined investor herding behavior for ten Pacific-Basin markets, as well as the USA. 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 USA, 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 percent of the transactions, of which 9 percent were positive and 14 percent negative. They used Sentana and Wadhwani's (1992) model, demonstrating the model's capacity to explain the behavior of investors toward 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 evidences 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.

3. Data and methodology

Table I contains information regarding our sample and includes data on daily closing prices and NAVs 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. 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 May 5, 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

ETF	Launch date	Market
BOVA11 – IShares Ibovespa	December 2, 2008	Brazil
PIBB11 – It Now PIBB IBrX-50	July 27, 2004	
SMAL11 – iShares BM&FBOVESPA Small Cap	December 2, 2008	
GLDJ – NewGold	November 2, 2004	South Africa
STX40J – Satrix 40	June 1, 2004	
STXSWXJ – Satrix Swix Top 40	September 3, 2007	
226490 – Samsung KODEX KOSPI 200 Securities	August 24, 2015	Korea
233740 – Samsung KODEX Leverage	December 17, 2015	
251340 – Samsung KODEX Inverse	August 10, 2016	
159915 – E Fund ChiNext	December 9, 2011	China
510050 – ChinaAMC China 50	October 16, 2006	
510900 – E Fund Hang Seng China Enterprises QDII	October 22, 2012	
GOMS – Goldman Sachs CPSE	May 20, 2014	India
BIRN – BIRLA Sun Life Nifty	July 27, 2011	
NBES – Goldman Sachs Nifty BeE	November 9, 2009	
ANGELD10 – Smartshares-ANGELD	October 27, 2010	Mexico
DIABLOI10 – Smartshares-DIABLOI	October 27, 2010	
NAFTRAC – iShares NAFTRAC	April 30, 2002	
XLF – Financial Select Sector SPDR	December 16, 1998	USA
IWM – iShares Russell 2000	May 26, 2000	
SPY – SPDR S&P 500	January 29, 1993	

Table I.
Selected ETFs by market and series launch date

aversion coefficient and ${\sigma_t}^2$ 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 quantity 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 0, and for negative, it is less than 0.

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:

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

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

$$r_t = \alpha - \gamma r_{t-1}\theta\sigma_t^2 + \theta\sigma_t^2 + \varepsilon_t. \tag{5}$$

Equation (5) shows that the first-order autocorrelation of returns varies according to market risk ${\sigma_t}^2$, 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.

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

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

Equation (6) measures the effect of existing market frictions through the coefficient φ_0, whereas φ_1 measures the presence of feedback trading. Given $\varphi_1 = -\theta\gamma$, if $\varphi_1 < 0$ 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 threshold GARCH) and exponential GARCH, may be more appropriate to capture another very 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 et al. (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 vs 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 0 otherwise; if the dummy's coefficient is found to be statistically significant, this would imply an asymmetric impact on behalf of positive vs negative innovations over volatility. Results are shown in Table II (A and B) and, since dummies' coefficients θ were found statistically significant at least at 10 percent, 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:

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

where 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 0 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:

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

In order to empirically estimate Equation (6), we define the conditional variance as an asymmetric GARCH process (Glosten *et al.*, 1993):

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

where 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 0. A significantly positive δ value indicates that a negative shock increases the volatility more strongly than a positive shock.

Table II.
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	226,490	233,740	251,340	159,915	510,050	510,900
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)

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			USA		
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)

Note: Parentheses include the p-values

4. Results and discussion

The descriptive statistics (mean, standard deviation, asymmetry and kurtosis) for the log-returns of the sample are found in panel A of Table III (A and B). All sampled ETFs displayed a leptokurtic distribution at 1 percent significance, and 13 of the 21 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 percent for 14 of the 21 ETFs and at 5 percent for 2 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 percent 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 of Table III (A and B) shows the 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 percent), 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 percent.

Table IV (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 percent 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 $(\beta+\delta)/\beta$. 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 a first-order autocorrelation. The φ_1 feedback trading coefficient (the main object this study), was statistically significant at 1 percent 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 US 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 US 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 V. We found evidence indicating a relationship between feedback trading and the occurrence of discounts in the three ETFs of the Brazilian and

Table III.
Descriptive statistics

	Brazil			South Africa			Korea			China		
	BOVA11	PIBB11	SMAL11	GLDJ	STX40J	STXSWXJ	226,490	233,740	251,340	159,915	510,050	510,900
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***	7,592.20***	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
No. of days with a premium	1.160	768	1.153	1.701	1.082	1.273	216	154	88	582	963	503
No. of 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
No. of days when premium > 0.25%	398	199	448	1,308	233	619	144	129	72	261	258	364
No. of days when premium > 0.50%	165	97	238	992	83	295	88	110	52	94	59	259
No. of days when premium > 0.75%	61	64	138	749	38	156	53	95	38	38	27	198
No. of days when premium > 1.00%	32	41	85	558	23	88	28	80	26	19	14	160
No. of days when discount < −0.25%	168	1.753	374	679	383	588	135	183	79	418	624	505
No. of days when discount < −0.50%	34	1.443	210	462	154	359	80	162	62	174	181	334
No. of days when discount < −0.75%	12	1.151	148	321	75	215	47	143	39	79	120	190
No. of days when discount < −1.00%	7	881	114	236	36	115	31	123	32	39	92	85

(*continued*)

Table III.

Panel C: properties of daily changes in percentage price deviations												
No. of days when change > 0.25%	335	763	511	1.056	470	650	153	142	83	375	518	402
No. of days when change > 0.50%	95	451	286	821	205	393	113	126	70	192	142	254
No. of days when change > 0.75%	48	265	190	634	102	271	81	115	55	101	47	169
No. of days when change > 1.00%	24	167	133	491	62	185	62	105	44	65	26	103
No. of days when change < −0.25%	312	764	524	1.043	466	681	169	169	71	380	525	398
No. of days when change < −0.50%	98	467	308	806	202	417	121	154	57	201	121	271
No. of days when change < −0.75%	50	279	199	628	102	274	85	137	52	95	43	170
No. of days when change < −1.00%	28	165	137	506	66	170	67	122	47	54	19	104

		India			Mexico			USA	
	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
No. of days with a premium	123	664	812	1.084	762	1.187	2.287	1.918	3.239
No. of 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

(*continued*)

Table III.

Average discount (%)	−0.27	−5.43	−0.33	−0.34	−0.11	−0.24	−0.13	−0.17	−0.12
No. of days when premium > 0.25%	45	650	370	549	50	708	325	228	302
No. of days when premium > 0.50%	8	634	166	229	17	438	68	28	46
No. of days when premium > 0.75%	4	618	27	80	12	253	27	4	21
No. of days when premium > 1.00%	1	601	9	37	10	128	14	3	6
No. of days when discount < −0.25%	387	823	533	230	78	174	302	394	423
No. of days when discount < −0.50%	22	801	297	103	28	55	76	95	89
No. of days when discount < −0.75%	3	778	127	68	17	21	26	35	29
No. of days when discount < −1.00%	2	759	17	46	15	10	17	15	12
Panel C: properties of daily changes in percentage price deviations									
No. of days when change > 0.25%	81	607	877	409	107	414	435	486	541
No. of days when change > 0.50%	24	543	480	203	38	205	177	137	126
No. of days when change > 0.75%	9	484	310	111	22	110	69	37	43
No. of days when change > 1.00%	2	416	199	67	16	62	33	15	21
No. of days when change < −0.25%	77	630	1.022	395	114	405	415	469	533
No. of days when change < −0.50%	25	557	556	195	35	215	175	140	148
No. of days when change < −0.75%	9	480	326	106	20	108	73	47	45
No. of days when change < −1.00%	3	420	187	69	15	62	32	16	14

Notes: μ, mean; σ, standard deviation; S, skewness; E (K), excess kurtosis; LB (10) e LB^2 (10), The L-Jung Box test-statistics for returns and square returns for 10 lags. **,***Significant at 5 and 1 percent levels, respectively

Table IV. 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	226,490	233,740	251,340	159,915	510,050	510,900
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)
$\phi0$	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)
$\phi1$	−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)
$(\beta+\delta)/\beta$	0.54	1.55	2.12	2.36	0.25	0.86	362.74	557.65	2.80	5.31	16.29	8.49

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			USA	
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)
$\phi0$	−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)
$\phi1$	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)

(*continued*)

Table IV.

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)
$(\beta+\delta)/\beta$	2.99	0.41	0.71	0.52	2.21	1.18	1.05	1.51	2.47

Note: Parentheses include the p-values

Table V. Maximum likelihood of the Sentana and Wadhwani (1992) model

Conditional mean equation: $r_t = \alpha + \theta\sigma_t^2 + D_t(\varphi_{0,0} + \varphi_{1,0}\sigma_t^2)r_{t-1} + (1-D_t)(\varphi_{0,1} + \varphi_{1,1}\sigma_t^2)r_{t-1} + \varepsilon_t$
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	226,490	233,740	251,340	159,915	510,050	510,900
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)
$(\beta+\delta)/\beta$	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

Conditional mean equation: $r_t = \alpha + \theta\sigma_t^2 + D_t(\varphi_{0,0} + \varphi_{1,0}\sigma_t^2)r_{t-1} + (1-D_t)(\varphi_{0,1} + \varphi_{1,1}\sigma_t^2)r_{t-1} + \varepsilon_t$
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			USA		
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

(*continued*)

Table V.

	(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)
$(\beta+\delta)/\beta$	4.92	0.39	0.77	0.53	2.46	1.21	1.16	1.54	2.73

Notes: Parentheses include the p-values. $\varphi_{0,0}=\varphi_{0,1}$ and $\varphi_{1,0}=\varphi_{1,1}$ hypotheses-estimates are generated by Wald's test. The effect of feedback trading when the ETF exhibits a lagged discount

South African markets, two ETFs in the Chinese, Indian and Mexican markets and one ETF in the US market, which is contrary to the findings of Charteris *et al.* (2014). Additionally, evidence of a first-order autocorrelation was found for ETFs in Brazil, South Africa, India, Mexico, China and the USA, of which $\phi_{0,0}$ and $\phi_{0,1}$ were significant at 1 percent for 14 ETFs of the sample.

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

5. GFC effects

The recent 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 define correctly the crisis period, studies on financial contagion are, to some degree, arbitrary.

We specified the length of GFC and its phases following both an economic and a statistical approach as follows. First, 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.*, 2010). These studies separate the timeline of GFC in four phases. Phase 1 is described as "initial financial turmoil" spans from August 1, 2007 to September 15, 2008; phase 2 is defined as "sharp financial market deterioration" (September 16, 2008–December 31, 2008); phase 3 is described as "macroeconomic deterioration" (January 1, 2009–March 31, 2009); and phase 4 is a phase of "stabilization and tentative signs of recovery" (post-crisis period) including a financial market rally (April 1, 2009 onwards, until the end of the sample period).

In order to simplify our analysis, we divided our sample into tree time periods: pre-crisis, before March 31, 2007; crisis, from August 1, 2007 to March 31, 2009; and post-crisis, from April 1, 2009 onwards. Since ETFs of our sample have different inception dates, we considered only those ones that were launched before the crisis period. Results are shown in Table VI (A and B), and suggest that post-crisis effects seem to be more persistent in our sample. In the case of the US market, for instance, results show positive feedback trading evidences in the pre-crisis period, in line with what was found by Chau *et al.* (2011) for SPY. Nevertheless, after the crisis period, investors seem to assume a fundamental-driven behavior, and feedback trading effects cannot be observed.

6. Conclusions and implications

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 *et al.*, 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 18 ETFs from the emerging markets of Brazil, China, South Africa, Korea, India and Mexico, as well as three

Table VI. 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)
$\phi0$	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)
$\phi1$	−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)
$(\beta + \delta)/\beta$	1.92	1.05	1.59	2.64	−3.93	−1.04	−0.21	1.15	1.11	0.48	1.13	0.70

Conditional mean equation: $r_t = \alpha + \theta\sigma_t^2 + (\phi_0 + \phi_1\sigma_t^2) r_t + \varepsilon_t$
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)			USA (SPY)			USA (XLF)			USA (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)
$\phi0$	−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)
$\phi1$	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

(*continued*)

	(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)
$(\beta + \delta)/\beta$	−1,41	−0.05	3.04	0.73	0.65	0.30	0.58	0.18	0.02	−1.36	−2.79	0.53

Note: Parentheses include the p-values

Table VI.

ETFs from the US 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 *et al.*, 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 US 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 a very small part of the global ETF market, led by the USA. Despite 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 the 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 ETF 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 (2016).

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 *et al.*, 2018).

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Further reading

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Appendix

Parameters	Definition
Equation (1)	$Q_t = \left(E_{t-1}(r_t) - \alpha/\theta\sigma_t^2\right)$
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
${\sigma_t}^2$	Conditional variance in t
Equation (2)	$Y_t = \gamma r_{t-1}$
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)	$r_t = \alpha + \theta\sigma_t^2 + \left(\phi_0 + \phi_1\sigma_t^2\right)r_{t-1} + \varepsilon_t$
r_t	Return of shares for the period t
α	Risk-free return
θ	Risk aversion coefficient
$\phi 0$	Market frictions coefficient
$\phi 1$	Feedback trading coefficient
Equation (9)	$r_t = \alpha + \theta\sigma_t^2 + D_t\left(\varphi_{0,0} + \varphi_{1,0}\sigma_t^2\right)r_{t-1} + (1-D_t)\left(\varphi_{0,1} + \varphi_{1,1}\sigma_t^2\right)r_{t-1} + \varepsilon_t$
r_t	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
D_t	Dummy variable
Equation (10)	$\sigma_t^2 = \omega + \beta\varepsilon_{t-1}^2 + \lambda\sigma_{t-1}^2 + \delta S_{t-1}\varepsilon_{t-1}^2$
δ	Volatility asymmetry after positive or negative shocks
S_{t-1}	Binary variable that takes the value of 1 if the shock at time $t-1$ is negative, and otherwise the value of 0
Sign bias test	$(\varepsilon_t/\sigma_t)^2 = \alpha + \theta S_{t-1} + u_t$
θ	Dummy variable
S_{t-1}	Binary variable that takes the value of 1 if the shock at time $t-1$ is negative, and otherwise the value of 0

Table AI. Variable definition table

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