Pricing inefficiencies and feedback trading: evidence from country ETFs

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Abstract

In view of the established presence of wide deviations of US-listed country ETFs' prices from their net asset values, we study whether feedback trading exists in this category of ETFs and whether it varies with their premiums and discounts. Using a sample of nineteen country ETFs for the 2000-2019 window, we find that feedback trading is present in several of them, particularly those targeting Asia Pacific markets. Feedback trading varies with the sign (i.e., premiums and discounts), level, and nature (observed/forecast) of these deviations, as well as prior to and after the outbreak of the 2008 crisis. Of particular note is the widespread feedback trading reported across the vast majority of country ETFs on those days for which there exist successful predictions of premiums/discounts, a fact suggesting that country ETFs' premiums/discounts contain useful information as per their trading dynamics.

JEL Classification: G02; G11; G15

Keywords: Feedback trading; Exchange traded funds; Premium; Discount

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1. Introduction

Research (Deville, 2008) on exchange traded funds (ETFs, hereafter) has denoted the presence of significant deviations of US country ETFs' prices from their underlying net asset values (NAV, hereafter), leading these ETFs to document substantial premiums and discounts. This has been fundamentally attributed to the non-synchronicity in trading between these ETFs (traded in the US) and their underlying benchmark portfolios' stocks (most US country ETFs cover markets in Europe and the Asia Pacific, whose trading sessions overlap partially or not at all with trading times in the US). As the US market and the markets of these ETFs' underlying benchmarks are not simultaneously open for trading, the deviations of these ETFs' prices from their NAVs cannot be arbitraged away real-time, thus raising the possibility of their exploitation via *ad hoc* designated trading strategies, whose profitability has been confirmed in several studies (Cherry, 2004; Jares and Lavin, 2004; Engle and Sarkar, 2006; Ackert and Tian, 2008). Considering that such strategies are essentially feedback in style (they utilize historical ETF prices and their deviations from NAVs), a question arising is whether US country ETFs' premiums/discounts give rise to distinct feedback trading patterns in these ETFs' trading process.

We address this issue drawing on a sample of nineteen US-listed country ETFs targeting a series of markets in the Americas, Asia Pacific and Europe by investigating whether they accommodate feedback trading and whether the latter's presence varies with these ETFs' *observed* price-deviations from their NAVs. What is more, we control for the possibility that feedback traders condition their trades on predicted (rather than observed) premium/discount values by examining whether feedback trading in US country ETFs varies with their *forecast* price-deviations from their NAVs. We further assess whether our findings hold before and after the outbreak of the 2008 financial crisis, given earlier evidence (Choe et al., 1999; Kim and Wei, 2002a, b; Charteris et al., 2014) on the effect of crises over investors' feedback trading internationally. Moreover, we explore whether the presence of feedback trading varies with the level of an ETF's observed/forecast price-deviation from its NAV (i.e., the size of its observed/forecast premium/discount); given that our study entails both observed and forecast premium/discount values, we also test whether successful premium/discount forecasts are associated with feedback trading patterns in our sample's ETFs.

Overall, our results reveal that feedback traders are active in several US-listed country ETFs, with their presence being sensitive to the time period examined (pre versus post 2008 crisis) and the sign and level of the (observed and forecast) price-deviations of each ETF from its NAV (i.e., premiums and discounts); we also find very strong evidence in support of feedback trading patterns emerging upon the realization of successful premium/discount forecasts for the vast majority of our sample ETFs. As a general observation, feedback traders are active the most in those ETFs targeting Asia Pacific markets, with less (very little) evidence of their presence documented in ETFs targeting markets in Europe (the Americas). It is possible that our findings are due to the noise trading often encountered in Asia Pacific markets, leading ETFs investing there to exhibit feedback trading either due to them mirroring (given their tracking nature) these markets' price trends, or due to these ETFs' investors choosing to feedback trade as a rational response to these markets' noise trading levels. Additionally, our results may also reflect the fact that the non-synchronous trading hours between the US and Asia Pacific markets lead these ETFs' NAVs to be known –and possibly used as reference points – before the start of trading in the US. This, in turn, may partly explain the feedback trading detected in some country ETFs targeting European markets, since the trading times of the latter exhibit only partial overlap with those of US markets.

Our research contributes to the extant ETF literature by showcasing that the widely documented premiums/discounts of US-listed country ETFs are related to feedback trading, particularly for those ETFs targeting markets in the Asia Pacific region. Although the literature has mainly focused on country ETFs' actual premiums/discounts, we demonstrate that forecast premiums/discounts are associated with feedback trading as much as actual ones, thus demonstrating that forecasting country ETFs' price-deviations from their NAVs can be used to attain insight into behavioural patterns in their trading. This is more so, considering the very strong evidence reported in support of feedback trading patterns emerging upon the realization of successful premium/discount forecasts for the vast majority of our sample ETFs. Furthermore, the evidence presented here is of key interest to country ETFs' investors (in particular those targeting Asia Pacific markets, in view of our results), as it allows them insight into the trading dynamics associated with these ETF's premiums/discounts that can be used to inform their trades. Considering the documented strong link between feedback trading and successful premium/discount forecasts, a country ETF trader could try to focus on improving on her premium/discount forecasts in order to not only gauge ETFs' future price-paths but also their anticipated feedback trading, which she could then try to exploit via *ad hoc* trading strategies.

The rest of this paper is organized as follows: the next section presents a review of the literature on feedback trading (section 2.1) and ETFs (section 2.2), while section 3 introduces the data utilized with descriptive statistics (section 3.1) and delineates the methodology employed (section 3.2). Section 4 presents and discusses the results and section 5 concludes by summarizing the study's main findings and outlining their implications.

2. Feedback trading and exchange-traded funds

2.1 Feedback trading

Feedback trading is an umbrella term encompassing any trading strategy based on the identification of patterns in historical market data, primarily past prices (but also other aggregate gauges, such as volume). Feedback traders believe that prices exhibit inertia (Farmer, 2002), characterized by trends of a repetitive (and, hence, predictable) nature that can be profitably exploited via *ad hoc* trading rules. The prevalence of feedback trading in the market can amplify existing price trends, leading prices to depart from fundamentals (De Long et al., 1990) and enhance serial correlation (Cutler et al., 1990) and excess volatility (Farmer, 2002; Farmer and Joshi, 2002) in the return generation process. Feedback traders are distinguished into positive (trading in the direction of trends in the market) and negative (trading against those trends) and their conduct can be motivated by a notably wide array of factors, both rational, as well as behavioural (Koutmos, 2014).

From a rational perspective, *rational speculation* (De Long et al., 1990) can lead informed investors to exploit their superior informational foresight by entering positions in stocks prior to the release of news, in order to launch price trends in the market and profitably exploit them (in anticipation of their uninformed, "noise" counterparts riding on those trends). Investors also engage in feedback trading believing they can extract useful information from historical prices when the *information risk* of their investments is high, in particular when the information available is either very little or hard to access/process. This is the case, for example, when investing in small capitalization stocks, about which little information is normally available (Lakonishok et al., 1992; Wermers, 1999; Sias, 2004; Voronkova and Bohl, 2005) and foreign stocks (given the perceived informational superiority of overseas markets' indigenous traders - see Brennan and Cao, 1997; Lin and Swanson, 2008). *Style investing* (Bennett et al., 2003) is a key driver of feedback trading, since several investment styles popular among institutional investors, including momentum and contrarian strategies (see Galariotis, 2014 for an excellent review on both), are based on historical prices. *Technical analysis* (see e.g. Fong and Yong, 2005) is another key expression of feedback trading, while the latter can also be driven by traditional trading practices, including *portfolio insurance* (Kodres, 1994), *stop-loss orders* (Osler, 2005), and *margin trading* (Watanabe, 2002; Hirose et al., 2009). *Professional reasons* are conducive to feedback trading as well, with fund managers often buying stocks with positive recent performance (i.e., are positive feedback trading) in order to generate a favourable impression as regards their skills, a practice known as "window-dressing" (Lakonishok et al., 1992).

From a behavioural perspective, investors resort to feedback trading primarily due to *observational learning*: prices provide a statistical summary of market activity (Holmes and Kallinterakis, 2014) that indirectly allows them insight into the trades of other market participants, without the need to actively monitor the latter.[1] The *representativeness heuristic* (i.e., inferring the properties of a population based on a small sample of recent observations) can motivate trend chasing (Barberis et al., 1998), since it can prompt investors to buy (sell) a stock after only a few days of positive (negative) performance. This can be further reinforced by the *availability bias* (Barberis and Thaler, 2003), according to which more (less) recent events are more (less) easily retrievable by human memory and enjoy a higher (lower) weight in decision making. *Anchoring* (Barberis and Thaler, 2003) is also relevant here, since using reference points in trading is very common among feedback-style strategies[2], while the *disposition effect*, namely the propensity to sell (keep) winning (losing) stocks, can enhance negative feedback trading (Brown et al., 2006).

Empirical evidence on feedback trading overall confirms its presence internationally across several markets, asset classes and investor types. As far as studies using micro data are concerned, positive feedback trading has been found to be popular among US fund managers, with its magnitude being greater during more recent time periods (Sias, 2004; Froot and Teo, 2008; Choi and Sias, 2009; Celiker et al., 2015; Frijns et al., 2016) compared to earlier ones

[1] Actively monitoring other investors' trades is both costly and constrained by the boundaries imposed on human perception by limited attention (Hirshleifer and Teoh, 2003; Hirshleifer et al, 2011).
[2] The case e.g. of relative strength strategies like momentum; see Jegadeesh and Titman (2001).

(Lakonishok et al., 1992; Grinblatt et al., 1995; Wermers, 1999). US retail investors engage less in positive feedback trading compared to their institutional counterparts (Nofsinger and Sias, 1999), while the sign of feedback trading of retail investors in Germany varies with the order type they employ (Dorn et al., 2008).[3] Walter and Weber (2006) report significant positive feedback trading among German mutual funds; conversely, Kremer and Nautz (2013) show that German funds are contrarian traders, similar to UK funds (Wylie, 2005). Choe et al. (1999) report significant positive feedback trading for overseas investors in South Korea prior to the Asian crisis, with this feedback trading largely dissipating following the crisis' outbreak. On the other hand, Kim and Wei (2002a; b) find that foreign institutional investors exhibit more positive feedback trading in the South Korean market in the aftermath (as opposed to before) the Asian crisis' outbreak, while Bowe and Domuta (2004) report very limited evidence of feedback trading for foreign and domestic investors in Indonesia before, during and after the Asian crisis. Hung et al. (2010) find that mutual funds tend to negative feedback trade in Taiwan, while Feng and Seasholes (2004) detect no evidence of feedback trading among retail investors in China. Finally, the global study by Choi and Skiba (2015) presents evidence indicating the prevalence of positive feedback trading among institutional investors internationally (31 out of 41 markets). Turning now to studies using aggregate (i.e., price) data, significant positive feedback trading has been documented for equity (Sentana and Wadhwani, 1992; Koutmos, 1997; Koutmos and Saidi, 2001; Watanabe, 2002; Koutmos et al., 2006; Bohl and Siklos, 2008; Schuppli and Bohl, 2010; Chau and Deesomsak, 2015), currency (Aguirre and Saidi, 1999; Laopodis, 2005; Daníelsson and Love, 2006) and energy (Chau et al., 2015) markets, while futures markets offer less consistent evidence of feedback trading presence (Antoniou et al., 2005; Chau et al., 2008; Kurov, 2008; Charteris and Musadziruma, 2017).

[3] Market orders (executed limit orders) follow positive (negative) feedback trading patterns.

2.2. Exchange-traded funds (ETFs)

An asset class that has experienced exponential growth since the late 1990s is that of exchange traded funds, which represent a financial innovation of huge popularity among both retail and institutional investors. In the US, the world's largest ETF market, there exist 2,100 ETFs of multiple types with a combined value of just over USD 4.4 trillion.[4] ETFs are essentially hybrid instruments, entailing features of open- and closed-end funds, in the sense that they both track a benchmark index[5] (similar to traditional mutual funds) and are publicly listed and traded (much like closed-end funds), thus allowing their holders to trade their index of choice via a single security. ETF-holders can, thus enter long or short positions in ETFs using any order type (market, limit, stop-loss etc.), just like they would on any other common stock, while authorized participants (primarily funds and market makers) can in-kind create/redeem ETF-units in the primary market.[6] ETFs possess a series of attractive properties, including low expense fees[7], instant exposure[8], transparency[9], dividend-treatment[10], risk management[11], and tax-efficiency[12], which have been delineated in a series of studies (Gasti-

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[4] Source: Investment Company Institute. The figures refer to January 2020.

[5] ETFs track various investment targets, including equity markets, sectors, fixed-income markets, currencies, commodities, metals, natural resources and investment styles.

[6] ETF units are created in-kind when an authorized participant borrows batches of shares and deposits them with the ETF's holding company, receiving ETF-shares in return. ETF units are redeemed in-kind when an authorized participant returns his in-kind created ETF units to the ETF's holding company, receiving in return the batch of stocks he deposited upon the in-kind creation of these units.

[7] ETFs are "trackers", engaging in passive investment strategies (they track benchmarks), thus requiring no active management on behalf of their managers; as a result, their management expense fees are far smaller than those of traditional mutual funds. Normally, less liquid ETFs (those e.g. investing in illiquid markets/sectors) are harder to manage (order-execution may take longer and transaction costs may be higher), thus commanding higher management expense fees.

[8] Aside from the obvious benefit of enabling their holders to trade an index or a sector through a single instrument (also known as tactical portfolio allocation; Ünal, 2009), ETFs also facilitate access to markets, entry into which would either be difficult *per se* (due e.g. to regulatory restrictions) or costly (due e.g. to the information costs involved).

[9] ETFs disclose their portfolio-structure in terms of assets and net asset value intraday, as opposed to traditional mutual funds, whose portfolio-holdings are disclosed at very low frequencies (often quarterly).

[10] Dividends received by the ETF via its investments in equities are deposited with the accounts of its investors, who are offered the option to invest these dividends into their ETF-position; conversely, open-end funds invest dividends automatically in the holder's position.

[11] Investors trading in a market (e.g. the UK) can use an ETF linked to that market's index (e.g. the FTSE100) for hedging purposes (Curcio et al., 2004).

[12] In the event of redemption of a holder's share in an open-end fund, its manager will have to sell shares from the fund's portfolio to undertake the redemption; assuming this sale leads to a profit, the manager has to pay

neau, 2001; Kostovetsky, 2003; Deville, 2008) and which help explain the wide popularity ETFs have been enjoying among both retail and institutional investors (Charteris et al., 2014).

Evidence on the behaviour of ETF-traders has indicated that they subscribe to feedback-style strategies. Drawing on high frequency data from US ETFs during the internet bubble, Madura and Richie (2004) demonstrate the presence of intraday overreaction patterns in their trading dynamics that correct themselves within the same day, thus presenting profitable opportunities to traders with intraday horizons. Chau et al. (2011) find that the US' three largest ETFs ("Spiders"; "Cubes"; "Diamonds") are characterized by significant positive feedback trading, whose presence grows more pronounced during bullish sentiment periods, while Chen et al. (2012) show that US institutional investors negative feedback trade when investing in ETFs (with that pattern being accompanied by significant herding). Charteris et al. (2014) report limited evidence of feedback trading among ETFs traded in four emerging markets, while Da Costa Neto et al. (2019) find evidence in support of strong feedback trading in ETFs from a wider cross section (eighteen) of emerging markets.

A factor capable of encouraging feedback trading in ETFs is their tracking error, namely the deviation between their market price and their net asset value (i.e., the value of all assets included in an ETF's portfolio), which can be either positive (when an ETF's price exceeds its NAV, i.e., the ETF trades at a premium) or negative (when an ETF's price is below its NAV, i.e., the ETF trades at a discount). The presence of large premiums/discounts in an ETF implies inefficiency in its pricing and, as such, would be expected to be arbitraged away, particularly given the in-kind creation/redemption mechanism discussed previously. However, for arbitrage to be feasible in this case it is necessary for the ETF and its portfolio's underlying assets to be traded simultaneously. This is not the case, though, for the specific category

capital gains' taxes, whose amount is levied over all remaining holders of the fund. Conversely, an ETF-holder can sell his ETF-shares without his trade imposing any taxes on his fellow holders, though, of course, he will be subject to capital gains' tax in case he sells at a profit.

of country ETFs, which are listed predominantly in the US and invest in equities in overseas markets, whose trading times are - in the vast majority of cases - only partially overlapping with the US ones (the case of country ETFs targeting European markets) or not at all (the case of country ETFs targeting Asia Pacific markets), thus rendering arbitrage a technical impossibility. In view of country ETFs' substantial premiums/discounts (Harper et al., 2006; Deville, 2008; Blitz and Huij, 2012), it is reasonable to expect that investors will attempt to exploit this pricing inefficiency by employing strategies based on these ETFs' historical premium/discount patterns; indeed, evidence to date (Cherry, 2004; Jares and Lavin, 2004; Engle and Sarkar, 2006; Ackert and Tian, 2008) has confirmed the profitability of such strategies. Being based on historical ETF prices and their deviations from NAVs, these strategies are essentially feedback in style and, although this suggests that they can potentially give rise to distinct feedback trading patterns in country ETFs, the latter has not been empirically assessed to date. Our study contributes to the literature by examining this issue drawing on a sample of nineteen US country ETFs and produces results indicating that these ETFs' (observed and forecast) premiums/discounts are associated with feedback trading, particularly for those ETFs targeting Asia Pacific markets (whose trading times do not overlap with the US market's). Of particular note here is the widespread feedback trading we report for days with successful premium/discount forecasts for the vast majority of our sample ETFs. The next section provides a detailed presentation of the ETFs included in our sample with detailed descriptive statistics, while also introducing the methodology utilized for our empirical investigation.

3. Data-Methodology

3.1 Data

Our data includes daily observations of the closing prices and net asset values of nineteen iShares MSCI ETFs, which are presented in Table 1 (panel A). The data covers the period between July 14th, 2000 and November 19th, 2019 and has been obtained from Thomson-Reuters DataStream (closing prices) and Black Rock iShares (NAVs), with the observations from both databases matched. The choice of July 14th, 2000 as the starting date of our sample coincides with the launch-date of the iShares MSCI Brazil ETF (the ETF with the latest launch date out of all nineteen ETFs) and the reason for this is that we aimed at including in our sample all US-listed country ETFs launched before 2001 in order to have a sufficiently long pre crisis window when testing for the effect of the 2008 crisis over our results. The historical changes of the market value (capitalisation) of these country ETFs are presented in Figure 1.

[PLEASE INSERT FIGURE 1 HERE]

Table 1 (panel B) provides a series of descriptive statistics (mean; standard deviation; skewness; kurtosis; Jarque-Bera normality test; Ljung–Box test statistic for returns and squared returns for ten lags) pertaining to the log-differenced returns of our sample ETFs. Fifteen (four) ETFs exhibit negative (positive) skewness, while all nineteen ETFs present us with rather large Jarque-Bera test statistics and leptokurtosis in their returns' distributions. To gauge whether these departures from normality are the products of temporal dependencies in the series' structures, we apply the Ljung–Box portmanteau test on the first and second moment of all ETFs' returns. All (except two) Ljung-Box test statistics on ETFs' returns are significant, indicating the presence of significant autocorrelations in our ETFs' return-distributions; this, however, is not in itself evidence in support of feedback trading, since dependencies in the first moment of returns can also be due to market inefficiencies, such as thin trading. In view of the documented (see e.g. Farmer and Joshi, 2002) ability of feedback traders to accentuate volatility in capital markets, we test for higher moment temporal dependencies by calculating the Ljung-Box test statistic for squared returns. As our results indicate, all, but one, of these test statistics are significant and always higher in value than the Ljung-Box test statistics calculated previously for returns, thus confirming the presence of time-varying volatility in our ETFs. The presence of significant first- and second-order temporal dependencies in financial time series is well-established in the literature (Bollerslev et al., 1994) and in the next section we shall investigate whether they are related to feedback trading.

Panel C in Table 1 presents some statistics on each ETF's percentage price deviations from its net asset value contingent on their sign (premiums, if the sign is positive; discounts, if it is negative). The average percentage deviation of ETFs' prices from their NAVs is positive (0.04%), denoting that US-listed country ETFs traded on average at a premium during the full sample period, with the majority (fifteen) of ETFs having traded on average at a premium over the entire sample period. On average, our sample ETFs traded 54% (46%) of the time at a premium (discount); the average premium across all nineteen ETFs[13] stands at 0.61% and tends to vary, with the lowest (highest) average premium value being detected for the iShares MSCI Canada ETF (iShares MSCI Taiwan ETF) at 0.4% (1.04%). The average discount[14] across all sample ETFs also varies, with the lowest (highest) average discount val-

[13] To calculate the average premium across all sample ETFs, we first calculate the average premium for each ETF by averaging all positive percentage deviations of its price from its NAV and then calculate the average value of all average premiums per ETF.

[14] To calculate the average discount across all sample ETFs, we first calculate the average discount for each ETF by averaging all negative percentage deviations of its price from its NAV and then calculate the average value of all average discounts per ETF.

ue being observed for the iShares MSCI Canada ETF (iShares MSCI Malaysia ETF) at -0.31% (-1.04%).

[PLEASE INSERT TABLE 1 HERE]

3.2 Methodology

To empirically address the research questions of our study, we rely on the model developed by Sentana and Wadhwani (1992), which assumes the interaction of two groups of traders in the market. The first group consists of rational speculators, who maximize their expected utility based on a mean-variance framework, as reflected in their demand function below

$$Q_t = \frac{\mathbb{E}_{t-1}(r_t)-\alpha}{\theta\sigma_t^2}. \quad (1)$$

In Equation (1) above, $\mathbb{E}_{t-1}(r_t)$ is the expectation in period $t-1$ of the ETF's return, r_t, in period t , α is the risk-free return, θ is the time-invariant coefficient of risk-aversion and σ_t^2 is the conditional variance (proxying for risk) at period t.

The second group comprises of feedback traders, who trade on the premises of historical prices, as reflected in their demand function

$$Y_t = \gamma r_{t-1}. \quad (2)$$

As Equation (2) suggests, feedback traders base their trades on the previous period's return, with the direction of their trades varying, depending on whether they positive (i.e., if $\gamma > 0$, in which case, they buy if $r_{t-1} > 0$ and sell if $r_{t-1} < 0$) or negative (i.e., if $\gamma < 0$, in which case, they buy if $r_{t-1} < 0$ and sell if $r_{t-1} > 0$) feedback trade. For the market to be in equilibrium, all shares must be held, in which case,

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

Substituting Equations (1) and (2) in Equation (3), we obtain

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

To estimate Equation (4), we convert the expected return, $\mathbb{E}_{t-1}(r_t)$, into a realized one (r_t) , by assuming the latter's rational expectation [$r_t = \mathbb{E}_{t-1}(r_t) + \varepsilon_t$], where $\varepsilon_t$is a stochastic error term

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

As Equation (5) shows, the first-order return-autocorrelation interacts both with risk (σ_t^2), and feedback trading (the first-order autocorrelation sign will be positive if $\gamma < 0$ and negative if $\gamma > 0$). However, autocorrelation can be the result of both inefficiencies in the market (such as, for example, thin trading) as well as feedback traders and Equation (5) does not allow us to disentangle between the two possibilities. To that end, Sentana and Wadhwani (1992) suggested the following *ad hoc* empirical specification of Equation (5),

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

Equation (6) – which we dub as Model 1 - distinguishes between the part of autocorrelation due to market inefficiencies (denoted by ϕ_0) and that due to feedback trading (denoted by ϕ_1). With $\phi_1 = -\theta\gamma$, significantly positive (negative) values for ϕ_1 will denote the presence of negative (positive) feedback trading.

To assess the interaction of feedback trading with the observed premiums/discounts of our sample ETFs, we employ Chau et al. (2011)'s empirical extension of the Sentana and Wadhwani (1992) model

$$r_t = \alpha_0 D_{t-1} + \alpha_1(1 - D_{t-1}) + \theta_0 D_{t-1}\sigma_t^2 + \theta_1(1 - D_{t-1})\sigma_t^2 + D_{t-1}\left(\phi_{0,0} + \phi_{1,0}\sigma_t^2\right)r_{t-1} + (1 - D_{t-1})\left(\phi_{0,1} + \phi_{1,1}\sigma_t^2\right)r_{t-1} + \varepsilon_t. \tag{7}$$

Equation (7) – which we dub Model 2 – entails the term "D_{t-1}", which is a dummy variable assuming the value of unity if the ETF has posted a discount in period $t-1$, zero otherwise.[15] Equation (7) allows all terms of Equation (6) to shift with the observed lagged premiums/discounts of the ETF and permits us to gauge how feedback trading manifests itself when the ETF's price exhibits a positive (the case of a premium) or negative (the case of a discount) deviation from its NAV in period t-1.[16,17]

To assess the presence of leverage effects (Bollerslev et al., 1994) in volatility, the conditional variance (σ_t^2) in all of the above equations follows an asymmetric GJR-GARCH specification (Glosten et al., 1993)

$$\sigma_t^2 = \omega + \beta\varepsilon_{t-1}^2 + \lambda\sigma_{t-1}^2 + \delta I_{t-1}\varepsilon_{t-1}^2. \quad (8)$$

In Equation (8), the parameter δ reveals whether volatility responds asymmetrically to positive versus negative shocks. I_{t-1} is a dummy variable, assuming the value of unity if the lagged shock is negative, zero otherwise; significantly positive estimates for δ denote that volatility is higher following negative (compared to positive) shocks.

Given country ETFs' documented wide premiums and discounts, it is possible that feedback traders condition their trades on forecast premiums/discounts when trading these ETFs. To explore this possibility, we assess the interaction between forecast premiums/discounts

[15] Given the daily frequency of our data, both the closing prices and NAVs employed are day-end observations; as a result, it is not possible for the feedback trader of Equation (7) to trade on the contemporaneous (period t) premium/discount, since he cannot observe it until the session is over (this would have been the case only if we were working on the premises of real-time data), hence we rely on lagged premiums/discounts. This is further supported by the fact that feedback traders in the Sentana and Wadhwani (1992) framework base their trades on the previous day's returns, not the contemporaneous ones (which, given the daily frequency of our data could not be traded on anyway, since they are day-end ones).

[16] Equation (7) combines the possibility of NAV-deviations interacting with feedback trading both *additively* and *multiplicatively*. As Chau et al. (2011) showed, the additive version of this interaction assumes the following feedback trading function: $Y_t = \gamma\, r_{t-1} + \kappa D_t$, in which case the combined function of rational and feedback traders becomes: $r_t = \alpha_0 D_t + \alpha_1(1-D_t) + \theta_0 D_t\sigma_t^2 + \theta_1(1-D_t)\sigma_t^2 + (\phi_{0,1} + \phi_{1,1}\sigma_t^2)r_{t-1} + \varepsilon_t$. The multiplicative version of this interaction assumes the following feedback trading function: $Y_t = [\gamma D_t + \kappa(1-D_t)]r_{t-1}$, in which case the combined function of rational and feedback traders assumes the following form: $r_t = \alpha + \theta\sigma_t^2 + D_t(\phi_{0,0} + \phi_{1,0}\sigma_t^2)r_{t-1} + (1-D_t)(\phi_{0,1} + \phi_{1,1}\sigma_t^2)r_{t-1} + \varepsilon_t$.

[17] We calculate an ETF's price-NAV deviations as follows: $(\frac{P_t - NAV_t}{NAVt})$ x 100, where P_t and NAV_t are the ETF's closing price and net asset value on day t.

and feedback trading, by first assuming that the dynamics of ETFs' percentage price deviations from their NAV follow a standard Ornstein-Uhlenbeck (OU) process[18], as follows:

$$dX_t = -\rho(X_t - \mu)dt + \xi dW_t. \quad (9)$$

X_t represents the percentage price deviation of the ETF from its NAV, ρ is the speed of mean reversion, W_t is a standard Brownian motion (on some probability space), and μ is the long term[19] equilibrium level of the ETF's percentage price deviation from its NAV. The solution of Equation (9) is provided by

$$X_{i+1} = X_i e^{-\rho t} + \mu(1 - e^{-\rho t}) + \xi \sqrt{\frac{1-e^{-\rho t}}{2\rho}} N_{0,1}, \quad (10)$$

where t denotes the fixed time steps and $N_{0,1}$ is the standard normal distribution. We then estimate the parameters using the maximum likelihood method, with the conditional probability density function derived as follows:

$$f\left(X_{i+1}|X_i;\mu,\rho,\hat{\xi}\right) = \frac{1}{\sqrt{2\pi\hat{\xi}^2}} exp\left(-\frac{\left(X_i - X_{i-1}e^{-\rho t} - \mu\left(1-e^{-\rho t}\right)\right)^2}{2\hat{\xi}^2}\right) \quad (11)$$

with

$$\hat{\xi}^2 = \xi^2 \frac{1-e^{-2\rho t}}{2\rho}. \quad (12)$$

The log-likelihood function of a set of observations $(X_0, X_1, \dots, X_n)$ can be derived as

$$\mathcal{L}\left(\mu,\rho,\hat{\xi}\right) = \sum_{i=1}^{n} lnf\left(X_{i+1}|X_i;\mu,\rho,\hat{\xi}\right) = -\frac{n}{2} ln(2\pi) - nln\left(\hat{\xi}^2\right) - \frac{1}{2\hat{\xi}^2} \sum_{i=1}^{n}\left(X_i - X_{i-1}e^{-\rho t} - \mu(1 - e^{-\rho t})\right)^2. \quad (13)$$

Algebraically, the following equations are derived from the above,

$$\mu = \frac{\sum_{i=1}^{n}\left(X_i - X_{i-1}e^{-\rho t}\right)}{n(1-e^{-\rho t})} \quad (14)$$

[18] Applications of the OU-process in finance include Bormetti et al. (2010) and Griffin (2010).
[19] The long-term equilibrium is equivalent here to a window of 252 days (i.e., a year's observations).

$$\rho = -\frac{1}{t} ln \frac{\sum_{i=1}^{n}(X_i-\mu)(X_{i-1}-\mu)}{\sum_{i=1}^{n}(X_{i-1}-\mu)^2} \tag{15}$$

and

$$\hat{\xi}^2 = \frac{1}{n}\sum_{i=1}^{n}[(X_i - \mu - e^{-\rho t})(X_{i-1} - \mu)]^2. \tag{16}$$

To gauge whether the forecast premiums/discounts generated from the OU-process affect feedback trading in our sample ETFs, we employ Equation (17) - a close variant of Equation (7) – which we dub Model 3

$$r_t = \alpha_0 D_t + \alpha_1(1 - D_t) + \theta_0 D_t \sigma_t^2 + \theta_1(1 - D_t)\sigma_t^2 + D_t(\phi_{0,0} + \phi_{1,0}\sigma_t^2)r_{t-1} + (1 - D_t)(\phi_{0,1} + \phi_{1,1}\sigma_t^2)r_{t-1} + \varepsilon_t. \tag{17}$$

In the above equation, "D_t" is equal to one, if the OU-process forecasts a discount for day *t*, zero otherwise. Finally, to test whether our findings hold in view of the outbreak of the 2008 global financial crisis, we partition our sample period into a pre (July 14th, 2000 - August 31st, 2008) and a post (September 1st, 2008[20] – November 19th, 2019) crisis-outbreak period and repeat all our estimations for both sub periods. This partition in our sample window is motivated mainly by the fact that the outbreak of financial crises has been found (Choe et al., 1999; Kim and Wei, 2002a, b; Charteris et al., 2014) to produce changes in investors' feedback trading internationally. A crisis' outbreak brings about a change in the market's directional trend, from upward to downward; with feedback traders extrapolating from historical price trends, any such ground-breaking shift in the market's direction is bound to affect their trading pattern. Additionally, the fact that crisis-periods encompass extreme price movements is expected to lead to wilder swings of country ETFs' prices and, quite possibly,

[20] The choice of September 2008 as the cut-off point in our sample window is motivated by the ground-breaking events that took place in the US during that month (including the bankruptcy of Lehman Brothers and the US government's decision to place mortgage providers Freddie Mac and Fannie May into conservatorship) and which changed the landscape of the US financial system in the post 2008 years.

amplify their deviations from their NAVs, given that arbitrage (which is difficult enough for country ETFs given their non-synchronous trading times vis-à-vis their underlying benchmarks' assets) is harder to practice during extreme market periods.

4. Results – Discussion

We begin our discussion with the presentation of the results from Equation (6), i.e., the original Sentana and Wadhwani (1992) model (Model 1). The estimates outlined in Table 2 indicate that several US-listed country ETFs exhibit inefficiencies in their returns, as demonstrated by the significantly[21] negative values of the first-order autocorrelation coefficient (ϕ_0) for nine ETFs. ϕ_1 assumes significantly negative values for eight ETFs, denoting the presence of positive feedback trading in their dynamics. Of those eight ETFs, five (iShares MSCI Australia ETF; iShares MSCI Japan ETF; iShares MSCI Singapore ETF; iShares MSCI South Korea Capped ETF; iShares MSCI Taiwan ETF) target markets in the Asia Pacific region (whose trading hours do not overlap with US trading hours), two (iShares MSCI Italy Capped ETF; iShares MSCI Sweden ETF) target European markets (whose trading hours only partially overlap with those of the US) and only one (iShares MSCI Brazil Capped ETF) enjoys overlapping trading hours with US markets. These results suggest that feedback trading in US country ETFs grows more potent among those ETFs targeting markets in the Asia Pacific region that maintain no common trading hours with those of the US.[22] A key issue regarding several Asia Pacific markets is that retail investors command a substantial fraction of their turnover (Chou et al., 2011), thus amplifying noise trading (Barber et al, 2007; 2009; Kuo et al., 2015). As a result, the feedback trading documented for country ETFs targeting

[21] In the interest of brevity, any reference to statistical significance in this section shall pertain to estimated coefficients, whose p-values are less than 0.1 (i.e., the 10 percent level of significance).
[22] Of those ETFs targeting Asia Pacific markets, only two (iShares Hong Kong ETF; iShares Malaysia ETF) exhibit no feedback trading.

markets in that region may be due either to these ETFs mirroring (given their tracking nature) these markets' performance (which can often entail price trends as a result of noise trading) or to these ETFs' investors opting for feedback trading as a rational strategy given the noise levels of these markets.[23] The large time difference between the Asia Pacific region and the US further facilitates feedback trading in those ETFs, since US investors trading them will be aware of their underlying benchmarks' NAVs for the day well before trading in the US has started, possibly choosing to use these NAVs as reference points.[24] As per the structure of their conditional variance, the significant (at the 1 percent level) λ values indicate that contemporaneous volatility is significantly related to lagged volatility, thus denoting its persistence. The volatility of almost all[25] ETFs responds significantly to news (as the significant β values indicate), with this response being asymmetric in all cases, since the coefficient δ is always significantly positive. Overall, the structure of the conditional variance of our study's ETFs reflects similar properties to those reported in prior studies on ETFs' feedback trading (Chau et al., 2011; Charteris et al., 2014; Da Costa Neto et al., 2019).

[PLEASE INSERT TABLE 2 HERE]

We now turn to assessing whether feedback trading varies in its presence in US-listed country ETFs with the sign of the observed lagged percentage price deviation of an ETF from its NAV (i.e., premium or discount). Table 3 presents the results from the estimation of Equa-

[23] The selection of feedback trading as a strategy by investors of country ETFs targeting Asia Pacific markets in this case can be motivated either by rational speculative reasons (to exploit the noise trading patterns in Asia Pacific markets' equity returns via those ETFs) or informational reasons (noise trading renders the public pool of information poorer and feedback trading has been shown – Brennan and Cao, 1997 – to be an option when trading in markets with informational uncertainty).

[24] Whereas the net asset value of a US ETF investing in domestic equities evolves throughout the session alongside its actual market price, the net asset value of an ETF investing e.g. in Malaysia will have evolved over a time window not corresponding to that ETF's trading times in the US. As a result, investors in that ETF would be aware of its net asset value at close (Malaysian time) long before that ETF's trading opens in the US.

[25] Except that of the iShares MSCI Mexico Capped ETF.

tion (7) – Model 2 - for our sample's ETFs. Our estimations, overall, reveal a rather limited presence of feedback trading contingent upon the realization of a lagged premium or discount. More specifically, two ETFs (iShares MSCI Italy Capped ETF; iShares MSCI Taiwan ETF) exhibit positive feedback trading when a premium is observed on the previous day, while three[26] (one)[27] exhibit(s) positive (negative) feedback trading in the presence of a lagged discount. Again here, it is interesting to note that three of those five ETFs are targeting Asia Pacific markets (in line with the evidence presented previously on feedback trading being more pronounced for them). Several ETFs exhibit inefficiencies in their return-generating process contingent on the presence of lagged premiums or discounts; when a discount (premium) has materialized on the previous day, $\phi_{0,0}$ ($\phi_{0,1}$) is significant for three (five) ETFs[28]. Regarding the volatility's structure, it appears highly persistent and asymmetric for all ETFs, in line with the results reported previously.

[PLEASE INSERT TABLE 3 HERE]

Table 4 presents the estimates from Equation (17) - i.e., Model 3 - controlling for the presence of a predicted (as opposed to observed) premium or discount. Significant positive feedback trading exists for predicted premiums for two ETFs (iShares MSCI Italy Capped ETF; iShares MSCI Taiwan ETF) and for predicted discounts for three ETFs (iShares MSCI Japan ETF; iShares MSCI Malaysia ETF and the iShares MSCI Taiwan ETF); significant negative feedback trading is reported for the iShares MSCI Belgium Capped ETF for predicted dis-

[26] These are the: iShares MSCI Italy Capped ETF, iShares MSCI Malaysia ETF and iShares MSCI Singapore ETF.
[27] iShares MSCI Belgium Capped ETF.
[28] For lagged discounts, we observe significantly negative autocorrelation for the ETFs targeting the French, Hong Kong and Mexican markets; for lagged premiums, we observe significantly negative (positive) autocorrelation for the ETFs targeting the Japanese and Swiss (Brazilian, Mexican and Taiwanese) markets.

counts. Again here, it is interesting to note that three of those five ETFs are targeting Asia Pacific markets, in line with the evidence presented in Tables 2 and 3 on those ETFs entailing more pronounced feedback trading. The presence of significant first-order autocorrelation is confirmed for four (five) ETFs for predicted discounts (premiums), thus confirming the presence of inefficiencies in their returns' structure, with their volatility again appearing highly persistent and asymmetric.[29]

[PLEASE INSERT TABLE 4 HERE]

To test whether the results reported in Tables 2-4 hold when controlling for the outbreak of the 2008 financial crisis, we repeat all of the above tests prior to (14/7/2000 – 31/8/2008) and after (1/9/2008 – 19/11/2019) the crisis' outbreak and report the results in Tables 5-6. Table 5 presents the estimates from the original Sentana and Wadhwani (1992) model (Model 1) pre and post crisis' outbreak, respectively. As the results indicate, feedback trading appears present in several ETFs within each of the two sub periods; indeed, significant positive feedback trading appears in six ETFs (iShares MSCI Brazil Capped ETF; iShares MSCI Canada ETF; iShares Italy Capped ETF; iShares Japan ETF; iShares Malaysia ETF; iShares MSCI Mexico Capped ETF) before and eight (iShares MSCI Australia ETF; iShares Italy Capped ETF; iShares Japan ETF; iShares MSCI Singapore ETF; iShares South Korea Capped ETF; iShares Sweden ETF; iShares Switzerland Capped ETF; iShares Taiwan ETF) after the crisis' outbreak. In total, we have twelve ETFs for which feedback trading surfaces before and/or after the crisis' outbreak; again here, the presence of feedback trading in country ETFs targeting Asia Pacific markets appears pronounced, with six of the twelve ETFs investing in markets from that region. Overall, the varying presence of feedback trading prior to and after the

[29] The sole exception here is the iShares MSCI Malaysia ETF, where no asymmetric volatility is detected.

events of September 2008 confirms prior evidence (Antoniou et al., 2005; Laopodis, 2005; Schuppli and Bohl, 2010; Charteris et al., 2014; Chau and Deesomsak, 2015) on the sensitivity of feedback trading to periods characterized by different market conditions. The presence of autocorrelation in the ETFs' return-structure is also confirmed, yet surfaces mainly pre crisis; as for the structure of our ETFs' volatility, it remains highly persistent and asymmetric[30] during both sub periods. Table 6 presents the estimates of the feedback coefficients ($\phi_{1,0}$; $\phi_{1,1}$) from the tests conditioning feedback trading on the lagged/predicted discounts/premiums (i.e., Models 2 and 3) before and after the crisis' outbreak. Results suggest that actual lagged premiums motivate feedback trading more strongly (in six ETFs pre and six ETFs post crisis) compared to actual lagged discounts (in three ETFs pre and one ETF post crisis); similar results are presented for predicted premiums (for which feedback trading is significant in four ETFs pre and three ETFs post crisis) and discounts (which motivate feedback trading in three ETFs pre and two ETFs post crisis). Of the 28 significant feedback trading coefficients detected in Table 6, half (14) correspond to country ETFs targeting Asia Pacific markets, 9 to country ETFs targeting European markets and only 5 to country ETFs targeting markets in the American continent. Taken together, these results confirm that the greater the difference in trading hours between the US and an ETF's target market, the more likely it is for feedback traders to surface in that ETF.

[PLEASE INSERT TABLES 5 & 6 HERE]

[30] No asymmetry is detected for the volatility of the iShares MSCI Malaysia ETF pre crisis, as δ is found to be insignificantly negative there.

As an additional robustness test, we assess the effect of various lagged (forecast) premium[31] and discount[32] levels over feedback trading by setting the variable D_{t-1} (D_t) equal to one for each of these levels in Equation (7) (Equation (17)) and re-estimating it for the full sample period and the two sub periods (pre-/post-crisis). Our estimates reveal the presence of positive feedback trading across several premium/discount levels for country ETFs targeting Asia Pacific markets (particularly for the full sample period and post crisis' outbreak), while several ETFs targeting European markets also furnished us with evidence of (positive and negative) feedback trading.[33]

Overall, our study has shown that feedback traders are active in several US-listed country ETFs, with their presence being sensitive to the time period examined and the sign and level of the (observed and forecast) percentage deviations of each ETF's price from its NAV (i.e., premiums and discounts). The fact that country ETFs targeting Asia Pacific markets are more susceptible to feedback trading, both in its conditional and unconditional versions (i.e., both when we do/not condition it upon observed/predicted premiums/discounts), raises interesting issues for those investing in these ETFs. As mentioned before, most Asian markets are typified by the enhanced presence of retail traders in their equity segments, leading the latter to accommodate substantial noise trading. It is, thus, possible that the feedback trading reported here for those ETFs is either due to them tracking these markets' performance (which can often entail price trends as a result of noise trading) or to these ETFs' investors choosing to feedback trade as a rational strategy given the noise trading levels of these markets. Considering the relatively limited evidence of feedback trading for country ETFs targeting markets with complete or partial overlap of trading sessions with the US (the case of country ETFs targeting markets in Europe and the Americas), it is likely that the time difference involved

[31] The premium-levels tested for are: +0.25%; +0.5%; +0.75%.
[32] The discount-levels tested for are: -0.25%; -0.5%, -0.75%.
[33] For brevity reasons these results are not reported here, but are available from the authors on request.

contributes to this. US investors of ETFs targeting Asia Pacific markets are faced with non-synchronicity of these ETFs' prices with their NAVs as these ETFs never trade real-time with their underlying benchmarks: they begin their trading in the US with their NAV of the day already known. Although it is possible that this foments feedback tendencies among their clientele (who can use these ETFs' NAVs as anchors when trading them), the validity of the latter can only be confirmed using real-time micro data (i.e., data on investors' transactions).

An issue of interest to country ETFs' investors, however, that we can examine in the context of this study, is whether there exists a relationship between successful predictions of these ETFs' premiums/discounts and their feedback trading. If, for example, successfully predicted discounts in an ETF are accompanied by significant positive feedback trading, this would suggest that the predictive model (in our case, the Ornstein-Uhlenbeck process) is capable of, indirectly, offering insight into that ETF's trading dynamics as well. This is a rather interesting issue and, to that end, we set the dummy D_t in Equation (17) equal to 1 for those days when the predicted sign of the ETF's percentage price deviation from its NAV equals the actual one[34], zero otherwise, and estimate the equation for all nineteen ETFs for the full sample period, prior to and after the crisis' outbreak. Results from the feedback coefficients of interest ($\phi_{1,0}$; $\phi_{1,1}$) are presented in Table 7 and indicate that successful premium/discount predictions are accompanied by significant feedback trading on far more occasions compared to unsuccessful ones, particularly for the full sample and post-crisis estimations and for the vast majority of sample-ETFs. This is a notably interesting finding, more so since the presence of feedback trading associated with successful premium/discount predictions is prolific among our sample ETFs, to an extent not witnessed before in Tables 2-6. This suggests that it is discount/premium predictability – rather than the observed or predicted values of those premiums/discounts – that encourages investors to feedback trade in country ETFs, thus

[34] This is the case when the Ornstein-Uhlenbeck process predicts a discount (premium) for day *t* and the ETF posts a discount (premium) on day *t*.

showcasing that successful premium/discount predictions are capable of predicting the presence of feedback traders as well. The usefulness of this is obvious, as it suggests that focusing on successfully forecasting premiums/discounts can yield valuable insight into not only future ETF-prices but also the presence of those tracking them (i.e., feedback traders), thus being capable of informing *ad hoc* trading strategies as per future trading dynamics in country ETFs.

[PLEASE INSERT TABLE 7 HERE]

5. Conclusion

This study investigates whether feedback traders are active in US-listed country ETFs and whether their presence is affected by the significant premiums and discounts that have been documented for these ETFs in the literature. Drawing on a sample of nineteen ETFs from that category for the 2000-2019 period we report significant feedback trading for several of them, with its presence varying with these ETFs' observed/forecast premiums/discounts and the level of the latter, as well as before and after the 2008 crisis' outbreak. A particularly interesting finding here is the widespread presence of feedback trading when the premium/discount predictions are successful, as this indicates that predictive success in country ETFs' pricing can also entail predictive power into their future trading dynamics. Feedback trading is encountered more frequently among country ETFs targeting Asia Pacific markets (followed by those targeting European markets, with those targeting markets in the American continent returning us with the least evidence of feedback trading) and we discuss how this might be related to the noise trading often encountered in these markets, as well as the non-synchronicity in trading times between them and their underlying benchmarks.

From a research perspective our findings bear important implications, as they offer novel insights into country ETFs' trading activity, by demonstrating how these ETFs' extensively documented wide premiums and discounts are related to feedback trading (particularly for those ETFs targeting Asia Pacific markets). The results reported here further raise the possibility that other behavioural trading patterns associated to feedback trading (such as herding or the disposition effect) may also be relevant to those ETFs' premiums/discounts and could be explored in future research. The evidence presented here is also of key relevance to investors, particularly those focusing on country ETFs, as it could be used to inform their trading strategies, by prompting them to utilize the relationship between feedback trading and country ETFs' premiums/discounts when trading those ETFs. Considering the documented strong link between feedback trading and successful premium/discount forecasts, a country ETF trader could try to focus on improving on her premium/discount forecasts in order to not only gauge ETFs' future price-paths but also their anticipated feedback trading, which she could then try to exploit via *ad hoc* trading strategies.[35]

[35] To illustrate this point, assume an investor who trades the iShares MSCI Taiwan ETF, one of those frequently entailing feedback trading in this study. As we have shown, this ETF accommodates significant positive feedback trading for our full sample period (unconditionally (Table 2); in the presence of observed lagged premiums (Table 3), forecast premiums and discounts (Table 4) and successful/unsuccessful premium/discount forecasts (Table 7)), pre crisis (in the presence of unsuccessful premium/discount forecasts (Table 7)) and post crisis (unconditionally (Table 5); in the presence of forecast discounts and actual premiums (Table 6); in the presence of successful premium/discount forecasts (Table 7)). Considering that we are now in year 2020 and the post crisis results are more contemporaneous (the post crisis period ends in November 2019), let us also assume that she chooses to use the Ornstein-Uhlenbeck forecasting model for the ETF's price-NAV deviations and trade when a discount has been forecasted. Considering that forecast/successfully forecasted discounts are associated with significant positive feedback trading for that ETF (Tables 6 and 7), let us further assume that she forecasts the ETF to realize a discount tomorrow and that the ETF's performance today is negative. If her forecast is successful, this suggests that the ETF is likely to realize positive feedback trading tomorrow and, based on today's negative return, this denotes that tomorrow's return will likely be negative too (since positive feedback traders track trends). In view of the above, one option she has is to sell at tomorrow's market opening, in order to front run the anticipated fall of price (if she owns shares of the ETF); another option would be to go short on that ETF, closing her position by the market's closing tomorrow (if she owns no shares of the ETF). Although she may well entail horizons longer than one day in her trading, we believe the above to constitute a possible depiction of how our findings could be used to inform the strategies of country ETFs' investors in the US.

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Table 1: Sample statistics.

Panel A: List of sample ETFs

iShares MSCI Australia ETF	iShares MSCI Japan ETF
iShares MSCI Austria Capped ETF	iShares MSCI Malaysia ETF
iShares MSCI Belgium Capped ETF	iShares MSCI Mexico Capped ETF
iShares MSCI Brazil Capped ETF	iShares MSCI Netherlands ETF
iShares MSCI Canada ETF	iShares MSCI Singapore ETF
iShares MSCI France ETF	iShares MSCI South Korea Capped ETF
iShares MSCI Germany ETF	iShares MSCI Spain Capped ETF
iShares MSCI Italy Capped ETF	iShares MSCI Sweden ETF
iShares MSCI Hong Kong ETF	iShares MSCI Switzerland Capped ETF
	iShares MSCI Taiwan ETF

Panel B: Descriptive statistics

ETF	Mean	Standard Deviation	Skewness	Kurtosis	Jarque-Bera	LB(10)	LB^2(10)
iShares MSCI Australia ETF	0.0162	0.0167	-0.2163	13.3251	21630.60***	67.42***	4407.94***
iShares MSCI Austria Capped ETF	0.0193	0.0167	-0.6439	12.4549	18442.07***	7.68	3508.05***
iShares MSCI Belgium Capped ETF	0.0072	0.0153	-0.5052	10.3827	11246.09***	26.96***	3168.28***
iShares MSCI Brazil Capped ETF	0.0155	0.0240	-0.3332	9.7623	9351.89***	32.70***	2935.57***
iShares MSCI Canada ETF	0.0066	0.0146	-1.6179	30.0843	150697.46***	17.29*	255.34***
iShares MSCI France ETF	0.0022	0.0160	-0.2639	9.7570	9303.77***	46.60***	2863.36***
iShares MSCI Germany ETF	0.0032	0.0165	-0.1575	11.6117	15040.88***	27.46***	2162.71***
iShares MSCI Hong Kong ETF	-0.0119	0.0175	-0.4257	9.5249	8769.92***	42.83***	1984.81***
iShares MSCI Italy Capped ETF	0.0116	0.0162	0.0643	11.4031	14305.25***	135.76***	4350.23***
iShares MSCI Japan ETF	0.0013	0.0138	0.1137	11.3683	14194.17***	66.67***	2971.12***
iShares MSCI Malaysia ETF	0.0031	0.0141	-2.4239	53.7016	525423.44***	52.44***	14.60
iShares MSCI Mexico Capped ETF	0.0195	0.0175	-0.0371	10.8606	12516.11***	14.73	2101.23***
iShares MSCI Netherlands ETF	0.0059	0.0157	-0.4211	10.2249	10716.06***	50.49***	3591.58***
iShares MSCI Singapore ETF	0.0100	0.0162	0.0116	11.0832	13233.64***	123.82***	3299.37***
iShares MSCI South Korea Capped ETF	0.0233	0.0209	0.0903	13.4907	22297.09***	66.56***	3427.59***
iShares MSCI Spain Capped ETF	0.0015	0.0175	-0.3340	10.3224	10950.28***	30.86***	1841.83***
iShares MSCI Sweden ETF	0.0003	0.0200	-0.4671	11.2571	13986.02***	43.88***	1933.21***
iShares MSCI Switzerland Capped ETF	0.0176	0.0132	-0.3642	9.3056	8160.56***	74.10***	3041.57***
iShares MSCI Taiwan ETF	0.0028	0.0188	-0.1243	8.3278	5761.75***	60.18***	2033.27***

Panel C: Statistics on percentage price deviations from NAV

	Average price deviation (%)	Average premium (%)	Average discount (%)	% of days when ETF trades at a premium	% of days when ETF trades at a discount
iShares MSCI Australia ETF	0.1235	0.7058	-0.7384	59.68	40.32
iShares MSCI Austria Capped ETF	-0.0208	0.5358	-0.6005	51.02	48.98
iShares MSCI Belgium Capped ETF	0.0083	0.5303	-0.5738	52.72	47.28
iShares MSCI Brazil Capped ETF	0.0996	0.6737	-0.5792	54.18	45.82
iShares MSCI Canada ETF	0.0787	0.4002	-0.3066	54.51	45.49
iShares MSCI France ETF	0.0508	0.4645	-0.4633	55.41	44.59
iShares MSCI Germany ETF	0.0343	0.4505	-0.4682	54.69	45.31
iShares MSCI Hong Kong ETF	0.0348	0.4987	-0.5196	54.45	45.55
iShares MSCI Italy Capped ETF	0.0122	0.7091	-0.7837	53.32	46.68
iShares MSCI Japan ETF	0.0662	0.7547	-0.7690	54.82	45.18
iShares MSCI Malaysia ETF	-0.1644	0.7336	-1.0394	49.35	50.65
iShares MSCI Mexico Capped ETF	-0.0388	0.4292	-0.4758	48.29	51.71
iShares MSCI Netherlands ETF	0.0321	0.4679	-0.5091	55.39	44.61
iShares MSCI Singapore ETF	-0.0400	0.6631	-0.8686	54.10	45.90
iShares MSCI South Korea Capped ETF	0.0340	0.9358	-0.9569	52.35	47.65
iShares MSCI Spain Capped ETF	0.0218	0.5016	-0.5186	52.97	47.03
iShares MSCI Sweden ETF	0.0722	0.6188	-0.6156	55.72	44.28
iShares MSCI Switzerland Capped ETF	0.1316	0.5208	-0.4465	59.77	40.23
iShares MSCI Taiwan ETF	0.1319	1.0362	-0.9034	53.38	46.62

The table above contains a series of information on the sample of ETFs used in our study. The list of the nineteen ETFs employed here is outlined in panel A. Panel B presents a series of descriptive statistics on the log-differenced returns of our nineteen ETFs; these statistics include the mean, standard deviation, skewness, kurtosis, Jarque-Bera normality test-statistics and Ljung-Box test-statistics at ten lags for the return- and squared return-series of the nineteen ETFs. Panel C contains summary statistics on the observed percentage price deviations of each ETF from its NAV; these statistics include the average price deviation (%), the average premium (%), the average discount (%) and the percentage of days for which an ETF has traded at a premium/discount.
*** p<0.01, ** p<0.05, * p<0.1.

Table 2: Parameter estimates for mean Model 1 (Sentana and Wadhwani (1992)) with variance model GJR-GARCH.

	α	θ	ϕ_0	ϕ_1	ω	β	λ	δ
AU	-0.0084	0.0122	-0.0245	-0.0055**	0.0388***	0.0241***	0.9125***	0.0852***
AT	0.0412	-0.0009	-0.0026	-0.0020	0.0441***	0.0212***	0.9204***	0.0705***
BE	0.0102	0.0058	-0.0410**	-0.0006	0.0349***	0.0352***	0.8977***	0.0959***
BR	-0.0175	0.0064	0.0293	-0.0028*	0.1016***	0.0237***	0.9120***	0.0872***
CA	0.0380**	-0.0171	0.0011	-0.0018	0.0039***	0.0116***	0.9591***	0.0549***
FR	0.0045	0.0067	-0.0529***	-0.0017	0.0368***	0.0316***	0.8952***	0.1096***
DE	0.0232	-0.0004	-0.0328*	-0.0026	0.0358***	0.0176**	0.9122***	0.1049***
HK	0.0071	-0.0006	-0.0880***	0.0013	0.0391***	0.0274***	0.9083***	0.0958***
IT	0.0330	-0.0067	-0.0257	-0.0115***	0.0255***	0.0266***	0.9203***	0.0807***
JP	0.0152	-0.0063	-0.0338*	-0.0118***	0.0217***	0.0470***	0.9037***	0.0759***
ML	-0.0144	0.0138	-0.0475***	-0.0022	0.0098***	0.0395***	0.9488***	0.0213***
MX	-0.0055	0.0087	0.0241	-0.0025	0.0569	0.0111	0.9033***	0.1276***
NL	0.0167	0.0008	-0.0463**	-0.0036	0.0291***	0.0235*	0.9073***	0.1061***
SG	0.0012	0.0020	-0.0386**	-0.0088***	0.0175***	0.0296***	0.9204***	0.0863***
SK	-0.0136	0.0097	-0.0149	-0.0030*	0.0232***	0.0222***	0.9428***	0.0550***
SP	-0.0019	0.0060	-0.0297	-0.0028	0.0436***	0.0263***	0.9079***	0.0964***
SW	-0.0011	0.0044	-0.0159	-0.0040*	0.0225***	0.0123**	0.9410***	0.0761***
CH	0.0284	0.0007	-0.0653***	-0.0073	0.0213***	0.0431***	0.9011***	0.0824***
TW	0.0307	-0.0066	0.0044	-0.0103***	0.0169***	0.0263***	0.9365***	0.0625***

The table presents the maximum likelihood estimates from the set of the following equations for the full sample period (14/7/2000- 19/11/2019):

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

$\sigma_t^2 = \omega + \beta\varepsilon_{t-1}^2 + \lambda\sigma_{t-1}^2 + \delta I_{t-1}\varepsilon_{t-1}^2.$

ETFs appear in the table with the following abbreviations: AU (iShares MSCI Australia ETF), AT (iShares MSCI Austria Capped ETF), BE (iShares MSCI Belgium Capped ETF), BR (iShares MSCI Brazil Capped ETF), CA (iShares MSCI Canada ETF), FR (iShares MSCI France ETF), DE (iShares MSCI Germany ETF), HK (iShares MSCI Hong Kong ETF), IT (iShares MSCI Italy Capped ETF), JP (iShares MSCI Japan ETF), ML (iShares MSCI Malaysia ETF), MX (iShares MSCI Mexico Capped ETF), NL (iShares MSCI Netherlands ETF), SG (iShares MSCI Singapore ETF), SK (iShares MSCI South Korea Capped ETF), SP (iShares MSCI Spain Capped ETF), SW (iShares MSCI Sweden ETF), CH (iShares MSCI Switzerland Capped ETF), TW (iShares MSCI Taiwan ETF).

*** p<0.01, ** p<0.05, * p<0.1.

Table 3: Parameter estimates for mean Model 2 (Sentana and Wadhwani (1992) model controlling for observed lagged premiums/discounts) with variance model GJR-GARCH.

	α_0	α_1	θ_0	θ_1	$\phi_{0,0}$	$\phi_{1,0}$	$\phi_{0,1}$	$\phi_{1,1}$	ω	β	λ	δ
AU	0.0512	-0.0363	0.0203	0.0099	0.0150	-0.0049	-0.0218	-0.0060	0.0392***	0.0260***	0.9110***	0.0841***
AT	0.1227***	-0.0224	0.0245	-0.0363	0.0169	0.0011	0.0417	-0.0036	0.0473***	0.0241***	0.9161***	0.0698***
BE	0.0308	0.0201	0.0718***	-0.0717***	-0.0116	0.0088*	-0.0246	0.0038	0.0343***	0.0355***	0.8996***	0.0910***
BR	0.1332**	-0.1343**	0.0093	-0.0010	0.0389	-0.0030	0.0635**	-0.0029	0.1077***	0.0258***	0.9090***	0.0864***
CA	0.0598**	0.0070	0.0050	-0.0342**	-0.0173	0.0032	0.0399	-0.0040	0.0038***	0.0142***	0.9597***	0.0488***
FR	0.0572	-0.0431	0.0186	0.0012	-0.0499*	0.0019	-0.0198	-0.0071	0.0369***	0.0309***	0.8951***	0.1109***
DE	0.0250	0.0248	0.0330*	-0.0252	-0.0121	0.0015	-0.0352	-0.0032	0.0363***	0.0179**	0.9115***	0.1049***
HK	0.1222***	-0.0768**	0.0261	-0.0256	-0.0524*	0.0041	-0.0457	-0.0019	0.0388***	0.0265***	0.9091***	0.0954***
IT	0.0813*	0.0064	0.0172	-0.0334*	0.0120	-0.0099**	-0.0057	-0.0095**	0.0265***	0.0286***	0.9174***	0.0815***
JP	0.0234	0.0410	0.0376*	-0.0580**	0.0168	-0.0087	-0.0532**	-0.0015	0.0223***	0.0471***	0.9016***	0.0797***
ML	0.0715**	-0.0637**	0.0102	-0.0150	0.0116	-0.0235***	0.0134	-0.0023	0.0098***	0.0395***	0.9487***	0.0215***
MX	0.0548	-0.0431	0.0353*	-0.0437**	0.0475*	-0.0018	0.0627**	0.0026	0.0569***	0.0117	0.9032***	0.1263***
NL	0.0604*	0.0062	0.0408**	-0.0429**	-0.0109	0.0015	-0.0331	-0.0029	0.0286***	0.0242***	0.9080***	0.1035***
SG	0.0111	0.0077	0.0165	-0.0309*	-0.0348	-0.0100**	-0.0170	-0.0052	0.0178***	0.0311***	0.9193***	0.0852***
SK	-0.0759*	0.0158	0.0463***	-0.0078	-0.0162	0.0023	-0.0146	-0.0031	0.0237***	0.0226***	0.9425***	0.0543***
SP	0.1004**	-0.0757*	0.0194	-0.0141	-0.0073	-0.0014	0.0083	-0.0047	0.0434***	0.0268***	0.9081***	0.0949***
SW	0.0066	0.0012	0.0424***	-0.0322**	-0.0059	-0.0014	0.0051	-0.0029	0.0233***	0.0131***	0.9397***	0.0765***
CH	0.0348	0.0466*	0.0909***	-0.0747***	-0.0196	0.0051	-0.0727***	0.0061	0.0211***	0.0429***	0.9019***	0.0812***
TW	0.0399	-0.0038	0.0248	-0.0329**	-0.0066	-0.0063	0.0568*	-0.0106**	0.0174***	0.0313***	0.9340***	0.0577***

The table presents the maximum likelihood estimates from the set of the following equations for the full sample period (14/7/2000- 19/11/2019):

$$r_t = \alpha_0 D_{t-1} + \alpha_1(1 - D_{t-1}) + \theta_0 D_{t-1}\sigma_t^2 + \theta_1(1 - D_{t-1})\sigma_t^2 + D_{t-1}\left(\phi_{0,0} + \phi_{1,0}\sigma_t^2\right)r_{t-1} + (1 - D_{t-1})\left(\phi_{0,1} + \phi_{1,1}\sigma_t^2\right)r_{t-1} + \varepsilon_t,$$

$$\sigma_t^2 = \omega + \beta\varepsilon_{t-1}^2 + \lambda\sigma_{t-1}^2 + \delta I_{t-1}\varepsilon_{t-1}^2.$$

D_{t-1} is a dummy variable assuming the value of unity if the ETF has posted a discount in period $t-1$, zero otherwise. ETFs appear in the table with the following abbreviations: AU (iShares MSCI Australia ETF), AT (iShares MSCI Austria Capped ETF), BE (iShares MSCI Belgium Capped ETF), BR (iShares MSCI Brazil Capped ETF), CA (iShares MSCI Canada ETF), FR (iShares MSCI France ETF), DE (iShares MSCI Germany ETF), HK (iShares MSCI Hong Kong ETF), IT (iShares MSCI Italy Capped ETF), JP (iShares MSCI Japan ETF), ML (iShares MSCI Malaysia ETF), MX (iShares MSCI Mexico Capped ETF), NL (iShares MSCI Netherlands ETF), SG (iShares MSCI Singapore ETF), SK (iShares MSCI South Korea Capped ETF), SP (iShares MSCI Spain Capped ETF), SW (iShares MSCI Sweden ETF), CH (iShares MSCI Switzerland Capped ETF), TW (iShares MSCI Taiwan ETF).
*** p<0.01, ** p<0.05, * p<0.1.

Table 4: Parameter estimates for mean Model 3 (Sentana and Wadhwani (1992) model controlling for forecast premiums/discounts) with variance model GJR-GARCH.

	α_0	α_1	θ_0	θ_1	$\phi_{0,0}$	$\phi_{1,0}$	$\phi_{0,1}$	$\phi_{1,1}$	ω	β	λ	δ
AU	-0.0196	-0.0149	0.0296	0.0079	-0.0308	-0.0016	-0.0160	-0.0070	0.0389***	0.0239***	0.9126***	0.0850***
AT	0.0432	0.0642	0.0296*	-0.0462*	0.0037	0.0011	0.0020	-0.0017	0.0454***	0.0225***	0.9183***	0.0709***
BE	0.0111	0.0120	0.0636***	-0.0519**	-0.0470*	0.0080*	-0.0279	-0.0004	0.0349***	0.0360***	0.8979***	0.0927***
BR	0.0028	-0.0398	0.0206	-0.0037	0.0430	-0.0016	0.0259	-0.0035	0.1028***	0.0243***	0.9112***	0.0872***
CA	0.0675**	0.0037	-0.0078	-0.0250	-0.0191	0.0009	0.0379	-0.0078	0.0039***	0.0123***	0.9590***	0.0539***
FR	0.0050	0.0054	0.0179	-0.0017	-0.0216	-0.0027	-0.0758***	-0.0002	0.0361***	0.0310***	0.8965***	0.1087***
DE	0.0000	0.0581	0.0096	-0.0175	-0.0207	-0.0041	-0.0519*	0.0018	0.0354***	0.0178**	0.9123***	0.1048***
HK	0.0057	-0.0048	0.0230	-0.0155	-0.0859***	0.0053	-0.0741**	-0.0034	0.0391***	0.0273***	0.9086***	0.0951***
IT	0.0175	0.0414	0.0293	-0.0385*	-0.0251	-0.0063	-0.0179	-0.0100**	0.0264***	0.0277***	0.9184***	0.0814***
JP	0.0418	0.0038	-0.0212	-0.0083	-0.0403	-0.0159**	-0.0239	-0.0086	0.0212***	0.0473***	0.9042***	0.0751***
ML	-0.0101	-0.0064	0.0369**	-0.0244	-0.0216	-0.0209**	-0.0160	-0.0021	0.0084***	0.0396***	0.9538***	0.0111
MX	-0.0114	-0.0099	0.0248	-0.0060	0.0131	0.0000	0.0431	-0.0035	0.0574***	0.0112	0.9031***	0.1272***
NL	0.0199	0.0241	0.0188	-0.0188	-0.0083	-0.0041	-0.0783***	0.0002	0.0292***	0.0252***	0.9062***	0.1049***
SG	-0.0183	0.0249	0.0293*	-0.0370**	-0.0560**	-0.0062	-0.0147	-0.0067	0.0180***	0.0312***	0.9188***	0.0860***
SK	-0.0579	0.0111	0.0324**	-0.0007	-0.0121	0.0004	-0.0221	-0.0037	0.0237***	0.0226***	0.9424***	0.0545***
SP	0.0197	-0.0176	0.0278*	-0.0170	-0.0189	-0.0007	-0.0309	-0.0028	0.0430***	0.0257***	0.9095***	0.0944***
SW	0.0008	-0.0120	0.0262*	-0.0116	-0.0220	-0.0007	-0.0020	-0.0059	0.0232***	0.0122*	0.9402***	0.0773***
CH	0.0334	0.0360	0.0377*	-0.0411*	-0.0527*	-0.0038	-0.0772***	0.0017	0.0212***	0.0440***	0.9012***	0.0806***
TW	0.0358	0.0262	0.0141	-0.0222	0.0257	-0.0094**	-0.0116	-0.0076*	0.0171***	0.0275***	0.9356***	0.0619***

The table presents the maximum likelihood estimates from the set of the following equations for the full sample period (14/7/2000- 19/11/2019):

$$r_t = \alpha_0 D_t + \alpha_1(1-D_t) + \theta_0 D_t \sigma_t^2 + \theta_1(1-D_t)\sigma_t^2 + D_t\left(\phi_{0,0} + \phi_{1,0}\sigma_t^2\right)r_{t-1} + (1-D_t)\left(\phi_{0,1} + \phi_{1,1}\sigma_t^2\right)r_{t-1} + \varepsilon_t,$$

$$\sigma_t^2 = \omega + \beta\varepsilon_{t-1}^2 + \lambda\sigma_{t-1}^2 + \delta I_{t-1}\varepsilon_{t-1}^2.$$

D_t is a dummy variable assuming the value of unity if a discount was forecast for the ETF for day t, zero otherwise. ETFs appear in the table with the following abbreviations: AU (iShares MSCI Australia ETF), AT (iShares MSCI Austria Capped ETF), BE (iShares MSCI Belgium Capped ETF), BR (iShares MSCI Brazil Capped ETF), CA (iShares MSCI Canada ETF), FR (iShares MSCI France ETF), DE (iShares MSCI Germany ETF), HK (iShares MSCI Hong Kong ETF), IT (iShares MSCI Italy Capped ETF), JP (iShares MSCI Japan ETF), ML (iShares MSCI Malaysia ETF), MX (iShares MSCI Mexico Capped ETF), NL (iShares MSCI Netherlands ETF), SG (iShares MSCI Singapore ETF), SK (iShares MSCI South Korea Capped ETF), SP (iShares MSCI Spain Capped ETF), SW (iShares MSCI Sweden ETF), CH (iShares MSCI Switzerland Capped ETF), TW (iShares MSCI Taiwan ETF).

*** p<0.01, ** p<0.05, * p<0.1.

Table 5: Parameter estimates comparison for mean Model 1 (Sentana and Wadhwani (1992)) with variance model GJR-GARCH, pre and post crisis' outbreak.

	α	θ	ϕ_0	ϕ_1	ω	β	λ	δ
Panel A: Pre crisis' outbreak								
AU	0.0234	0.0114	-0.0413	-0.0102	0.0998***	0.0000	0.8848***	0.1157***
AT	0.1946**	-0.0678	-0.0502	-0.0040	0.0924***	0.0000	0.9046***	0.0785***
BE	0.0213	0.0074	-0.1141***	0.0067	0.0623***	0.0192	0.8877***	0.1189***
BR	0.0176	0.0084	0.0761*	-0.0107*	0.1983**	0.0000	0.9120***	0.0985***
CA	0.1380**	-0.0568	0.0236	-0.0356*	0.0249**	0.0166	0.9384***	0.0585***
FR	0.0105	0.0048	-0.0817**	0.0017	0.0305***	0.0000	0.9334***	0.0941***
DE	0.0774	-0.0224	-0.0767**	0.0054	0.0425***	0.0091	0.9188***	0.1024***
HK	0.0265	-0.0058	-0.1378***	0.0155	0.0468***	0.0003	0.9090***	0.1191***
IT	0.0637	-0.0213	-0.0560	-0.0250**	0.0280***	0.0184**	0.9390***	0.0646***
JP	-0.0334	0.0109	0.0198	-0.0326*	0.0322***	0.0446***	0.9193***	0.0411**
ML	0.0049	0.0119	-0.0376	-0.0275***	0.0076***	0.0311***	0.9699***	-0.0069
MX	0.0670	-0.0065	0.0712**	-0.0222***	0.0753***	0.0000	0.9109***	0.1237***
NL	0.0161	-0.0041	-0.0855***	0.0023	0.0315***	0.0000	0.9263***	0.1128***
SG	0.0023	0.0072	-0.0884***	-0.0108	0.0783***	0.0264*	0.8895***	0.1138***
SK	0.0693	-0.0048	-0.0310	-0.0039	0.0347***	0.0131*	0.9568***	0.0435***
SP	0.0678***	-0.0133***	-0.0297	-0.0167	0.0217***	0.0000	0.9503***	0.0743***
SW	0.0840*	-0.0210	-0.0156	-0.0055	0.0154***	0.0000	0.9664***	0.0564***
CH	0.0382	-0.0060	-0.1383***	0.0051	0.0383***	0.0218*	0.9058***	0.0940***
TW	0.0513	-0.0144	-0.0320	-0.0094	0.0333**	0.0239	0.9464***	0.0446***
Panel B: Post crisis' outbreak								
AU	-0.0290	0.0102	-0.0125	-0.0048*	0.0229***	0.0221**	0.9230***	0.0845***
AT	0.0026	0.0011	0.0275	-0.0026	0.0318***	0.0320***	0.9179***	0.0697***
BE	0.0032	0.0042	0.0013	-0.0021	0.0254***	0.0424***	0.8991***	0.0879***
BR	-0.0447	0.0053	0.0228	-0.0021	0.0906***	0.0411***	0.8931***	0.0949***
CA	-0.0022	0.0024	0.0159	-0.0006	0.0083***	0.0017	0.9375***	0.1036***
FR	0.0045	0.0053	-0.0231	-0.0029	0.0371***	0.0621***	0.8657***	0.1198***
DE	0.0011	0.0068	-0.0099	-0.0041	0.0329***	0.0213**	0.9069***	0.1092***
HK	-0.0085	0.0016	-0.0588**	-0.0010	0.0511***	0.0420***	0.8971***	0.0905***
IT	0.0133	0.0069	0.0275	-0.0106***	0.0344***	0.0302***	0.8965***	0.0992***
JP	0.0198	-0.0027	-0.0403*	-0.0106**	0.0280***	0.0426***	0.8813***	0.1130***
ML	-0.0266	0.0095	0.0106	-0.0005	0.0219***	0.0260***	0.9111***	0.1238***
MX	-0.0408	0.0152	0.0200	0.0011	0.0499***	0.0282**	0.8920***	0.1180***
NL	0.0197	0.0029	-0.0209	-0.0047	0.0300***	0.0457***	0.8871***	0.1030***
SG	-0.0103	0.0059	0.0027	-0.0080**	0.0142***	0.0205**	0.9248***	0.0898***
SK	-0.0389	0.0171	-0.0035	-0.0029*	0.0339***	0.0234**	0.9264***	0.0682***
SP	-0.0514	0.0123	-0.0021	-0.0029	0.0590***	0.0551***	0.8796***	0.0959***
SW	-0.0312	0.0140	-0.0091	-0.0040*	0.0405***	0.0457***	0.8898***	0.0978***
CH	0.0204	0.0057	-0.0213	-0.0102*	0.0176***	0.0511***	0.8960***	0.0792***
TW	0.0054	0.0113	0.0234	-0.0097**	0.0304***	0.0204**	0.9132***	0.0961***

The table presents the maximum likelihood estimates from the set of the following equations before (14/7/2000- 31/8/2008) and after the crisis' outbreak (1/9/2008- 19/11/2019):

$r_t = \alpha + \theta\sigma_t^2 + (\phi_0 + \phi_1\sigma_t^2)r_{t-1} + \varepsilon_t,\ \sigma_t^2 = \omega + \beta\varepsilon_{t-1}^2 + \lambda\sigma_{t-1}^2 + \delta I_{t-1}\varepsilon_{t-1}^2.$

ETFs appear in the table with the following abbreviations: AU (iShares MSCI Australia ETF), AT (iShares MSCI Austria Capped ETF), BE (iShares MSCI Belgium Capped ETF), BR (iShares MSCI Brazil Capped ETF), CA (iShares MSCI Canada ETF), FR (iShares MSCI France ETF), DE (iShares MSCI Germany ETF), HK (iShares MSCI Hong Kong ETF), IT (iShares MSCI Italy Capped ETF), JP (iShares MSCI Japan ETF), ML (iShares MSCI Malaysia ETF), MX (iShares MSCI Mexico Capped ETF), NL (iShares MSCI Netherlands ETF), SG (iShares MSCI Singapore ETF), SK (iShares MSCI South Korea Capped ETF), SP (iShares MSCI Spain Capped ETF), SW (iShares MSCI Sweden ETF), CH (iShares MSCI Switzerland Capped ETF), TW (iShares MSCI Taiwan ETF).*** p<0.01, ** p<0.05, * p<0.1.

Table 6: Parameter estimates' comparison between mean Model 2 (Sentana and Wadhwani (1992) model controlling for observed lagged premiums/discounts) and mean Model 3 (Sentana and Wadhwani (1992) model controlling for forecast premiums/discounts) with variance model GJR-GARCH, pre and post crisis' outbreak.

	Pre crisis' outbreak				Post crisis' outbreak			
	$\phi_{1,0}$		$\phi_{1,1}$		$\phi_{1,0}$		$\phi_{1,1}$	
	Actual discount	Forecast discount	Actual premium	Forecast premium	Actual discount	Forecast discount	Actual premium	Forecast premium
iShares MSCI Australia ETF	0.0261	-0.0101	0.0130	0.0139	0.0009	-0.0020	-0.0111**	-0.0101**
iShares MSCI Austria Capped ETF	0.0205	0.0684*	0.0351	-0.0568	0.0015	-0.0012	-0.0028	-0.0007
iShares MSCI Belgium Capped ETF	0.0202	0.0193	0.0042	0.0023	0.0005	0.0037	-0.0062	-0.0038
iShares MSCI Brazil Capped ETF	0.0016	-0.0061	-0.0158*	-0.0180	-0.0015	-0.0016	-0.0007	-0.0019
iShares MSCI Canada ETF	-0.1247**	-0.0318	-0.1983***	-0.2395***	0.0043	0.0073	0.0040	-0.0056
iShares MSCI France ETF	0.0344*	0.0095	-0.0134	-0.0040	0.0062	-0.0038	0.0023	-0.0009
iShares MSCI Germany ETF	0.0184	-0.0111	0.0064	0.0312**	-0.0023	-0.0025	-0.0010	-0.0040
iShares MSCI Hong Kong ETF	0.0404**	0.0165	0.0301*	0.0191	0.0063	0.0018	0.0027	-0.0051
iShares MSCI Italy Capped ETF	-0.0293	-0.0149	0.0183	-0.0311*	-0.0032	-0.0069	-0.0185***	-0.0097*
iShares MSCI Japan ETF	-0.0184	-0.0595**	-0.0058	-0.0067	-0.0092	-0.0101	-0.0173**	-0.0064
iShares MSCI Malaysia ETF	0.0203	-0.0165	-0.0974***	-0.0285	-0.0114	-0.0214**	0.0014	-0.0003
iShares MSCI Mexico Capped ETF	-0.0218	-0.0189**	-0.0099	-0.0230	-0.0013	0.0046	0.0065	-0.0018
iShares MSCI Netherlands ETF	0.0044	-0.0034	0.0038	0.0101	-0.0013	-0.0052	-0.0009	-0.0018
iShares MSCI Singapore ETF	0.0000	-0.0113	-0.0344*	-0.0091	-0.0067	-0.0054	-0.0155***	-0.0071
iShares MSCI South Korea Capped ETF	0.0030	-0.0052	0.0045	0.0024	0.0021	0.0002	-0.0091***	-0.0059*
iShares MSCI Spain Capped ETF	0.0095	0.0068	-0.0272	-0.0310	0.0109*	-0.0021	0.0004	-0.0044
iShares MSCI Sweden ETF	-0.0044	0.0010	-0.0175*	-0.0215**	-0.0003	-0.0025	-0.0037	-0.0036
iShares MSCI Switzerland Capped ETF	-0.0130	0.0085	0.0028	0.0275	-0.0104	-0.0106	-0.0151	-0.0090
iShares MSCI Taiwan ETF	0.0021	-0.0057	-0.0055	-0.0111	-0.0130	-0.0108*	-0.0283***	-0.0080

The table presents the maximum likelihood estimates for the feedback coefficients when feedback trading is conditioned upon actual lagged/forecast discounts ($\phi_{1,0}$) and premiums ($\phi_{1,1}$) based on estimations from the following set of equations before (14/7/2000- 31/8/2008) and after the crisis' outbreak (1/9/2008- 19/11/2019):

Actual (lagged) premiums/discounts:

$$r_t = \alpha_0 D_{t-1} + \alpha_1(1 - D_{t-1}) + \theta_0 D_{t-1}\sigma_t^2 + \theta_1(1 - D_{t-1})\sigma_t^2 + D_{t-1}(\phi_{0,0} + \phi_{1,0}\sigma_t^2)r_{t-1} + (1 - D_{t-1})(\phi_{0,1} + \phi_{1,1}\sigma_t^2)r_{t-1} + \varepsilon_t,$$

$$\sigma_t^2 = \omega + \beta\varepsilon_{t-1}^2 + \lambda\sigma_{t-1}^2 + \delta I_{t-1}\varepsilon_{t-1}^2.$$

Forecast premiums/discounts:

$$r_t = \alpha_0 D_t + \alpha_1(1 - D_t) + \theta_0 D_t\sigma_t^2 + \theta_1(1 - D_t)\sigma_t^2 + D_t(\phi_{0,0} + \phi_{1,0}\sigma_t^2)r_{t-1} + (1 - D_t)(\phi_{0,1} + \phi_{1,1}\sigma_t^2)r_{t-1} + \varepsilon_t,$$

$$\sigma_t^2 = \omega + \beta\varepsilon_{t-1}^2 + \lambda\sigma_{t-1}^2 + \delta I_{t-1}\varepsilon_{t-1}^2.$$

*** p<0.01, ** p<0.05, * p<0.1.

Table 7: Parameter estimates' comparison for mean Model 3 (Sentana and Wadhwani (1992) model accounting for successful premium/discount forecasts) with variance model GJR-GARCH, for full sample period, pre and post crisis' outbreak.

	Full period		Pre crisis' outbreak		Post crisis' outbreak	
	$\phi_{1,0}$	$\phi_{1,1}$	$\phi_{1,0}$	$\phi_{1,1}$	$\phi_{1,0}$	$\phi_{1,1}$
iShares MSCI Australia ETF	-0.0123***	0.0066	-0.0122	0.0224	-0.0130***	0.0066
iShares MSCI Austria Capped ETF	-0.0053	0.0022	0.0167	-0.0194	-0.0068	0.0020
iShares MSCI Belgium Capped ETF	-0.0095*	0.0074	0.0103	0.0087	-0.0147**	0.0074
iShares MSCI Brazil Capped ETF	-0.0021	-0.0024	-0.0161*	-0.0030	-0.0011	-0.0024
iShares MSCI Canada ETF	0.0005	-0.0024	-0.7376***	-0.0425	0.0023	-0.0043
iShares MSCI France ETF	-0.0043	0.0028	-0.0181	0.0128	-0.0041	-0.0007
iShares MSCI Germany ETF	-0.0060	0.0075	0.0082	0.0067	-0.0088*	0.0079
iShares MSCI Hong Kong ETF	0.0015	0.0057	-0.0121	0.0270*	0.0017	-0.0008
iShares MSCI Italy Capped ETF	-0.0172***	-0.0055	-0.0291*	-0.0054	-0.0152***	-0.0066
iShares MSCI Japan ETF	-0.0178***	-0.0043	-0.0226	-0.0339	-0.0190**	-0.0017
iShares MSCI Malaysia ETF	-0.0511***	-0.0016	-0.0846***	0.0130	-0.0370***	-0.0011
iShares MSCI Mexico Capped ETF	-0.0066	0.0008	-0.0221**	-0.0125	-0.0012	0.0015
iShares MSCI Netherlands ETF	-0.0059	0.0000	0.0081	-0.0022	-0.0086*	0.0008
iShares MSCI Singapore ETF	-0.0108**	-0.0075**	-0.0051	-0.0143*	-0.0126**	-0.0061
iShares MSCI South Korea Capped ETF	-0.0083***	0.0000	0.0011	-0.0078	-0.0087***	0.0011
iShares MSCI Spain Capped ETF	-0.0025	0.0035	-0.0199	-0.0070	-0.0018	0.0018
iShares MSCI Sweden ETF	-0.0110***	0.0011	-0.0261**	-0.0044	-0.0087***	0.0029
iShares MSCI Switzerland Capped ETF	-0.0246***	0.0126	-0.0137	0.0172	-0.0282***	0.0124
iShares MSCI Taiwan ETF	-0.0177***	-0.0080*	-0.0012	-0.0147*	-0.0225***	-0.0029

The table presents the maximum likelihood estimates for the feedback coefficients when feedback trading is conditioned upon successful ($\phi_{1,0}$) and unsuccessful ($\phi_{1,1}$) premium/discount predictions based on estimations from the following set of equations for the full sample period (14/7/2000- 19/11/2019), before (14/7/2000- 31/8/2008) and after the crisis' outbreak (1/9/2008- 19/11/2019):

$$r_t = \alpha_0 D_t + \alpha_1(1 - D_t) + \theta_0 D_t \sigma_t^2 + \theta_1(1 - D_t)\sigma_t^2 + D_t\left(\phi_{0,0} + \phi_{1,0}\sigma_t^2\right)r_{t-1} + (1 - D_t)\left(\phi_{0,1} + \phi_{1,1}\sigma_t^2\right)r_{t-1} + \varepsilon_t,$$

$$\sigma_t^2 = \omega + \beta\varepsilon_{t-1}^2 + \lambda\sigma_{t-1}^2 + \delta I_{t-1}\varepsilon_{t-1}^2.$$

D_t is a dummy variable assuming the value of unity if the predicted sign of the ETF's percentage price deviation from its NAV for day t equals the actual one, zero otherwise.

*** p<0.01, ** p<0.05, * p<0.1.

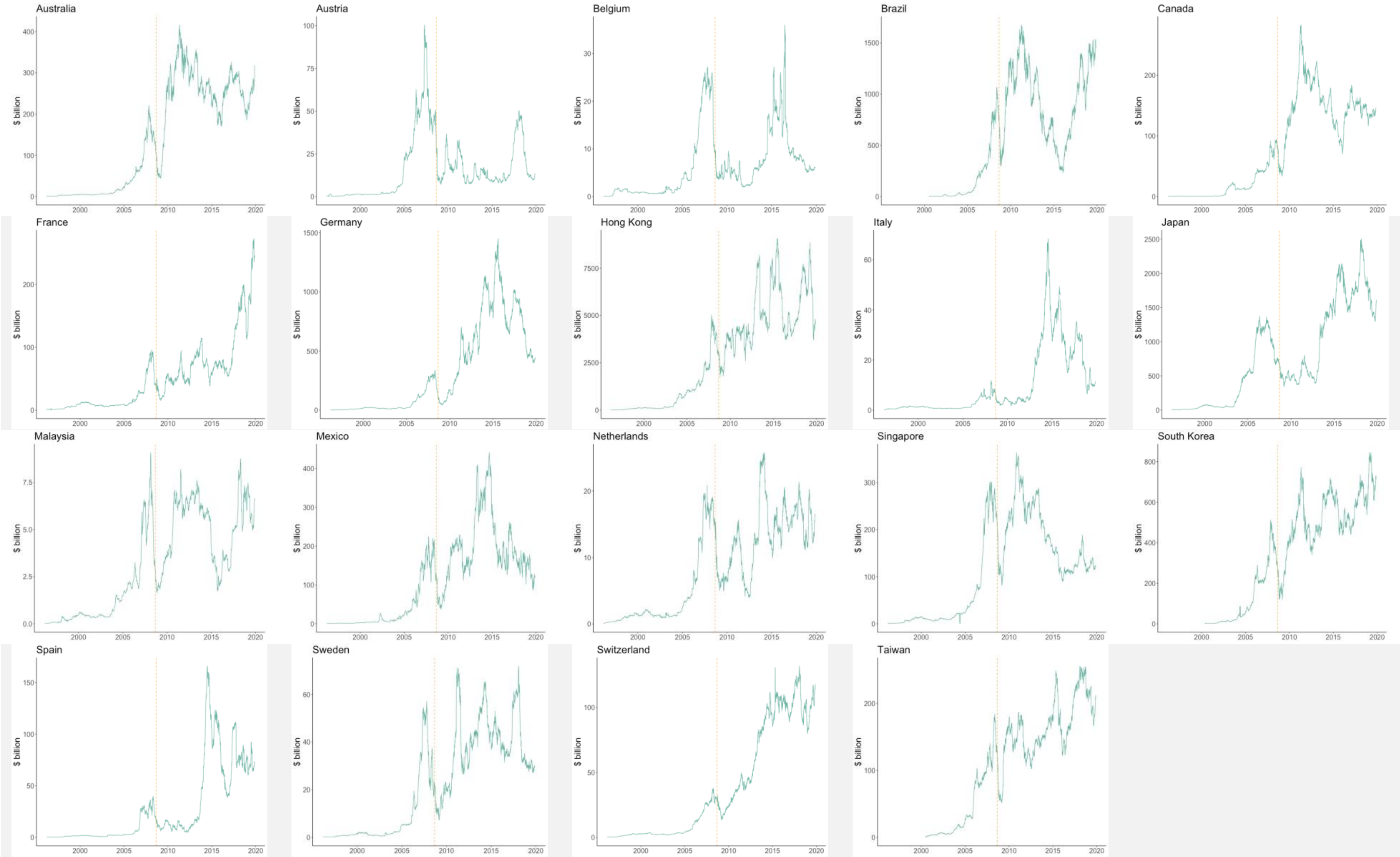

Figure 1. The figure presents the historical changes of the market value (capitalisation) of the nineteen US-listed country ETFs for the 2000-2019 window. The vertical dot line separates the pre with the post 2008 financial crisis.