ETF Arbitrage and International Diversification

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December 24, 2021

Abstract

We show that investment decisions of country ETF market participants measured by ETF market order imbalances are driven by global shocks, rather than local risks. We argue that the ETF arbitrage mechanism is one of the key channels through which global shocks propagate to local economies leading to increased return correlation with the U.S. market, limiting the benefits from international diversification. Staggered introduction of country ETFs increases the return correlations between underlying foreign and U.S. market indices. We find that countries with stronger ETF price discovery and lower limits to arbitrage have a higher comovement with the U.S. market lending further support for the proposed arbitrage mechanism.

Keywords: ETFs, equity market correlation, limits to arbitrage, VIX shocks
JEL Classification: G11, G15.

Acknowledgements: We thank Jay Cao (discussant), Mike Dong (discussant), Roman Kozhan, Michael Moore, Pedro Matos, Philippe Mueller, Alvaro Pedraza (discussant), Alexi Savov, Tomas Williams, Chendi Zhang as well as seminar participants at CICF 2019, FMA Annual Meeting 2019, 27^{th} Finance Forum (Madrid), University of Hebrew, Fulcrum Asset Management, Jupiter-Bristol PhD conference, Warwick Business School and at the Lancaster-Warwick workshop for very useful comments. We thank Diego del Hoyo for excellent research assistance. The previous version was circulated under "ETF Arbitrage and International Correlation". Filippou (Corresponding author): John M. Olin Business School, Washington University in St. Louis, St. Louis, MO 63130-4899, USA. Email: iliasfilippou@wustl.edu; Gozluklu: The University of Warwick, Warwick Business School, UK. Email: Arie.Gozluklu@wbs.ac.uk; Rozental: Ryedale Inc., UK. Email: hari.rozental@ryedale.com.

1. Introduction

Significant innovations in financial products made international investments increasingly possible. Over recent years, exchange-traded funds experienced double-digit growth in assets under management. Low management fees allow ETFs to compete for market share with more expensive mutual funds and futures contracts (e.g., Ben-David, Franzoni, and Moussawi, 2017). However, trading across major country ETFs and its association with local and global uncertainty remains understudied. Country ETFs are a low-cost vehicle for foreign investments in benchmark country indices worldwide and hence provide access to foreign markets, especially for retail investors. Many exchange-traded fund providers refer to international diversification as one of the key advantages of investing in this type of products.[1] While most earlier studies focus on the effects of ETFs on the underlying securities in the basket that it tracks, we propose a transmission mechanism of global shocks to foreign country equity markets via ETF trading.

We provide a view that as the U.S. accommodates the largest share of ETF global trading volume, global shocks first affect the decisions of country ETF investors, which are then transmitted to local markets.[2] We show that international ETF market participants trade based on CBOE Volatility Index (VIX) shocks related to both U.S. and global fundamentals rather than local ones, and propagate those shocks to local markets. The shock transmission is performed via ETF arbitrage. We argue that such arbitrage activity is one of the few mechanisms responsible for increasing the correlation between the underlying U.S. market and the rest of the world. This high cross-country correlation limits the ability of investors to diversify U.S. risk via international ETF investments cheaply. Country ETFs often provide easier access to less integrated emerging markets or countries where direct investments are costly (e.g., Brazil). Such ETFs have become increasingly popular, with iShares Emerging Markets ETF being the second-largest ETF by trading volume in the world.[3] However, the transmission of global shocks to those markets limits the diversification benefits of emerging market strategies.

[1]Blackrock: https://www.ishares.com/us/strategies/invest-internationally.

[2]According to Deutsche Bank's ETF Annual Review & Outlook (2017), U.S. equity ETFs turnover was $16.38 trillion (90%) out of $18.26 trillion globally in 2016.

[3]http://etfdb.com/compare/volume/.

We first test the hypothesis of whether country ETF investors react to changes in the U.S. VIX rather than local economic uncertainty, as measured by its local counterparts. To this end, we compute both order imbalances of each country's ETF and correlations of each underlying MSCI market return with the U.S. market. Our data span the period of January 2006 until June 2018. Using a large cross-section of 41 countries, we find a strong association between ETF order imbalances (return correlations) and the U.S. VIX, indicating that international investment decisions are mainly driven by the latter measure rather than local shocks. We show that an increase in the VIX results in selling pressure in the country ETF and increases correlations between underlying foreign and U.S. stock market indices due to the ETF market's arbitrage mechanism. Such a result is robust to different volatility regimes and is consistent across different types of investors. We isolate pure U.S. shocks from VIX shocks that represent both U.S. and global shocks. Our results are mainly driven by global shocks rather than pure U.S. shocks. More specifically, we find that there is a transmission of both U.S. and global shocks to other economies but global shocks have stronger economic effects. We also compute the economic uncertainty and risk aversion components and find that traders react more strongly to economic uncertainty changes rather than the risk aversion component of the VIX.

We then show that ETF order imbalances carry fundamental information about future country index returns. We also run both predictive panel regressions and a portfolio sort of MSCI returns on lagged ETF order imbalances. Both tests demonstrate the predictive ability of past ETF order imbalances on future MSCI returns. To access ETF arbitrage's impact on the correlation of country returns with the U.S. market, we regress weekly innovations in such correlation both on a dummy variable capturing staggered introduction of ETF markets across countries and during different volatility regimes. We provide time-series evidence that the introduction of the ETF market results in an increase in innovation in such weekly correlation of the underlying country stock market indices and more so during periods of high volatility. This result is consistent with the literature on global contagion, especially during high volatility regimes. However, the channel is different. Our cross-sectional portfolio analysis reveals that the return correlations with the U.S. market increases for those countries that benefit from better price discovery and suffer less from limits to arbitrage in the ETF market. This finding offers support for our claim that the ETF arbitrage mechanism reduces benefits to international diversification.

Our result is related to Levy and Lieberman (2013) who show the overreaction to U.S. returns during non-synchronized trading hours. They observe that since ETF and local market (mostly Asian) are open during different market-hours, intra-day price formation is often driven by S&P 500 returns rather than changes in the fund's net asset value. In contrast to their study, we focus on ETF order imbalances and return correlations using returns in lower (weekly) frequency. This approach allows us to assess ETF market participants' trading decisions that are not driven by non-synchronicity effects. Furthermore, we utilize a much broader cross-sectional sample. In addition, our result is in line with a recent study of Converse, Levy-Yeyati, and Williams (2020) who show that ETF fund flows are much more (less) sensitive to global (local) risk factors than mutual funds. The authors relate this effect to ETFs attracting uninformed investors. In contrast, our analysis shows that the reaction to VIX shocks is common to all investor types.

We also explain cross-country variation in return correlation with the U.S. market. According to Ben-David, Franzoni, and Moussawi (2018), non-fundamental shocks must be reversed over time. This finding suggests that if all shocks transmitted from the ETF market to local economies were non-fundamental, ETF arbitrage would not contribute towards increased correlation. In contrast, if the price deviation from the NAV is due to the faster incorporation of fundamental information in the ETF market, then arbitrage should affect returns of the underlying index, and such effect should not be reverted. If such fundamental information is common both to the U.S. and local market, one should observe a higher correlation. Section 2 provides the details of this mechanism, which leads to increased correlation. Consistent with the literature, we argue that ETF transmits fundamental and noise shocks to the underlying economies. We show that countries that have a higher degree of price discovery in their ETFs have, on average, a higher correlation (integration) with the U.S. market. In these markets, fundamental information gets incorporated into ETF prices faster than in the Net Asset Value (NAV). Therefore, market makers closely follow and learn from changes in ETF prices. This is the case when derivative securities price the underlying assets, rather than the other way around. In addition, in order for fundamental shocks to get transmitted to underlying markets, the authorized participants (AP) must engage in arbitrage activity. We find that the lower the limits to ETF arbitrage, the higher is the correlation (integration) between a country and the U.S. market.

To better understand the impact of the ETF market on return correlations of the underlying foreign markets (MSCI) with the U.S. market, we exploit the fact that ETFs were introduced at different times throughout the sample. We construct a dummy variable that takes the value of 1 at the fund's inception date and throughout its life. Our sample is extended from January 1992 until June 2018 to ensure that we have at least eight years of data before the introduction of the first ETF. Thus, this exercise also serves as an out-of-sample test of our findings. We find that the ETF market's introduction leads to higher (abnormal) correlations with the U.S. market regardless of the VIX state. However, the effect is much stronger in high VIX (risk-off) states. This finding emphasizes ETF markets' importance as a transmission mechanism of adverse global shocks to local markets inducing higher correlations and limited international diversification.

We perform several robustness tests and verify that our main results hold. Specifically, our results are robust for both developed and emerging economies. We also consider alternative specifications of the return correlation measure using different estimation windows and the Dynamic Conditional Correlation (DCC) model and find similar results. Our results are robust to a battery of placebo tests. One could argue that the VIX index, ETF flows, and country index returns are likely driven by the same fundamental force. To this end, we construct a news-based measure of economic uncertainty using articles from the *Wall Street Journal* and find similar results. Finally, we compute ETF order imbalances for different types of traders, such as retail and institutional investors, and we find that VIX shocks have a similar effect.

Related Literature. Most ETF research focuses on the evaluation of negative and positive consequences of ETF trading on underlying markets (see, for example, Ben-David et al. (2017), Karmaziene and Sokolovski (2021)). Malamud (2016) theoretically shows that demand shocks can be propagated to the underlying markets. A strong debate is about whether such shocks reflect fundamental information incorporated into ETF faster than to NAV or reflect non-fundamental liquidity shocks that diminish information efficiency of underlying stock prices. There is mixed evidence of both effects. Glosten, Nallareddy, and Zou (2021) show that ETF trading can partially transmit information about systematic fundamentals to the underlying stocks leading to information efficiency improvement. Lettau and Madhavan (2016) and Wermers and Xue (2015) argue for the existence of price discovery in ETF market. Madhavan and Sobczyk (2016) make a similar argument and develop a theoretical model incorporating both noise and price discovery in ETF prices. Marshall, Nguyen, and Visaltanachoti (2013) find that when the stock market's underlying liquidity is low, ETF prices adjust faster than NAV. In contrast, Ben-David et al. (2018) show that ETFs increase the volatility of underlying assets due to the propagation of noise via arbitrage mechanism. They show that such an additional layer of volatility is non-fundamental. Israeli, Lee, and Sridharan (2017) show that an increase in ETF ownership leads to a rise in trading costs of the underlying markets and a potential shift of retail traders to the ETF market, leading to a decline in information efficiency over a longer-term (due to less analyst coverage). Brown, Davies, and Ringgenberg (2021) demonstrate that the ETF market's arbitrage activity negatively predicts future stock returns suggesting a non-fundamental based view. Da and Shive (2018) show that arbitrage in U.S. domestic ETFs can cause an excessive comovement amount stocks in the underlying basket of securities. They show that shocks propagated from ETF markets also include non-fundamental ones due to price pressure and are reflected in negative autocorrelation in stocks and ETF returns. Our study complements this literature and studies the consequences of the price discovery process in the ETF market on the cross-country correlations.

A large strand of literature focuses on the effect of one central economy, the U.S., on the rest of the world (e.g., Longstaff, Pan, Pedersen, and Singleton (2011)). Rapach, Strauss, and Zhou (2013) highlight the leading role of the U.S. market and show the predictability of country-level returns by U.S. returns. Miranda-Agrippino and Rey (2015) and Miranda-Agrippino and Rey

(2020) examine the effect of the U.S. economy and monetary policy on global financial variables (e.g., cross-border credit flows, leverage). They highlight the role of a global factor that can explain a large portion of the variation in global asset returns and is related to global risk aversion and aggregate volatility. Atanasov (2014) shows that a single "global consumption factor" can explain more than 70% of cross-sectional variation in stock returns. Rey (2015) documents the existence of a global financial cycle. A "central country" impacts the leverage of banks, growth, and credit availability across the world. CBOE Volatility Index (VIX), that is, implied volatility of options written on S&P 500, is often used as a measure of uncertainty and is generally perceived as an indicator of market fear. VIX is significantly correlated with a global risk factor affecting international stock returns. Rey (2015) shows that when VIX is low for a long time, there is a boom in the global financial cycle and inflation of stock prices. In contrast, high values of VIX are negatively associated with capital inflows, credit growth, and leverage in all of the leading financial centers across the world. Forbes and Warnock (2012) highlights the relationship between VIX, a proxy for global risk, and international capital flows. Therefore, we use VIX as a critical variable in our empirical analysis in the context of passive international investment via ETFs.

The central role in earlier models is often allocated to large international banks (via leverage and risk appetite) that use U.S. dollars as a funding currency and provide credit across borders and foreign direct investments. Another set of literature studies the role of mutual funds that are being affected by investor redemptions during crisis periods on the international transmission of shocks (e.g., Jotikasthira, Lundblad, and Ramadorai, 2012; Raddatz and Schmukler, 2012). However, the role of indirect investment via ETFs is often overlooked. In contrast, we look at the ETF arbitrage that propagates fundamental and non-fundamental shocks to the underlying economies. We argue that due to the ETF arbitrage mechanism, global shocks are transmitted into underlying local market returns, resulting in a higher positive correlation of local market returns with the U.S. market.

Another strand of the literature studies the role of increased correlation during periods of high volatility (e.g., Solnik, Boucrelle, and Le Fur, 1996). In particular, a paramount concern is the comovement of countries during crisis periods, but there is a disagreement on what can be classified as contagion. Forbes (2012) treats it more generally, as a strong negative shock transmitted to other countries. He suggests four important and often interlinked channels for contagion: trade, banks, portfolio investors, and wake-up calls. In contrast, Bekaert, Ehrmann, Fratzscher, and Mehl (2014) define contagion as an increase in correlation across stocks beyond what can be explained by fundamentals. They explore different contagion types during the recent financial crisis and find support for the wake-up call hypothesis. According to the wake-up call hypothesis (first proposed by Goldstein (1998)), the crisis originated in one market provides a piece of new information about the true value of fundamentals to other markets. We complement this literature by showing that the ETF arbitrage mechanism is an important channel that transmits global shocks to individual countries and increases cross-country equity market correlations beyond crises.

In what follows, Section 2 describes the link between ETF arbitrage and cross-country correlation. Section 3 introduces the data sources and the construction of key variables. Section 4 provides empirical results. Section 5 shows the results of our robustness tests. Section 6 concludes.

2. ETF Arbitrage and Correlation: Mechanism

The ETF arbitrage mechanism is a unique feature of the market that theoretically allows prices to track underlying stocks continuously. A fund is traded at a premium (discount) when the ETF price is higher (lower) than the NAV. The authorized participant (AP) –designated dealer in the ETF market– has an incentive to correct the emergence of arbitrage by placing opposing trades in local and ETF markets. For example, to correct the ETF premium, AP can sell ETF shares and buy the securities of the underlying basket. This basket's constituents are published daily by ETF sponsors in the portfolio composition file (PCF). At the end of the day, AP can deliver and exchange such basket of securities to ETF sponsor for newly created ETF shares (“in-kind" creation). As a result of such arbitrage activity, the gap between ETF price and NAV should be closed.

Despite the existence of such a mechanism, deviations of prices from the NAV of the fund are common and may last up to a week. Rappoport W and Tuzun (2020) show a strong link between ETF liquidity and mispricing. Pan and Zeng (2018) show that when there is a liquidity mismatch between ETF and underlying market, APs may not be willing to correct the existing deviations. Petajisto (2017) highlights the existence of limits to arbitrage in the ETF market, especially for international funds. He shows that such deviations can last for days. We are interested in the consequences of such arbitrage incidents on the return of the underlying index. As argued by Ben-David et al. (2018) when the arbitrage mechanism transmits non-fundamental shocks to underlying stocks, over time, stock and ETF prices move back to fundamental levels. In contrast to such a view, Madhavan and Sobczyk (2016) argue that although the indicative NAV is published throughout the day (every 15 seconds), the “true" NAV is often hard to estimate. U.S. market often trades when underlying markets are closed, in which case NAV is a closing value of a previous day corrected by foreign exchange return. International equity ETFs specifically suffer from such a problem. In addition, for a basket with a large composition, the correct estimation of the total value of assets is often complicated. As such, any deviation between price and NAV can be either due to transitory liquidity shocks or due to price discovery in the ETF market.[4]

Similarly to this view, we argue that any deviation between ETF price and NAV reflects a mix of noise and fundamental information. The mechanism is illustrated in Figure 1. When U.S. investors experience an increase in VIX (e.g., bad news about future U.S. and/or global fundamentals arrives in the market), the following happens:

[4]Section A1 of the Internet Appendix describes the model of Madhavan and Sobczyk (2016).

1. U.S. investors negatively react to an increase in market uncertainty and sell ETF of country A. We show such a response in section 4.4.2. Investors also sell S&P constituents (negative return of U.S. market).
2. A sell-off of ETF leads to a decrease in its market price below the NAV of the fund. When the decrease is significant enough, and limits to arbitrage are low, AP intervenes, exploiting the ETF arbitrage mechanism outlined above.
3. AP buys ETF shares and short-sells (or reduces his inventory) the underlying stocks of country A (in a correct proportion in line with portfolio composition file). As a result, the prices of underlying stocks are reduced. ETF shares are delivered to ETF sponsor and get redeemed for the underlying stocks. AP closes his short position.
4. If a local dealer uses the ETF market to price the underlying market (i.e., price discovery happens in the ETF market), the decrease in underlying stocks' prices is permanent (negative return of county's A market). This results in a positive correlation between the U.S. market and country A. If the decrease in ETF price is considered noise –if VIX changes are not fundamental news for country A– both ETF and underlying stock prices will move back to fundamental level (as in Ben-David et al. (2018)). Therefore, there should not be any positive effect on correlation. This mechanism will be impaired if the ETF market's price discovery is distorted due to noise trading.

[Figure 1 about here]

3. Data and Methodology

This section offers a detailed description of the data and the construction of the measures of order imbalances and economic uncertainty.

3.1. MSCI Country Indices and iShare ETFs

Our focus is on exchange-traded funds provided by iShares (Blackrock, Inc.) that track a general MSCI index of a single country, do not hedge their currency exposure, and are traded on one of the U.S. exchanges.[5] The final sample consists of 41 funds traded on NYSE Arca, NASDAQ or CBOE BZX (Bats). U.S. ETF market is one of the most developed. It represents a significant portion of the world ETF trading volume. Our sample covers developed and emerging economies and has a broad geographical reach: 22 ETFs are from Europe, Middle East, or African; 13 ETFs are from Asia and Pacific regions; 6 ETFs are from Latin America and North America. The majority of our analysis is on a weekly level and covers January 2006 – June 2018. We obtain ETF prices, MSCI daily index (in USD), and its turnover from Thomson Reuters Datastream and Bloomberg. Officially published end-of-day net asset values (NAV) of funds are available directly from the iShares website.[6]

3.2. Order Imbalance

We obtain intra-day quote and trade data for 41 ETFs from TAQ. The ETF order flow (OI) is constructed by matching quote and trade data from the TAQ database using the Holden and Jacobsen (2014) time interpolation method. We use the Lee and Ready (1991) algorithm in order to sign the trades.[7] Thus, we measure the total ETF order imbalance as:

$$OI_t = \frac{buy_t - sell_t}{buy_t + sell_t} \tag{1}$$

where buy_t ($sell_t$) denote the buy (sell) dollar volume at time t. We also consider order imbalances of different trader types based on trade size and retail investor identification (Boehmer, Jones, Zhang, and Zhang, 2021). Such differentiation allows us to conduct a deeper

[5]Many of the single-country ETFs in our sample are on the list of top 100 funds by traded volume on etfdb.com. Our sample's most popular countries are Brazil, Japan, China, Taiwan, India, Hong Kong, Mexico, Germany, and South Korea.

[6]Our analysis focuses on weekly frequencies. However, our results are robust to monthly frequencies and they are available on demand.

[7]Section A2 of the Internet Appendix offers a detailed description of the two methods.

analysis of similarities and differences between these types of investors in how they react to new information. We report these results in section A4 of the Internet Appendix.

3.3. Economic Uncertainty

Volatility Measures. Our main goal is to identify the main economic forces that drive investor demand in the ETF market and its implications for the underlying indices around the world. To this end, we use the VIX shocks (ΔVIX) as a proxy of economic uncertainty worldwide and examine the reaction of ETF traders to changes of U.S. VIX and local VIX measures (e.g., $\Delta LVIX$). We also report our results for different VIX levels in order to distinguish between good (risk-on) and bad (risk-off) states of the world in terms of global equity investments (e.g., Caballero and Kamber, 2019; Chari, Stedman, and Lundblad, 2020).[8]

The data for the CBOE Volatility Index (VIX) is collected from the CBOE website. We also obtain a local alternative of VIX from Bloomberg. A few countries do not have a similar volatility measure to VIX. Thus, for a few European countries, we use the general European index (VSTOXX Volatility Index) as a proxy of VIX. Other countries that are missing local VIXs are replaced with realized volatility. Table A1 of the Internet Appendix provides a detailed description of the names, tickers of ETFs, and the volatility measures that we use as a proxy of VIX per country. Table A2 of the Internet Appendix shows correlations of VIX and local VIX shocks. We find that the local VIX is highly correlated with U.S. VIX for some countries, especially developed ones. Hence we orthogonalize changes in LVIX to changes in VIX and conduct our analysis using a measure of local VIX that is unrelated to VIX, and we denote it by $\Delta LVIX^o$.

News-based Measure. We also construct a weekly news-based measure of uncertainty using articles from Factiva that belong to the economics category. Our data contain articles from January 2006 to June 2018. Specifically, we collect 9,472 articles from the *Wall Street Journal*

[8]The VIX is a measure of economic uncertainty, and it is less related to other types of uncertainty such as political uncertainty (e.g., Filippou, Gozluklu, and Taylor, 2018).

that mention the word "uncertainty" and belong to the economics category.[9] Our original data are daily and we convert them to weekly by aggregating all the available articles within a week. Then, we calculate the percentage change of the number of articles every week. Thus, our uncertainty measure (ΔUNC) is defined as

$$\Delta UNC_t = \frac{n_t^{Articles} - n_{t-1}^{Articles}}{n_{t-1}^{Articles}}, \tag{2}$$

where ΔUNC_t represents the uncertainty in week t and $n_t^{Articles}$ denotes the number of articles in week t.

4. Empirical Results

This section evaluates the effects of changes in local and global economic uncertainty on the trading decision of international ETF investors. We further show the implication of such decisions revealed via order imbalances on the correlation and returns of underlying foreign markets with the U.S. market and emphasize ETF trading's role as a transmission mechanism of global uncertainty to local markets.

4.1. Descriptive Statistics

Figure 2 shows the 36-week rolling correlations between returns on the S&P 500 index and the rest of the world (ROW, proxied by returns on MSCI EAFE index). Over the last three decades, the value of correlation was volatile but higher in the second half of the sample and is increasing during recessions. We observe that the minimum correlation of around 0 occurs only at the beginning of the sample around 1990. During the Global Financial Crisis (GFC), the correlation significantly increases and reaches its peak at around 0.9 in 2011. Such a high

[9]Manela and Moreira (2017) construct a news-implied VIX index using articles from *Wall Street Journal*. In our setting, we construct a measure that proxies the level of economic uncertainty.

correlation is in line with the evidence that cross-country correlation increases at times of high market volatility. Figure 2 also shows the 36-week moving average of the VIX level. The rolling correlation between the U.S. market and the ROW closely follows the slow-moving fluctuations in VIX. Overall, correlation with the U.S. market experiences significant time variation but remains high in the recent sample period.

[Figure 2 about here.]

Table 1 provides the summary statistics of each country ETF's order imbalance, weekly returns of underlying MSCI index, correlation of index returns with S&P500 returns, and local uncertainty measures. On average, the order imbalance for all countries is small but positive (with few exceptions such as Australia, Israel, and Peru), suggesting that investors are net buyers of ETFs over our sample. Among all countries, the largest average order imbalance is for Colombia (16.38%) and Saudi Arabia (14.16%). The ETF markets for Colombia and Saudi Arabia are relatively undeveloped and not very liquid. Over our sample, we observe a few days with a net order imbalance of 1 for such countries (likely due to only a few buy trades per day).[10]

The average MSCI index returns are positive for most countries (apart from Colombia, Qatar, and U.A.E.) over our sample period with more considerable volatility for emerging markets. We see that the average correlations of the underlying MSCI index returns and S&P500 return are all positive and relatively high, with a maximum correlation of 0.76 in Canada's case followed by the U.K. (0.74). This finding is not surprising and can be explained by geographic and cultural proximity and trade relations. Also, as expected, developed markets are more correlated with the U.S. market compared to emerging markets. The local uncertainty measures, that is, local VIX or realized volatility shocks, fluctuate around zero, but with a larger standard deviation for countries where uncertainty is measured by local VIX shocks.

[Table 1 about here.]

[10]This illiquidity problem is not significant in our sample with most of the countries (even for Colombia and Saudi Arabia) having a significant number of buys and sells per day.

4.2. The Role of VIX: Panel Results

We first analyze how ETF traders make their investment decisions. Our primary interest is to investigate the key risk factors affecting investors' order imbalances and changes in cross-market correlations. To understand how an increase in global uncertainty (vs. local uncertainty) affects foreign country ETFs, we first run panel regressions with fixed effects for all countries in our sample. In particular, we regress weekly total ETF order imbalances (Panel A of Tabel 2) and innovations of country-level MSCI return correlations with the S&P 500 returns (Panel B of Table 2) at time t on the percentage change in VIX and its local counterparts. The correlations are estimated based on a 36-week rolling window. The innovations are measured as the residuals of an AR(1) process.

$$X_{i,t} = \alpha_i + \beta_1 \Delta VIX_t + \beta_2 \Delta LVIX^o_{i,t} + \beta_3 NFDemand_{i,t} + \beta_4 R_{ETF,i,t-1} + \gamma' \boldsymbol{Z}_{i,t} + \varepsilon_{i,t}, \quad (3)$$

where $X_{i,t}$ represents the ETF order imbalance (e.g., $OI_{i,t}$) or correlation innovations (e.g., $\Delta\rho_{i,t}$) of country i at time t.

The mechanism described in Section 2 postulates that ETF order flow in the secondary market reflects the fundamental shocks transmitted via VIX shocks. Thus, we explicitly control for flows from the ETF primary market which is likely to capture non fundamental demand shocks. Following Brown et al. (2021) we measure non fundamental demand ($NFDemand$) as the percentage change in ETF shares outstanding for country i at time t,

$$NFDemand_{i,t} = \frac{SharesOutstanding_{i,t} - SharesOutstanding_{i,t-1}}{SharesOutstanding_{i,t-1}}. \quad (4)$$

Creation/redemption results in a change of the number of shares in the ETF, and therefore, this measure captures the arbitrage trades due to excess demand (Brown et al., 2021).

We also control for lagged values of ETF returns to capture any effect of feedback trading and add other control variables. Our set of other controls (e.g., $\boldsymbol{Z_{i,t}}$) include spot exchange rate changes (e.g., ΔS), the effect of indexing over time, and a price discovery proxy in the

ETF market. Baltussen, van Bekkum, and Da (2019) show that indexing (via futures, ETFs, and index mutual funds) change the time-series properties of stock market returns. Indexing is measured as innovations from AR(1) regressions to capture changes in serial dependence of foreign market returns over time. We follow Broman (2016) to determine the degree of price discovery in each ETF. If a demand shock related to fundamentals increases the price of ETF above NAV (premium), such faster incorporation of prices reflects a price discovery. Next period, such premium (discount) should translate into a positive (negative) NAV return, as new information gets to the underlying market. We measure price discovery by running 36-week rolling regressions of NAV returns of each country on the past ETF premium and use the rolling beta estimate as a control.

[Table 2 about here.]

Table 2 shows the results of panel regressions with country fixed effects. The first specification includes only the shocks to local VIX. In Panel A, we see that a positive shock to local VIX leads to a significant outflow in the foreign market ETF and increased correlations. However, when we include U.S. VIX shocks and the other controls, we see that global shocks dominate the effect of local VIX shocks, and $\Delta LVIX$ becomes insignificant in both order imbalance and correlation regressions. Importantly, VIX shocks significantly reduce capital flows to country ETFs and increase correlations with the U.S. market, even once we include all the controls. We can also clearly reject the null hypothesis that local and global uncertainty has the same effect on order imbalances and cross-country correlations. Overall, the results suggest that ETF traders mainly react to changes in global uncertainty. Local news has only a second-order effect on order imbalances of country ETF investors and cross-country correlations of the underlying country indices.

We next test whether the results we document above depend on the VIX states. In particular, we rank the time-series of VIX level and show results for low, medium, and high VIX states using the same specification of Table 2.[11] The results are reported in Table 3. Panel A shows

[11]In Table A7 of the Internet Appendix we show the results for predictive panel regressions.

that the effect of global uncertainty on ETF order imbalances is lower (nearly half) in low VIX states. The difference between the effect of local and global VIX shocks is not significant. This result is consistent with the risk-off idea of Caballero and Kamber (2019) that ETF investors exit the equity ETF market in bad states of the world.

[Table 3 about here.]

Panel B of Table 3 shows that local VIX shocks reduce foreign market correlations with the U.S. market in low VIX (risk-on) states. In contrast, global uncertainty shocks increase such correlations. The effect of VIX shocks on correlations is much stronger (four times) in high (risk-off) VIX states. In such bad states of the world, local VIX shocks have the opposite effect on correlations in the same direction as the VIX shocks. However, the effect of global shocks dominates the local ones in magnitude. Therefore, it is important to highlight different VIX states' effect on both country ETF flows and cross-country correlations.

4.3. MSCI Returns and ETF Trading

In the previous section, we establish the contemporaneous link between VIX shocks and ETF order imbalances and changes in cross-country correlations. We test whether ETF order imbalances carry any information about the future returns of the underlying country indices. We do this by running predictive panel regressions with fixed effects and conducting portfolio sort based on lagged order imbalance information. In particular, in Table A4 of the Internet Appendix we show the panel regressions results where we regress underlying MSCI index returns on lagged ETF order imbalance, lagged shocks to VIX and local VIX as well as lagged MSCI returns. We also include the same controls as before, namely, spot exchange rate changes, proxies for indexing, non fundamental demand, and price discovery.

We only include the lagged order imbalance in the first specification and gradually add other variables and controls. Each specification also includes country fixed effects. We note that past ETF order imbalance predicts a higher return for the underlying country index, and this result is robust when we include other variables in the specification. We also see that VIX shocks predict lower returns. In contrast, past local VIX shocks are not significant in the last column of Table A4 of the Internet Appendix which reports the full specification of the model.

In Table 4 we also show the results of single portfolio sorts (Panel A) of MSCI returns based on lagged ETF order imbalance and double-sorts using both past order imbalance and VIX betas (Panel B) as well as non fundamental demand (Panel C). VIX betas are measured by regressing contemporaneously MSCI returns on VIX innovations using a 36-week rolling window while non fundamental demand is defined in Equation 4.

[Table 4 about here.]

The single portfolio sorts reveal almost monotonic (apart from portfolio 2) relation between past ETF order imbalances and future MSCI returns. A long-short (HML) portfolio, purchasing (selling) the country indices with the highest (lowest) past week ETF order imbalance delivers 6.34% (p.a.) and a Sharpe ratio of 0.72. On the other hand, double-sorts in Panel B show that past ETF order imbalances are particularly informative for countries whose returns are sensitive (high VIX betas) to U.S. VIX shocks. This finding confirms the close link between global uncertainty shocks, ETF order imbalances, and underlying MSCI country index returns. The last panel shows that this link is not driven by non fundamental demand shocks.

4.4. Staggered Introduction of Country ETFs

In order to pin down the effect of ETF market on foreign market (MSCI) return correlations with the U.S. market, we exploit the fact that ETFs were introduced at different times throughout the sample (see table A1 of the Internet Appendix for fund inception dates). We create the dummy variable $Intro^{ETF}$ that takes the value of 1 at the fund's inception date, and throughout its life. In other words, such a dummy reflects if the ETF is traded in the market. We also control for past innovations to correlations, and past MSCI returns. We run separate panel regressions for each VIX state to see whether the introduction of ETF markets had different effects on correlations in different VIX states.

$$\Delta\rho_{i,t} = \alpha_i + \beta_1 Intro_{i,t}^{ETF} + \beta_2 \Delta\rho_{i,t-1} + \beta_3 R_{MSCI,i,t-1} + \varepsilon_{i,t},$$

where $\Delta\rho_{i,t}$ represents innovations of rolling correlations between MSCI returns of country i and S&P 500 at time t.

Our sample for this regression is extended from January 1992 until June 2018 to ensure that we have at least eight years of data before the introduction of the first ETF.[12] Table 5 shows the panel regression results. We see that the ETF market's introduction leads to higher (abnormal) correlations with the U.S. market regardless of the VIX state. However, the effect is much stronger –the coefficient is three times larger– in high VIX (risk-off) states. This finding hints at the importance of ETF markets as a transmission mechanism of adverse global shocks to local markets inducing higher correlations and limited international diversification.

[Table 5 about here.]

4.5. *Cross-country Differences*

We proceed to explore the cross-country differences in ETF markets and their effect on underlying MSCI return correlations with the U.S. market. Bhattacharya and O'Hara (2018) show that when the underlying assets are hard to trade (e.g., fixed income), price discovery happens in the ETF market. "Hard to trade" situation also arises in international funds with non-overlapping trading hours. As mentioned before, Madhavan and Sobczyk (2016) show that a price discovery component of ETF premium is negatively related to the variance of transitory liquidity shocks and positively related to the efficiency of arbitrage. We hypothesize that countries with exchange-traded funds that have a high price discovery component –and therefore, for which market makers are closely following ETFs to price the underlying assets–

[12] As a consequence of extended sample for this test we use the realized volatility (RV), measured as a squared MSCI return, instead of VIX. Most of the subsequent analysis continues to use VIX.

have a higher correlation with the U.S. stock market. Since all types of investors trade based on global risks, they affect the ETF price with global fundamentals. Then the ETF arbitrage works as a transmission mechanism of global risk to foreign countries. However, if the noise in the ETF market (e.g., via retail participation) clouds the price discovery process, we expect the transmission mechanism to be weaker. Overall, we expect the magnitude of correlation to be related to price discovery and the ease of arbitrage in the ETF market.

Price Discovery. To test this, we follow Broman (2016) to determine the degree of price discovery in the ETF market. If a demand shock related to fundamentals increases the price of ETF above NAV (premium), such faster incorporation of prices reflects a price discovery. Next period, such premium (discount) should translate into a positive (negative) NAV return, as new information gets to the underlying market. To compare the extent to which price discovery happens in the ETF market, we regress NAV return on the past ETF premium. Higher β loading represents a stronger adjustment to NAV and higher price discovery in ETF.

$$R_{i,t}^{NAV} = \alpha + \beta_i \left(\frac{P_{i,t-1} - NAV_{i,t-1}}{NAV_{i,t-1}} \right) + \varepsilon \quad (5)$$

Table 6 shows the average correlations of three portfolios formed based on the degree of price discovery. We pre-sort countries into portfolios one week before computing correlations. The low group correlation (ρ_t^L) is defined as the average correlation across all counties within this group:

$$\rho_t^L = \frac{1}{N_t^L} \sum_{i=1}^{N_t^L} Corr(\Delta MSCI_i, \Delta S\&P500) \quad (6)$$

where N_t^L is the number of countries in the group L in week $t-1$. The correlation of returns is computed using a 36-week rolling window (we test the alternative measures in section 5). The correlation between medium and high groups is defined in the same manner.

[Table 6 about here.]

In the last step of the mechanism described in Section 2, the effect (or lack thereof) on correlations with the U.S. market depends on whether the ETF market helps with the price discovery about the fundamentals of underlying country indices. If the ETF market incorporates not only noise but also information about global shocks into prices of the underlying indices, then we should see an impact on the correlations. In fact, the first sort based on β from equation 5 shows a significant increase in correlation for funds with high price discovery. The difference in average correlation across low and high groups is 0.106 (t-statistics= 22.57). We also repeat the same sorting exercise in different VIX states. Although correlations are higher across all portfolios in high VIX states, the mechanism works regardless of the VIX state.

Pukthuanthong and Roll (2009); Berger, Pukthuanthong, and Yang (2011) argue that the correlation is an *imperfect* measure of market integration and propose a measure that is based on the first principal component of equity returns. To this end, Table 6 also offers average adjusted R-squares that are estimated based on 36-week rolling contemporaneous regressions of MSCI index returns on the first principal component (PC1) of all available stock returns in our sample. The principal components are estimated based on a 36-week rolling window. We find that the average adjusted R-squares follow the same direction as the average rolling correlations.

Limits to Arbitrage. Table 7 shows the portfolio sorts results based on a proxy for limits to arbitrage. We use Amihud's illiquidity ratio (Amihud, 2002) of underlying markets. The idea is that limits to arbitrage in the ETF market would hinder the price discovery process and distort the mechanism via ETF arbitrage, resulting in lower correlations of the underlying MSCI index returns with the U.S. market. As can be seen from this sort, an increase in illiquidity leads to a relatively lower correlation with the U.S., on average (0.073). Lower liquidity of the underlying market limits the profitability of the arbitrage (due to higher price impact). As such, global shocks are less likely to get propagated to local economies. Again, we repeat the same analysis for different VIX states and find that the mechanism does not depend on the VIX state.

[Table 7 about here.]

Double sorts. Rappoport W and Tuzun (2020) document that liquidity is an important determinant for ETF arbitrage for both equity and bond ETFs. Pan and Zeng (2018) show that for the corporate bond ETF market, due to the existence of liquidity mismatch between the fund and the underlying index, the inventory management effect may be dominant.[13] This makes authorized participants (APs) reluctant to close the price deviations. We extend this argument to the ETF market for international equities. While there may not be a significant mismatch for highly liquid developed market ETFs, our sample also includes small emerging market economies. Their underlying index is much more illiquid than the corresponding ETF fund. In contrast to Pan and Zeng (2018), as we have a broad range of different countries in our sample, we consider ETF liquidity to have enough variability to be included in our measure. We compute the liquidity mismatch as a percentage difference in Amihud's illiquidity measures for ETF and local index.

$$Mismatch = \frac{ILLIQ_{ETF} - ILLIQ_{index}}{ILLIQ_{index}} \tag{7}$$

We use this mismatch measure as another limits to arbitrage proxy (in our definition, the lower the value of mismatch, the stronger the limits). In contrast to previous measures, this variable combines both ETF and the local market. Figure A1 of the Internet Appendix plots the mismatch together with an average GNI per capita (as a proxy to identify developed markets) obtained from the World Bank database.[14] Countries with higher GNI per capita tend to have lower liquidity mismatches (more positive).

[Table 8 about here.]

In Panel A (Panel B) of table 8 we show the result of double sorting the funds by price discovery and the limits to arbitrage measured by Amihud illiquidity ratio (liquidity mismatch). As can be seen from these sorts, countries where the difference in illiquidity is the largest (the most negative mismatch), have on average lower correlation with the U.S. market. This is

[13] In this market, APs maintain an inventory of illiquid corporate bonds.

[14] MSCI uses GNI per capita as one of many criteria for developed market classification.

consistent with previous evidence of limits to arbitrage, preventing global shocks' propagation to local economies.

5. Robustness Tests

In this section, we perform numerous robustness tests to ensure that results demonstrated in previous sections are not sensitive to our choice of methodologies. We start with the analysis of our cross-sectional sample choice. Then we control for alternative types of risks and market participants that may affect the result. We follow by investigating how different volatility conditions affect our results and conclude by computing alternative correlation measures.

5.1. Developed vs. Emerging Markets

As shown in Figure 3, our choice of 41 counties has a wide geographical dispersion. We test if our results are robust to our sample selection. It may be possible that the dominant effect of VIX comes from countries that are more integrated with the U.S. market. We split our sample by the level of economic development based on MSCI classification: into developed and emerging markets. Our sample is not dominated by developed countries, as almost half of the sample (20 countries) consists of emerging countries. Tables 9 (developed) and 10 (emerging) show the results of such split in the panel regressions where we test the effect VIX shocks (and its counterparts) on ETF order imbalances, MSCI return correlations and future MSCI returns.

[Tables 9 and 10 about here.]

When we compare the result in Table 9 and 10, we note that local VIX shocks alone do affect ETF order imbalances for both developed and emerging markets. However, they are only significant in developed markets when we include U.S. VIX shocks in the specification. The coefficients are larger (in magnitude) for emerging markets. In contrast, local VIX shocks increase MSCI return correlations with the U.S. market only for emerging markets in the full specification with U.S. shocks. In Panel B of both tables, we also see that ETF order imbalances predict future underlying MSCI returns for developed and emerging markets, with a larger coefficient for emerging markets.

5.2. *VIX Decomposition*

Here, we examine which part of the VIX explains ETF order imbalances. In particular, we extract the *economic uncertainty* and *risk aversion* components of VIX following Bekaert, Hoerova, and Duca (2013); Bekaert and Hoerova (2014).[15] Specifically, the VIX component that serves as a proxy of *economic uncertainty* is the forecast of the following month stock market variance (e.g., 22 trading days) that is estimated based on a model that includes as independent variables a squared value of VIX that is annualized and expressed in percentage terms as well as the continuous component of the daily quadratic variation of stock returns (e.g., $C_t = RV_t - J_t$, where RV is the daily realized variance of the stock market return that is computed as the sums of squared five-minute returns as well as the squared close-to-open return and J_t represents the jump component) over the previous day, week and month. Thus, we denote the conditional (physical) variance by VIX^{CV}. The *risk aversion* (e.g., VIX^{RA}) component of VIX reflects the variance risk premium which is measured as the difference between the implied and conditional variance (e.g., $VIX_t^2 - E_t[RV_{t+1}^{(22)}]$, where $RV_{t+1}^{(22)}$ is the realized variance of the S&P 500 over the next month). We run contemporaneous panel regressions with fixed effects in case of ETF order imbalances and MSCI return correlations, as well as predictive panel regressions for future MSCI returns.

[Table 11 about here.]

Table 11 shows the results of such panel regressions. We find that the economic uncertainty component of VIX has a stronger effect on both ETF order imbalances and return correlation. However, both components are significant in contemporaneous panel regressions (see Panel

[15] We would like to thank the authors for making the data available on their webpage.

A). Adding two VIX components does not change the conclusion about the predictive ability of ETF order imbalance on underlying future MSCI returns. It seems that both components of VIX contain some information about future returns.

5.3. U.S. or Global Shocks?

Our analysis highlights that shocks to the global component of U.S. VIX are transmitted to other economies driving trading patterns in the ETF market. Here, we examine whether U.S. shocks unrelated to the global economy are transferred to other markets. To this end, we construct a measure of U.S. VIX that is orthogonal to global VIX changes' information content. We construct two different measures of U.S. VIX that isolate its global component.

U.S. VIX and Country-level VIX. In the first measure, we regress U.S. VIX changes contemporaneously on the first three principal components of a panel of VIX shocks of G10 countries in our sample excluding U.S. VIX. Thus, our orthogonalized VIX measure is the residual of the regression, as mentioned above. Panel A of Table 12 shows results of contemporaneous regressions on ETF order imbalances on orthogonalized U.S. VIX and orthogonalized local VIX and a number of controls. We find that the U.S. component of VIX is also affecting the trading activity in the ETF market. However, in terms of economic value, we find that the global component of U.S. VIX demonstrates a stronger impact on ETF trading as the coefficient in Table 2 is -0.104 as opposed to -0.002 for the orthogonalized VIX changes measure. Interestingly, the country-level VIX changes become negative and statistically significant, indicating that once we isolate the U.S. component of VIX in the regression model, local shocks drive ETF traders' trading activity. Panel B shows the corresponding results when the response variable is the return correlation. Similarly to our previous findings, we observe that the orthogonalized U.S. VIX has a positive and statistically significant impact on return correlations. However, the orthogonalized U.S. VIX's economic value is not as strong as in the VIX measure that includes its global component. The local VIX measure is highly positive and significant.

[Table 12 about here.]

U.S. VIX and Macro Announcements. Our second measure of U.S. VIX is the residual of a contemporaneous regression of U.S. VIX on a dummy variable that takes a value of 1 if there is macro news announcement in that week and zero otherwise. We collect daily data on U.S. macroeconomic announcements from S&P Capital IQ, and we focus on General Macro announcements. These announcements include FOMC meetings, Fed presidents' speeches, auctions, and releases of the Fed's Beige Book and related conferences. Panel A of Table 13 displays results for ETF order imbalances, and Panel B shows results for return correlations. We find that our results are not affected but U.S. macroeconomic announcements. Table A6 of the Internet Appendix shows the corresponding results if we define the macro announcements variable as the number of announcements each week. Our results are robust to this alternative definition of the macro announcements variable.

[Table 13 about here.]

5.4. News-based Uncertainty

One could argue that the VIX index, ETF flows, and country index returns are likely driven by the same fundamental force. Moreover, the VIX index captures both economic uncertainty and time-varying risk aversion as discussed earlier. In order to isolate the uncertainty component, we construct a news-based measure of economic uncertainty (please see the data section for a detailed explanation of the measure). *Panel A* of Table 14 show contemporaneous regressions of ETF order imbalances on economic uncertainty, local VIX and a number of controls. Similarly to the VIX measure we find that economic uncertainty is a strong negative predictor of ETF order imbalances. *Panel B* shows contemporaneous regressions of correlation innovations on economic uncertainty, local VIX and a number of controls. Consistent with our previous findings, we find that economic uncertainty has a strong positive relation with correlation innovations.

[Table 14 about here.]

5.5. Placebo Tests

We further examine the impact of VIX on return correlations around ETF introductions. Table A5 of the Internet Appendix shows contemporaneous panel regressions with country fixed effects (FE) of innovations of return correlations on a dummy variable $Intro^{ETF}$ that takes a value of one during the life of the ETF, VIX changes and their interaction as well as lagged values of MSCI returns, lagged correlations and a number of control variables. The correlations are estimated based on a 36-week rolling window and the innovations are measured as the residuals of an AR(1) process. We also consider different specifications of the dummy variable. Our goal is to examine whether the increase in return correlation is truly due to the ETF introduction. Thus, we construct dummy variables with lead and lag specifications. Specifically, $Intro^{ETF}_{-24}$ ($Intro^{ETF}_{-12}$) is a dummy variable that takes a value one, 24 months (12 months) before an ETF introduction, and until the end of the sample. Similarly, $Intro^{ETF}_{24}$ ($Intro^{ETF}_{12}$) is a dummy variable that takes a value one, 24 months (12 months) after the introduction and until the end of the sample. We also construct a dummy variable that we label as $Intro^{ETF}_{Random}$ where we randomly assign one in the dummy variable 12 months or 24 months before or after an ETF introduction. Our model takes the form below:

$$\Delta\rho_{i,t} = \alpha_i + \beta_1 Intro^{ETF}_{LeadLag,i,t} + \beta_2 Intro^{ETF}_{LeadLag,i,t} \times \Delta VIX_t + \beta_3 \Delta VIX_t + \beta_4 \Delta\rho_{i,t-1} + \beta_5 R_{MSCI,i,t-1} + \varepsilon_{i,t},$$

where $LeadLag$ represents the number of months before or after the ETF introduction, $\Delta\rho_{i,t}$ represents innovations of rolling correlations between MSCI returns of country i and S&P 500 at time t.

We find that the interaction between $Intro^{ETF}$ and VIX changes is highly positive and significant. This result is stronger when we consider dummy variables that take a value of one, 12 months or 24 months after an ETF introduction, indicating that an introduction of an ETF, especially after some initial period, has a strong positive impact on return correlations when VIX increases. On the other hand, we find that the interaction is not statistically significant when we include interactions that take a value of one, 12 months or 24 months before an ETF introduction. We also find that the interaction of the $Intro^{ETF}_{Random}$ with changes of VIX is not statistically significant which reinforces our previous findings regarding the role of ETFs on the correlations of the underlying securities.

5.6. *Alternative Specifications*

Estimation Windows. In the main analysis, we have used a 36-week rolling window to compute time-varying correlations. As part of robustness checks, we also compute innovations to MSCI return correlations using longer estimation windows, i.e., 60-week and 100-week rolling windows. The results are reported in Tables A8 and A9 of the Internet Appendix. Our main results are not sensitive to the choice of window length.

DCC. In order to overcome the need to choose the length of the rolling window (longer length may result in smoother correlation estimates), we employ an alternative measure of correlation –Dynamic Conditional Correlation (DCC) of Engle (2002). Table A10 of the internet Appendix shows the mechanism we described in the paper does not depend on how we measure time-varying correlations.

Different Types of Traders. Country ETF products offer diversification benefits to both retail and institutional investors. However, their order flows are likely to react to different types of news, and hence the effect of VIX shocks might differ across trader types. Section A4 of the Internet Appendix describes how we construct the proxies for order imbalance measures of different trader types. Table A11 of the Internet Appendix shows that VIX shocks have a similar effect, albeit a smaller effect for small investors, on the order imbalances of different ETF traders.

6. Conclusion

In this paper, we investigate how country ETF traders make investment decisions and analyze the effect of those decisions on the underlying country indices' returns. We show that the order imbalance of country ETF trades mainly reflect changes in the U.S. implied volatility index rather than local VIX. Such a result is robust to different volatility regimes and a sub-sample analysis.

We use these results to investigate the mechanism of transmission of U.S. shocks to foreign countries that results in high cross-country correlation. We argue that such shocks are propagated to different countries via the ETF arbitrage mechanism. Consistent with this argument, our time-series analysis shows that the ETF market's introduction results in a positive innovation in the country's stock market correlation with the U.S. market.

Finally, we investigate the cross-sectional differences in countries' correlations with the U.S. market. APs engage in arbitrage activity to correct the deviations between the ETF price and the NAV. If such deviation is caused due to transitory liquidity shock, the adjustment to ETF price and NAV should be reverted. In contrast, we argue that if such deviation results from faster incorporation of fundamentals in ETF price, arbitrage should lead to a higher correlation of a country with the U.S. equity market. In support of this hypothesis, we find that countries with higher price discovery and lower limits to arbitrage have a higher correlation with the U.S. market.

Our work is important for international investors seeking to diversify their U.S. exposure by investing in international ETFs. Our analysis suggests that even emerging countries with low integration are still significantly affected by the U.S. stock market. While previous research focuses on the role of global banks and the U.S. as the central economy on cross-country correlation, our study's novelty is that we discover a new channel of country connectedness via ETF arbitrage.

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Figure 1. Correlation Mechanism

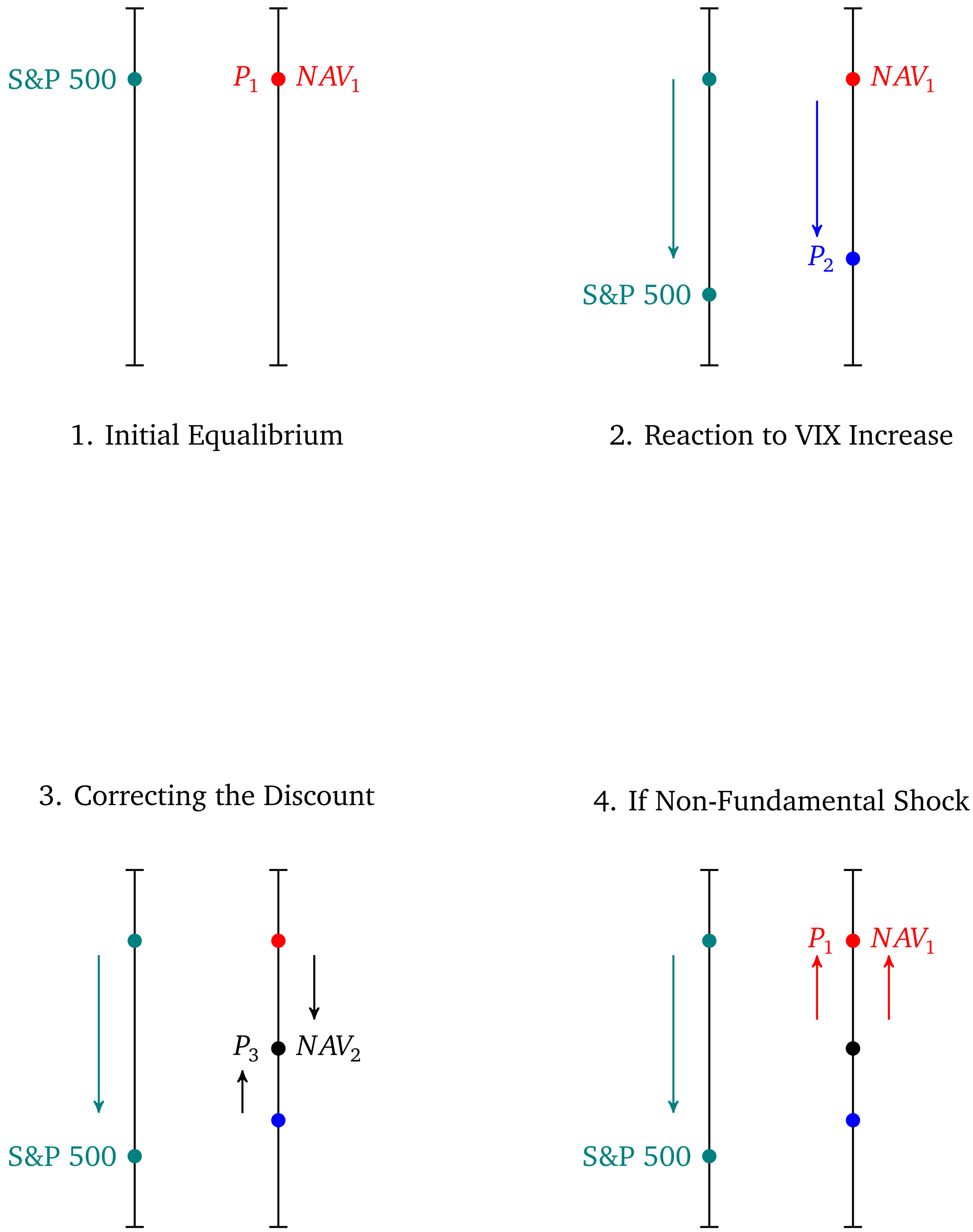
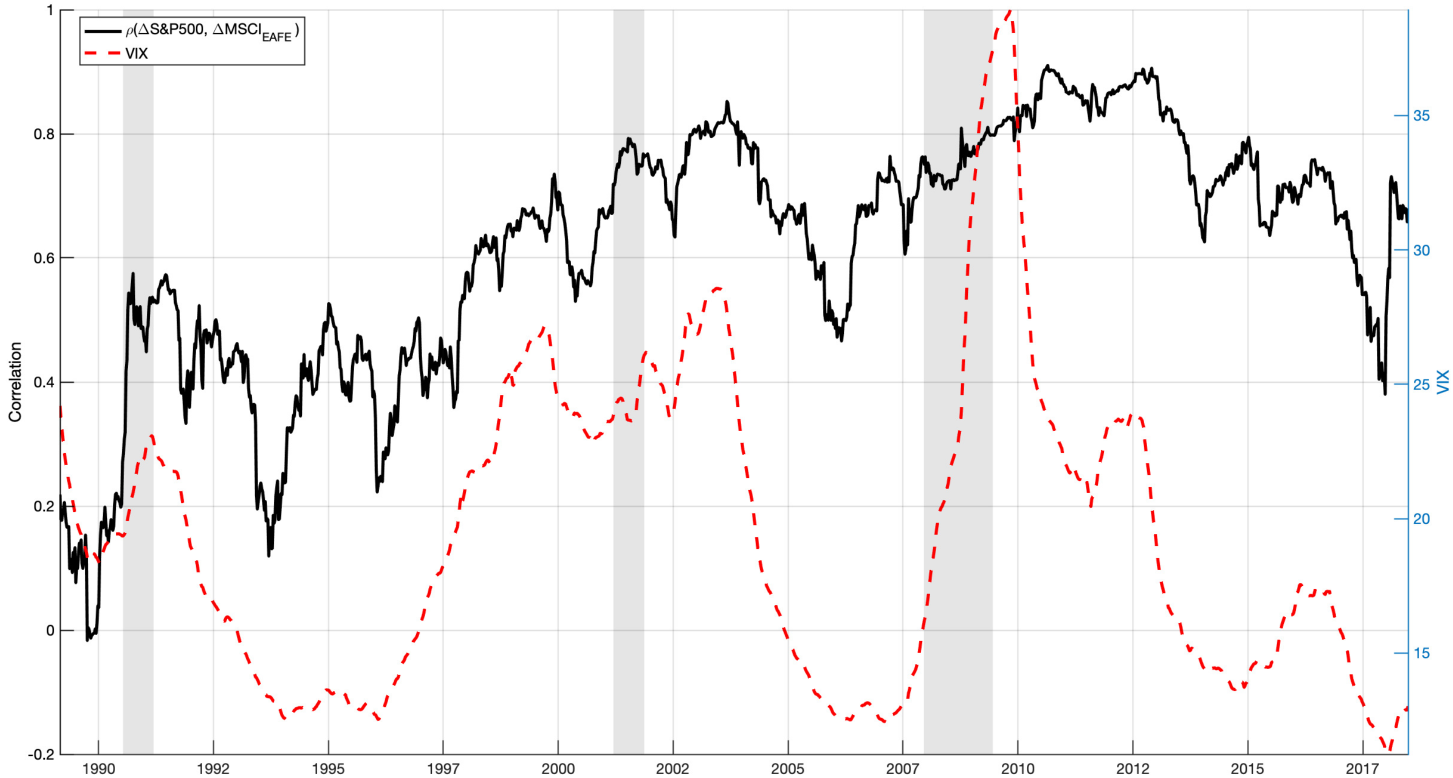
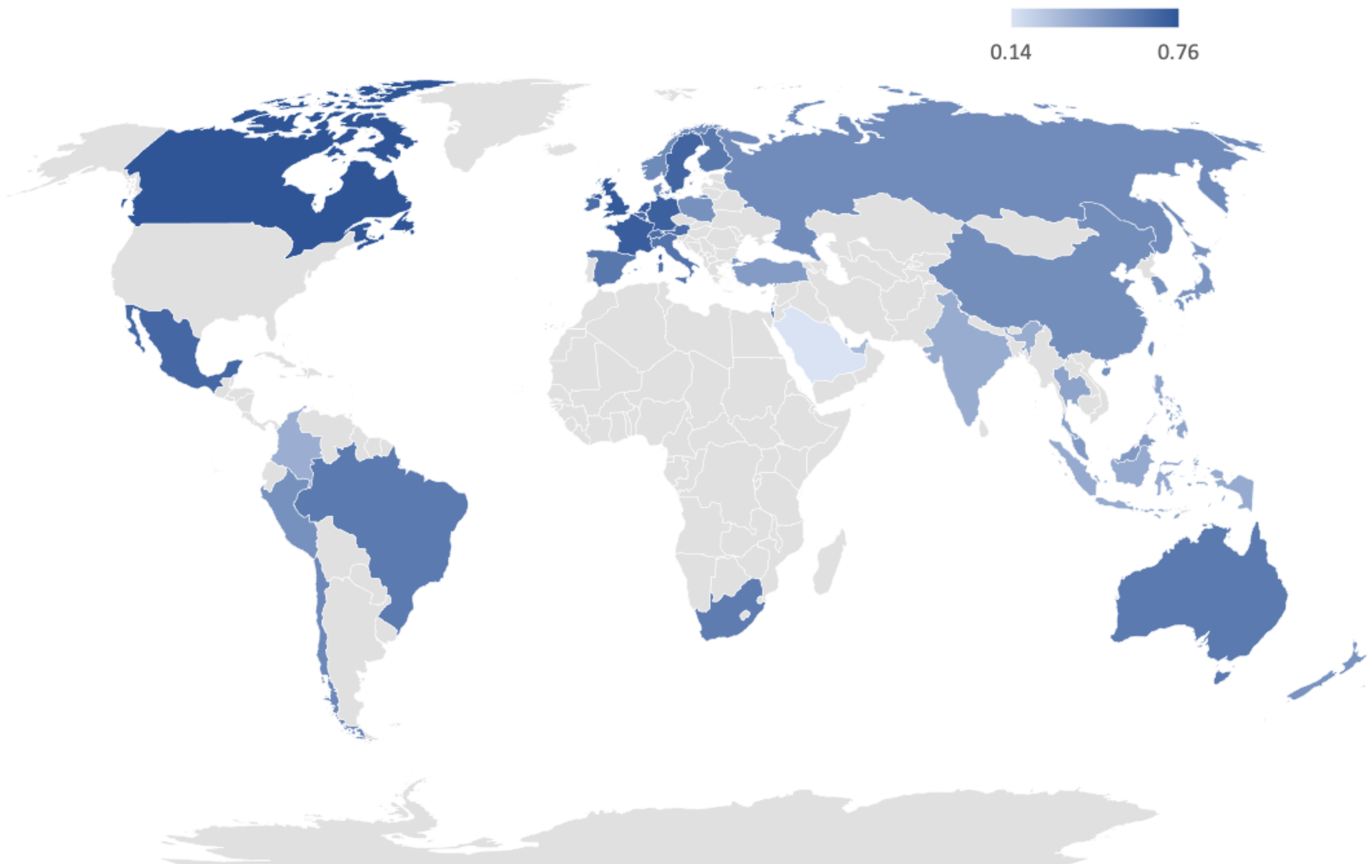


Figure 2. ***Correlations between the U.S. Market and the Rest of the World***



The figure displays 36-week rolling correlations (black solid line) between the S&P 500 and MSCI EAFE total returns (e.g., $\rho(\Delta S\&P500, \Delta MSCI_{EAFE})$). The MSCI EAFE index includes more than 900 stocks from Europe, Australia, Asia, and the Far East. We show the 36-week moving averages of the level of CBOE VIX in red dashed line. Shaded areas represent NBER recessions. The data span the period from January 1992 to June 2018.

Figure 3. Correlations Map of U.S. Returns with the rest of the World



This map shows the 36-week correlation between return of S&P 500 and returns of MSCI indices ($\rho_i = Corr(\Delta S\&P500, \Delta MSCI_i)$) of 41 countries used in the sample (see table A1 for the full list of ETFs and the corresponding indices). Countries with darker blue colors exhibit higher average correlations. The data span the period from January 1992 to June 2018.

Table 1: Summary Statistics

This table presents summary statistics of weekly order imbalances (OI) which as defined as the difference between buy and sell dollar volume over the sum of the buy and sell dollar volume. We also report summary statistics of MSCI returns (R_{MSCI}), correlations between MSCI return of foreign countries with S&P500 ($Corr(R_{MSCI}, R_{S\&P500})$) and local VIX innovations ($\Delta LVIX$). We report the mean and standard deviation of each measure in percent. The average returns and the corresponding standard deviations are annualized. The data span the period of January 2006 to June 2018.

	OI		R_{MSCI}		$Corr(R_{MSCI}, R_{S\&P500})$		$\Delta LVIX$	
Country	Mean	Std	Mean	Std	Mean	Std	Mean	Std
AUS	1.57	9.38	8.73	25.91	60.44	16.55	0.67	12.62
AUT	−2.11	25.10	3.83	28.74	65.62	15.26	0.81	13.14
BEL	1.13	26.14	5.24	23.67	67.79	13.73	0.38	7.60
BRA	0.26	4.92	8.44	35.07	60.16	22.86	0.24	2.19
CAN	1.87	12.31	7.09	23.37	76.05	12.25	0.81	14.58
CHL	2.09	18.24	3.76	23.63	53.64	19.59	−0.31	1.65
CHN	6.19	20.56	7.89	22.10	50.53	15.85	0.52	10.56
COL	16.38	36.02	−5.44	25.27	36.97	22.24	−0.18	1.92
DNK	6.70	27.87	15.25	16.03	54.31	14.48	0.81	13.14
FIN	8.01	31.50	9.88	18.46	61.22	14.03	0.81	13.14
FRA	1.39	16.71	5.86	24.16	72.13	13.31	0.84	13.35
DEU	2.34	13.44	7.48	24.14	71.00	13.26	0.74	12.54
HKG	1.04	9.05	10.71	21.50	55.27	15.95	0.67	11.94
IND	8.34	21.94	5.87	19.52	38.32	16.69	0.41	11.01
IDN	4.20	19.05	3.96	23.59	39.00	15.88	0.11	2.51
IRL	2.75	28.68	12.42	19.84	65.57	11.76	0.81	13.14
ISR	−0.80	23.69	4.82	19.23	58.45	17.80	−0.41	1.57
ITA	1.93	17.62	1.12	28.55	63.01	15.39	0.11	2.23
JPN	0.68	7.71	3.90	19.63	47.80	17.43	0.84	15.42
MYS	0.40	10.79	8.88	18.02	46.08	16.60	−0.68	1.31
MEX	0.53	6.11	5.47	26.73	68.39	20.10	0.33	8.67
NLD	0.26	22.83	7.72	23.17	72.99	11.11	0.78	13.16
NZL	2.09	23.07	13.75	16.60	48.53	19.63	−0.55	1.24
NOR	9.06	28.58	4.97	20.99	53.44	20.52	0.81	13.14
PER	−2.49	24.74	9.99	21.63	50.37	19.12	0.73	2.97
PHL	2.28	17.42	5.41	20.13	40.62	15.85	−0.06	2.04
POL	2.88	17.82	4.92	25.80	50.13	17.74	0.08	2.16
QAT	6.99	36.97	−3.62	19.18	31.09	17.64	0.06	2.47
RUS	1.49	19.56	0.66	28.30	51.52	21.04	0.89	14.33
SAU	14.16	35.25	12.74	18.20	13.66	18.56	−0.04	2.00
SGP	1.19	10.79	8.82	21.08	57.29	17.10	−0.29	1.86
ZAF	0.34	11.68	8.59	30.89	58.58	16.50	0.16	6.51
KOR	0.03	6.64	9.38	28.98	49.41	17.04	0.60	12.05
ESP	1.27	18.49	5.48	28.83	60.54	14.99	0.81	13.14
SWE	1.11	19.47	5.22	28.33	68.60	13.11	0.93	13.85
CHE	2.88	15.88	6.60	17.69	66.29	14.42	0.71	12.40
TWN	0.49	6.65	8.41	22.87	49.75	15.22	−0.17	1.89
THA	2.49	17.47	9.95	24.44	41.62	16.03	0.06	2.20
TUR	0.21	15.12	4.19	34.93	44.82	21.15	0.44	2.61
ARE	1.30	33.80	−4.61	22.63	31.60	19.85	0.58	3.21
GBR	3.09	14.15	5.33	21.72	74.15	12.87	0.92	14.06

Table 2. Panel Regressions

This table presents contemporaneous panel regressions with country fixed effects (FE) of ETF order imbalances (*Panel A*) and innovations of country-level MSCI index return (in local currency) correlations with the S&P 500 return (*Panel B*) on U.S. and orthogonalised local VIX changes as well as non fundamental demand ($NFDemand$), lagged values of ETF returns, and a number of other control variables. The correlations are estimated based on a 36-week rolling window and the innovations are measured as the residuals of an AR(1) process. We consider the model (and nested specifications) below:

$$X_{i,t} = \alpha_i + \beta_1 \Delta VIX_t + \beta_2 \Delta LVIX^o_{i,t} + \beta_3 NFDemand_{i,t} + \beta_4 R_{ETF,i,t-1} + \gamma' \boldsymbol{Z}_{i,t} + \varepsilon_{i,t},$$

where $X_{i,t}$ represents the ETF order imbalance (e.g., $OI_{i,t}$) or correlation innovations (e.g., $\Delta\rho_{i,t}$) of country i at time t. Our set of other controls (e.g., $\boldsymbol{Z}$) include spot exchange rate changes (e.g., ΔS), indexing, price discovery. We report t-statistics with robust standard errors. We include in curly brackets *p-values* that are associated with a hypothesis test of higher (lower) beta coefficients of VIX relatively to local VIX –in panel regressions with order imbalances (correlations) as independent variables– under the null hypothesis. ***,**,* denote 1%, 5% and 10% significance levels. The data contain weekly series from January 2006 to June 2018.

Panel A: Order Imbalances

	(1) OI_t	(2) OI_t	(3) OI_t
ΔVIX_t		-0.104***	-0.100***
		(-8.63)	(-7.77)
$\Delta LVIX_t$	-0.114***	-0.034**	-0.018
	(-7.74)	(-2.41)	(-1.17)
$NFDemand_t$			0.470***
			(7.55)
$\hat{R}_{ETF,i,t-1}$			0.521***
			(6.42)
Constant	0.020***	0.021***	0.051***
	(399.01)	(187.85)	(7.18)
$H_0 : \beta_1 \geq \beta_2$			{0.00}
Controls	No	No	Yes
Country FE	Yes	Yes	Yes
Observations	20,684	20,684	19,301
R-squared	0.3%	0.9%	4.5%

Panel B: Correlations

	(1) $\Delta\rho_t$	(2) $\Delta\rho_t$	(3) $\Delta\rho_t$
ΔVIX_t		0.033***	0.034***
		(13.97)	(13.76)
$\Delta LVIX_t$	0.031***	0.006	0.007
	(7.62)	(1.12)	(1.31)
$NFDemand_t$			-0.002
			(-0.31)
$\hat{R}_{ETF,i,t-1}$			-0.041***
			(-5.29)
Constant	-0.000***	-0.000***	-0.000
	(-6.47)	(-15.67)	(-0.25)
$H_0 : \beta_1 \leq \beta_2$			{0.00}
Controls	No	No	Yes
Country FE	Yes	Yes	Yes
Observations	19,427	19,427	18,817
R-squared	0.8%	2.5%	2.8%

Table 3. Panel Regressions: VIX States

This table presents contemporaneous panel regressions with country fixed effects (FE) of ETF order imbalances (*Panel A*) and innovations of country-level MSCI index return (in local currency) correlations with the S&P 500 return (*Panel B*) on U.S. (ΔVIX) and local VIX ($\Delta LVIX$) changes as well as non fundamental demand ($NFDemand$), lagged values of ETF returns, and a number of other control variables. The correlations are estimated based on a 36-week rolling window and the innovations are measured as the residuals of an AR(1) process. We show results for low, medium and high VIX regimes. We consider the model (and nested specifications) below:

$$X_{i,t} = \alpha_i + \beta_1 \Delta VIX_t + \beta_2 \Delta LVIX^o_{i,t} + \beta_3 NFDemand_{i,t} + \beta_4 R_{ETF,i,t-1} + \gamma' \boldsymbol{Z}_{i,t} + \varepsilon_{i,t},$$

where $X_{i,t}$ represents the ETF order imbalance (e.g., $OI_{i,t}$) or correlation innovations (e.g., $\Delta\rho_{i,t}$) of country i at time t. Our set of other controls (e.g., $\boldsymbol{Z}$) include spot exchange rate changes (e.g., ΔS), indexing, price discovery. We report t-statistics with robust standard errors. We report t-statistics with robust standard errors. We include in curly brackets p-$values$ that are associated with a hypothesis test of higher (lower) beta coefficients of VIX relatively to local VIX –in panel regressions with order imbalances (correlations) as independent variables– under the null hypothesis. ***,**,* denote 1%, 5% and 10% significance levels. The data contain weekly series from January 2006 to June 2018.

Panel A: Order Imbalances

	(1) OI_t	(2) OI_t	(3) OI_t	(4) OI_t	(5) OI_t	(6) OI_t	(7) OI_t	(8) OI_t	(9) OI_t
		Low VIX			*Medium VIX*			*High VIX*	
ΔVIX_t		-0.031	-0.058**		-0.100***	-0.106***		-0.110***	-0.101***
		(-1.21)	(-2.21)		(-5.57)	(-6.13)		(-5.13)	(-4.88)
$\Delta LVIX_t$	-0.038**	-0.026	-0.037*	-0.103***	-0.024	0.004	-0.108***	-0.011	-0.002
	(-2.54)	(-1.29)	(-1.72)	(-4.31)	(-0.91)	(0.14)	(-5.23)	(-0.47)	(-0.11)
$NFDemand_t$			0.525***			0.446***			0.403***
			(3.71)			(4.46)			(5.93)
$\hat{R}_{ETF,i,t-1}$			0.493***			0.588***			0.434***
			(3.19)			(4.88)			(6.47)
Constant	0.039***	0.038***	0.089***	0.022***	0.023***	0.048***	-0.005***	-0.001	0.047***
	(302.69)	(85.20)	(5.94)	(317.79)	(161.56)	(4.83)	(-12.15)	(-1.15)	(4.28)
$H_0: \beta_1 \geq \beta_2$			{0.32}			{0.00}			{0.00}
Controls	No	No	Yes	No	No	Yes	No	No	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,314	7,314	6,690	7,325	7,325	6,861	6,045	6,045	5,750
R-squared	0.0%	0.0%	3.1%	0.2%	0.7%	3.8%	0.5%	1.5%	6.4%

Panel B: Correlations

	(1) $\Delta\rho_t$	(2) $\Delta\rho_t$	(3) $\Delta\rho_t$	(4) $\Delta\rho_t$	(5) $\Delta\rho_t$	(6) $\Delta\rho_t$	(7) $\Delta\rho_t$	(8) $\Delta\rho_t$	(9) $\Delta\rho_t$
		Low VIX			*Medium VIX*			*High VIX*	
ΔVIX_t		0.011**	0.012***		0.006**	0.006**		0.049***	0.047***
		(2.55)	(2.80)		(2.49)	(2.46)		(10.04)	(9.10)
$\Delta LVIX_t$	-0.025***	-0.029***	-0.029***	0.003	-0.002	-0.001	0.068***	0.025**	0.023**
	(-4.78)	(-5.55)	(-5.59)	(0.69)	(-0.39)	(-0.24)	(10.64)	(2.62)	(2.35)
$NFDemand_t$			0.001			0.005			-0.009
			(0.16)			(0.77)			(-1.02)
$\hat{R}_{ETF,i,t-1}$			-0.024*			-0.021*			-0.035***
			(-1.70)			(-1.71)			(-3.25)
Constant	-0.004***	-0.004***	-0.005***	-0.001***	-0.001***	-0.002**	0.004***	0.002***	0.005***
	(-81.62)	(-38.27)	(-4.02)	(-49.26)	(-30.72)	(-2.44)	(32.22)	(12.13)	(3.16)
$H_0: \beta_1 \leq \beta_2$			{0.00}			{0.15}			{0.04}
Controls	No	No	Yes	No	No	Yes	No	No	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,833	6,833	6,640	6,860	6,860	6,657	5,734	5,734	5,520
R-squared	0.3%	0.4%	1.4%	0.0%	0.1%	1.1%	5.5%	10.6%	11.3%

Table 4. MSCI Returns and ETF Trading: Portfolio Sorts

This table presents summary statistics of MSCI index returns (in USD) portfolios that are sorted into quintiles based on their previous week ETF order imbalance. *Panel A* reports annualized return, standard deviation and sharpe ratio of portfolio sorted on order imbalances. We rebalance our portfolios weekly. *Panel B* shows the corresponding results of unconditional sorts of MSCI index returns that are sorted based on VIX betas and order imbalances. *Panel C* shows results of unconditional sorts of MSCI index returns that are sorted based on non fundamental demand and order imbalances. We estimate VIX betas by regressing contemporaneously MSCI returns on VIX innovations using a 36-week rolling window. We report in squared brackets t-statistics with robust standard errors. ***,**,* denote 1%, 5% and 10% significance levels. The data contain weekly series from January 2006 to June 2018.

Panel A: ETF Order Imbalance Portfolios

	P1	P2	P3	P4	P5	HML
Mean	1.24	4.78	3.69	5.45	7.58	6.34***
						[2.63]
Std	20.39	19.75	19.55	20.38	19.72	8.77
SR	0.06	0.24	0.19	0.27	0.38	0.72***

Panel B: Double-Sorts based on ETF Order Imbalances and VIX betas

	Low OI	Mid OI	High OI	HML
Mean β_{VIX}^{Low}	0.68	5.33	4.31	3.63
				[1.31]
Std	24.15	23.55	24.17	9.68
SR	0.03	0.23	0.18	0.37
Mean β_{VIX}^{High}	-1.60	6.41	12.20	13.80***
				[5.10]
Std	16.75	17.88	16.58	9.38
SR	-0.10	0.36	0.74	1.47

Panel C: Double-Sorts based on ETF Order Imbalances and Non Fundamental Demand

	Low OI	Mid OI	High OI	HML
Mean $\beta_{NFDemand}^{Low}$	1.53	6.62	7.44	5.90**
				[2.37]
Std	20.21	20.08	20.13	8.83
SR	0.08	0.33	0.37	0.67
Mean $\beta_{NFDemand}^{High}$	0.81	4.34	9.89	9.08**
				[2.42]
Std	20.53	20.57	20.79	12.74
SR	0.04	0.21	0.48	0.71

Table 5. Underlying Return Correlations and Staggered Introduction of ETFs

This table presents contemporaneous panel regressions with country fixed effects (FE) of innovations of return correlations on a dummy variable that takes a value of one during the life of the ETF, VIX changes, and their interaction as well as lagged values of MSCI returns. The correlations are estimated based on a 36-week rolling window and the innovations are measured as the residuals of an AR(1) process. We show results for low, medium and high VIX regimes. We consider the model (and nested specifications) below:

$$\Delta\rho_{i,t} = \alpha_i + \beta_1 Intro^{ETF}_{i,t} + \beta_2 \Delta\rho_{i,t-1} + \beta_3 R_{MSCI,i,t-1} + \varepsilon_{i,t},$$

where $\Delta\rho_{i,t}$ represents innovations of rolling correlations between MSCI returns of country i and S&P 500 at time t. $Intro^{ETF}$ is a dummy variable which takes the value of 1 throughout the life of an ETF (from the inception date until the fund end date) and 0 otherwise. We report t-statistics with robust standard errors. ***,**,* denote 1%, 5% and 10% significance levels. The data contain weekly series from January 1992 to June 2018.

Correlations and ETF Introductions

	(1) $\Delta\rho_t$	(2) $\Delta\rho_t$	(3) $\Delta\rho_t$	(4) $\Delta\rho_t$	(5) $\Delta\rho_t$	(6) $\Delta\rho_t$	(7) $\Delta\rho_t$	(8) $\Delta\rho_t$	(9) $\Delta\rho_t$	(10) $\Delta\rho_t$	(11) $\Delta\rho_t$	(12) $\Delta\rho_t$
	Full Sample			*Low VIX*			*Medium VIX*			*High VIX*		
$Intro^{ETF}$	0.002***	0.003***	0.003***	0.002***	0.002***	0.002***	0.002**	0.002***	0.002***	0.006***	0.006***	0.006***
	(8.02)	(7.98)	(7.80)	(4.30)	(4.18)	(4.00)	(2.54)	(2.94)	(2.91)	(4.92)	(4.95)	(4.90)
$\Delta_{\rho_{t-1}}$		-0.004	-0.006		0.021**	0.023**		-0.002	-0.003		-0.040***	-0.044***
		(-0.70)	(-1.00)		(2.26)	(2.46)		(-0.27)	(-0.38)		(-3.66)	(-4.01)
$R_{MSCI,i,t-1}$			-0.027***			-0.033***			-0.014			-0.024***
			(-5.51)			(-3.87)			(-1.37)			(-3.59)
Constant	-0.002***	-0.002***	-0.002***	-0.004***	-0.004***	-0.004***	-0.002***	-0.002***	-0.002***	0.000	0.000	0.000
	(-9.14)	(-9.15)	(-8.64)	(-19.95)	(-19.40)	(-18.75)	(-4.56)	(-5.09)	(-4.96)	(0.28)	(0.29)	(0.30)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	53,251	53,210	53,210	17,628	17,617	17,617	17,711	17,681	17,681	17,912	17,912	17,912
R-squared	0.1%	0.1%	0.2%	0.0%	0.1%	0.2%	0.0%	0.1%	0.1%	0.2%	0.3%	0.4%

Table 6. Underlying Return Correlations and ETF Price Discovery

This table presents average correlations of MSCI index returns (in local currency) on S&P 500 returns. We also report average adjusted R-squares of MSCI index returns on the first principal component (PC1) of all available countries. The correlations are estimated based on a 36-week rolling window. We allocate countries, on a weekly basis, into terciles based on their price discovery. Our proxy price discovery is defined as the NAV sensitivity to the ETF premium. Specifically, we regress NAV returns of each country on their past ETF premium and use the estimated beta as proxy of price discovery. The estimation of the beta coefficient is based on 36-week rolling window. A higher beta coefficients represents a stronger adjustment to NAV implying a higher price discovery in the ETF market. The regression takes the form:

$$R_t^{NAV} = \alpha + \beta_{PD}\left(\frac{P_{t-1} - NAV_{t-1}}{NAV_{t-1}}\right) + \varepsilon_t,$$

where β_{PD} denotes ours proxy of price discovery. We estimate the measure for all the countries in our sample. *Panel A* shows results for the full sample. *Panel B* (*Panel C*) shows results for low (high) VIX states. We report t-statistics with HAC standard errors as in Newey and West (1987). The data contain weekly series from January 2006 to June 2018.

Panel A: Price Discovery - Full Sample					
	Low β_{PD}	Medium β_{PD}	High β_{PD}	HML	t-stat
	Correlations				
$\overline{\rho}$	0.533	0.590	0.639	0.106	(22.57)
	Adjusted R-squared based on PC1				
$\overline{\text{Adj } R^2}$	51%	61%	67%	16%	(24.19)
***Panel B*: Price Discovery - Low VIX**					
	Low β_{PD}	Medium β_{PD}	High β_{PD}	HML	t-stat
	Correlations				
$\overline{\rho}$	0.398	0.480	0.535	0.138	(20.77)
	Adjusted R-squared based on PC1				
$\overline{\text{Adj } R^2}$	41%	53%	60%	19%	(17.95)
***Panel C*: Price Discovery - High VIX**					
	Low β_{PD}	Medium β_{PD}	High β_{PD}	HML	t-stat
	Correlations				
$\overline{\rho}$	0.632	0.672	0.724	0.092	(11.11)
	Adjusted R-squared based on PC1				
$\overline{\text{Adj } R^2}$	59%	68%	75%	16%	(14.54)

Table 7. Underlying Return Correlations and Limits to Arbitrage

This table presents average correlations of MSCI index returns on S&P 500 returns. We also report average adjusted R-squares of MSCI index returns on the first principal component (PC1) of all available countries. The correlations are estimated based on a 36-week rolling window. We allocate countries, on a weekly basis, into terciles based on our proxy of limits to arbitrage. We proxy limits to arbitrage with the Amihud's illiquidity ratio (e.g., Amihud, 2002) of the underlying markets (*ILLIQ*). Panel A shows results for the full sample. *Panel B* (*Panel C*) shows results for low (high) VIX states. We report t-statistics with HAC standard errors as in Newey and West (1987). The data contain weekly series from January 2006 to June 2018.

Panel A: Limits to Arbitrage - Full Sample					
	Low $ILLIQ$	Medium $ILLIQ$	High $ILLIQ$	HML	t-stat
			Correlations		
$\overline{\rho}$	0.625	0.584	0.552	-0.073	(-22.61)
			Adjusted R-squared based on PC1		
$\overline{\text{Adj } R^2}$	65%	60%	55%	-10%	(-23.48)

Panel B: Limits to Arbitrage - Low VIX					
	Low $ILLIQ$	Medium $ILLIQ$	High $ILLIQ$	HML	t-stat
			Correlations		
$\overline{\rho}$	0.519	0.457	0.427	-0.092	(-19.66)
			Adjusted R-squared based on PC1		
$\overline{\text{Adj } R^2}$	58%	51%	48%	-10%	(-15.88)

Panel C: Limits to Arbitrage - High VIX					
	Low $ILLIQ$	Medium $ILLIQ$	High $ILLIQ$	HML	t-stat
			Correlations		
$\overline{\rho}$	0.709	0.684	0.647	-0.061	(-10.99)
			Adjusted R-squared based on PC1		
$\overline{\text{Adj } R^2}$	73%	69%	64%	-9%	(-14.36)

Table 8. Double Sorts

This table presents average correlations of MSCI index returns on S&P 500 returns. The correlations are estimated based on a 36-week rolling window. We allocate countries, on a weekly basis, into terciles based on our proxy of limits to arbitrage. We proxy limits to arbitrage with the Amihud's illiquidity ratio (e.g., Amihud, 2002) of the underlying markets (*ILLIQ*). Our proxy price discovery is defined as the NAV sensitivity to the ETF premium. Specifically, we regress NAV returns of each country on their past ETF premium and use the estimated beta as proxy of price discovery. The estimation of the beta coefficients is based on a 36-week rolling window. A higher beta coefficients represents a stronger adjustment to NAV implying a higher price discovery in the ETF market. The regression takes the form:

$$R_t^{NAV} = \alpha + \beta_{PD}\left(\frac{P_{t-1} - NAV_{t-1}}{NAV_{t-1}}\right) + \varepsilon_t,$$

where β_{PD} denotes ours proxy of price discovery. We compute the liquidity mismatch as a percentage difference between the Amihud's illiquidity measures of ETF and local indices.

$$Mismatch = \frac{ILLIQ_{ETF} - ILLIQ_{index}}{ILLIQ_{index}}.$$

The measure serves as a limits to arbitrage proxy (e.g., a higher value of mismatch indicates more pronounced limits to arbitrage). *Panel A* shows average correlation innovations of portfolios that are double sorted based on median price discovery and limits to arbitrage measures. *Panel B* shows average correlation innovations of portfolios that are double sorted based on median price discovery and liquidity mismatch. We report t-statistics with HAC standard errors as in Newey and West (1987). The data contain weekly series from January 2006 to June 2018.

Panel A: Limits to Arbitrage					
	Low $ILLIQ$	Medium $ILLIQ$	High $ILLIQ$	HML	t-stat
			Correlations		
Low β_{PD}	0.598	0.488	0.529	-0.069	(-3.75)
Medium β_{PD}	0.581	0.597	0.552	-0.029	(-2.30)
High β_{PD}	0.655	0.610	0.623	-0.032	(-3.40)
Panel B: Liquidity Mismatch					
	Low $Mismatch$	Medium $Mismatch$	High $Mismatch$	HML	t-stat
			Correlations		
Low β_{PD}	0.520	0.518	0.559	0.039	(4.01)
Medium β_{PD}	0.548	0.558	0.612	0.065	(5.01)
High β_{PD}	0.614	0.626	0.668	0.054	(5.73)

Table 9. Panel Regressions: *Developed Economies*

Panel A of this table presents contemporaneous panel regressions with country fixed effects (FE) of ETF order imbalances and innovations of country-level MSCI return correlations with the S&P 500 return on U.S. and local VIX changes as well as lagged values of ETF returns, non fundamental demand ($NFDemand$), and a number of other control variables. *Panel B* shows predictive panel regressions with country fixed effects (FE) of MSCI index returns (in local currency) on lagged ETF order imbalances as well as non fundamental demand ($NFDemand$), lagged values of MSCI returns, and a number of other control variables. The correlations are estimated based on a 36-week rolling window and the innovations are measured as the residuals of an AR(1) process. We consider the model (and nested specifications) below:

$$X_{i,t} = \alpha_i + \beta_1 \Delta VIX_t + \beta_2 \Delta LVIX^o_{i,t} + \beta_3 NFDemand_{i,t} + \beta_4 R_{ETF,i,t-1} + \gamma' \boldsymbol{Z}_{i,t} + \varepsilon_{i,t},$$

where $X_{i,t}$ represents the ETF order imbalance (e.g., $OI_{i,t}$) or correlation innovations (e.g., $\Delta\rho_{i,t}$) of country i at time t. Our set of other controls (e.g., $\boldsymbol{Z}$) include spot exchange rate changes (e.g., ΔS), indexation, and price discovery. We report t-statistics with robust standard errors. ***,**,* denote 1%, 5% and 10% significance levels. The data contain weekly series from January 2006 to June 2018.

Panel A: Order Imbalances and Correlations

	(1) OI_t	(2) OI_t	(3) OI_t	(4) $\Delta\rho_t$	(5) $\Delta\rho_t$	(6) $\Delta\rho_t$
ΔVIX_t		-0.081***	-0.079***		0.037***	0.039***
		(-6.19)	(-5.54)		(9.32)	(9.44)
$\Delta LVIX_t$	-0.114***	-0.051***	-0.041**	0.025***	-0.004	-0.003
	(-7.07)	(-3.81)	(-2.75)	(5.88)	(-0.65)	(-0.49)
$NFDemand_t$			0.497***			-0.000
			(5.15)			(-0.07)
$\hat{R}_{ETF,i,t-1}$			0.800***			-0.065***
			(7.75)			(-10.70)
Constant	0.018***	0.018***	0.067***	-0.000***	-0.000***	-0.000
	(201.30)	(136.89)	(6.62)	(-5.40)	(-11.28)	(-0.20)
Controls	No	No	Yes	No	No	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,742	11,742	10,628	11,093	11,093	10,483
R-squared	0.5%	0.7%	5.5%	0.9%	2.9%	3.6%

Panel B: Returns of Underlying Country Indices

	(1) $R_{MSCI,i,t}$	(2) $R_{MSCI,i,t}$	(3) $R_{MSCI,i,t}$	(4) $R_{MSCI,i,t}$	(5) $R_{MSCI,i,t}$
OI_{t-1}	0.004**	0.005**	0.003	0.003*	0.004**
	(2.13)	(2.51)	(1.70)	(1.84)	(2.22)
ΔVIX_{t-1}			-0.013***	-0.021***	-0.027***
			(-5.25)	(-5.48)	(-8.04)
$\Delta LVIX_{t-1}$				0.019***	0.002
				(4.64)	(0.33)
$NFDemand_{t-1}$		-0.003			-0.002
		(-0.44)			(-0.29)
$\hat{R}_{MSCI,i,t-1}$		-0.145***			-0.194***
		(-7.03)			(-8.41)
Constant	0.001***	0.002**	0.001***	0.001***	0.003**
	(36.48)	(2.38)	(35.17)	(33.65)	(2.72)
Controls	No	Yes	No	No	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Observations	12,023	10,830	12,023	11,725	10,604
R-squared	0.1%	2.6%	0.4%	0.7%	3.9%

Table 10. Panel Regressions: *Emerging Economies*

Panel A of this table presents contemporaneous panel regressions with country fixed effects (FE) of ETF order imbalances and innovations of country-level MSCI return correlations with the S&P 500 return on U.S. and local VIX changes as well as non fundamental demand ($NFDemand$), lagged values of ETF returns, and a number of other control variables. *Panel B* shows predictive panel regressions with country fixed effects (FE) of MSCI index returns (in local currency) on lagged ETF order imbalances as well as lagged values of MSCI returns, non fundemantel demand ($NFDemand$), and a number of other control variables. The correlations are estimated based on a 36-week rolling window and the innovations are measured as the residuals of an AR(1) process. We consider the model (and nested specifications) below:

$$X_{i,t} = \alpha_i + \beta_1 \Delta VIX_t + \beta_2 \Delta LVIX^o_{i,t} + \beta_3 NFDemand_{i,t} + \beta_4 R_{ETF,i,t-1} + \gamma' \boldsymbol{Z}_{i,t} + \varepsilon_{i,t},$$

where $X_{i,t}$ represents the ETF order imbalance (e.g., $OI_{i,t}$) or correlation innovations (e.g., $\Delta\rho_{i,t}$) of country i at time t. Our set of other controls (e.g., $\boldsymbol{Z}$) include spot exchange rate changes (e.g., ΔS), indexation and price discovery. ***,**,* denote 1%, 5% and 10% significance levels. The data contain weekly series from January 2006 to June 2018.

Panel A: Order Imbalances and Correlations

	(1) OI_t	(2) OI_t	(3) OI_t	(4) $\Delta\rho_t$	(5) $\Delta\rho_t$	(6) $\Delta\rho_t$
ΔVIX_t		-0.124***	-0.113***		0.030***	0.031***
		(-6.48)	(-5.67)		(11.18)	(10.83)
$\Delta LVIX_t$	-0.116***	-0.029	0.012	0.065***	0.043***	0.043***
	(-2.95)	(-0.75)	(0.27)	(5.56)	(3.61)	(3.60)
$NFDemand_t$			0.441***			-0.006
			(5.46)			(-0.46)
$\hat{R}_{ETF,i,t-1}$			0.273***			-0.016
			(3.16)			(-1.59)
Constant	0.023***	0.024***	0.038***	0.000	-0.000***	-0.000
	(954.72)	(126.84)	(4.86)	(1.10)	(-10.77)	(-0.01)
Controls	No	No	Yes	No	No	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,942	8,942	8,673	8,334	8,334	8,334
R-squared	0.2%	1.2%	3.9%	1.1%	2.5%	2.7%

Panel B: Returns of Underlying Country Indices

	(1) $R_{MSCI,i,t}$	(2) $R_{MSCI,i,t}$	(3) $R_{MSCI,i,t}$	(4) $R_{MSCI,i,t}$	(5) $R_{MSCI,i,t}$
OI_{t-1}	0.009***	0.013***	0.008***	0.008***	0.012***
	(3.94)	(3.93)	(3.69)	(3.73)	(3.82)
ΔVIX_{t-1}			-0.008**	-0.011***	-0.015***
			(-2.60)	(-3.01)	(-3.69)
$\Delta LVIX_{t-1}$				0.020***	0.014**
				(4.07)	(2.62)
$NFDemand_{t-1}$		-0.007			-0.006
		(-0.91)			(-0.87)
$\hat{R}_{MSCI,i,t-1}$		-0.153***			-0.170***
		(-3.89)			(-4.15)
Constant	0.001***	0.000	0.001***	0.001***	0.001
	(17.91)	(0.18)	(16.72)	(16.78)	(0.46)
Controls	No	Yes	No	No	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Observations	9,125	8,816	9,125	8,934	8,661
R-squared	0.2%	2.3%	0.3%	0.5%	2.7%

Table 11. Panel Regressions: *VIX Decomposition*

Panel A of this table presents contemporaneous panel regressions with country fixed effects (FE) of ETF order imbalances and innovations of country-level MSCI return correlations with the S&P 500 return on U.S. and local VIX changes as well as non fundamental demand ($NFDemand$), lagged values of ETF returns, and a number of other control variables. *Panel B* shows predictive panel regressions with country fixed effects (FE) of MSCI index returns (in local currency) on lagged ETF order imbalances as well as lagged values of MSCI returns, non fundamental demand, and a number of other control variables. Our models include both components of VIX. The correlations are estimated based on a 36-week rolling window and the innovations are measured as the residuals of an AR(1) process. We consider the model (and nested specifications) below:

$$X_{i,t} = \alpha_i + \beta_1 \Delta VIX_t^{CV} + \beta_2 \Delta VIX_t^{RA} + \beta_3 \Delta LVIX_{i,t}^{o} + \beta_4 NFDemand_{i,t} + \beta_5 R_{ETF,i,t-1} + \gamma' \boldsymbol{Z}_{i,t} + \varepsilon_{i,t},$$

where $X_{i,t}$ represents the ETF order imbalance (e.g., $OI_{i,t}$) or correlation innovations (e.g., $\Delta\rho_{i,t}$) of country i at time t. Our set of other controls (e.g., $\boldsymbol{Z}$) include spot exchange rate changes (e.g., ΔS), indexing and price discovery. We report t-statistics with robust standard errors. ***,**,* denote 1%, 5% and 10% significance levels. The data contain weekly series from January 2006 to December 2016.

Panel A: Order Imbalances and Correlations

	(1) OI_t	(2) OI_t	(3) $\Delta\rho_t$	(4) $\Delta\rho_t$
ΔVIX_t^{CV}	-0.021***	-0.014***	0.011***	0.011***
	(-7.45)	(-5.05)	(10.89)	(10.43)
ΔVIX_t^{RA}	-0.001	-0.002**	-0.001***	-0.001***
	(-1.65)	(-2.36)	(-5.75)	(-5.61)
$\Delta LVIX_t$	-0.078***	-0.066***	0.006	0.006
	(-5.00)	(-3.97)	(1.40)	(1.32)
$NFDemand_t$		0.487***		-0.004
		(7.53)		(-0.81)
$\hat{R}_{ETF,i,t-1}$		0.491***		-0.011
		(6.13)		(-1.35)
Constant	0.023***	0.052***	0.000	-0.000
	(107.96)	(6.53)	(1.17)	(-0.18)
Controls	No	Yes	No	Yes
Country FE	Yes	Yes	Yes	Yes
Observations	17,619	16,314	16,362	15,830
R-squared	0.7%	4.7%	4.5%	4.8%

Panel B: Returns of Underlying Securities

	(1) $R_{MSCI,i,t}$	(2) $R_{MSCI,i,t}$	(3) $R_{MSCI,i,t}$
OI_{t-1}	0.006***	0.007***	0.009***
	(4.05)	(4.06)	(4.45)
ΔVIX_{t-1}^{CV}	0.001**	0.001	-0.001**
	(2.28)	(1.41)	(-2.14)
ΔVIX_{t-1}^{RA}	-0.000***	-0.000***	-0.000**
	(-3.12)	(-2.86)	(-2.62)
$\Delta LVIX_{t-1}$		0.004	-0.010**
		(1.25)	(-2.56)
$NFDemand_{t-1}$			-0.004
			(-0.85)
$\hat{R}_{MSCI,i,t-1}$			-0.178***
			(-7.26)
Constant	0.001***	0.001***	0.002
	(16.78)	(15.78)	(1.67)
Controls	No	No	Yes
Country FE	Yes	Yes	Yes
Observations	17,950	17,594	16,278
R-squared	0.2%	0.2%	2.9%

Table 12. Panel Regressions: *U.S. VIX Shocks*

This table presents contemporaneous panel regressions with country fixed effects (FE) of ETF order imbalances (*Panel A*) and innovations of country-level MSCI index return (in local currency) correlations with the S&P 500 return (*Panel B*) on orthogonalized U.S. and orthogonalised local VIX changes as well as non fundamental demand ($NFDemand$), lagged values of ETF returns, and a number other of control variables. The correlations are estimated based on a 36-week rolling window and the innovations are measured as the residuals of an AR(1) process. We consider the model (and nested specifications) below:

$$X_{i,t} = \alpha_i + \beta_1 \Delta VIX_t^{US} + \beta_2 \Delta LVIX_{i,t}^{o} + \beta_3 NFDemand_{i,t} + \beta_4 R_{ETF,i,t-1} + \gamma' \boldsymbol{Z}_{i,t} + \varepsilon_{i,t},$$

where $X_{i,t}$ represents the ETF order imbalance (e.g., $OI_{i,t}$) or correlation innovations (e.g., $\Delta\rho_{i,t}$) of country i at time t. ΔVIX^{US} represent U.S. VIX changes that are orthogonal to global shocks. Our set of other controls (e.g., $\boldsymbol{Z}$) include spot exchange rate changes (e.g., ΔS), indexing and price discovery. We report t-statistics with robust standard errors. ***,**,* denote 1%, 5% and 10% significance levels. The data contain weekly series from January 2006 to June 2018.

Panel A: Order Imbalances

	(1) OI_t	(2) OI_t	(3) OI_t
ΔVIX_t^{US}		-0.002***	-0.002***
		(-2.75)	(-2.99)
$\Delta LVIX_t$	-0.114***	-0.114***	-0.092***
	(-7.74)	(-7.64)	(-5.77)
$NFDemand_t$			0.473***
			(7.60)
$\hat{R}_{ETF,i,t-1}$			0.497***
			(6.15)
Constant	0.020***	0.020***	0.050***
	(399.01)	(376.88)	(7.02)
Controls	No	No	Yes
Country FE	Yes	Yes	Yes
Observations	20,684	20,684	19,301
R-squared	0.3%	0.4%	4.0%

Panel B: Correlations

	(1) $\Delta\rho_t$	(2) $\Delta\rho_t$	(3) $\Delta\rho_t$
ΔVIX_t^{US}		0.002***	0.002***
		(15.83)	(14.73)
$\Delta LVIX_t$	0.031***	0.031***	0.032***
	(7.62)	(7.65)	(7.71)
$\hat{R}_{ETF,i,t-1}$			-0.039***
			(-4.77)
$NFDemand_t$			-0.003
			(-0.55)
Constant	-0.000***	-0.000**	0.000
	(-6.47)	(-2.26)	(0.34)
Controls	No	No	Yes
Country FE	Yes	Yes	Yes
Observations	19,427	19,427	18,817
R-squared	0.8%	1.7%	2.0%

Table 13. Panel Regressions: *U.S. Macro Announcements*

This table presents contemporaneous panel regressions with country fixed effects (FE) of ETF order imbalances (*Panel A*) and innovations of country-level MSCI index return (in local currency) correlations with the S&P 500 return (*Panel B*) on orthogonalized U.S. and orthogonalised local VIX changes as well as non fundamental demand ($NFDemand$), lagged values of ETF returns, and a number of other control variables. The correlations are estimated based on a 36-week rolling window and the innovations are measured as the residuals of an AR(1) process. We consider the model (and nested specifications) below:

$$X_{i,t} = \alpha_i + \beta_1 \Delta VIX_t^{o,\, US\ Macro} + \beta_2 \Delta LVIX_{i,t}^{o} + \beta_3 NFDemand_{i,t} + \beta_4 R_{ETF,i,t-1} + \gamma' \boldsymbol{Z}_{i,t} + \varepsilon_{i,t},$$

where $X_{i,t}$ represents the ETF order imbalance (e.g., $OI_{i,t}$) or correlation innovations (e.g., $\Delta\rho_{i,t}$) of country i at time t. $\Delta VIX_t^{o\ ,US\ Macro}$ represents the U.S. VIX that is orthogonal to U.S. macro announcements. We define macro announcement based on a dummy variable that takes the value of 1 if there is an announcement and zero otherwise. Our set of other controls (e.g., $\boldsymbol{Z}$) include spot exchange rate changes (e.g., ΔS), indexing and price discovery. We report t-statistics with robust standard errors. ***,**,* denote 1%, 5% and 10% significance levels. The data contain weekly series from January 2006 to June 2018.

Panel A: Order Imbalances

	(1) OI_t	(2) OI_t	(3) OI_t
$\Delta VIX_t^{o,\, US\ Macro}$		-0.104***	-0.099***
		(-8.53)	(-7.71)
$\Delta LVIX_t$	-0.114***	-0.035**	-0.018
	(-7.74)	(-2.41)	(-1.18)
$NFDemand_t$			0.470***
			(7.55)
$\hat{R}_{ETF,i,t-1}$			0.521***
			(6.42)
Constant	0.020***	0.020***	0.050***
	(399.01)	(367.70)	(7.06)
Controls	No	No	Yes
Country FE	Yes	Yes	Yes
Observations	20,684	20,684	19,301
R-squared	0.3%	0.9%	4.5%

Panel B: Correlations

	(1) $\Delta\rho_t$	(2) $\Delta\rho_t$	(3) $\Delta\rho_t$
$\Delta VIX_t^{o,\, US\ Macro}$		0.033***	0.034***
		(13.94)	(13.73)
$\Delta LVIX_t$	0.031***	0.006	0.007
	(7.62)	(1.12)	(1.30)
$NFDemand_t$			-0.002
			(-0.32)
$\hat{R}_{ETF,i,t-1}$			-0.041***
			(-5.29)
Constant	-0.000***	0.000	0.000
	(-6.47)	(0.95)	(0.18)
Controls	No	No	Yes
Country FE	Yes	Yes	Yes
Observations	19,427	19,427	18,817
R-squared	0.8%	2.5%	2.8%

Table 14. Panel Regressions: *News-based Uncertainty*

This table presents contemporaneous panel regressions with country fixed effects (FE) of ETF order imbalances (*Panel A*) and innovations of country-level MSCI index return (in local currency) correlations with the S&P 500 return (*Panel B*) on U.S. news-based uncertainty changes (ΔUNC) and orthogonalised local VIX changes ($\Delta LVIX$) as well as non fundamental demand ($NFDemand$), lagged values of ETF returns, and a number of other control variables. The correlations are estimated based on a 36-week rolling window and the innovations are measured as the residuals of an AR(1) process. We consider the model (and nested specifications) below:

$$X_{i,t} = \alpha_i + \beta_1 \Delta UNC_t + \beta_2 \Delta LVIX^o_{i,t} + \beta_3 NFDemand_{i,t} + \beta_4 R_{ETF,i,t-1} + \gamma' \boldsymbol{Z}_{i,t} + \varepsilon_{i,t},$$

where $X_{i,t}$ represents the ETF order imbalance (e.g., $OI_{i,t}$) or correlation innovations (e.g., $\Delta\rho_{i,t}$) of country i at time t. Our set of other controls (e.g., $\boldsymbol{Z}$) include spot exchange rate changes (e.g., ΔS), indexing and price discovery. We report t-statistics with robust standard errors. ***,**,* denote 1%, 5% and 10% significance levels. The data contain weekly series from January 2006 to June 2018.

Panel A: Order Imbalances

	(1) OI_t	(2) OI_t	(3) OI_t
ΔUNC_t		-0.278***	-0.277***
		(-3.28)	(-3.50)
$\Delta LVIX_t$	-0.114***	-0.112***	-0.089***
	(-7.74)	(-7.61)	(-5.73)
$NFDemand_t$			0.474***
			(7.60)
$\hat{R}_{ETF,i,t-1}$			0.481***
			(6.03)
Constant	0.020***	0.020***	0.051***
	(399.01)	(94.02)	(7.08)
Controls	No	No	Yes
Country FE	Yes	Yes	Yes
Observations	20,684	20,666	19,301
R-squared	0.3%	0.4%	4.0%

Panel B: Correlations

	(1) $\Delta\rho_t$	(2) $\Delta\rho_t$	(3) $\Delta\rho_t$
ΔUNC_t		0.108***	0.108***
		(8.03)	(7.65)
$\Delta LVIX_t$	0.031***	0.030***	0.031***
	(7.62)	(7.46)	(7.28)
$NFDemand_t$			-0.003
			(-0.56)
$\hat{R}_{ETF,i,t-1}$			-0.027***
			(-3.39)
Constant	-0.000***	-0.000***	-0.000
	(-6.47)	(-9.51)	(-0.22)
Controls	No	No	Yes
Country FE	Yes	Yes	Yes
Observations	19,427	19,427	18,817
R-squared	0.8%	0.9%	1.2%

Internet Appendix to

"ETF Arbitrage and International Diversification"

A1. Madhavan and Sobczyk Model

We briefly introduce the Madhavan and Sobczyk (2016) model of ETF price and NAV. Unobservable expected value of the underlying assets is modelled as a random walk:

$$v_t = v_{t-1} + r_t, \qquad \textit{where } r_t \sim (\mu_r, \sigma_r^2) \tag{8}$$

Price is the fundamental value plus a "true premium":

$$p_t = v_t + u_t \tag{9}$$

The true premium is represented as an autoregressive model with a coefficient ψ that represents the speed of error correction and a liquidity shock $\varepsilon_t \sim (\mu_\varepsilon, \sigma_\varepsilon^2)$.

$$u_t = \psi u_{t-1} + \varepsilon_t \tag{10}$$

Defining the official NAV of the fund as n_t we can show the premium at any point in time as:

$$\pi_t = p_t - n_t = (p_t - v_t) + (v_t - n_t) = u_t + (v_t - n_t) \tag{11}$$

The deviation of price from NAV can be due to staleness in NAV or due to the impact of secondary market on ETF price through shock ε and slow arbitrage $\psi > 0$. When $u_t = 0$ the entire premium represents the staleness in NAV and the deviation represents a price discovery in ETF market. The portion of variance not due to transitory component u_t is:

$$D = 1 - \left(\frac{\sigma_u}{\sigma_\pi}\right)^2, \qquad \textit{where } \sigma_u = \frac{\sigma_\varepsilon}{\sqrt{1-\psi^2}} \tag{12}$$

This is defined as a price discovery component and is negatively related to variance of liquidity shock and is positively related to the speed of arbitrage.

A2. Methods for Order Imbalance Construction

Lee and Ready (1991) provide an algorithm for classifying trades into buys and sells. Trade price is compared to prevailing quote. Prevailing quote is a current quote if it is older than 5 seconds. It is a quote 5 seconds ago, otherwise.

1. If price=bid - trade is classified as a sell trade
2. If price=ask - trade is classified as a buy trade
3. If price is at mid-point of bid-ask spread tick test is used:
   (a) If price is larger than of a previous trade price it is a buy trade
   (b) If price is smaller than of a previous trade price it is a sell trade
4. If price is inside bid-ask spread, but not at mid-quote classification is based on proximity to either bid or ask. Trades closer to the bid (ask) are sell (buy) trades.

Holden and Jacobsen (2014) provide an Interpolated Time technique to match trades and quotes happening within a millisecond. There are N trades and K orders happening in 1 millisecond and we know the order for trades and for quotes. The method assumes a uniform distribution of trades and quotes. Trade n in second s is assigned to time:

$$s + \frac{2n-1}{2N}, \qquad n = 1, 2 \dots N$$

Similarly, trade k in second s is assigned to time:

$$s + \frac{2k-1}{2K}, \qquad k = 1, 2 \dots K$$

A3. DCC Model

In order to overcome the need to choose the length of the rolling window (longer length may result in a smoother correlation estimates), we employ an alternative measure of correlation - Dynamic Conditional Correlation (DCC) of Engle (2002). The assumption is that returns conditional on prior available information is normally distributed with mean 0 and time-varying covariance matrix H_t: $r_t|\mathscr{F}_{t-1} \sim (0, H_t)$. Then covariance matrix can be represented as:

$$H_t = D_t R_t D_t \qquad (13)$$

D_t is the square root of diagonal matrix of H_t and R_t is the time-varying correlation matrix. We model the volatility of returns for each country using GARCH(1,1) process. Matrix R_t can be further decomposed into:

$$R_t = diag(Q_t)^{-1/2} Q_t diag(Q_t)^{-1/2} \tag{14}$$

Then auxiliary variable Q_t can in turn be represented using GARCH(1,1) process as:

$$Q_{ij,t} = \bar{\rho}_{ij} + \alpha(\varepsilon_{i,t-1}\varepsilon_{j,t-1} - \bar{\rho}_{ij}) + \beta(Q_{ij,t-1} - \bar{\rho}_{ij}) \tag{15}$$

In this equation, $\varepsilon_{i,t-1} = D_{t-1}^{-1} r_{t-1}$ and $\bar{\rho} = \mathbb{E}[\varepsilon_{i,t}\varepsilon_{j,t}]$.

A4. Types of ETF Investors

4.1. Order Imbalance: Small vs. Large Trades

ETFs are designed for retail investors. Lack of access to foreign markets and inability to invest directly into underlying securities due to significant cost barriers (e.g., trading costs) are only a few reasons why individual investors use ETFs to invest in general market indices. Due to several institutional factors (e.g., commission based advisory practice) retail participation in European ETF markets is still low. In contrast, participation of U.S. retail investors in this market is relatively higher. As such, in contrast to other markets the analysis of this type of investors in the context of U.S. ETF trading is important.

We first consider a measure of retail trading activity based on trade size (Peress and Schmidt, 2018). Using equation 1, we obtain order imbalance for small trades (OI_s). Retail trades are usually identified as the smallest trades of less than or equal to $\$5,000$ (e.g., Barber, Odean, and Zhu, 2009). The limitation of this method is that with the rise of high-frequency algorithmic trading orders are often sliced into small quantities (e.g., Hendershott, Jones, and Menkveld, 2011) and therefore, small trades are likely to be a noisy measure of retail trading activity.

High-frequency traders often submit a large number of quotes that do not result in trades in order to uncover the direction of the market. Some exchanges introduced a fee to deter such activity.[16] Hangströmer and Lars (2013) distinguish between two types of high-frequency trading: market making strategies and opportunistic trading. They show that order-to-trade ratio (OTR) is much higher for the former group. High-frequency market makers tend to have

[16] For example see Friederich and Payne (2015) on regulatory fees in Borsa Italiana, Malinova, Park, and Riordan (2013) in Canada and Jørgensen, Skjeltorp, and Ødegaard (2017) in Oslo Stock Exchange.

zero inventory on average. Therefore, their trades might only reflect temporary inventory adjustments and do not contain any additional information about the direction of the market.

We follow Skjeltorp, Sojli, and Tham (2015) to construct the OTR. The variable is based on the number of daily quote updates in TAQ database relative to the total number of executed trades. Our measure of quote updates includes any changes in the best bid or ask prices across all exchanges, as well as changes in quantities at such prices.

In order to clean the order imbalance measure from the effect of high frequency market making activity, we regress the raw measure of small trades (OI_s) on the OTR:

$$OI_{s,i,t} = \alpha + \beta_{1,i} OTR_{i,t} + \varepsilon_{i,t} \tag{16}$$

We take a residual from equation 16 to find an order imbalance that is uncorrelated with a measure of high frequency market making activity. Thus, we denote as $smallOI_{i,t}$ the innovation of equation 16, which serves as a cleaner proxy for small retail trades. However, we acknowledge that small trades are also likely to capture the activity of institutional investors who use high frequency algorithms to minimise the impact of their trades (through smaller trade size and by routing orders to more liquid trading venues). Therefore, we capture the retail trading activity with an alternative measure following Boehmer et al. (2021). We also compute order imbalance for trades over a threshold of $\$20,000$ ($largeOI$) in a similar fashion to Barber et al. (2009). This measure is likely to capture the trading activity of institutions (e.g., pension funds etc.).

4.2. Retail Order Imbalance

We use an alternative method suggested by Boehmer et al. (2021) to sign the retail trades. The authors recognise that in contrast to institutional orders many retail trades are happening off-exchange and are internalized or executed by a wholesaler. Such trades are reported to FINRA Trade Reporting Facility (TRF), marked with exchange code "D" in the TAQ trade database and usually executed at prices slightly above National Best Bid or Offer. The retail seller initiated transactions receive a small price improvement and are identified by prices with a fraction of a penny in a range of (0, 0.4). The retail buyer transactions receive a price improvement as a discount and are identified by prices with a fraction of a penny in a range of (0.6,1). The Boehmer et al. (2021) type of retail order imbalance ($retailOI$) is then calculated in the same way as in equation 1.

One of the limitations of this measure is that it only incorporates market orders, while retail traders often use limit orders. Nonetheless, Boehmer et al. (2021) suggest that more than half of trades on NYSE are captured by this methodology.

Figure A1. GNI per capita and Liquidity Mismatch

Scatter plot of average Gross National Income (GNI) per capita and liquidity mismatch (as defined in equation 7) for 41 countries over the sample period of 2006-2018. Trend line is shown in red. Regression and adjusted R^2 is provided. GNI per capita is from World Bank database and is expressed in 10^4.

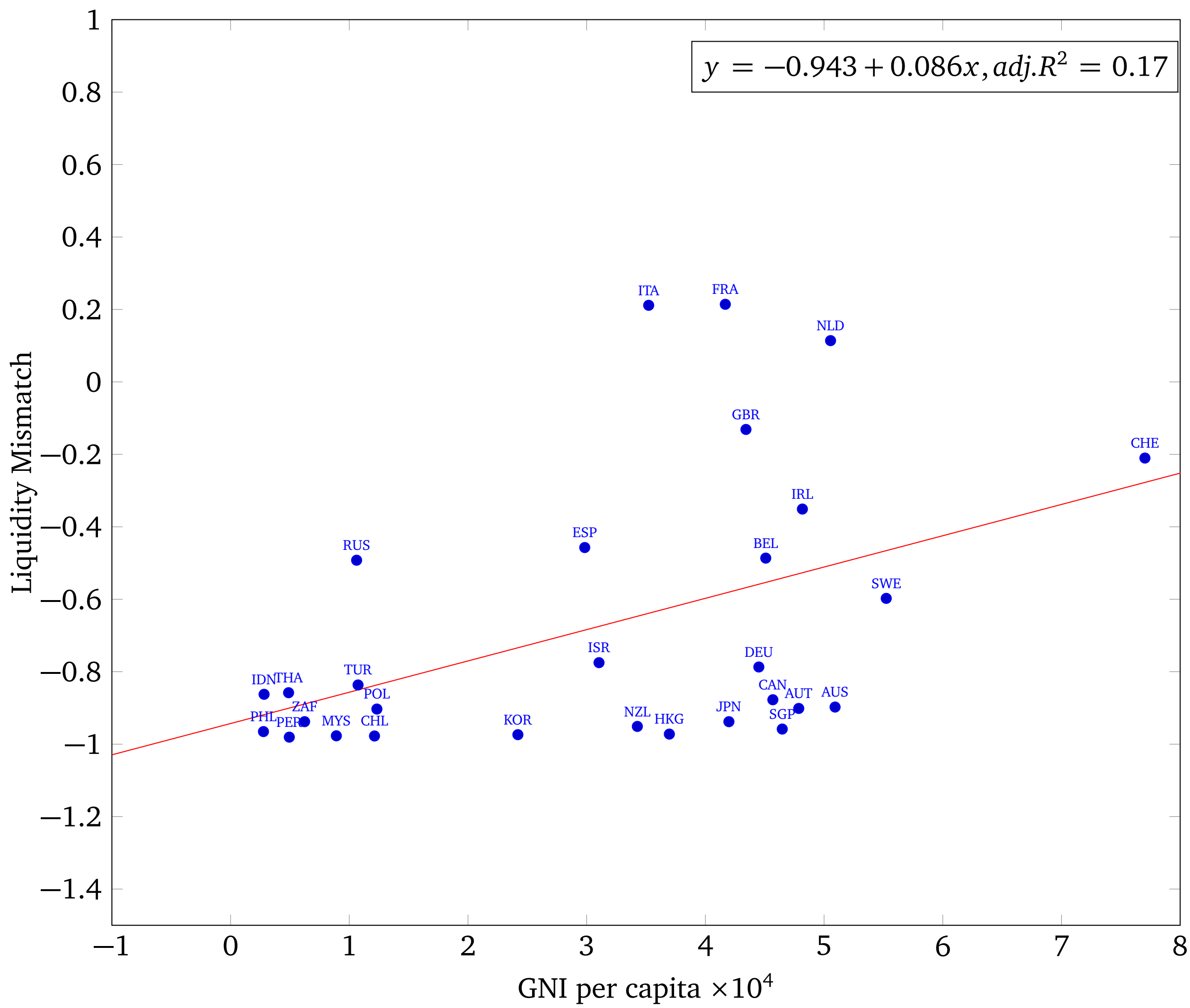


Table A1: ETF Details

Countries in the sample, corresponding iShares country-level ETFs, their tickers, local market indices that funds track and the version of local volatility indices. Not all local market volatility indices are available. For some countries, general European index VSTOXX is used as a substitute. LVIX data is from Bloomberg.

Country	Ticker	Name: iShares MSCI	Tracking Index: MSCI	Volatility Index	Inception Date
AUS	EWA	Australia	Australia Index	S&P/ASX 200	12/03/1996
AUT	EWO	Austria Capped	Austria IMI 25/50	VSTOXX	12/03/1996
BEL	EWK	Belgium Capped	Belgium IMI 25/50	BEL 20	12/03/1996
BRA	EWZ	Brazil Capped	Brazil 25/50	-	10/07/2000
CAN	EWC	Canada	Canada Index	S&P/TSX 60 VIX	12/03/1996
CHL	ECH	Chile Capped	Chile IMI 25/50	-	12/11/2007
CHN	MCHI	China	China Index	ALPHASHARES CHINA	29/03/2011
COL	ICOL	Colombia	All Colombia Capped Index	-	18/06/2013
DNK	EDEN	Denmark	Denmark IMI 25/50 Index	-	25/01/2012
FIN	EFNL	Finland	Finland IMI 25/50 Index	VSTOXX	25/01/2012
FRA	EWQ	France	France Index	CAC40	12/03/1996
DEU	EWG	Germany	Germany Index	VDAX-NEW	12/03/1996
HKG	EWH	Hong Kong	Hong Kong Index	HSI	12/03/1996
IND	INDA	India	India Index	India VIX	02/02/2012
IDN	EIDO	Indonesia	Indonesia IMI	-	05/05/2010
IRL	EIRL	Ireland Capped	All Ireland Capped Index	VSTOXX	05/05/2010
ISR	EIS	Israel Capped	Israel Capped IMI	-	26/03/2008
ITA	EWI	Italy Capped	Italy 25/50	VSTOXX	12/03/1996
JPN	EWJ	Japan	Japan Index	NIKKEI STOCK AVERAGE	12/03/1996
MYS	EWM	Malaysia	Malaysia Index	-	12/03/1996
MEX	EWW	Mexico Capped	Mexico IMI 25/50	MEXICO	12/03/1996
NLD	EWN	Netherlands	Netherlands IMI	AEX	12/03/1996
NZL	ENZL	New Zealand Capped	New Zealand IMI 25/50	-	01/09/2010
NOR	ENOR	Norway	Norway IMI 25/50 Index	-	23/01/2012
PER	EPU	All Peru Capped	All Peru Capped Index	-	19/06/2009
PHL	EPHE	Philippines	Philippines Investable Market Index	-	28/09/2010
POL	EPOL	Poland Capped	Poland IMI 25/50	-	25/05/2010
QAT	QAT	Qatar	All Qatar Capped Index	-	29/04/2014
RUS	ERUS	Russia Capped	Russia 25/50 Index	RTS	09/11/2010
SAU	KSA	Saudi Arabia	Saudi Arabia IMI 25/50 Index	-	16/09/2015
SGP	EWS	Singapore	Singapore Index	-	12/03/1996
ZAF	EZA	South Africa	South Africa Index	SOUTH AFRICA	03/02/2003
KOR	EWY	South Korea	Korea 25/50 Index	VKOSPI	09/05/2000
ESP	EWP	Spain Capped	Spain 25/50	VSTOXX	12/03/1996
SWE	EWD	Sweden	Sweden Index	SIXVX	13/03/1996
CHE	EWL	Switzerland Capped	Switzerland 25/50	VSMI	12/03/1996
TWN	EWT	Taiwan Capped	Taiwan 25/50 Index	-	20/06/2000
THA	THD	Thailand Capped	Thailand IMI 25/50	-	26/03/2008
TUR	TUR	Turkey	Turkey IMI	-	26/03/2008
ARE	UAE	UAE	All UAE Capped Index	-	29/04/2014
GBR	EWU	United Kingdom	United Kingdom Index	FTSE 100	12/03/1996

Table A2: Summary Statistics of VIX and LVIX

Summary statistics of daily changes in CBOE volatility index (VIX) and local alternatives (LVIX) for the period of 2006-2018. Details for LVIX are available in table A1 .

Country	Corr(ΔVIX, $\Delta LVIX$)	*p-value*	Mean	Std
AUS	0.573	< 0.01	0.67%	12.62%
AUT	0.761	< 0.01	0.81%	12.13%
BEL	0.382	< 0.01	0.38%	7.60%
BRA	0.057	0.15	0.24%	2.19%
CAN	0.622	< 0.01	0.81%	14.58%
CHL	0.078	0.05	−0.31%	1.64%
CHN	0.623	< 0.01	0.52%	10.56%
COL	0.115	< 0.01	−0.17%	1.92%
DNK	0.761	< 0.01	0.81%	13.14%
FIN	0.761	< 0.01	0.81%	13.14%
FRA	0.721	< 0.01	0.84%	13.35%
DEU	0.736	< 0.01	0.74%	12.54%
HKG	0.585	< 0.01	0.67%	11.94%
IND	0.318	< 0.01	0.41%	11.01%
IDN	0.056	0.15	0.11%	2.52%
IRL	0.761	< 0.01	0.81%	13.14%
ISR	0.112	< 0.01	−0.41%	1.57%
ITA	0.133	< 0.01	0.11%	2.23%
JPN	0.537	< 0.01	0.84%	15.42%
MYS	0.021	0.60	−0.68%	1.31%
MEX	0.591	< 0.01	0.33%	8.67%
NLD	0.775	< 0.01	0.78%	13.16%
NZL	0.064	0.10	−0.55%	1.24%
NOR	0.761	< 0.01	0.81%	13.14%
PER	0.007	0.85	0.73%	2.97%
PHL	0.084	0.03	−0.06%	2.04%
POL	0.158	< 0.01	0.08%	2.16%
QAT	0.024	0.54	0.06%	2.47%
RUS	0.401	< 0.01	0.89%	14.33%
SAU	0.055	0.44	−0.04%	1.99%
SGP	0.135	< 0.01	−0.29%	1.86%
ZAF	0.450	< 0.01	0.16%	6.51%
KOR	0.576	< 0.01	0.60%	12.05%
ESP	0.761	< 0.01	0.81%	13.14%
SWE	0.656	< 0.01	0.93%	13.85%
CHE	0.727	< 0.01	0.71%	12.40%
TWN	0.110	< 0.01	−0.17%	1.89%
THA	0.062	0.11	0.06%	2.20%
TUR	0.099	< 0.01	0.44%	2.61%
ARE	−0.002	0.94	0.58%	3.21%
GBR	0.753	< 0.01	0.92%	14.06%

Table A3. Predictive Panel Regressions

This table presents predictive panel regressions with country fixed effects (FE) of ETF order imbalances (*Panel A*) and innovations of country-level MSCI return correlations with the S&P 500 return (*Panel B*) on U.S. and local VIX changes as well as non fundamental demand ($NFDemand$), lagged values of ETF return, and a number of other control variables. The correlations are estimated based on a 36-week rolling window and the innovations are measured as the residuals of an AR(1) process. We consider the model (and nested specifications) below:

$$X_{i,t} = \alpha_i + \beta_1 \Delta VIX_{t-1} + \beta_2 \Delta LVIX_{i,t-1} + \beta_3 NFDemand_{i,t} + \beta_4 R_{ETF,i,t-1} + \gamma' \boldsymbol{Z}_{i,t} + \varepsilon_{i,t},$$

where $X_{i,t}$ represents the ETF order imbalance (e.g., $OI_{i,t}$) or correlation innovations (e.g., $\Delta\rho_{i,t}$) of country i at time t. Our set of other controls (e.g., $\boldsymbol{Z}$) include spot exchange rate changes (e.g., ΔS), indexation and price discovery. We report t-statistics with robust standard errors. ***,**,* denote 1%, 5% and 10% significance levels. The data contain weekly series from January 2006 to June 2018.

Panel A: Order Imbalances

	(1) OI_t	(2) OI_t	(3) OI_t
ΔVIX_{t-1}		-0.032***	0.031***
		(-3.36)	(3.41)
$\Delta LVIX_{t-1}$	-0.064***	-0.039**	0.002
	(-3.47)	(-2.09)	(0.13)
$NFDemand_t$			0.472***
			(7.59)
$\hat{R}_{ETF,i,t-1}$			0.556***
			(6.04)
Constant	0.019***	0.020***	0.049***
	(313.16)	(206.05)	(6.93)
Controls	No	No	Yes
Country FE	Yes	Yes	Yes
Observations	20,704	20,704	19,338
R-squared	0.1%	0.2%	3.8%

Panel B: Correlations

	(1) $\Delta\rho_t$	(2) $\Delta\rho_t$	(3) $\Delta\rho_t$
ΔVIX_{t-1}		-0.006***	-0.010***
		(-3.52)	(-5.17)
$\Delta LVIX_{t-1}$	0.006***	0.011***	0.008***
	(2.73)	(3.94)	(2.93)
$NFDemand_t$			-0.004
			(-0.63)
$\hat{R}_{ETF,i,t-1}$			-0.040***
			(-4.62)
Constant	0.000	0.000***	0.000
	(1.27)	(3.75)	(0.55)
Controls	No	No	Yes
Country FE	Yes	Yes	Yes
Observations	19,465	19,465	18,854
R-squared	0.0%	0.1%	0.5%

Table A4. MSCI Returns and ETF Trading: Predictive Panel Regressions

This table presents predictive panel regressions with country fixed effects (FE) of MSCI index returns (in local currency) on lagged ETF order imbalances as well as non fundamental demand ($NFDemand$), lagged values of MSCI returns, and a number of other control variables. We consider the model (and nested specifications) below:

$$R_{MSCI,i,t} = \alpha_i + \beta_1 OI_{t-1} + \beta_2 \Delta VIX_{t-1} + \beta_3 \Delta LVIX^o_{i,t-1} + \beta_4 NFDemand_{i,t-1} + \beta_5 R_{MSCI,i,t-1} + \gamma' \boldsymbol{Z}_{i,t} + \varepsilon_{i,t},$$

where $R_{MSCI,i,t}$ represents the MSCI return of country i at time t. Our set of other controls (e.g., $\boldsymbol{Z}$) include spot exchange rate changes (e.g., ΔS), indexing and price discovery. We report t-statistics with robust standard errors. ***,**,* denote 1%, 5% and 10% significance levels. The data contain weekly series from January 2006 to June 2018.

Returns of Underlying Indices					
	(1) $R_{MSCI,i,t}$	(2) $R_{MSCI,i,t}$	(3) $R_{MSCI,i,t}$	(4) $R_{MSCI,i,t}$	(5) $R_{MSCI,i,t}$
OI_{t-1}	0.006***	0.008***	0.005***	0.005***	0.007***
	(4.01)	(4.46)	(3.52)	(3.63)	(4.15)
ΔVIX_{t-1}			-0.011***	-0.016***	-0.021***
			(-5.54)	(-5.79)	(-7.57)
$\Delta LVIX_{t-1}$				0.016***	0.002
				(5.30)	(0.52)
$NFDemand_{t-1}$		-0.004			-0.004
		(-0.98)			(-0.84)
$\hat{R}_{MSCI,i,t-1}$		-0.147***			-0.180***
		(-7.30)			(-8.26)
Constant	0.001***	0.001	0.001***	0.001***	0.002*
	(36.82)	(1.51)	(34.13)	(32.55)	(1.95)
Controls	No	Yes	No	No	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Observations	21,148	19,646	21,148	20,659	19,265
R-squared	0.1%	2.4%	0.4%	0.5%	3.1%

Table A5. *Placebo Tests:* Staggered Introduction of ETFs

This table presents contemporaneous panel regressions with country fixed effects (FE) of innovations of return correlations on a dummy variable that takes a value of one during the life of the ETF, VIX changes and their interaction as well as lagged values of MSCI returns and lagged correlations. The correlations are estimated based on a 36-week rolling window and the innovations are measured as the residuals of an AR(1) process. We consider the model below:

$$\Delta\rho_{i,t} = \alpha_i + \beta_1 Intro^{ETF}_{LeadLag,i,t} + \beta_2 Intro^{ETF}_{LeadLag,i,t} \times \Delta VIX_t + \beta_3 \Delta VIX_t + \beta_4 \Delta\rho_{i,t-1} + \beta_5 R_{MSCI,i,t-1} + \varepsilon_{i,t},$$

where $LeadLag$ represents the of months before or after the ETF introduction, $\Delta\rho_{i,t}$ represents innovations of rolling correlations between MSCI returns of country i and S&P 500 at time t. $Intro^{ETF}$ is a dummy variable which takes the value of 1 throughout the life of an ETF (from the inception date until the fund end date) and 0 otherwise. $Intro^{ETF}_{Random}$ is a dummy variable where we randomly assign one in the dummy variable 12 months or 24 months before or after an ETF introduction. We report t-statistics with robust standard errors. ***,**,* denote 1%, 5% and 10% significance levels. The data contain weekly series from January 1992 to June 2018.

Correlations and ETF Introductions								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$\Delta\rho_t$	$\Delta\rho_t$	$\Delta\rho_t$	$\Delta\rho_t$	$\Delta\rho_t$	$\Delta\rho_t$	$\Delta\rho_t$	$\Delta\rho_t$
$Intro^{ETF}$	0.002***	0.002***	0.002***					
	(8.02)	(7.56)	(7.34)					
$Intro^{ETF} \times \Delta VIX_t$		0.006*	0.006*					
		(1.95)	(1.92)					
$Intro^{ETF}_{Random}$				0.002***				
				(8.26)				
$Intro^{ETF}_{Random} \times \Delta VIX_t$				0.005				
				(1.47)				
$Intro^{ETF}_{-24m}$					0.002***			
					(9.14)			
$Intro^{ETF}_{-24m} \times \Delta VIX_t$					0.000			
					(0.07)			
$Intro^{ETF}_{-12m}$						0.002***		
						(8.49)		
$Intro^{ETF}_{-12m} \times \Delta VIX_t$						0.002		
						(0.67)		
$Intro^{ETF}_{12m}$							0.002***	
							(6.99)	
$Intro^{ETF}_{12m} \times \Delta VIX_t$							0.008**	
							(2.43)	
$Intro^{ETF}_{24m}$								0.002***
								(6.62)
$Intro^{ETF}_{24m} \times \Delta VIX_t$								0.007**
								(2.17)
ΔVIX_t		0.038***	0.039***	0.040***	0.043***	0.042***	0.038***	0.039***
		(13.29)	(13.51)	(13.77)	(15.29)	(14.86)	(12.89)	(14.25)
$\Delta_{\rho_{i,t-1}}$		0.003	0.001	0.000	0.000	0.000	0.001	0.001
		(0.46)	(0.10)	(0.08)	(0.07)	(0.08)	(0.10)	(0.11)
$R_{MSCI,i,t-1}$			-0.036***	-0.035***	-0.036***	-0.036***	-0.036***	-0.036***
			(-7.00)	(-6.97)	(-7.00)	(-7.00)	(-7.00)	(-7.02)
Constant	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***
	(-9.14)	(-10.47)	(-9.87)	(-10.88)	(-11.96)	(-11.29)	(-9.45)	(-9.13)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	53,251	53,210	53,210	53,210	53,210	53,210	53,210	53,210
R-squared	0.1%	2.4%	2.5%	2.5%	2.5%	2.5%	2.5%	2.5%

Table A6. Panel Regressions: *U.S. Macro Announcements*

This table presents contemporaneous panel regressions with country fixed effects (FE) of ETF order imbalances (*Panel A*) and innovations of country-level MSCI index return (in local currency) correlations with the S&P 500 return (*Panel B*) on orthogonalized U.S. and orthogonalised local VIX changes as well as non fundamental demand ($NFDemand$), lagged values of ETF returns, and a number of other control variables. The correlations are estimated based on a 36-week rolling window and the innovations are measured as the residuals of an AR(1) process. We consider the model (and nested specifications) below:

$$X_{i,t} = \alpha_i + \beta_1 \Delta VIX_t^{o,\, US\ Macro} + \beta_2 \Delta LVIX_{i,t}^{o} + \beta_3 NFDemand_{i,t} + \beta_4 R_{ETF,i,t-1} + \gamma' \boldsymbol{Z}_{i,t} + \varepsilon_{i,t},$$

where $X_{i,t}$ represents the ETF order imbalance (e.g., $OI_{i,t}$) or correlation innovations (e.g., $\Delta\rho_{i,t}$) of country i at time t. $\Delta VIX_t^{o,\, US\ Macro}$ represents the U.S. VIX that is orthogonal to U.S. macro announcements that are measure based on the number of macro announcements at time t. Our set of other controls (e.g., $\boldsymbol{Z}$) include spot exchange rate changes (e.g., ΔS), indexing and price discovery. We report t-statistics with robust standard errors. ***,**,* denote 1%, 5% and 10% significance levels. The data contain weekly series from January 2006 to June 2018.

Panel A: Order Imbalances

	(1) OI_t	(2) OI_t	(3) OI_t
$\Delta VIX_t^{o,\, US\ Macro}$		-0.105***	-0.100***
		(-8.67)	(-7.76)
$\Delta LVIX_t$	-0.114***	-0.034**	-0.017
	(-7.74)	(-2.37)	(-1.15)
$NFDemand_t$			0.470***
			(7.55)
$\hat{R}_{ETF,i,t-1}$			0.521***
			(6.41)
Constant	0.020***	0.020***	0.050***
	(399.01)	(381.29)	(7.05)
Controls	No	No	Yes
Country FE	Yes	Yes	Yes
Observations	20,684	20,684	19,301
R-squared	0.3%	0.9%	4.5%

Panel B: Correlations

	(1) $\Delta\rho_t$	(2) $\Delta\rho_t$	(3) $\Delta\rho_t$
$\Delta VIX_t^{o,\, US\ Macro}$		0.034***	0.034***
		(14.30)	(14.12)
$\Delta LVIX_t$	0.031***	0.005	0.007
	(7.62)	(1.04)	(1.23)
$NFDemand_t$			-0.002
			(-0.29)
$\hat{R}_{ETF,i,t-1}$			-0.041***
			(-5.32)
Constant	-0.000***	0.000	0.000
	(-6.47)	(0.47)	(0.22)
Controls	No	No	Yes
Country FE	Yes	Yes	Yes
Observations	19,427	19,427	18,817
R-squared	0.8%	2.6%	2.9%

Table A7. Predictive Panel Regressions: VIX States

This table presents predictive panel regressions with country fixed effects (FE) of ETF order imbalances (*Panel A*) and innovations of country-level MSCI return correlations with the S&P 500 return (*Panel B*) on U.S. and local VIX changes as well as non fundamental demand ($NFDemand$), lagged values of ETF returns, and a number of other control variables. The correlations are estimated based on a 36-week rolling window and the innovations are measured as the residuals of an AR(1) process. We show results for low, medium and high VIX regimes. We consider the model (and nested specifications) below:

$$X_{i,t} = \alpha_i + \beta_1 \Delta VIX_{t-1} + \beta_2 \Delta LVIX_{i,t-1} + \beta_3 NFDemand_{i,t} + \beta_4 R_{ETF,i,t-1} + \gamma' \boldsymbol{Z}_{i,t} + \varepsilon_{i,t},$$

where $X_{i,t}$ represents the ETF order imbalance (e.g., $OI_{i,t}$) or correlation innovations (e.g., $\Delta\rho_{i,t}$) of country i at time t. Our set of other controls (e.g., $\boldsymbol{Z}$) include spot exchange rate changes (e.g., ΔS), indexation and price discovery. We report t-statistics with robust standard errors. We include in curly brackets p-$values$ that are associated with a hypothesis test of higher (lower) beta coefficients of VIX relatively to local VIX –in panel regressions with order imbalances (correlations) as independent variables– under the null hypothesis. ***,**,* denote 1%, 5% and 10% significance levels. The data contain weekly series from January 2006 to June 2018.

Panel A: Order Imbalances

	(1) OI_t	(2) OI_t	(3) OI_t	(4) OI_t	(5) OI_t	(6) OI_t	(7) OI_t	(8) OI_t	(9) OI_t
		Low VIX			*Medium VIX*			*High VIX*	
ΔVIX_{t-1}		0.012	0.034*		-0.042***	0.013		-0.039**	0.051***
		(0.73)	(1.95)		(-3.11)	(0.94)		(-2.20)	(2.75)
$\Delta LVIX_{t-1}$	-0.019	-0.025	-0.002	-0.029	0.004	0.039	-0.069***	-0.035	0.003
	(-0.81)	(-1.12)	(-0.09)	(-1.09)	(0.15)	(1.48)	(-3.86)	(-1.60)	(0.12)
$NFDemand_t$			0.525***			0.443***			0.411***
			(3.72)			(4.44)			(5.97)
$\hat{R}_{ETF,i,t-1}$			0.516***			0.592***			0.520***
			(3.29)			(4.26)			(6.11)
Constant	0.038***	0.039***	0.090***	0.021***	0.022***	0.049***	-0.006***	-0.005***	0.040***
	(243.45)	(169.70)	(6.01)	(218.92)	(114.73)	(4.90)	(-20.14)	(-12.44)	(3.77)
Controls	No	No	Yes	No	No	Yes	No	No	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,297	7,297	6,691	7,364	7,364	6,899	6,043	6,043	5,748
R-squared	0.0%	0.0%	3.0%	0.0%	0.1%	3.1%	0.2%	0.3%	5.4%

Panel B: Correlations

	(1) $\Delta\rho_t$	(2) $\Delta\rho_t$	(3) $\Delta\rho_t$	(4) $\Delta\rho_t$	(5) $\Delta\rho_t$	(6) $\Delta\rho_t$	(7) $\Delta\rho_t$	(8) $\Delta\rho_t$	(9) $\Delta\rho_t$
		Low VIX			*Medium VIX*			*High VIX*	
ΔVIX_{t-1}		-0.014***	-0.018***		-0.013***	-0.018***		0.004	0.003
		(-3.88)	(-4.45)		(-4.57)	(-6.22)		(1.23)	(0.59)
$\Delta LVIX_{t-1}$	0.010**	0.018***	0.014**	-0.005	0.005	0.001	0.006	0.003	0.003
	(2.22)	(3.44)	(2.44)	(-1.66)	(1.31)	(0.27)	(1.52)	(0.48)	(0.59)
$\hat{R}_{ETF,i,t-1}$			-0.042**			-0.065***			-0.012
			(-2.58)			(-5.19)			(-0.76)
$NFDemand_t$			0.002			0.004			-0.016
			(0.17)			(0.61)			(-1.53)
Constant	-0.004***	-0.004***	-0.005***	-0.001***	-0.000***	-0.002**	0.005***	0.005***	0.008***
	(-100.61)	(-89.65)	(-4.20)	(-50.52)	(-9.73)	(-2.04)	(78.11)	(81.02)	(5.21)
Controls	No	No	Yes	No	No	Yes	No	No	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,834	6,834	6,641	6,899	6,899	6,695	5,732	5,732	5,518
R-squared	0.1%	0.3%	1.4%	0.0%	0.4%	1.7%	0.0%	0.1%	3.1%

Table A8. Panel Regressions: Alternative Estimation Windows

This table presents contemporaneous panel regressions with country fixed effects (FE) of 60-week innovations of country-level MSCI return correlations with the S&P 500 return (*Panel A*) on U.S. and local VIX changes as well as non fundamental demand ($NFDemand$), lagged values of ETF returns, and a number of other control variables. *Panel B* shows results for 100-week innovations of country-level MSCI return correlations with the S&P 500 return. The innovations are measured as the residuals of an AR(1) process. We consider the model (and nested specifications) below:

$$\Delta\rho_{i,t} = \alpha_i + \beta_1 \Delta VIX_t + \beta_2 \Delta LVIX_{i,t} + \beta_3 NFDemand_{i,t} + \beta_4 R_{ETF,i,t-1} + \gamma' \boldsymbol{Z}_{i,t} + \varepsilon_{i,t},$$

where $\Delta\rho_{i,t}$ represents correlation innovations of country i at time t. Our set of other controls (e.g., $\boldsymbol{Z}$) include spot exchange rate changes (e.g., ΔS), indexation and price discovery. We report t-statistics with robust standard errors. ***,**,* denote 1%, 5% and 10% significance levels. The data contain weekly series from January 2006 to June 2018.

Panel A: 60-week Correlations

	(1) $\Delta\rho_t$	(2) $\Delta\rho_t$	(3) $\Delta\rho_t$
ΔVIX_t		0.025***	0.025***
		(15.84)	(14.90)
$\Delta LVIX_t$	0.019***	-0.000	-0.002
	(8.01)	(-0.15)	(-0.65)
$NFDemand_t$			-0.004*
			(-1.84)
$\hat{R}_{ETF,i,t-1}$			-0.026***
			(-4.91)
Constant	-0.000***	-0.000***	-0.000
	(-12.29)	(-17.50)	(-0.44)
Controls	No	No	Yes
Country FE	Yes	Yes	Yes
Observations	21,411	21,411	18,217
R-squared	0.8%	3.2%	3.7%

Panel B: 100-week Correlations

	(1) $\Delta\rho_t$	(2) $\Delta\rho_t$	(3) $\Delta\rho_t$
ΔVIX_t		0.012***	0.011***
		(10.82)	(9.51)
$\Delta LVIX_t$	0.014***	0.005**	0.004
	(8.23)	(2.44)	(1.67)
$NFDemand_t$			0.005
			(0.86)
$\hat{R}_{ETF,i,t-1}$			-0.008*
			(-1.75)
Constant	-0.000***	-0.000***	0.000
	(-9.51)	(-12.49)	(0.24)
Controls	No	No	Yes
Country FE	Yes	Yes	Yes
Observations	20,051	20,051	17,497
R-squared	1.1%	2.6%	2.9%

Table A9. Panel Regressions: VIX States and Alternative Estimation Windows

This table presents contemporaneous panel regressions with country fixed effects (FE) of 60-week innovations of country-level MSCI return correlations with the S&P 500 return (*Panel A*) on U.S. and local VIX changes as well as non fundamental demand ($NFDemand$), lagged values of ETF returns, and a number of other control variables. *Panel B* shows results for 100-week innovations of country-level MSCI return correlations with the S&P 500 return. The innovations are measured as the residuals of an AR(1) process. We show results for low, medium and high VIX regimes. We consider the model (and nested specifications) below:

$$\Delta\rho_{i,t} = \alpha_i + \beta_1 \Delta VIX_t + \beta_2 \Delta LVIX_{i,t} + \beta_3 NFDemand_{i,t} + \beta_4 R_{ETF,i,t-1} + \gamma' \boldsymbol{Z}_{i,t} + \varepsilon_{i,t},$$

where $\Delta\rho_{i,t}$ represents correlation innovations (e.g., $\Delta\rho_{i,t}$) of country i at time t. Our set of other controls (e.g., $\boldsymbol{Z}$) include spot exchange rate changes (e.g., ΔS), indexation and price discovery. We report t-statistics with robust standard errors. ***,**,* denote 1%, 5% and 10% significance levels. The data contain weekly series from January 2006 to June 2018.

Panel A: 60-week Correlations

	(1) $\Delta\rho_t$	(2) $\Delta\rho_t$	(3) $\Delta\rho_t$	(4) $\Delta\rho_t$	(5) $\Delta\rho_t$	(6) $\Delta\rho_t$	(7) $\Delta\rho_t$	(8) $\Delta\rho_t$	(9) $\Delta\rho_t$
		Low VIX			*Medium VIX*			*High VIX*	
ΔVIX_t		-0.014***	-0.013***		0.003*	0.003**		0.044***	0.045***
		(-5.32)	(-4.67)		(1.73)	(2.50)		(13.51)	(11.35)
$\Delta LVIX_t$	-0.021***	-0.015***	-0.017***	0.002	-0.000	-0.002	0.038***	-0.001	-0.002
	(-6.35)	(-4.37)	(-4.54)	(0.86)	(-0.01)	(-0.63)	(11.46)	(-0.15)	(-0.39)
$\hat{R}_{ETF,i,t-1}$			0.038***			-0.050***			-0.016**
			(4.20)			(-7.92)			(-2.16)
$NFDemand_t$			-0.005			-0.000			-0.005**
			(-0.97)			(-0.06)			(-2.19)
Constant	-0.003***	-0.004***	-0.003***	-0.001***	-0.001***	-0.002***	0.003***	0.001***	0.001
	(-102.81)	(-62.24)	(-2.75)	(-216.74)	(-79.55)	(-3.88)	(45.63)	(11.04)	(1.51)
Controls	No	No	Yes	No	No	Yes	No	No	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,363	6,363	6,011	7,401	7,401	6,551	7,647	7,647	5,655
R-squared	0.6%	1.0%	2.2%	0.0%	0.0%	2.7%	3.8%	13.0%	15.6%

Panel B: 100-week Correlations

	(1) $\Delta\rho_t$	(2) $\Delta\rho_t$	(3) $\Delta\rho_t$	(4) $\Delta\rho_t$	(5) $\Delta\rho_t$	(6) $\Delta\rho_t$	(7) $\Delta\rho_t$	(8) $\Delta\rho_t$	(9) $\Delta\rho_t$
		Low VIX			*Medium VIX*			*High VIX*	
ΔVIX_t		-0.014***	-0.013***		0.000	0.001		0.021***	0.020***
		(-5.32)	(-4.67)		(0.32)	(0.76)		(9.53)	(7.66)
$\Delta LVIX_t$	-0.010***	-0.015***	-0.017***	0.001	0.001	0.001	0.026***	0.008**	0.007*
	(-6.49)	(-4.37)	(-4.54)	(1.04)	(0.62)	(0.66)	(11.85)	(2.56)	(1.73)
$NFDemand_t$			-0.005			0.001			0.011
			(-0.97)			(0.53)			(1.13)
$\hat{R}_{ETF,i,t-1}$			0.038***			-0.019***			0.003
			(4.20)			(-3.20)			(0.59)
Constant	-0.002***	-0.004***	-0.003***	0.000***	0.000***	0.000	0.001***	0.001***	0.001
	(-162.25)	(-62.24)	(-2.75)	(268.66)	(55.98)	(0.48)	(34.78)	(8.76)	(1.08)
Controls	No	No	Yes	No	No	Yes	No	No	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,023	6,363	6,011	6,891	6,891	6,281	7,137	7,137	5,385
R-squared	0.3%	1.0%	2.2%	0.0%	0.0%	1.1%	4.3%	9.2%	11.1%

Table A10. Underlying Return Correlations and ETF Price Discovery: DCC

This table presents average correlations of MSCI index returns on S&P 500 returns. We also report average adjusted R-squares of MSCI index returns on the first principal component (PC1) of all available countries. The correlations are estimated based on the Dynamic Conditional Correlation (DCC) model of Engle (2002). In *Panel A* we allocate countries, on a weekly basis, into terciles based on their price discovery. Our proxy price discovery is defined as the NAV sensitivity to the ETF premium. Specifically, we regress NAV returns of each country on their past ETF premium and use the estimated beta as proxy of price discovery. A higher beta coefficients represents a stronger adjustment to NAV implying a higher price discovery in the ETF market. The regression takes the form:

$$R_t^{NAV} = \alpha + \beta_{PD}\left(\frac{P_{t-1} - NAV_{t-1}}{NAV_{t-1}}\right) + \varepsilon_t,$$

where β_{PD} denotes ours proxy of price discovery. We estimate the measure for all the countries in our sample. *Panel B* show average correlation for countries that are allocated, on a weekly basis, into terciles based on a proxy of limits to arbitrage. We proxy limits to arbitrage with the Amihud's illiquidity ratio (e.g., Amihud, 2002) of the underlying markets (*ILLIQ*). We report results for low (high) VIX states. We report t-statistics with HAC standard errors as in Newey and West (1987). The data contain weekly series from January 2006 to June 2018.

Panel A: Price Discovery					
	Low β_{PD}	Medium β_{PD}	High β_{PD}	HML	t-stat
			Full Sample		
$\overline{DCC}$	0.545	0.594	0.645	0.101	(23.59)
			Low VIX		
$\overline{DCC}$	0.481	0.546	0.606	0.125	(21.52)
			High VIX		
$\overline{DCC}$	0.595	0.642	0.686	0.091	(11.67)
Panel B: Limits to Arbitrage					
	Low $ILLIQ$	Medium $ILLIQ$	High $ILLIQ$	HML	t-stat
			Full Sample		
$\overline{DCC}$	0.643	0.608	0.573	-0.070	(-47.79)
			Low VIX		
$\overline{DCC}$	0.607	0.563	0.531	-0.075	(-31.17)
			High VIX		
$\overline{DCC}$	0.681	0.652	0.616	-0.065	(-26.31)

Table A11. Panel Regressions: Types of ETF Investors

This table presents contemporaneous panel regressions with country fixed effects (FE) of ETF order imbalances of different types of investors on U.S. and local VIX changes as well as lagged values of ETF returns and a number of control variables. The correlations are estimated based on a 36-week rolling window and the innovations are measured as the residuals of an AR(1) process. We consider the model (and nested specifications) below:

$$OI_{i,t} = \alpha_i + \beta_1 \Delta VIX_t + \beta_2 \Delta LVIX_{i,t} + \beta_3 R_{ETF,i,t-1} + \beta_4 NFDemand_{i,t} + \gamma' \boldsymbol{Z}_{i,t} + \varepsilon_{i,t},$$

where $OI_{i,t}$ represents the ETF order imbalance of large (OI_t^{Large}), small (OI_t^{Small}) and retail (OI_t^{Retail}) investors of country i at time t. Our set of controls (e.g., $\boldsymbol{Z}$) include spot exchange rate changes (e.g., ΔS), indexation, non fundamental demand ($NFDemand$) and price discovery. We report t-statistics with robust standard errors. ***,**,* denote 1%, 5% and 10% significance levels. The data contain weekly series from January 2006 to June 2018.

	Order Imbalances								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	OI_t^{Large}	OI_t^{Large}	OI_t^{Large}	OI_t^{Small}	OI_t^{Small}	OI_t^{Small}	OI_t^{Retail}	OI_t^{Retail}	OI_t^{Retail}
ΔVIX_t		-0.117***	-0.115***		-0.073***	-0.074***		-0.125***	-0.131***
		(-7.82)	(-7.48)		(-5.41)	(-5.36)		(-9.25)	(-9.75)
$\Delta LVIX_t$	-0.117***	-0.027	-0.012	-0.071***	-0.014	0.000	-0.125***	-0.029	-0.011
	(-7.25)	(-1.51)	(-0.61)	(-4.19)	(-0.81)	(0.02)	(-6.82)	(-1.52)	(-0.55)
$\hat{R}_{ETF,i,t-1}$			0.537***			0.534***			0.720***
			(6.14)			(7.04)			(8.89)
$NFDemand_t$			0.482***			0.400***			0.507***
			(5.94)			(7.36)			(5.19)
Constant	0.017***	0.018***	0.044***	0.000**	0.001***	0.030**	0.012***	0.013***	0.035***
	(303.47)	(139.48)	(6.09)	(2.68)	(5.79)	(2.42)	(212.04)	(102.74)	(2.77)
Controls	No	No	Yes	No	No	Yes	No	No	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,374	20,374	19,017	19,339	19,339	17,977	20,054	20,054	19,023
R-squared	0.2%	0.5%	2.0%	0.1%	0.2%	1.9%	0.2%	0.6%	3.0%