Sakarya, Burçhan; Ekinci, Aykut

Article

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Exchange-traded funds and FX volatility: Evidence from Turkey

Burçhan Sakarya [a, *], Aykut Ekinci [b]

[a] T.R. Presidency Strategy and Budget Office, Expert, Assoc. Prof., Turkey
[b] Samsun University, Department of Economics and Finance Assoc. Prof., Turkey

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ABSTRACT

Exchange-Traded Funds (ETFs) have become one of the most popular passive investment instruments since they bring together the advantages of stocks and mutual funds. As passive investors are more risk averse and sensitive to possible adverse market developments, ETF's fund flows can provide distinct information in certain periods in comparison with active funds. This study looks at ETF fund flows in foreign exchange uncertainty by using EGARCH models, together with added control variables. The main results are that the large inflows of ETFs increases exchange rate volatility for contemporaneous and lagged effect models, yet large outflows have a negative and statistically significant effect on the exchange rate volatility in lagged variance equation. These findings suggest an asymmetric behavior as outflows of ETFs are followed by an exchange rate depreciation with less exchange rate FX uncertainty, while significantly large inflows of ETFs lead to higher FX uncertainty.

1. Introduction and background

An exchange-traded fund (ETF) is broadly defined as a basket of securities similar to a mutual fund. Borsa Istanbul (BIST, 2018) describes ETFs as "mutual funds traded on equity-exchanges, which are based on an index and aim to reflect the performance of its base index to the investors". In addition, SEC (2015) also points out that exchange-traded funds (ETFs) typically focus on a single market, industry, or geographical area. Hence, ETFs are exemplary of the so-called "passive investment" tools by which an investor, willing to invest in a particular index, invests in an ETF rather than purchasing the equities of the index separately.

Passive strategies use ruled-based investing to track an index or a focused fund, by holding its constituent assets whereas active strategies give portfolio managers a broader room for maneuver, and independence in selecting individual securities. Thus, exchange traded funds are portfolios created by authorized intermediary institutions through the purchase of securities on the base index or other instruments such as gold, bond, foreign exchange, etc. On the base index. Unlike mutual funds, on the other hand, ETFs are traded on market exchange. Therefore, even though they are considered as passive investments, ETF prices fluctuate throughout the day as market prices do. Globally, over the past couple of decades, a substantial shift from active to passive investment strategy was reported in the asset management preferences (see Anadu et al., 2018; Fidelity, 2019), which signifies the increased preference of ETFs by investors.

This article contributes to the literature on ETFs and exchange rate volatility by investigating the relation between ETF fund flows, rather than changes in net asset value to a given market and the return of that particular exchange rate. Specifically, the study focuses on the effect of fund flows related to the Turkish stock exchange market on the volatility of the return of USD/TL exchange rate for the period March 2008–June 2019 for weekly frequency by using the various EGARCH models. Thus, the study also focuses on the post-2018 period when Turkey experienced a sell-off by mid-August of 2018.

Turkish stock exchange market Borsa Istanbul (BIST) has a well-documented history of significant foreign participation, fluctuating around 65%. Typically, this share consists of larger, more active and aggressive investors with considerably longer investment horizon compared to domestic and smaller investors. Thus, during sell-off episodes, such as in 2018, conventional investors tend to adjust

* Corresponding author.
E-mail addresses: burchan.sakarya@sbb.gov.tr (B. Sakarya), aykut.ekinci@samsun.edu.tr (A. Ekinci).

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with higher risk appetite than passive investors such as ETFs. Hence, ETFs fund flows provide other distinct information periods.

The rest of the article is organized as follows: Section 2 describes a brief background on applied studies about ETFs. The next section provides information on data and on the iShares MSCI Turkey Exchange Traded Fund in particular. The fundamental model is presented in section 4 and the empirical results are presented in section 5 and extensions to the main model in section 6, and the final section concludes the discussion.

2. Background of ETFs

The literature on ETFs mainly focuses on the instrument itself. For example, Aber et al. (2009), Johnson (2009), Charupat and Miu (2013) analyze how effectively ETFs track their respective benchmark indices. Several other studies provide findings on ETF market structure and quality. Chou and Chung (2006) indicate that increased competition and information such as enhanced tick size have improved market quality, measured by liquidity and spreads. Boehmer and Boehmer (2003) and Nguyen et al. (2007) also debate that multimarket trading improves the liquidity of most popular ETFs.

Agapova (2011) finds that index mutual funds and ETFs are imperfect substitutes. Dedi, Yavas, McMillan (2016) investigate linkages among equity market returns and volatility spillovers for Germany, United Kingdom, China, Russia, and Turkey by using the MARMA, GARCH, GARCH-in-mean, and EGARCH models. MSCI indices of the country ETFs were applied on daily data for the period of March 2011−March 2016. The empirical results show strong evidence of volatility spillovers. They also find that, only in the UK, the volatility of the market had a positive effect on its future returns, i.e. an increase in volatility led to a rise in future ETF returns in the UK.

Shank and Vianna (2016) examine the of US listed currency hedged ETF investors's behavior towards the changes in the underlying benchmark and foreign exchange rate from July 2011 to November 2015 by using a panel VAR approach. They find that investors proactively traded before large real exchange rate movements by investing in currency hedged ETFs. These results show that the use of ETFs to hedge against exchange rate volatility may have itself become a source of volatility.

A small number of studies investigate the relation between returns and volatility for foreign exchange market, and fewer studies on the effect of ETFs on foreign exchange volatility, specifically on emerging countries such as Turkey. Most of these studies support asymmetric relation between return and risk in equity markets (see Black, 1976 and Christie, 1982 for the leverage hypothesis, and French et al., 1987, Campbell and Hentschel, 1992 and Bekaert and Wu, 2000 for the volatility feedback hypothesis). However, the evidence in foreign exchange markets is conflicting. Theodossiou (1994) finds no asymmetry in the volatility of five exchange rates against the Canadian dollar by using EGARCH-M model. More recently, Wang and Yang (2009) find no asymmetric volatility in EUR against USD. On the other hand, Tse and Tsui (1997) find asymmetric volatility for Malaysian ringgit, McKenzie (2002) for Australian dollar, and Adler and Qi (2003) for Mexican peso, all against USD. In the light of the recent literature, this paper investigates the link between the passive investor decisions and FX volatility for the Turkish case by using EGARCH model.

3. iShares MSCI Turkey ETF and the data

The iShares MSCI Turkey ETF seeks to track the investment results of a broad-based index composed of Turkish equities. Thus, this displays one of the most significant characteristics of an ETF: following an index. The fund tracks the investment results of the MSCI Turkey IMI 25/50 Index (described as the "Underlying Index"), which is designed to measure the performance of the large, medium and small capitalization segments of Borsa Istanbul (iShares, 2018). The Underlying Index consists of stocks traded primarily on the Istanbul Stock Exchange (ISE). According to iShares principal investment strategy "*capping methodology is applied that limits the weight of any single issuer to a maximum of 25% of the Underlying Index*". Although the components of the so-called underlying index might change over time, the weights mentioned by the ETFs prospectus clearly describe a passive investor profile. As such, *the sum of the issuers that individually constitutes more than 5% of the weight of the Underlying Index cannot exceed a maximum of 50% of the weight of the Underlying Index in the aggregate*.

The iShares MSCI Turkey ETF was established in March 2008. As similar to all other ETFs, iShares MSCI Turkey also has a low expense ratio of 0.59%. Traded in NASDAQ and Borsa Istanbul, the holdings of the fund are mainly comprised of major financials such as Isbank, Garanti Bank and Akbank, industrials such as TÜPRAŞ, Ereğli Demir Çelik, and ASELSAN, holdings such as KOÇ and SABANCI, and several services such as TURKCELL and BIM. According to its manual, the holdings of the fund is 28.99% financial, followed by 22.14% industrial, 13.54% consumer staples, 11.56% materials, 7.55% energy and 16.22% others. The net asset value of iShares MSCI Turkey ETF can be seen in Fig. 1. The fund has a beta against S&P500 of 0.24. The three-year standard deviation stands at 33.92%. The price to earnings ratio is 6.17 and to book ratio is 1.03.

Since its inception in March 2008, this main Turkish ETF has been rather active and lured (passive) investors globally. The financial strains can easily be observed by simply looking at the flows of this ETF (see Fig. 2). Additionally, the outflow periods coincide with domestic currency depreciations and the inflow periods indicate to appreciations. While the relationship between the ETF fund flows and the exchange rate is quite apparent, the conditional volatility of the exchange rate changes, and ETF fund flows deserve further investigation. This issue is significantly evident prior to the Turkish sell-off in August 2018. By mid-August 2018, Turkish financial markets had negatively decoupled from other emerging market economies while the USD/TRY rate spiked considerably. While mainly several geo-political risks were associated with this development, an increased positive flow of Turkish ETFs had been observed prior to this period. Similar but rather smaller sized episodes were also observed in the sample period.

The closing price of USD/TRY exchange rate is retrieved from Bloomberg as weekly frequency for the period from March 28, 2008 to June 07, 2019. We use weekly return rather than price (exchange)

Fig. 1. iShares MSCI Turkey ETF Net Asset Value (mio USD).
Source: Bloomberg.

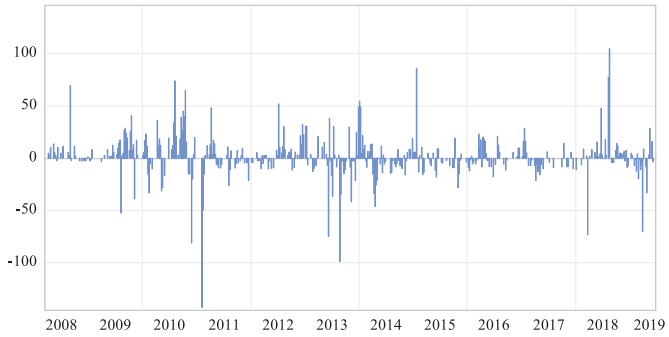

Fig. 2. Etf fund flows (mio USD).
Source: Bloomberg, IShares Markit.

rate to provide stationarity. Return, $\Delta ex \lim_{x \to \infty}$, is measured as the first difference of the log of the USD/TRY exchange rate as follows:

$$\Delta ex_t = \log(ex_t) - \log(ex_{t-1}) \quad (1)$$

where ex_t is the exchange rate during the time t. Fig. 3 shows the weekly return of USD/TRY exchange rate, Δex, and Table 1 presents statistical properties of the data. The mean value of the return of the exchange rate is very close to zero but, as expected, it has high skewness (2.22) and leptokurtic kurtosis (25.07). A leptokurtic distribution (greater than three) means that the tails of the returns are fatter than the normal distribution and positive skewness as a degree of distortion means that the return distribution has right tail. We should note that the maximum value at August 10, 2018 with 0.23% is a clear outlier and has sizeable effect on higher skewness and kurtosis values. Thus, skewness and kurtosis are respectively 0.4067 and 6.7551 when the outlier is omitted.

The iShares MSCI Turkey ETF data are compiled from Bloomberg as weekly for the period from March 28, 2008 to June 07, 2019. As mentioned in the previous section this data is compiled by Bloomberg from iShares MSCI Turkey transactions. The data on this fund have two major dimensions as the net asset value, which tracks the market price for this financial asset, and the actual size of fund flows (in or out) to this financial instrument, i.e. the size of net transaction for this asset (The iShares MSCI Turkey ETF in our case).

The size of inflows and outflows to Turkish ETF in million USD terms can be traced from Figs. 2 and 3. Looking at the flow data, weekly changes in investor preferences are rather small in volume compared to the flows to BIST equity market and government securities. The mean fund flow size for ETFs is 1.13 million USD, while it is 30.40 million USD for BIST net equity transactions and 63.23 million USD for net government debt securities transactions for

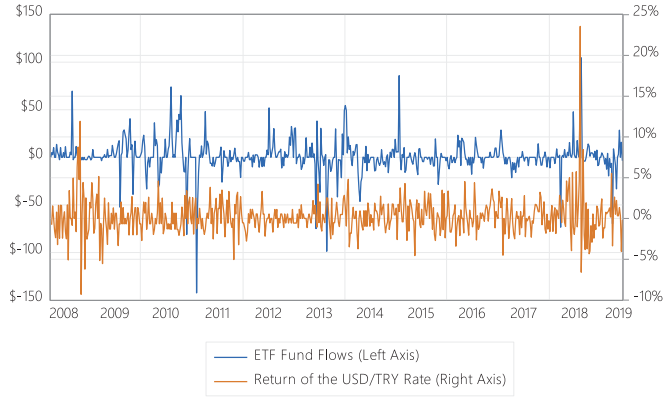

Fig. 3. Etf fund flows (mio USD) and return of the USD/TRY rate (%).
Source: Bloomberg, IShares Markit.

non-residents, for the same sample period and frequency. However, as stated earlier, the passive investment nature of the ETFs is assumed to provide a distinct type of signal to the foreign exchange market (see Fig. 3).

Investigating further times series properties of the data, the Augmented Dickey–Fuller (ADF) and Phillips-Perron (PP) tests were carried out for the Δex and FF variables. It can be seen from Table 2 that all ADF and PP test results are statistically significant at the 1% level, thereby indicating that variables are stationary.

4. Model

Autoregressive conditional heteroskedastic (ARCH) models (Engle, 1982) and generalized autoregressive conditional heteroskedastic (GARCH) models (Bollerslev, 1986) are popular in modelling the volatility of financial variables. Moreover, Exponential GARCH (EGARCH) models, based on Nelson (1991), are among the most common univariate asymmetric conditional volatility models in GARCH type estimations. These models are specifically employed in capturing leverage and asymmetry effects. Thus, we prefer the EGARCH model to analyze the effect of ETF on exchange rate. The mean equation is as follows:

$$\Delta ex_t = \alpha + \beta d081018 + \varepsilon_t \quad (2)$$

where Δex represents the FX return series as defined in data section, α is the constant term, $d081018$ shows the dummy variable for the August 10, 2018, and the date represents the Turkish sell-off since it produces 10.5 standardized residual value in the mean equation. The optimal lag lengths of AR or MA terms are zero based on the Akaike, Schwartz and Hannan-Quinn information criterion.

The specification of the EGARCH model is given by:

$$\log\left(h_t^2\right) = \theta + \gamma\left|\frac{\varepsilon_{t-1}}{h_{t-1}}\right| + \delta\frac{\varepsilon_{t-1}}{h_{t-1}} + \alpha\log\left(h_{t-1}^2\right) \quad (3)$$

where $\log(h_t^2)$ is the log of the conditional variance, θ is the constant parameter, γ parameter represents the volatility responds for a magnitude effect or the symmetric effect in the short-run, δ measures the asymmetric effect as explained below, and α captures the long-run volatility effect in conditional volatility. Modelling the volatility with EGARCH has several advantages over the classic GARCH models. The first one is about relaxing the nonnegative assumption on coefficients by modelling the volatility as the log of the conditional variance. Second, δ measures the asymmetric effect. If $\delta = 0$, there is no asymmetric effect. If $\delta > 0$, it implies that positive shocks generate higher volatility more than negative shocks. If $-1 < \delta < 0$, a positive shock increases volatility less than a negative shock. If $\delta < -1$, then a positive surprise actually reduces volatility (see Berument et al., 2012).

We add two kinds of dummies into the conditional variance equation to see the effect of ETF on foreign exchange volatility. Size, τ, is a dummy for fund flow if it is bigger than the average of inflow (14 million USD) or smaller than the average of outflow (−12.94 million USD) of fund flows (see equation (4)). We also create the positive and negative dummies of the *size* dummy to separate the inflow and outflow effects. $size_{positive}$, τ_1, aims to capture the effect of the inflows over the average fund flow, i.e. *FF>14 million USD;* and $size_{negative}$ τ_2, aims to measure the effect of the outflow over the average fund flow, i.e. *FF < -12,9 million USD* (see equation (5)).

$$\log\left(h_t^2\right) = \theta + \gamma\left|\frac{\varepsilon_{t-1}}{h_{t-1}}\right| + \delta\frac{\varepsilon_{t-1}}{h_{t-1}} + \alpha log\left(h_{t-1}^2\right) + \tau size_t \quad (4)$$

Table 1
Data properties.

	Mean	Median	Max.	Min.	Std. Dev.	Skewness	Kurtosis	Jarque-Bera	Prob.
Δex_t	0.0025	0.0000	0.2356	−0.0929	0.0222	2.2233	25.0735	12337.3	0.0000
FF	1.1302	0.0000	104.69	−142.57	17.535	−0.6679	18.7428	6074.15	0.0000

FF: Fund Flows of ETF.
Source: Authors calculation.

Table 2
Unit root test results.

	ADF (constant)	ADF (constant + trend)	*PP (constant)*	PP (constant + trend)
Δex	−24.8302***	−24.8662 **	−24.8239***	−24.8557 ***
FF	−17.4260***	−17.4548***	−17.6633***	−17.6784***

Notes: Specifications for ADF tests: The optimal lag length based on SIC, maxlag = 18. Specifications for PP tests: Spectral estimation method: Barlett-Kernell, the optimal lag length based on Newey-West bandwidth.
***Significance at 1 percent level.

$$\log\left(h_t^2\right) = \theta + \gamma\left|\frac{\varepsilon_{t-1}}{h_{t-1}}\right| + \delta\frac{\varepsilon_{t-1}}{h_{t-1}} + \alpha log\left(h_{t-1}^2\right) + \tau_1 size_{positive,\,t} + \tau_2 size_{negative,\,t} \quad (5)$$

$$\log\left(h_t^2\right) = \theta + \gamma\left|\frac{\varepsilon_{t-1}}{h_{t-1}}\right| + \delta\frac{\varepsilon_{t-1}}{h_{t-1}} + \alpha\log\left(h_{t-1}^2\right) + \varnothing d1.5_t \quad (6)$$

$$\log\left(h_t^2\right) = \theta + \gamma\left|\frac{\varepsilon_{t-1}}{h_{t-1}}\right| + \delta\frac{\varepsilon_{t-1}}{h_{t-1}} + \alpha\log\left(h_{t-1}^2\right) + \varnothing_1 d1.5_{positive,\,t} + \varnothing_2 d1.5_{negative,\,t} \quad (7)$$

The second type of dummy is $d1.5$ and represents the effect of a much larger inflow and outflow by using the dummy as 1, if the fund flow is bigger than 1.5 standard deviation from standardized fund flows (see equation (6)). Similarly, $d1.5_{positive}$, $\varnothing_1$, represents the inflows, i.e. *FF>36.22 million USD*; and $d1.5_{negative}$, $\varnothing_2$, represents the outflow bigger than 1.5 standard deviation, i.e. *FF < -31.33 million USD*, from the standardized fund flows (see equation (7)).

$$\log\left(h_t^2\right) = \theta + \gamma\left|\frac{\varepsilon_{t-1}}{h_{t-1}}\right| + \delta\frac{\varepsilon_{t-1}}{h_{t-1}} + \alpha\log\left(h_{t-1}^2\right) + \tau size_{t-1} \quad (8)$$

$$\log\left(h_t^2\right) = \theta + \gamma\left|\frac{\varepsilon_{t-1}}{h_{t-1}}\right| + \delta\frac{\varepsilon_{t-1}}{h_{t-1}} + \alpha\log\left(h_{t-1}^2\right) + \tau_1 size_{positive,\,t-1} + \tau_2 size_{negative,\,t-1} \quad (9)$$

$$\log\left(h_t^2\right) = \theta + \gamma\left|\frac{\varepsilon_{t-1}}{h_{t-1}}\right| + \delta\frac{\varepsilon_{t-1}}{h_{t-1}} + \alpha\log\left(h_{t-1}^2\right) + \varnothing d1.5_{t-1} \quad (10)$$

$$\log\left(h_t^2\right) = \theta + \gamma\left|\frac{\varepsilon_{t-1}}{h_{t-1}}\right| + \delta\frac{\varepsilon_{t-1}}{h_{t-1}} + \alpha\log\left(h_{t-1}^2\right) + \varnothing_1 d1.5_{positive,\,t-1} + \varnothing_2 d1.5_{negative,\,t-1} \quad (11)$$

While we can confirm the contemporaneous effect of fund flows on the volatility of foreign exchange via equations (4)–(7), it is also interesting to investigate whether the effect of fund flows on the volatility of foreign exchange has a delay by using the first lag of dummies as in equations (8)–(11).

5. Results

Table 3 presents the model results and residual diagnostics for equations (2)–(11). The mean equation with dummy (2) has 0.1869 adjusted R^2 and Ljung-Box Q test statistics for autocorrelation up to 6 do not reject the null hypothesis of no serial correlation. However, Ljung-Box statistics of the squared residuals (Q^2) confirm the presence of heteroscedasticity at the 1% level. These residual diagnostics for equations (3)–(11) are very similar on adjusted R^2 and we cannot identify any autocorrelation or heteroscedasticity issue according to Ljung-Box Q and to Ljung-Box Q^2 test results. We assume that the conditional distribution of the error term has normal distribution. On the other hand, the results did not change significantly when the Generalized Error Distribution (GED) was used for the errors following Nelson (1991).

The initial result is about the behavior of the exchange rate volatility. The persistence coefficient of the FX volatility, α, is around 0.95 with 1% significant level. The coefficient of asymmetry, δ, is positive and statistically significant for all EGARCH models. This simply implies that a positive shock generates a higher volatility compared to a negative shock.

As we know from the model section, *size* and *d1.5* dummies represent the large flows of ETF. The coefficient of size, τ, and *d1.5*, $\varnothing$, are positive but statistically insignificant. Thus, there is no evidence on the effects of larger ETF flows on the exchange rate volatility. On the other hand, $size_{positive}$, τ_1, *and* $d1.5_{positive}$, $\varnothing_1$, which respectively represent large inflows in ETF, are positive and statistically significant at 1% level for equations (11) and (5)% level for equations (5), (7) and (9). However, $size_{negative}$, τ_2, and $d1.5_{negative}$, $\varnothing_2$, are negative but statistically insignificant for equations (5) and (7) while $size_{negative}$, τ_2 and $d1.5_{negative}$, $\varnothing_2$, are negative and statistically significant at 10% level for equations (9) and (5)% level for equation (11) when considered with the lag effect.

6. Alternative models: adding control variables and GFC dummy

First, we add a Global Financial Crisis dummy (GFC) into the mean equation as follows:

$$\Delta ex_t = \alpha + \beta_1 dGFC + \beta_2 d081018 + \varepsilon_t \quad (12)$$

The GFC dummy captures the global financial crisis effect for October 10, 2008 and October 24, 2008, which respectively have 5.8 and 4.3 standardized residual values for the mean equation in equation (12). All other models are the same variance models and

Table 3
Model results and residual diagnostics.

Coefficient/Equation	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*	*(11)*
Mean eq.										
A	0.0021***	0.0024***	0.0024***	0.0025***	0.0023***	0.0023***	0.0024***	0.0024***	0.0023***	0.0022***
B	0.2334***	0.2001***	0.2013***	0.2087***	0.2058***	0.2172***	0.2013***	0.2101***	0.2052***	0.2185***
Variace eq.										
Θ		−0.5201***	−0.5146***	−0.4798***	−0.5130***	−0.5511***	−0.5156***	−0.4922***	−0.5148***	−0.6135***
Γ		0.1591***	0.1600**	0.1479***	0.1552***	0.1426***	0.1599***	0.1481***	0.1560***	0.1456***
Δ		0.1279***	0.1307***	0.1380***	0.1269***	0.1361***	0.1296***	0.1411***	0.1260***	0.1439***
A		0.9506***	0.9523***	0.9550***	0.9521***	0.9460***	0.9519***	0.9532***	0.9517***	0.9383***
τ/θ			0.0358		0.1183		0.0271		0.0924	
τ_1/θ_1				0.0984**		0.3268**		0.1046**		0.3764***
τ_2/θ_2				−0.1007		−0.1792		−0.1476*		−0.3444**
Diagnostics										
Adj. R^2	0.1869	0.1829	0.1832	0.1846	0.1842	0.1859	0.1832	0.1849	0.1840	0.1861
Q_1	0.0870	0.0108	0.0059	0.0294	0.0089	0.0309	0.0059	0.0196	0.0078	0.0200
Q_6	6.4338	3.8562	4.1112	4.4975	4.1694	3.7875	4.0338	4.4085	4.1071	3.4225
Q_1^2	64.317***	0.0186	0.0322	0.0389	0.0501	0.0635	0.0333	O.0l78	0.0483	0.0409
Q_6^2	209.18***	96.183	9.6831	8.8004	8.6747	7.8045	9.7148	8.5084	8.9323	7.3454

Notes: Q_i is the ith order Ljung-Box test of the null of residual serial independence with degrees of freedom adjusted for AR parameter estimation; Q_i^2 is the ith order Ljung - Box test of serial independence in the squared residuals.* Significance at 10 percent level.** Significance at 5 percent level.*** Significance at 1 percent level.

can be followed as equation 13 to 21 at Table 4.

Then, we add several control variables into the conditional variance model to control the external factors on USD/TRY FX volatility. To begin with, we add VIX index to incorporate the global risk appetite and control the effect of global risk perception on USD/TRY FX volatility. VIX index measures the stock market's expectation of volatility as implied by S&P 500 index options, which is a common proxy for global investors risk appetite. Next, we include the dollar index (DXY) to capture the effect of the changes in USD against other major currencies, excluding TRY. DXY tracks the strength of the dollar against a basket of major currencies such as Euro, Japanese Yen, Great British Pound, Canadian Dollar, Swedish Krona and Swiss Franc. We use the logarithmic first differences of all control variables.

The mean and variance equations are the same for all extension models shown at Tables 4–6. Table 4 presents the models, which cover the GFC dummy into the mean equation as β_1 starting from equation (12)–(21). We add VIX control variable into the variance equation as ϑ, which can be followed from equation 22 to 31 at Table 5. The effect of DXY control variable, ϑ, can be traced from equation 32 to 41 at Table 6.

VIX coefficient, ϑ, is positive and statistically significant, which implies that an increase in VIX has a positive effect on USD/TRY FX volatility (see Table 5). DXY coefficient is also positive and statistically significant (see Table 6). An increase in dollar value against a basket of major currencies has a strong positive effect on USD/TRY conditional FX volatility. As explained below, the main results do not change after controlling VIX or DXY.

The coefficient of asymmetry, δ, is still positive and statistically significant at 1% significance level for all alternative EGARCH models, i.e. mean equation with GFC dummy models (see Table 4) and models with VIX and DXY control variables (see respectively Tables 5 and 6). The empirical findings show that a positive FX shock will generate a higher FX volatility as compared to a negative FX shock.

The large flows of ETF, τ and $\varnothing$, are still positive and statistically insignificant for all models except equations (36) and (40) in Table 6. equations (36) and (40) show the EGARCH model with DXY control variable as follows:

Table 4
Model Results and Residual Diagnostics (adding GFC dummy into the mean equation as β_1).

Coefficient/equation	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
Mean eq.										
α	0.0018**	0.0023***	0.0023***	0.0024***	0.0023***	0.0023***	0.0023***	0.0024***	0.0023***	0.0021***
β_1	0.1016***	0.0750***	0.0742***	0.0755***	0.0742***	0.0741***	0.0745***	0.0760***	0.0744***	0.0742***
β_2	0.2338***	0.2036***	0.2048***	0.2128***	0.2090***	0.2195***	0.2047***	0.2141***	0.2083***	0.2204***
Variance eq.										
θ		−0.4348***	−0.4302***	−0.3988***	−0.4299***	−0.4726***	−0.4309***	−0.4095***	−0.4305***	−0.5299***
γ		0.1427***	0.1440***	0.1334***	0.1395***	0.1299***	0.1437***	0.1340***	0.1400***	0.1329***
δ		0.1147***	0.1170***	0.1259***	0.1137***	0.1231***	0.1161***	0.1294***	0.1129***	0.1308***
α		0.9598***	0.9612***	0.9637***	0.9609***	0.9546***	0.9609***	0.9622***	0.9607***	0.9476***
$\tau/\varnothing$			0.0305		0.1072		0.0227		0.0837	
$\tau_1/\varnothing_1$				0.0929**		0.2969**		0.0989**		0.3444***
$\tau_2/\varnothing_2$				−0.0993		−0.1600		−0.1404*		−0.3081**
Diagnostic st.										
Adj. R^2	0.2595	0.2511	0.2511	0.2527	0.2519	0.2532	0.2512	0.2532	0.2519	0.2536
Q_1	0.9708	0.3686	0.3408	0.4434	0.3511	0.3987	0.3418	0.3860	0.3479	0.3320
Q_6	9.5970	4.3390	4.5639	5.0885	4.6064	4.2804	4.4953	5.0222	4.5793	3.9477
Q_1^2	0.1581	1.3938	1.3321	1.2197	1.2782	0.9540	1.3223	1.2907	1.2745	0.8908
Q_6^2	133.44***	11.110	11.236	10.191	10.518	9.1175	11.185	9.8528	10.770	8.6905

Notes: Q_i is the ith order Ljung-Box test of the null of residual serial independence with degrees of freedom adjusted for AR parameter estimation; Q_i^2 is the ith order Ljung-Box test of serial independence in the squared residuals.* Significance at 10 percent level.** Significance at 5 percent level.*** Significance at 1 percent level.

Table 5
Model Results and Residual Diagnostics (adding VIX control variable into the variance equation as ϑ).

Coefficient/equation	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)	(31)
Mean eq.										
α	0.0018**	0.0023***	0.0019***	0.0020***	0.0019***	0.0019***	0.0019***	0.0020***	0.0019***	0.0018***
β_1	0.1016***	0.0750***	0.0775***	0.0890**	0.0776***	0.0773***	0.0778***	0.0800***	0.0779***	0.0768***
β_2	0.2338***	0.2036***	0.2116***	0.2219***	0.2145***	0.2243***	0.2114***	0.2219***	0.2137***	0.2237***
Variance eq.										
θ		−0.4348***	−0.3560***	−0.3131***	−0.3583***	−0.4032***	−0.3579***	−0.3275***	−0.3597***	−0.4548***
γ		0.1427***	0.1323***	0.1207***	0.1280***	0.1218***	0.1325***	0.1220***	0.1288***	0.1266***
δ		0.1147***	0.0946***	0.1019***	0.0926***	0.1032***	0.0940***	0.1059***	0.0919***	0.1116***
α		0.9598***	0.9694***	0.9733***	0.9686***	0.9623***	0.9690***	0.9715***	0.9683***	0.9563***
ϑ			0.6831***	0.7276***	0.6420***	0.6211***	0.6834***	0.6766***	0.6563***	0.5509**
τ/ $\varnothing$			0.0305		0.0832		0.0252		0.0655	
τ_1/ $\varnothing_1$				0.0960**		0.2579**		0.0995**		0.2935**
τ_2/ $\varnothing_2$				−0.0960		−0.1682		−0.1221*		−0.2745*
Diagnostic st.										
Adj. R^2	0.2595	0.2511	0.2538	0.2579	0.2542	0.2551	0.2538	0.2557	0.2542	
Q_1	0.9708	0.3686	0.3276	0.4486	0.3463	0.3792	0.3237	0.3404	0.3417	
Q_6	9.5970	4.3390	4.1154	4.6664	4.1286	3.8151	4.0606	4.5926	4.1046	
Q_1^2	0.1581	1.3938	1.0492	0.9590	1.0178	0.7093	1.0342	0.8755	1.0189	
Q_6^2	133.44***	11.110	9.7772	8.8449	9.3430	8.5280	9.7772	8.3050	9.5432	

Notes: $Q_i$is the ith order Ljung-Box test of the null of residual serial independence with degrees of freedom adjusted for AR parameter estimation; Q_i^2 is the ith order Ljung-Box test of serial independence in the squared residuals.* Significance at 10 percent level.** Significance at 5 percent level.*** Significance at 1 percent level.

Table 6
Model Results and Residual Diagnostics (adding DXY control variable into the variance equation as ϑ).

Coefficient/equation	(32)	(33)	(34)	(35)	(36)	(37)	(38)	(39)	(40)	(41)
Mean eq.										
α	0.0018**	0.0023***	0.0016**	0.0017***	0.0016**	0.0019***	0.0016***	0.0016**	0.0016***	0.0015**
β_1	0.1016***	0.0750***	0.0916**	0.0919**	0.0816***	0.0773***	0.0811***	0.0919**	0.0818***	0.0806***
β_2	0.2338***	0.2036***	0.2100***	0.2200***	0.2143***	0.2243***	0.2098***	0.2206***	0.2140***	0.2230***
Variance eq.										
θ		−0.4348***	−0.3855***	−0.3539***	−0.3893***	−0.4463***	−0.3913***	−0.3642***	−0.3929***	−0.4982***
γ		0.1427***	0.1302***	0.1172***	0.1228***	0.1168***	0.1301***	0.1187***	0.1237***	0.1200***
δ		0.1147***	0.0857***	0.0961***	0.0814***	0.0923***	0.0858***	0.0986***	0.0803***	0.0996***
α		0.9598***	0.9666***	0.9690***	0.9652***	0.9575***	0.9657***	0.9676***	0.9647***	0.9512***
ϑ			7.1105***	7.5875***	6.9297***	7.0629***	6.9399***	7.3586***	6.9741***	6.6510***
τ/ $\varnothing$			0.0505		0.1275*		0.0439		0.1132*	
τ_1/ $\varnothing_1$				0.1245***		0.3046**		0.1251***		0.3397***
τ_2/ $\varnothing_2$				−0.0961		−0.1326		−0.1261*		−0.2390
Diagnostic st.										
Adj. R^2	0.2595	0.2511	0.2567	0.2581	0.2553	0.2582	0.2545	0.2582	0.2553	0.2558
Q_1	0.9708	0.3686	0.3448	0.3745	0.3215	0.3873	0.2840	0.2922	0.3075	0.2667
Q_6	9.5970	4.3390	3.4443	3.8856	3.4042	3.2145	3.3629	3.8152	3.4197	3.0382
Q_1^2	0.1581	1.3938	1.4684	1.2990	1.2616	1.1042	1.2400	1.3278	1.1888	0.9230
Q_6^2	133.44***	11.110	7.2913	6.2346	7.1261	7.1673	7.0407	6.3729	7.1655	7.0083

Notes: Q_i is the ith order Ljung-Box test of the null of residual serial independence with degrees of freedom adjusted for AR parameter estimation; Q_i^2 is the ith order Ljung-Box test of serial independence in the squared residuals.* Significance at 10 percent level.** Significance at 5 percent level.*** Significance at 1 percent level.

$$\log\left(h_t^2\right) = \theta + \gamma\left|\frac{\varepsilon_{t-1}}{h_{t-1}}\right| + \delta\frac{\varepsilon_{t-1}}{h_{t-1}} + \alpha log h_{t-1}^2 + \vartheta DXY + \varnothing d1.5_t \tag{36}$$

$$\log\left(h_t^2\right) = \theta + \gamma\left|\frac{\varepsilon_{t-1}}{h_{t-1}}\right| + \delta\frac{\varepsilon_{t-1}}{h_{t-1}} + \alpha log h_{t-1}^2 + \vartheta DXY + \varnothing d1.5_{t-1} \tag{40}$$

In that case, when the DXY is added as a control variable into the conditional variance equation and if the fund flow is bigger than 1.5 standard deviation from the standardized fund flows, we show a positive effect of large inflows and outflows of ETF on USD/TRY FX volatility but just at 10% significance level. Thus, there is weak evidence on the effects of larger ETF flows on exchange rate volatility.

The large inflows, τ_1 and $\varnothing_1$, are still positive and statistically significant at 1and 5% significance level for all alternative models in Tables 4–6. The large outflows, τ_2, and $\varnothing_2$, are still negative and statistically insignificant for the alternative models in Tables 4–6. The large outflows with one lag are still negative and statistically significant at 5 or 10% level in Tables 4–6 except the coefficient of $\varnothing_2$ in equation 41 in Table 6, which is still negative but insignificant.

7. Conclusion

Exchange-Traded Funds (ETFs) have become one of the most popular passive investment instruments for the investors since they bring together the advantages of stocks and mutual funds. The birth of the first ETF was in 1990 in Canada, and has spread globally since then. The asset value of ETFs has now reached over 2.5 trillion USD in USA and 3.5 trillion USD in the world (see Ben-David et al., 2018). Gaining popularity and share in international portfolio flows, this instrument has yet to be investigated for its implications in host economies exchange rate. In this study, we have examined the relationship between the exchange rate volatility and ETF fund

flows. The role of ETF fund flows on foreign exchange uncertainty has been tested by employing various EGARCH-M models for the period from March 2008 to June 2019 by using weekly frequency. We used three types of dummies in the conditional variance equation to catch the effect of large flows, inflows and outflows of iShares MSCI Turkey ETF on USD/TRY FX volatility. Then two different control variables were added to the EGARCH model to catch the external effects on FX volatility, VIX for controlling the foreign market risk, and DXY for controlling the change in USD against major currencies.

The empirical findings support that the FX volatility has an asymmetry effect. The asymmetry effect is positive and statistically significant for all EGARCH models, implying that a positive flow shock will generate a higher FX volatility as compared to a negative shock. We have found that the large inflows of Turkish ETF increased the exchange rate volatility for the sample period. This finding was still valid when the lag effect was included, the definition of large inflows was changed and/or the control variables were used. On the other hand, large outflows are negative but statistically insignificant for contemporaneous models including alternative models; negative and statistically significant in lagged models including alternative models on the exchange rate volatility. Thus, large outflows of ETFs to Turkey are to be followed by an exchange rate depreciation with less uncertainty (volatility) attached to the FX market. This can be attributed to the possible hedging behavior of ETF managers. However, TL appreciates with significantly large inflows of ETFs while the uncertainty (volatility) regarding exchange rate also increases. While going long on a specific instrument with a particular currency, the latter action will be going short on this particular currency and going long on a major currency, USD in this case. Since these are defined as passive investment instruments, such behavior is expected and could provide a signal for the rest of the market participants as well. As for the Turkish case, as inflows naturally support TL against USD, an increase in volatility is estimated. This indicates a rather reluctant investment position perception for Turkish ETFs, as TL appreciates with increasing volatility. Thus, as stated earlier, this was evident prior to the Turkish sell-off in August 2018, leading financial market participants to monitor ETF fund flows for exchange rate volatility.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cbrev.2020.06.002.

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