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The Price Formation of GCC Country iShares: The Role of Unsynchronized Trading Days between the US and the GCC Markets

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Abstract: Some US-listed country exchange-traded funds (ETFs) suffer from chronic and meaningful mispricing in the form of premiums or discounts relative to their fundamental value despite the presence of the creation/redemption mechanism. This mispricing is mainly attributed to the staggered information flow due to nonoverlapping time zones between the market where the ETF is listed and its underlying home market. This study provides out-of-sample evidence on the price formation of Gulf Cooperation Council (GCC) country ETFs and gauges the impact of mispricing on their underlying home markets. The GCC context is particularly insightful because these markets have nonoverlapping time zones with the US and follow distinct trading schedules. Our sample comprises daily data from three countries' iShares that exclusively track the Qatari, Saudi, and Emirati stock markets from 17 September 2015 to 14 March 2023. The results show that GCC ETFs are driven mainly by their net asset values (NAVs), albeit imperfectly, while the S&P500 exerts a relatively mild influence on these ETFs compared to other country ETFs, as reported by prior studies. Moreover, we find that crude oil prices positively and significantly impact GCC ETFs' pricing. When we control for unsynchronized trading days between the US and the GCC home markets, we find a structural difference between overlapping and nonoverlapping trading days. This structural difference manifests in a sluggish adjustment to correct mispricing in the ETF market on the day the home market is closed; however, other variables, including the S&P500, show no discernible difference, which refutes the overreaction explanation. This recurrent pattern is reflected in a clear day-of-the-week pattern in the price discovery these ETFs offer to their underlying home markets.

Keywords: ETF; market efficiency; arbitrage; gulf cooperation council; non-bank financial intermediation; financial markets

JEL Classification: G13; G14; G15; G23

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1. Introduction

Exchange-traded funds (ETFs) have been perhaps the most successful financial innovation in the past two decades. The exponential growth in their assets under management (AUM) is a testimony to their success.[1] The ingenuity of the ETF design resides in its ability to offer both retail and institutional investors convenient access to hard-to-trade markets (bond, commodity, and foreign stock markets) where other investment vehicles failed to do so (Bhattacharya and O'Hara 2018). The distinguishing feature behind the success of ETFs is the creation/redemption mechanism, which is executed via designated institutional investors called authorized participants (APs). This mechanism effectively eliminates the differences between the ETF price in the secondary market and the value of its underlying assets (NAV) via in-kind transactions exclusively executed in the primary market between the APs and the ETF sponsor. The ETF products, by design, motivate APs to exploit arbitrage opportunities that arise when the prices of the ETFs deviate from their NAV with substantially lower risks compared to index futures, which explains their popularity, especially in tracking hard-to-trade markets (Bhattacharya and O'Hara 2018).[2]

Indeed, the very features that differentiate ETFs from rival investment vehicles (close-ended and open-ended index mutual funds), including the creation/redemption mechanism, high intraday liquidity, and low short-selling costs, make them more conducive to herding strategies (Bhattacharya and O'Hara 2020). This is because ETFs appeal to a short-term investor clientele with nonfundamental demand for certain ETF styles (Broman 2016). Nonfundamental demand shocks lead to a strong positive correlation between ETFs with similar styles, while a negative correlation is documented for distant styles (Broman 2016). Moreover, such shocks ultimately propagate from the ETFs to their underlying assets, increasing their volatility (Ben-David et al. 2018) and synchronization (Da and Shive 2018).[3]

While the above-cited studies offer valuable insights into the unintended consequences of ETFs, they restrict their samples to ETFs that invest in US-listed equities and overlook the hard-to-trade markets' ETF segments. Among the hard-to-trade markets' ETF segments, the foreign stock markets segment received increased attention recently (Chari 2023; Converse et al. 2023; Filippou et al. 2022; Yousefi and Najand 2022). As a passive investment vehicle, the selling point of foreign stock markets' ETFs is their potential to provide diversification benefits with relatively high liquidity and low cost (see Madhavan 2014). To deliver on this promise, foreign stock markets' ETFs should be ideally exposed only to their home-market risk despite being traded in another market. However, empirical evidence shows that these ETFs are exposed to the market risk of the market where they are traded in addition to their home-market risk (Levy and Lieberman 2013; Ma et al. 2018; Ou 2023). These findings cast doubt on the diversification benefits that this segment of ETFs can provide and motivate further research on their price formation process.

On the other hand, the proliferation of capital flows from non-bank intermediaries, including open-end mutual funds and ETFs, to emerging markets (Chari 2023) stimulated a parallel stream of research. This line of inquiry argues that flows from non-bank intermediaries constitute a potential risk transmission channel that transmits global shocks to domestic markets (Chari 2023). Converse et al. (2023) show that ETFs are more sensitive to global shocks than open-ended mutual funds. This is because of the short-term investor clientele of ETFs, who are more inclined to engage in noise trading in the wake of shocks. Filippou et al. (2022) show that the creation/redemption mechanism is a crucial conduit via which global shocks that initially affect foreign investors in the market where the ETF is traded spill over to the underlying domestic markets. The presence of this channel raises concerns about the financial stability of the underlying ETFs' home (domestic) markets.

A salient feature particularly characteristic of the pricing of foreign stock markets' ETFs is the relatively large and prolonged discrepancies between the ETFs' prices and their NAVs (R. F. Engle and Sarkar 2006; Petajisto 2017). These differences arise mainly due to the non-overlapping time zones between the US and some foreign markets, which halts the arbitrage mechanism required to eliminate these deviations. Using intraday data, Levy and Lieberman (2013) examine the price formation of ETFs by regressing ETFs' returns on their respective NAV returns, S&P500 returns, and an error correction term. Disentangling the overlapping and non-overlapping trading hours using dummy variables, they find a structural difference between overlapping and non-overlapping trading hours—the role of the S&P500 in ETFs' price formation dominates their NAVs during non-overlapping trading hours. Levy and Lieberman (2013) show that this effect exceeds the correlation between the S&P500 and the ETFs' benchmark indices. They attribute this finding to the ETFs' investors' overreaction to the US market during foreign markets' closures.

Using daily data on Asian-Pacific country ETFs, Ou (2023) confirms the findings of Levy and Lieberman (2013) regarding the importance of the S&P500 returns in the price formation of these ETFs, which lack any overlapping trading time with their underlying domestic markets. However, Ou (2023) cogently argues that the correlation between ETFs and the S&P500 is driven by the underlying integration between the ETF's underlying domestic markets and the US market rather than a behavioral bias (overreaction) of the participants in the ETF market. He justifies the lower correlation between the S&P 500 and the ETFs' benchmark indices on the grounds of non-overlapping trading hours, implying that the price of the two indices reflects different information released during their corresponding trading times that do not overlap. This means that the available NAVs based on the underlying domestic markets become stale by the US market opening. Therefore, the changes in ETFs' prices are not solely determined by their underlying NAVs but also reflect investors' expectations of the performance of the underlying domestic market the next day based on the new information released after the closure of the corresponding domestic markets. This is evident in the predictive power of ETFs,' and the S&P500 returns for the next trading day's NAV, highlighting the importance of price discovery in the ETFs market for domestic markets' investors.

While the few studies cited above attended to the debate on the price formation of foreign stock markets' ETFs listed in the US (Levy and Lieberman 2013; Ou 2023), they differ on whether the documented strong co-movement between the returns of these ETFs and the S&P500 emanates from the behavioral biases of the US market participants or constitutes a price discovery in the US market. Furthermore, while these studies expand the determinants of foreign stock market ETF returns to include the S&P500 returns in addition to those used in older studies (Tse and Martinez 2007), viz., NAVs and the error correction term, they overlook important factors that could potentially play a role in the ETFs' price formation. In addition, the sampled ETFs in these studies only track Asian-Pacific and European countries' stock markets. Moreover, these studies employ ordinary least squares (OLS), which only offers a prediction of the conditional mean (see Alexander 2008, p. 302). These shortcomings serve as our research motivation. We, therefore, attempt to address these research gaps by performing a careful examination of the price formation of the Gulf Cooperation Council (GCC) country stock market ETFs, considering additional factors, including crude oil price and measures of uncertainty (VIX and OVX) in addition to the variables used in prior studies, namely, NAV, S&P500, and lagged premium or discount. Additionally, we examine the extent of price discovery in the ETFs' market by measuring the adjustment of the underlying ETFs' NAVs on the following day to reflect the new information contained in the close price of the ETFs. To obtain a more complete picture of the joint distribution of the ETFs' price and NAV returns, we carry out the analysis using quantile regression (QR) along with OLS.

The contribution of the present study predominantly resides in the conducive settings of the GCC markets, which enable us to inspect whether the conclusions of prior studies hold out-of-sample. To begin with, the GCC markets not only have nonoverlapping trading hours with the US (the underlying GCC markets close before the US market opens), but also their trading days of the week differ. The trading week in these markets starts on Sundays and ends on Thursdays, whereas Fridays and Saturdays are the weekend days. Such a misalliance in trading days halts arbitrage due to the domestic market closure, leading US market participants to rely on even more outdated Thursday's NAV quotes from the underlying market on Fridays. Therefore, the speed of adjustment of ETFs' prices towards their NAVs is expected to slow down, if not come to a halt, due to the lack of updated NAV quotes. The accumulated mispricing (premium/discount) on Fridays is supposedly transmitted to the NAVs on Monday (the first trading day of the week in the US) via the arbitrage mechanism. Such arbitrage transactions potentially induce a seasonal pattern in price discovery of the home (domestic) markets of these ETFs, ultimately affecting the efficiency and potentially compromising the stability of these markets.

Another distinguishing feature of the GCC markets is their nexus with crude oil. The returns on broad stock market indices of these markets exhibit a significant positive relationship with oil price changes (Mohanty et al. 2011; Mokni and Youssef 2019), whereas the stock markets of advanced economies are negatively affected by the changes in oil prices (Driesprong et al. 2008; Miller and Ratti 2009; Nandha and Faff 2008). Oil uncertainty (OVX) is also a relevant determinant of stock returns and volatilities, affecting the GCC market differently compared to the advanced economies (Alqahtani et al. 2019; Bouri et al.

2023; Joo and Park 2021; López et al. 2023). Finally, the GCC markets are relatively less integrated globally (Ziadat et al. 2020), showing, generally, less vulnerability to global and regional financial crises (Neaime 2016). This highlights the potential of GCC markets to offer diversification benefits for foreign investors when needed the most. Moreover, the contributions associated with the specificities of GCC markets, we are the first to apply the QR estimation technique in this context, which enables us to capture quantile-specific time series behaviors, including bullish and bearish market phases (see Alexander 2008; Connolly 1989; Uribe and Guillen 2020; Xiao 2012).

The remainder of the paper proceeds as follows: The econometric models and estimation techniques are introduced in Section 2, and the dataset and descriptive statistics are presented in Section 3. Sections 4 and 5 report and discuss the empirical findings, while Section 6 wraps up the paper with concluding remarks and suggestions for future research avenues.

2. Research Methodology

This section starts by laying out the econometric models we adopt to examine the determinants of the ETFs' price changes and gauge the extent of price discovery offered by the ETFs' market. Then, the estimation techniques used to carry out the econometric analysis are discussed. Before we introduce the econometric models, a word on the notations for the time series variables used in these models is warranted. The notations are described as follows: $p_t = lnP_t$ is the natural logarithm for the ETF's price, $nav_t = lnNAV_t$ is the natural logarithm for the ETF's net asset value, $prem_t = p_t - nav_t$ is the difference between the ETF's price and its net asset value, which is referred to as the premium or discount[4], $sp_t = lnSP_t$ is the natural logarithm for the S&P500 index, $op_t = lnOP_t$ is the natural logarithm for the Brent crude price, $vix_t = lnVIX_t$ is the natural logarithm for the Chicago Board Options Exchange (CBOE) volatility index, and $ovx_t = lnOVX_t$ is the natural logarithm for the CBOE crude oil volatility index.

2.1. Econometric Models

2.1.1. Price Formation

The model we use to study the determinants of the ETFs' price changes is a simple extension of the model proposed by Levy and Lieberman (2013). We add three variables to the model: oil prices and uncertainty measures (VIX and OVX). These newly added variables, together with the S&P500, capture the information released after the closure of the GCC markets, whereas the NAV and the lagged premiums or discounts reflect the ETF's fundamentals. Also, we changed the definition of the dummy variables that Levy and Lieberman (2013) used by including a day-of-the-week dummy variable instead of the intraday dummies. This adjustment is necessary given that we use daily data to determine whether the difference in the trading days of the week between the US, where these ETFs are trading, and their underlying home (domestic) GCC markets affects the price formation processes of these ETFs. The price formation regression model for these ETFs is specified as follows:

$$\begin{aligned}\Delta p_t = {} & \alpha + \beta^{nav}\Delta nav_t + \beta^{sp}\Delta sp_t + \beta^{op}\Delta op_t + \beta^{vix}\Delta vix_t + \beta^{ovx}\Delta ovx_t \\ & +\beta^{prem} prem_{t-1} + \alpha_5 D_{5,t} + \delta^{nav}\Delta nav_t \times D_{5,t} \\ & +\delta^{sp}\Delta sp_t \\ & \times D_{5,t} + \delta^{op}\Delta op_t \times D_{5,t} + \delta^{vix}\Delta vix_t \times D_{5,t} + \delta^{ovx}\Delta ovx_t \times D_{5,t} \\ & +\delta^{prem}\Delta prem_{t-1} \times D_{5,t} + \varepsilon_t\end{aligned} \tag{1}$$

where Δp_t is the continuously compounded price return for the corresponding ETF on day t, Δnav_t is the continuously compounded NAV return for the corresponding ETF on day t, Δsp_t is the continuously compounded return for the S&P500 index on day t, Δop_t is the continuously compounded return for the Brent crude price on day t, Δvix_t and Δovx_t are, respectively, the CBOE volatility and the crude oil volatility indices' innovations, and $prem_{t-1}$ is the error correction term represented by the lagged premium or discount.

$D_{i=5,t}$ is a dummy variable that takes the value 1 if the return on day t coincides with a Friday (i.e., $i = 5$) and 0 on the remaining trading days of the week ($D_{i=1,t}$ = Monday, $D_{i=2,t}$ = Tuesday, $D_{i=3,t}$ = Wednesday, and $D_{i=4,t}$ = Thursday).[5] As we allow the dummy variable to affect both the intercept and the slope coefficient, a word on the interpretation of the regression parameters might be useful. In the case of $D_{i,t} = 1$ for $1 \le i \le 4$ and $D_{i=5,t} = 0$, Equation (1) will collapse to

$$\Delta p_t = \alpha + \beta^{nav}\Delta nav_t + \beta^{sp}\Delta sp_t + \beta^{op}\Delta op_t + \beta^{vix}\Delta vix_t + \beta^{ovx}\Delta ovx_t + \beta^{prem}prem_{t-1} + \varepsilon_t \tag{1a}$$

whereby the intercept and slope parameters represent the price formation process during the first four days of the week. On the other hand, if $D_{i=5,t} = 1$ while $D_{i,t} = 0$ for $1 \le i \le 4$, we obtain

$$\begin{aligned}\Delta p_t = {} & (\alpha + \alpha_5) + (\beta^{nav} + \delta^{nav})\,\Delta nav_t + (\beta^{sp} + \delta^{sp})\Delta sp_t + (\beta^{op} + \delta^{op})\,\Delta op_t + \left(\beta^{vix} + \delta^{vix}\right)\Delta vix_t \\ & + (\beta^{ovx} + \delta^{ovx})\Delta ovx_t + (\beta^{prem} + \delta^{prem})\,prem_{t-1} + \varepsilon_t\end{aligned} \tag{1b}$$

here, the resultant intercept parameter $(\alpha + \alpha_5)$ and slopes parameters $(\beta^{nav} + \delta^{nav})$, $(\beta^{sp} + \delta^{sp})$, $(\beta^{op} + \delta^{op})$, $\left(\beta^{vix} + \delta^{vix}\right)$, $(\beta^{ovx} + \delta^{ovx})$ and $(\beta^{prem} + \delta^{prem})$ represent the price formation process, exclusively, on Fridays. We, therefore, can see that the intercept α_5 represents the potential shift in the intercept and that the slope parameters δ^{nav}, δ^{sp}, δ^{op}, δ^{vix}, δ^{ovx} and δ^{prem} capture the potential differential impact of the corresponding variable on the price formation process of these ETFs on Friday (the reference category) compared to the remaining trading days of the week.

2.1.2. Price Discovery

To measure the extent of price discovery in the market where the ETFs trade (the US market), we expand the model proposed by Broman (2016) by adding the day-of-the-week dummy variables. These dummies enable us to ascertain whether the difference in the trading days of the week between the US, where these ETFs are trading, and their underlying domestic GCC markets affects the price discovery offered by the ETFs' market. The price discovery regression model for these ETFs is specified as follows:

$$\Delta nav_t = \theta + \sum_{i=1}^{4}\theta_i D_{i,t} + \phi prem_{t-1} + \sum_{i=1}^{4}\phi_i prem_{t-1} \times D_{i,t} + \varepsilon_t \tag{2}$$

where θ is the intercept of the price discovery model on Fridays, θ_i represents the potential shifts in the intercept for $1 \le i \le 4$ which correspond to each of the remaining trading days of the week, the slope coefficient ϕ measures the adjustment of NAV to correct the previous trading day's mispricing (premium or discount) on Fridays, while ϕ_i for $1 \le i \le 4$ capture the potential differential adjustment of NAV to correct the previous trading day's mispricing during each of the remaining trading days of the week compared to Friday (the reference category). The intercept and (slope) on Mondays, Tuesdays, Wednesdays, and Thursdays can be obtained, respectively, by $\theta + \theta_1$ and $(\phi + \phi_1)$, $\theta + \theta_2$ and $(\phi + \phi_2)$, $\theta + \theta_3$ and $(\phi + \phi_3)$, and $\theta + \theta_4$ and $(\phi + \phi_4)$.

2.2. Estimation Techniques

Following Levy and Lieberman (2013) and Ou (2023), we estimate the baseline ETF price formation regression (with no dummy variables) and its corresponding dummy-augmented counterpart using OLS. The OLS estimation technique is also used to estimate the price discovery regression in the spirit of Broman (2016). Despite OLS's simplicity, R. Engle (2001, p. 157) refers to it as "the great workhorse of applied econometrics" and suggests it is a natural choice for multivariate analysis. Moreover, OLS estimates constitute a benchmark for alternative techniques and enable us to compare our results against the above-cited studies.

However, it is almost common knowledge that distributional assumptions of OLS's error term rarely hold for stock return data. In a pioneering study, Connolly (1989) cautions against ignoring the violation of the distributional assumptions of OLS's error term. He highlights that the stylized features of stock returns, particularly fat tails that manifest in the form of outliers and breaks, undermine the reliability of parameter estimates and their standard errors. Connolly (1989) argues that distribution-free estimation techniques, particularly the QR developed by Koenker and Bassett (1978), are less sensitive to outliers, skewness, and heterogeneity in the dependent variable (Koenker 2017).

The inherent features of the QR, including robustness to outliers, minimal distributional assumptions, and allowing for quantile-specific dynamics, make it conducive to financial time series analyses. These features enable researchers to model quantile-specific dynamics beyond the conditional mean, whereby they can capture heterogeneities, asymmetries, and quantile-specific time series behaviors, including bullish and bearish market phases that manifest during exuberant and crisis periods, respectively (Uribe and Guillen 2020; Xiao 2012).

To explore the impact of the various market dynamics in the sample period, we estimate both the price formation and price discovery models using QR. We select three quantiles (0.10, 0.50, and 0.90) that correspond to bearish, normal, and bullish markets, respectively.

3. Data and Descriptive Statistics

The GCC comprises six member countries: Bahrain, Kuwait, Qatar, Saudi Arabia, Oman, and the United Arab Emirates. Because of the unavailability of country iShares that exclusively track the Bahraini and Omani markets and the short sample for the recently launched Kuwaiti ETF, the study sample is restricted to three GCC iShares MSCI country ETFs. These are the iShares MSCI Qatar ETF, iShares MSCI Saudi Arabia ETF, and the iShares MSCI UAE ETF. Moreover, the difference in trading days between the GCC markets and the rest of the world, which is the primary motivation for studying these ETFs, the country iShares that track these markets are among the largest in the Middle East and Africa region. As of the time of writing this paper, the iShares MSCI Saudi Arabia ETF is the largest in the Middle East and Africa region (etf.com 2023). For the sake of comparison, we include the iShares Core S&P 500 ETF and report its key facts and descriptive statistics.

The other variables we use in this study include the S&P 500 index, which we use as a proxy for the US stock market, the Brent crude price as a proxy for oil prices, and the VIX and OVX to proxy for uncertainty. The sample period begins on 17 September 2015 and ends on 14 March 2023 to obtain a common sample of 1885 observations for all the time series variables we analyze in this study. The price data for the ETFs, the S&P 500 index, Brent crude prices, and the VIX and OVX are obtained from Refinitiv Eikon. The NAV data are downloaded from the official page of each ETF on the iShares website. All the time series are converted to continuously compounded returns by taking the first logarithm difference of daily closing prices. The key facts for the ETFs are given in Table 1.

Table 1. Key facts for the ETFs.

Country	Qatar	Saudi Arabia	United Arab Emirates	United States
Ticker	QAT	KSA	UAE	IVV
Fund name	iShares MSCI Qatar ETF	iShares MSCI Saudi Arabia ETF	iShares MSCI UAE ETF	iShares Core S&P 500 ETF
Inception date	29 April 2014	16 September 2015	29 April 2014	15 May 2000
Total asset value				
At inception	7.28	3.74	17.53	21.79
Max	114.31	1573.22	62.22	339,649
Min	35.93	3.62	12.07	61,798
Exchange	NASDAQ	NYSE Arca	NASDAQ	NYSE Arca
Benchmark index	MSCI All Qatar Capped	MSCI Saudi Arabia IMI 25/50	MSCI All UAE Capped	S&P 500

Table 1. *Cont.*

Country	Qatar	Saudi Arabia	United Arab Emirates	United States
Expense Ratio	0.59%	0.74%	0.59%	0.03%
Trading Times ‡	Sun-Thurs 09:30–13:00	Sun-Thurs 10:00–15:00	Sun-Thurs 10:00–14:45 †	Mon-Fri 09:30–16:00
Time zone offset ‡	UTC +03:00	UTC +03:00	UTC +04:00	UTC −05:00

Notes: The total asset value figures are expressed in million US dollars; the maximum and minimum of the total asset values are based on a sample we use in our analysis, which spans 17 September 2015 to 14 March 2023. ‡ This timing information applies to the underlying domestic market where the constituents of the ETFs trade. The trading times of the actual ETFs, however, are of the exchange where they are listed, i.e., NASDAQ for the Qatari and Emirati ETFs and NYSE Arca for the Saudi ETF. † From 1 January 2022, the UAE shifted its weekend to Saturday and Sunday to align more closely with the global markets (El-Naggar 2021).

Table 1 shows that the iShares Core S&P 500 ETF was launched nearly a decade and a half before the GCC ETFs.[6] Interestingly, the total asset values of all ETFs display moderate disparity at inception; however, the enormous growth in the iShares Core S&P 500 ETF dwarfs the asset value of the GCC ETFs. That being said, the GCC ETFs witnessed steady growth relative to their regional peers (etf.com 2023). Figure 1 provides a visual depiction of the evolution of the total asset values of the ETFs under investigation over the sample period.

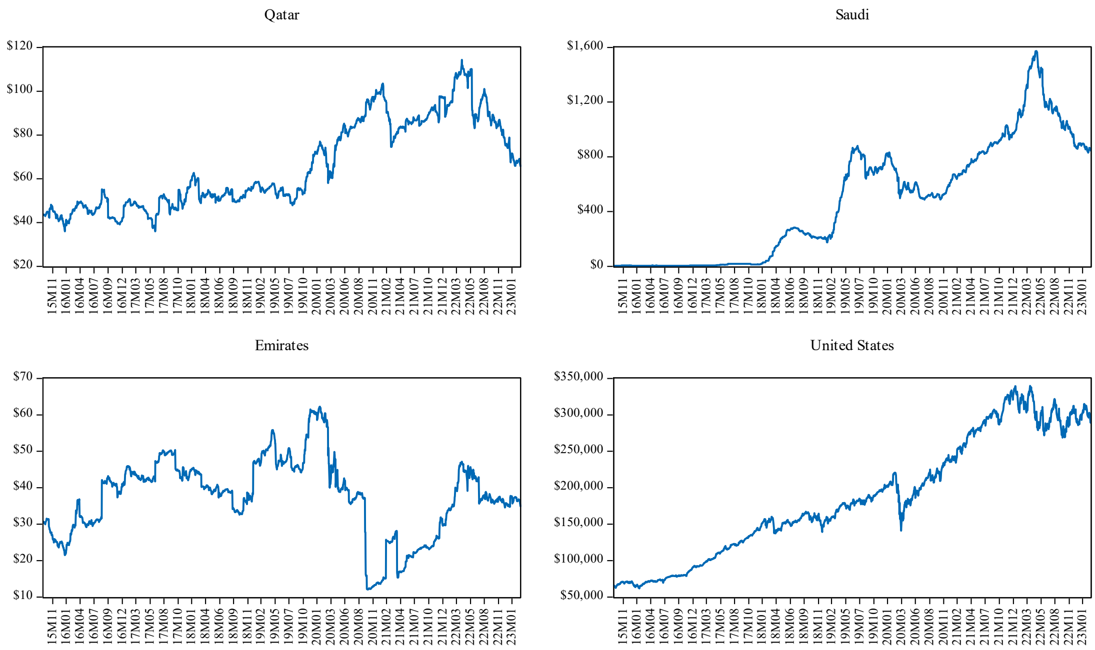

Figure 1. Total asset values of the country ETFs, expressed in million US dollars.

A glimpse of Figure 1 shows that the COVID-19 pandemic and the tight US monetary policy have negatively impacted all ETFs, albeit with varying severity. Table 2 reports the summary statistics of the ETFs' price and NAV returns and their associated premiums or discounts. The means and medians of all ETFs' price returns presented in Panel A of Table 2 are close to zero, consistent with the results reported by Ou (2023), who analyzes Asian-Pacific iShares. The results also show, on a risk-adjusted basis, that the iShares Core S&P 500 ETF outperforms all three GCC-country ETFs, having the highest average returns and the lowest volatility as measured by standard deviation. Panel B of Table 2 shows that averages (means and medians) of the NAV returns paint a similar story. However, comparing the results contained in Panels A and B, we can see that the volatilities of the ETFs' price returns are higher than those of their corresponding NAVs' returns for the GCC ETFs while being virtually equal for the iShares Core S&P 500 ETF. This is in line with the findings of Tse and Martinez (2007). It is argued that the larger the disparity is between the volatility of the price return and that of NAV returns, the more prevalent noise trading is in these country ETFs (Pontiff 1997; Tse and Martinez 2007). A look at the remaining measures of dispersion shows that the GCC ETFs fluctuate by a broader range, especially at the downside of the distribution compared to their US counterpart. All ETFs show negative skewness and appear to be highly leptokurtic, highlighting the vulnerability of these ETFs to fire sale reallocations (Chari 2023; Jotikasthira et al. 2012). This finding motivates the use of the QR technique that provides a more complete picture of the joint distribution of ETFs' returns during turbulent times.

Table 2. Descriptive statistics.

Variable/Country	Min	25th	Median	Mean	75th	Max	Std. Dev.	Skewness	Kurtosis
Panel A: Price returns (%)									
Qatar	−13.76	−0.57	0.00	−0.01	0.58	7.42	1.26	−1.16	16.26
Saudi Arabia	−18.73	−0.55	0.00	0.02	0.63	14.86	1.41	−0.70	31.95
United Arab Emirates	−14.59	−0.63	0.00	−0.01	0.62	8.48	1.33	−0.75	15.20
United States	−12.30	−0.38	0.06	0.04	0.60	9.03	1.21	−0.81	17.80
Panel B: NAV returns (%)									
Qatar	−13.83	−0.33	0.00	−0.01	0.39	4.80	1.03	−1.70	24.41
Saudi Arabia	−17.00	−0.36	0.00	0.02	0.48	6.60	1.12	−2.30	35.64
United Arab Emirates	−14.81	−0.35	0.00	−0.01	0.40	7.57	1.10	−1.84	30.46
United States	−12.75	−0.38	0.06	0.04	0.58	8.98	1.21	−0.82	18.30
Panel C: Premiums/discounts (%)									
Qatar	−7.21	−0.72	−0.13	−0.08	0.55	4.93	1.04	−0.08	5.39
Saudi Arabia	−8.27	−0.22	0.35	0.48	1.15	6.84	1.22	0.00	6.76
United Arab Emirates	−4.39	−0.81	−0.12	−0.09	0.65	5.88	1.10	0.19	4.32
United States	−0.42	−0.14	−0.11	−0.07	0.00	0.43	0.08	0.31	2.96
Panel D: Factors' returns (%)									
S&P500	−12.77	−0.38	0.06	0.04	0.58	8.97	1.21	−0.83	18.53
Oil price	−27.98	−1.13	0.21	0.02	1.31	19.08	2.68	−1.02	19.62
VIX	−29.98	−4.63	−0.75	0.01	3.58	76.82	8.12	1.34	10.63
OVX	−62.23	−2.98	−0.36	0.00	2.59	85.77	6.51	1.92	33.43

Notes: The 25th and 75th are the lower and upper quartiles.

A look at the premiums or discounts, as presented in Panel C of Table 2, reveals that averages (means and medians) of premiums or discounts are marginally negative for all ETFs except Saudi. However, the premiums or discounts for all ETFs appear to be positively skewed, which is largely consistent with the findings of Ou (2023). Considering the measures of dispersion completes our understanding by revealing a stark difference in pricing efficiency between the GCC and US ETFs. Interestingly, the premiums (discounts) of the GCC ETFs fall between 4.93 and (−7.21) percent for Qatar, 6.84 and (−8.27) percent for Saudi Arabia, and 5.88 and (−4.39) percent for the UAE, while narrowly moving between 0.43 and (−0.42) percent for the iShares Core S&P 500 ETF. These findings are in accordance with those of Ou (2023). For a visual inspection, we plot the time path of ETFs' price and NAV levels and their associated premiums or discounts in Figure 2.

Based on Figure 2, we can see that extreme premiums or discounts occurred amid the COVID-19 pandemic. It is evidenced that these premiums or discounts are eventually arbitraged away; however, the level of premiums or discounts that lures APs to create or redeem the ETFs' share is considerably lower and shorter-lived for the US domestic ETF compared to its foreign stock market counterparts. This is primarily due to the lower limits to arbitrage on the US domestic ETF. On the other hand, the foreign stock markets' ETFs are subject to higher limits to arbitrage, perhaps due to the relatively lower number of APs, the higher costs and risk associated with creation/redemption transactions, the restriction on short selling, and the somewhat less active secondary market for the ETFs' shares (Al-Nassar 2021). These arbitrage impediments are exacerbated by the nonoverlapping trading hours with the US and the difference in trading days, a feature that distinguishes the GCC ETFs from other foreign stock markets' ETFs domiciled in the US.

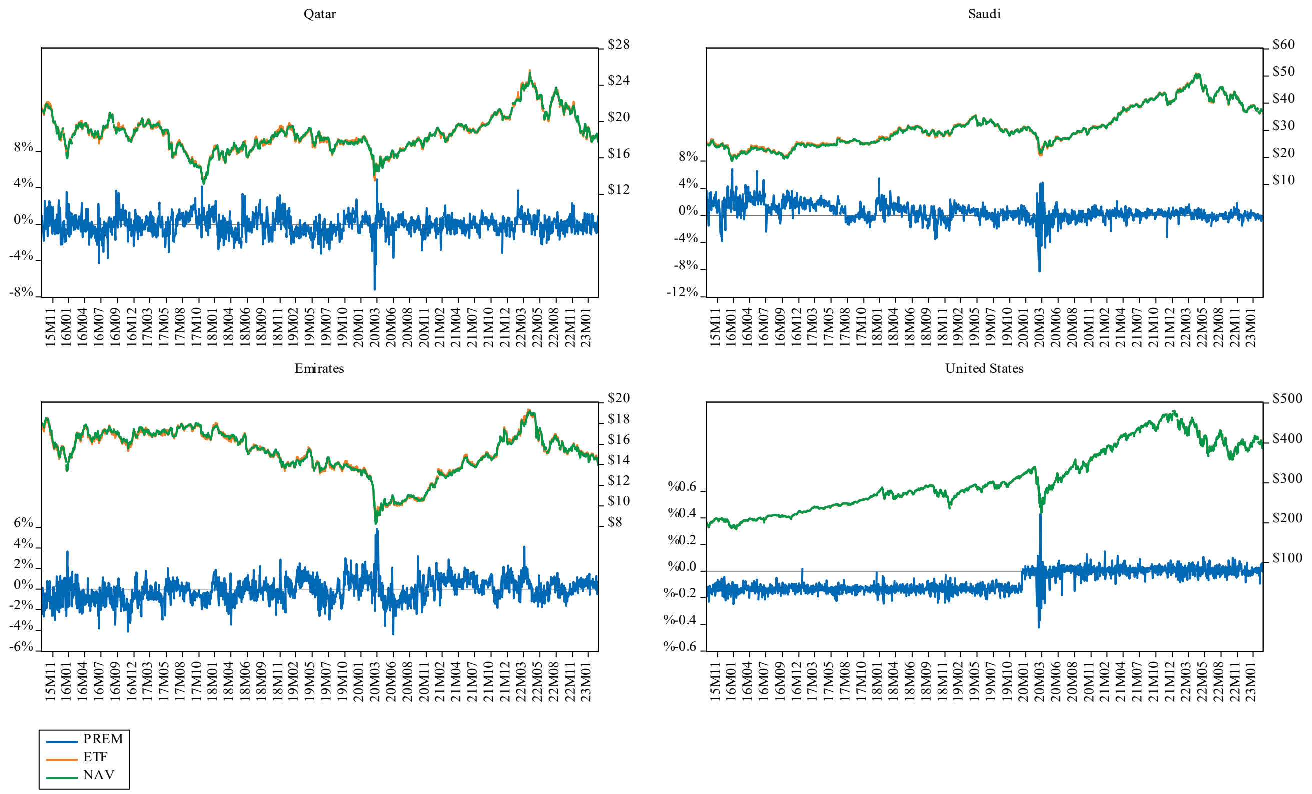

Figure 2. Time series plot of NAV and ETF price levels, expressed in US dollars, and their associated premiums and discounts in percentages.

Before estimating the econometric models, we subjected all the returns and the premiums/discount series to unit root tests to ascertain their order of integration. The results pertaining to the unit root tests are presented in Table 3.

Table 3. Unit root tests.

Variable/Country	Unit Root Tests		
	ADF		PP
Panel A: Price returns			
Qatar	−47.98 ***	[0]	−47.78 ***
Saudi Arabia	−15.66 ***	[7]	−50.63 ***
United Arab Emirates	−22.87 ***	[2]	−49.42 ***
Panel B: NAV returns			
Qatar	−39.96 ***	[0]	−40.11 ***
Saudi Arabia	−16.54 ***	[5]	−43.88 ***
United Arab Emirates	−21.93 ***	[2]	−41.41 ***
Panel C: Premiums/discounts			
Qatar	−10.10 ***	[5]	−31.87 ***
Saudi Arabia	−5.40 ***	[10]	−28.18 ***
United Arab Emirates	−8.36 ***	[4]	−32.40 ***
Panel D: Factors' returns			
S&P500	−13.54 ***	[8]	−50.90 ***
Oil price	−43.98 ***	[0]	−43.97 ***
VIX	−47.47 ***	[0]	−49.91 ***
OVX	−33.34 ***	[1]	−45.76 ***

Note: ADF = Augmented Dickey and Fuller (1981); PP = Phillips and Perron (1988); the auxiliary regressions for the unit root tests include a drift term only; the lag lengths for the ADF test are based on the Schwarz Information Criterion (SIC); the selected lag lengths are given in [ ]. *** denotes significance at the 1% level.

Table 3 shows that the null of a unit root is strongly rejected using both the ADF and PP unit root tests at the 1% level of statistical significance. This confirms that all series are stationary across tests, countries, and factor series, with no exception. Therefore, we can safely proceed to regression analysis in the sequel.

4. Empirical Results

4.1. OLS Regression Estimation Results

We initially estimate the price formation model, excluding the day-of-the-week dummy variable from Equation (1) (we refer to it as the baseline regression model) to enable comparison against prior studies. We consider five specifications of this model whereby specific parameters are restricted to zero. The first specification is the most parsimonious, containing the variables proposed by Levy and Lieberman (2013) and Ou (2023), while the fifth specification is the complete model that includes all the proposed variables, and all four specifications are nested within it. The estimates of the baseline regression parameters for the five model specifications are reported in Table 4.

Based on Table 4, we can see that the estimates of the intercept parameter α, are predominantly significant, but their signs and magnitude differ across countries. The Saudi ETF displays the highest intercept estimates, which are positive and strongly significant across all five specifications at the 1% significance level. However, the intercept estimates of the Qatari and Emirati ETFs are negatively signed and less significant. The Qatari ETF shows statistically significant intercept estimates at the 10% level for the first two specifications and the 5% level for the remaining three. The Emirati ETF shows marginally significant intercept parameters at the 10% level for the second and third specifications, while the fifth specification exhibits strong significance at the 1% level—the intercept parameters lack statistical significance for the first and fourth specifications. These findings of mixed signs and varying levels of significance align with the results of Ou (2023) but are at odds with the findings of Levy and Lieberman (2013). These significant intercepts are indicative of the presence of arbitrage opportunities.

Another look at Table 4 shows that the slope parameter estimates of the NAV, S&P500, and lagged premium or discount, which were previously studied in Levy and Lieberman (2013) and Ou (2023), are found to be strongly significant at the 1% level across the board. Furthermore, the signs and magnitudes of the parameters' estimates are robust across model specifications for each country and bear resemblance across countries. The NAV seems to play a dominant role in determining the ETFs' returns, with parameter estimates ranging from 0.85 (for the first specification for Saudi) to around 0.80 for the Qatari and Emirati ETFs. Moreover, the hypothesis that ETF's returns vary in a one-to-one correspondence with their NAV is strongly rejected at the 1% level for all ETFs. Indeed, these outcomes align with those of Ou (2023). The S&P500 exerts a weaker influence on ETFs' returns compared to NAV, with parameters' estimates ranging from 0.36 (for the third and fifth specifications for Saudi) to 0.24 (for the second through to the fourth specifications for Qatar and the third and fifth specifications for the UAE). Interestingly, the role of the S&P500 in the price formation of the GCC ETFs is much smaller than their Asian-Pacific counterparts, as reported in Ou (2023). Considering the lagged premium or discount parameters' estimates, we found that their negative sign aligns with prior studies, clearly reflecting the reversal in ETFs' prices in the opposite direction to correct the remaining premium or discount from the previous trading day. The parameters' estimates range from -0.43 for Qatar to -0.27 (for Saudi Arabia third and fifth specifications). Indeed, the magnitude of this parameter reflects the speed of adjustment for the realignment between ETFs' price and their underlying NAVs, which is much slower when compared to that of the Asian-Pacific ETFs, as reported in Ou (2023).

Table 4. The baseline regression estimation results for the determinants of ETFs' price changes.

	Qatar					Saudi					UAE				
	1	**2**	**3**	**4**	**5**	**1**	**2**	**3**	**4**	**5**	**1**	**2**	**3**	**4**	**5**
Regression Estimates															
α	−0.04 *	−0.04 *	−0.05 **	−0.04 **	−0.04 **	0.12 ***	0.12 ***	0.12 ***	0.12 ***	0.12 ***	−0.04	−0.04 *	−0.04 *	−0.04	−0.04 ***
	(−1.77)	(−1.67)	(−2.00)	(−2.07)	(−2.02)	(4.86)	(4.80)	(4.80)	(5.66)	(5.69)	(−1.37)	(−1.74)	(−1.86)	(−1.42)	(−2.62)
β^{nav}	0.79 ***	0.78 ***	0.78 ***	0.78 ***	0.78 ***	0.85 ***	0.83 ***	0.82 ***	0.82 ***	0.81 ***	0.81 ***	0.79 ***	0.80 ***	0.80 ***	0.80 ***
	(25.02)	(25.12)	(25.56)	(25.47)	(25.56)	(19.92)	(23.06)	(26.04)	(24.39)	(28.49)	(38.62)	(35.45)	(36.43)	(34.74)	(31.80)
β^{sp}	0.26 ***	0.24 ***	0.24 ***	0.24 ***	0.24 ***	0.35 ***	0.31 ***	0.36 ***	0.30 ***	0.36 ***	0.28 ***	0.26 ***	0.24 ***	0.26 ***	0.24 ***
	(8.57)	(8.36)	(7.56)	(8.87)	(7.53)	(5.82)	(5.38)	(5.86)	(5.78)	(6.25)	(11.28)	(9.63)	(7.84)	(9.52)	(6.34)
β^{op}		0.04 ***	0.04 ***	0.04 ***	0.04 ***		0.07 ***	0.08 ***	0.07 ***	0.07 ***		0.04 ***	0.04 ***	0.04 ***	0.04 ***
		(3.52)	(3.74)	(3.43)	(3.43)		(6.45)	(6.20)	(5.20)	(5.21)		(3.49)	(3.57)	(3.49)	(3.74)
β^{vix}			0.001		0.001			0.02 **		0.02 ***			−0.006 **		−0.007
			(0.24)		(0.25)			(2.29)		(2.61)			(−2.03)		(−1.51)
β^{ovx}				−0.0002	−0.0003				−0.006	−0.009 *				0.001	0.002
				(−0.05)	(−0.09)				(−1.45)	(−1.81)				(0.17)	(0.44)
β^{prem}	−0.43 ***	−0.43 ***	−0.43 ***	−0.43 ***	−0.43 ***	−0.28 ***	−0.28 ***	−0.27 ***	−0.28 ***	−0.27 ***	−0.35 ***	−0.35 ***	−0.35 ***	−0.35 ***	−0.35 ***
	(−16.17)	(−15.81)	(−16.90)	(−16.95)	(−16.92)	(−8.17)	(−8.08)	(−9.75)	(−9.15)	(−10.95)	(−13.12)	(−14.90)	(−15.32)	(−13.34)	(−18.14)
Coeff restrictions															
$\beta^{nav} = 1$	42.81	50.58	52.42	52.01	52.48	11.96	23.84	34.82	27.04	42.78	82.42	83.58	86.13	80.01	65.12
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Goodness of fit															
R^2 adj	0.586	**0.593**	0.593	0.592	0.592	0.682	0.700	0.706	0.700	**0.707**	0.631	0.636	**0.637**	0.636	0.637
Stability diagnostics															
Chow Test (11 March 2020)															
F-stat	3.77	2.63	3.06	2.45	2.78	35.58	27.43	23.61	23.54	20.61	17.68	14.13	11.03	11.779	9.424
p-value	[0.00]	[0.02]	[0.01]	[0.02]	[0.01]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]

Notes: This table contains the OLS estimation results with the heteroscedasticity and autocorrelation consistent (HAC) standard errors of Newey and West (1987) for the regression defined in Equation (1) excluding the day-of-the-week dummy variables (i.e., $D_{i,t} = 0$ for $1 \leq i \leq 5$): $\Delta p_t = \alpha + \beta^{nav}\Delta nav_t + \beta^{sp}\Delta sp_t + \beta^{op}\Delta op_t + \beta^{vix}\Delta vix_t + \beta^{ovx}\Delta ovx_t + \beta^{prem} prem_{t-1} + \varepsilon_t$. The *t*-statistics are in ( ), and the *p*-values are in [ ]. The restriction imposed on the NAV parameter is tested using the Wald test χ^2 statistic with $\chi^2(1)$ degree of freedom. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Next, we turn our attention to the results of the variables we added to the Levy and Lieberman (2013)-proposed model, namely the Brent crude price, the VIX, and OVX. The results of specifications 2 through 5 in Table 4 show that the Brent crude price changes slope parameter estimates are strongly significant at the 1% level across the board. The values of the parameters' estimates are higher for Saudi Arabia, reaching 0.08 for the third specification while being 0.04 for all specifications for Qatar and the UAE. The positive sign of the parameter is in accordance with prior GCC stock market studies, including those of Mohanty et al. (2011) and Mokni and Youssef (2019). Despite being statistically significant, the estimated slope parameters for changes in Brent crude price are considerably smaller in magnitude when compared to their NAV and S&P500 counterparts. The uncertainty variables (VIX and OVX) are relatively less relevant for the ETFs' price formation, showing no statistical significance for Qatar, while a relatively sparse statistical significance is found for Saudi Arabia and the UAE. The VIX appears to be more important than OVX, showing persistent statistical significance at the 5% and 1% in the third and fifth specifications, respectively, for Saudi, while only being significant at the 5% level in one case (the third specification) for UAE. Interestingly, the parameters' estimates for the changes in VIX are positive for Saudi, which hints that the Saudi market is perhaps considered a safe haven from the perspective of US investors. The goodness of fit represented by adjusted R^2 suggests a relatively good explanatory power as most of the variation in the ETFs' returns is explained by the independent variables in the regression model. The adjusted R^2 ranges from 0.707 for the Saudi ETF's fifth specification to 0.586 for the first specification for the Qatari ETF. These figures are comparable to those of Ou (2023).

To ascertain whether the closure of the GCC markets on Friday has a bearing on the impact of these variables, we estimate Equation (1) with a day-of-the-week (Friday) dummy variable that captures the potential effect of the difference in trading days between the iShares GCC ETFs and their underlying stock markets on the ETFs' price formation. The estimates of the regression parameters for the five specifications of the dummy-augmented model are presented in Table 5.

Based on Table 5, we can see that the estimates of the intercept parameter α on the first four days of the week are predominantly significant, but their signs differ across countries. The Saudi ETF displays the highest intercept estimates that are positive and strongly significant across all five specifications at the 1% significance level. The intercept estimates of the Qatari and Emirati ETFs are, however, negatively signed and less statistically significant, showing statistical significance at 5% for the third, fourth, and fifth specifications for Qatar, while the first two specifications show marginally significant intercept parameters at the 10% level. Only the second and fourth specifications for the Emirati ETF exhibit statistical significance at the marginal significance level of 10%, while the remaining specifications lack statistical significance. The shift in the intercept parameter's estimates α_5 on Fridays is statistically indistinguishable from zero without exception.

The slope parameters' estimates pertaining to the NAV, S&P500, and lagged premium or discount in Table 5 measure the impact of these variables on the ETFs' price changes on the first four days of the week. These estimates generally resemble those reported in Table 4, albeit slightly larger in some instances. These parameters' estimates are strongly significant at the 1% level across the board. Considering the parameters' estimates of the Friday interaction terms, we can see the differential impacts of the NAV, S&P500, and lagged premium or discount on Fridays. The results reveal a striking regime shift between overlapping and nonoverlapping trading days for Friday interaction term with lagged premium or discount parameters' estimates, which turn out to be strongly significant at the 1% level across the complete spectrum, ranging from 0.19 (for the first and second specifications for Qatar) to 0.14 (for the second through to the fifth specification for Saudi). The positive sign means that the adjustment in ETF price to correct the previous trading day's mispricing is slower when the underlying stock market is closed on Fridays. On the contrary, the Friday interaction terms with the S&P500 parameter's estimates are statistically insignificant for all cases. The remaining interaction terms with NAV, Brent crude price, VIX, and OVX are mixed. The interaction terms with the NAV parameter's estimates are found to be negatively signed and strongly significant for Qatar while showing only marginal significance, if any, in the case of Saudi Arabia and the UAE. Furthermore, the Friday interaction terms with Brent crude price changes parameter estimates only show marginal significance in one specification for Saudi Arabia and Qatar, while the remaining cases are statistically insignificant. Similarly, the Friday interaction terms with VIX are significant at the 1% level only for the UAE, while the interaction terms with OVX show mild significance for the fourth and fifth specifications in Saudi Arabia only at the 10% and 5% levels, respectively.

To measure how the mispricing (in the form of a premium or a discount) is corrected mainly through the creation/redemption mechanism that ultimately affects the NAV of the ETFs' and whether this mechanism is subjected to regime shifts, we estimate Equation (2). This enables us to find out the extent of price discovery in the market where the ETFs trade (the US market). The estimates of the regression parameters are given in Table 6. As presented in Table 6, the estimation results show that neither the intercept of the price discovery model on Fridays nor any intercept shift dummy on the other week's trading days show a significant effect at conventional significance levels for Qatar and UAE. The Saudi ETF, however, displays a significant downward shift in the intercept on Mondays at the 5% level. This may reflect increased selling pressure on Mondays to realign the ETF's NAV with its price in the US market, which is plausible given the relatively high and positive premium, on average, recorded for the Saudi ETF (see Table 2). Indeed, the slope parameters' estimated results are more compelling. On the one hand, the slope parameter pertaining to the NAV adjustment on Fridays to correct the previous trading day's mispricing is virtually zero across the board. This finding aligns with common sense, as the underlying GCC stock markets are closed on Friday. On the other hand, most of the slope parameter's estimates of the day-of-the-week interaction terms with lagged premium or discount are significantly larger than Friday's slope parameter. Monday's parameter is the largest in magnitude, indicating that most of the NAV adjustments to correct the previous trading day's mispricing take place on Mondays.

4.2. QR Estimation Results

As a precursor to using QR, we apply the Chow test to OLS estimates to check for a potential break due to the COVID-19 pandemic.[7] The results in Table 4 show that the Chow test strongly rejects the null of no break across the board in the wake of the pandemic, at least at the 5% level.

These results motivate the use of the QR. As discussed in Section 2.2, the QR is better suited to deal with tail dependence and asymmetries exacerbated during extreme market conditions. To this end, we first estimate the price formation baseline regressions (without the day-of-the-week dummy variable) using the QR. We select three quantiles (0.10, 0.50, and 0.90) corresponding to bearish, normal, and bullish markets, respectively. The estimation results for the baseline model for the five model specifications are presented in Table 7A–C, corresponding to the Qatari, Saudi, and Emirati ETFs, respectively. A look at these tables reveals that apart from the intercepts corresponding to extreme quantiles, i.e., 0.10th and the 0.90th (which is to be expected by design), the main results are largely similar to those obtained using OLS with few variations. Indeed, considering the results pertaining to the 0.50th quantile (the median regression) representing normal market phases, we can see that the intercept parameters' estimates are qualitatively the same as those obtained using OLS across all specifications and countries, retaining the same sign with similar significance levels and magnitudes.

Table 5. The dummy-augmented regression estimation results for the determinants of ETFs' price changes.

	Qatar					Saudi					UAE				
	1	**2**	**3**	**4**	**5**	**1**	**2**	**3**	**4**	**5**	**1**	**2**	**3**	**4**	**5**
Regression Estimates															
α	−0.05 *	−0.05 *	−0.05 **	−0.05 **	−0.05 **	0.13 ***	0.14 ***	0.12 ***	0.14 ***	0.12 ***	−0.04	−0.04 *	−0.04	−0.04	−0.04 *
	(−1.85)	(−1.80)	(−2.26)	(−2.07)	(−2.22)	(4.66)	(4.87)	(4.64)	(6.13)	(5.60)	(−1.01)	(−1.75)	(−1.49)	(−1.23)	(−1.65)
β^{nav}	0.81 ***	0.80 ***	0.80 ***	0.80 ***	0.80 ***	0.86 ***	0.84 ***	0.83 ***	0.84 ***	0.83 ***	0.81 ***	0.80 ***	0.80 ***	0.80 ***	0.80 ***
	(27.79)	(28.21)	(28.07)	(27.82)	(27.94)	(19.50)	(22.13)	(24.90)	(23.33)	(27.48)	(34.36)	(32.14)	(32.26)	(30.80)	(32.24)
β^{sp}	0.26 ***	0.24 ***	0.25 ***	0.24 ***	0.25 ***	0.35 ***	0.31 ***	0.36 ***	0.31 ***	0.36 ***	0.27 ***	0.25 ***	0.25 ***	0.25 ***	0.25 ***
	(6.32)	(6.31)	(6.62)	(6.79)	(6.39)	(5.48)	(5.08)	(5.54)	(6.71)	(6.32)	(9.21)	(9.79)	(7.22)	(8.26)	(7.73)
β^{op}		0.03 ***	0.03 ***	0.03 ***	0.03 ***		0.07 ***	0.07 ***	0.07 ***	0.06 ***		0.03 ***	0.03 ***	0.04 ***	0.04 ***
		(2.79)	(2.88)	(2.72)	(2.79)		(5.85)	(5.89)	(4.78)	(4.76)		(3.54)	(3.59)	(3.67)	(3.66)
β^{vix}			0.005		0.005			0.02 **		0.02 ***			−0.001		−0.001
			(1.15)		(1.12)			(2.29)		(2.67)			(−0.15)		(−0.22)
β^{ovx}				0.002	0.001				−0.002	−0.004				0.003	0.003
				(0.46)	(0.32)				(−0.36)	(−0.78)				(0.67)	(0.69)
β^{prem}	−0.46 ***	−0.46 ***	−0.46 ***	−0.46 ***	−0.46 ***	−0.31 ***	−0.31 ***	−0.30 ***	−0.31 ***	−0.30 ***	−0.39 ***	−0.38 ***	−0.38 ***	−0.38 ***	−0.38 ***
	(−15.28)	(−15.32)	(−17.00)	(−16.41)	(−16.84)	(−8.17)	(−8.49)	(−9.52)	(−10.47)	(−10.87)	(−12.41)	(−16.54)	(−15.38)	(−14.27)	(−15.91)
α_5	0.03	0.01	0.004	0.01	0.004	−0.05	−0.06	−0.03	−0.06	−0.04	−0.01	−0.01	−0.06	−0.02	−0.06
	(0.56)	(0.32)	(0.08)	(0.29)	(0.08)	(−1.16)	(−1.46)	(−0.88)	(−1.41)	(−0.92)	(−0.22)	(−0.28)	(−1.08)	(−0.34)	(−1.07)
δ^{nav}	−0.58 ***	−0.59 ***	−0.59 ***	−0.59 ***	−0.59 ***	−0.64 *	−0.49	−0.43	−0.48 *	−0.40 *	0.89 *	0.77 *	0.65	0.78	0.65 *
	(−3.31)	(−3.57)	(−3.23)	(−3.30)	(−3.23)	(−1.91)	(−1.62)	(−1.56)	(−1.82)	(−1.66)	(1.77)	(1.79)	(1.62)	(1.61)	(1.66)
δ^{sp}	0.06	0.04	−0.01	0.03	−0.01	0.09 *	0.05	0.04	0.03	0.02	0.04	0.03	−0.06	0.02	−0.06
	(0.91)	(0.58)	(−0.21)	(0.50)	(−0.24)	(1.66)	(0.98)	(0.73)	(0.57)	(0.45)	(0.27)	(0.26)	(−0.48)	(0.12)	(−0.55)
δ^{op}		0.04 *	0.04	0.04	0.03		0.03	0.04 *	0.01	0.02		0.01	−0.02	−0.01	−0.03
		(1.83)	(1.62)	(1.43)	(1.34)		(1.48)	(1.79)	(0.46)	(0.76)		(0.20)	(−0.87)	(−0.36)	(−0.84)
δ^{vix}			−0.02		−0.01			−0.002		0.002			−0.03 ***		−0.03 ***
			(−1.62)		(−1.55)			(−0.28)		(0.25)			(−2.67)		(−2.81)
δ^{ovx}				−0.01	−0.003				−0.02 *	−0.02 **				−0.01	−0.003
				(−0.62)	(−0.29)				(−1.88)	(−2.12)				(−1.51)	(−0.41)
δ^{prem}	0.19 ***	0.19 ***	0.17 ***	0.18 ***	0.17 ***	0.16 ***	0.14 ***	0.14 ***	0.14 ***	0.14 ***	0.18 ***	0.18 ***	0.18 ***	0.18 ***	0.18 ***
	(3.66)	(3.65)	(3.46)	(3.77)	(3.45)	(3.12)	(2.79)	(2.80)	(2.64)	(3.07)	(3.58)	(3.58)	(3.70)	(3.61)	(3.65)
Goodness of fit															
R^2 adj	0.593	0.600	0.600	0.599	0.600	0.686	0.703	0.710	0.704	0.711	0.636	0.640	0.646	0.640	0.645

Notes: This table contains the OLS estimation results with the heteroscedasticity and autocorrelation consistent (HAC) standard errors of Newey and West (1987) for the regression defined in Equation (1) with the Friday dummy variable (i.e., $D_{5,t} = 1$ for $i = 5$ and zero otherwise): $\Delta p_t = \alpha + \beta^{nav}\Delta nav_t + \beta^{sp}\Delta sp_t + \beta^{op}\Delta op_t + \beta^{vix}\Delta vix_t + \beta^{ovx}\Delta ovx_t + \beta^{prem} prem_{t-1} + \alpha_5 D_{5,t} + \delta^{nav}\Delta nav_t \times D_{5,t} + \delta^{sp}\Delta sp_t \times D_{5,t} + \delta^{op}\Delta op_t \times D_{5,t} + \delta^{vix}\Delta vix_t \times D_{5,t} + \delta^{ovx}\Delta ovx_t \times D_{5,t} + \delta^{prem}\Delta prem_{t-1} \times D_{5,t} + \varepsilon_t$. The t-statistics are in ( ), and the p-values are in [ ]. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6. Regression results for ETF price discovery.

	Qatar	Saudi	UAE
Regression Estimates			
θ	−0.01	0.01	0.03
	(−0.70)	(0.69)	(1.60)
θ_1	−0.10	−0.35 **	−0.16
	(−1.20)	(−2.22)	(−1.44)
θ_2	0.05	0.12	0.04
	(0.96)	(1.33)	(0.67)
θ_3	0.04	−0.01	0.00
	(0.86)	(−0.21)	(−0.02)
θ_4	0.06	−0.06	−0.03
	(1.14)	(−1.08)	(−0.54)
ϕ	0.03	−0.01	0.02
	(1.35)	(−1.01)	(1.54)
ϕ_1	0.41 ***	0.52 ***	0.31 ***
	(4.53)	(3.10)	(3.69)
ϕ_2	0.05	−0.06	0.11 *
	(0.80)	(−0.62)	(1.74)
ϕ_3	0.15 **	0.10 **	0.15
	(2.00)	(2.26)	(1.57)
ϕ_4	0.12 **	0.20 ***	0.14 ***
	(2.29)	(4.24)	(2.83)
Goodness of fit			
R^2 adj	0.05	0.08	0.04
Stability diagnostics			
Chow Test (11 March 2020)			
F-stat	2.00	4.60	0.95
p-value	[0.03]	[0.00]	[0.48]

Notes: This table contains the OLS estimation results with the heteroscedasticity and autocorrelation consistent (HAC) standard errors of Newey and West (1987) for the regression defined in Equation (2): $\Delta nav_t = \theta + \sum_{i=1}^{4}\theta_i D_{i,t} + \phi prem_{t-1} + \sum_{i=1}^{4}\phi_i prem_{t-1} \times D_{i,t} + \varepsilon_t$. The *t*-statistics are in ( ). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Moving to the 10th quantile representing bearish market phases, we can see that the Qatari ETF displays increased sensitivity to both uncertainty measures (VIX and OVX), while the Saudi ETF shows increased sensitivity to OVX only. In contrast, the Emirati ETF becomes less sensitive to oil price changes and uncertainty measures during bearish market phases. During bullish markets (the 90th quantile), we can see the Qatari ETF becomes insensitive to changes in both uncertainty measures (VIX and OVX), whereas the Saudi ETF only maintains its positive relation with one measure of uncertainty, i.e., VIX. The Emirati ETF remains sensitive to oil prices during bullish market phases.

Most results resemble those obtained by OLS regardless of the considered quantile. Across all specifications, countries, and quantiles, the lagged premiums or discount parameter estimates maintain the same sign and remain statistically significant at the 1% level. Likewise, the null of one-to-one co-movement between the ETFs' prices and NAVs is rejected at the 1% level.

In addition to the baseline model, we also estimate Equation (1) with a day-of-the-week (Friday) dummy variable using QR, considering the same quantiles (0.10, 0.50, 0.90). The results are reported for each country in Table 8A–C. Here, we direct our attention to the intercept shift and the differential impacts of the variables on Fridays as captured by α_5, δ^{nav}, δ^{sp}, δ^{op}, δ^{vix}, δ^{ovx} and δ^{prem}. Considering the intercept shift on Fridays α_5, we find traces of a weekend shift for the Qatari and Saudi ETFs, albeit for specific quantiles and specifications. A positive but weak weekend effect is found for the Qatari ETF during the bearish market (the first and second specifications) and normal market (the first, second, and third specifications). During bullish market phases, a negative weekend effect is documented for the Saudi ETF across all specifications except the fifth, whereas the Qatari ETFs only show marginal significance in one specification, namely the second. On the other hand, the UAE ETF shows no statistically meaningful evidence for a weekend shift.

Table 7. (**A**) The baseline QR estimation results for the determinants of the ETF's price changes for the Qatari ETF. (**B**) The baseline QR estimation results for the determinants of ETF's price changes for Saudi ETF. (**C**) The baseline QR estimation results for the determinants of the ETF's price changes for the Emirati ETF.

	Bearish Market (τ=0.10)					**Normal Market (τ=0.5)**					**Bullish Market (τ=0.90)**				
	1	**2**	**3**	**4**	**5**	**1**	**2**	**3**	**4**	**5**	**1**	**2**	**3**	**4**	**5**
								(A)							
Regression Estimates															
α	−0.97 ***	−0.97 ***	−0.98 ***	−0.98 ***	−0.98 ***	−0.04 *	−0.04 *	−0.04 **	−0.04 *	−0.04 **	0.87 ***	0.85 ***	0.85 ***	0.86 ***	0.85 ***
	(−27.63)	(−26.36)	(−26.54)	(−26.77)	(−27.58)	(−1.84)	(−1.93)	(−2.11)	(−1.93)	(−2.09)	(26.32)	(25.13)	(25.16)	(23.90)	(23.80)
β^{nav}	0.85 ***	0.84 ***	0.84 ***	0.83 ***	0.85 ***	0.76 ***	0.75 ***	0.75 ***	0.75 ***	0.75 ***	0.72 ***	0.72 ***	0.70 ***	0.72 ***	0.71 ***
	(37.41)	(22.21)	(20.01)	(20.25)	(18.49)	(23.83)	(23.93)	(23.65)	(23.90)	(23.63)	(27.59)	(30.03)	(21.75)	(27.19)	(20.87)
β^{sp}	0.26 ***	0.28 ***	0.24 ***	0.27 ***	0.23 ***	0.24 ***	0.20 ***	0.20 ***	0.20 ***	0.20 ***	0.22 ***	0.20 ***	0.22 ***	0.21 ***	0.22 ***
	(9.61)	(8.60)	(7.95)	(8.48)	(7.72)	(16.58)	(13.50)	(13.61)	(13.31)	(13.45)	(7.21)	(8.91)	(6.52)	(8.34)	(6.33)
β^{op}		0.04 ***	0.05 ***	0.04 ***	0.04 ***		0.04 ***	0.05 ***	0.04 ***	0.05 ***		0.03 **	0.03 **	0.04 **	0.04 **
		(3.83)	(4.61)	(3.76)	(2.65)		(4.09)	(4.21)	(4.00)	(4.10)		(2.22)	(2.33)	(2.25)	(2.88)
β^{vix}			−0.010 ***		−0.007 **			0.001		0.000			0.005		0.007
			(−2.74)		(−2.07)			(0.22)		(0.20)			(0.80)		(1.06)
β^{ovx}				−0.011 ***	−0.009 **				0.000	0.000				0.009	0.010
				(−2.75)	(−2.28)				(−0.08)	(−0.01)				(1.24)	(1.60)
β^{prem}	−0.48 ***	−0.48 ***	−0.48 ***	−0.48 ***	−0.47 ***	−0.33 ***	−0.35 ***	−0.35 ***	−0.35 ***	−0.35 ***	−0.45 ***	−0.44 ***	−0.43 ***	−0.45 ***	−0.44 ***
	(−14.72)	(−14.41)	(−14.15)	(−14.01)	(−13.57)	(−15.37)	(−16.34)	(−16.24)	(−16.23)	(−16.16)	(−16.88)	(−16.40)	(−15.21)	(−16.00)	(−15.58)
Coeff restrictions	46.86	18.04	14.45	16.07	10.94	54.50	65.23	63.87	65.65	63.51	119.15	141.62	84.78	109.78	69.38
$\beta^{nav} = 1$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Goodness of fit															
R^2 adj	0.385	0.389	0.391	0.391	0.393	0.278	0.285	0.284	0.284	0.284	0.325	0.328	0.328	0.329	0.329
								(B)							
Regression Estimates															
α	−0.70 ***	−0.67 ***	−0.69 ***	−0.68 ***	−0.70 ***	0.08 ***	0.08 ***	0.09 ***	0.09 ***	0.09 ***	0.95 ***	0.94 ***	0.93 ***	0.93 ***	0.93 ***
	(−20.74)	(−20.82)	(−21.34)	(−21.87)	(−21.87)	(4.18)	(4.07)	(4.62)	(4.38)	(4.62)	(25.87)	(27.46)	(28.17)	(29.10)	(28.97)
β^{nav}	0.86 ***	0.83 ***	0.83 ***	0.84 ***	0.82 ***	0.86 ***	0.85 ***	0.85 ***	0.85 ***	0.85 ***	0.80 ***	0.79 ***	0.78 ***	0.78 ***	0.78 ***
	(22.25)	(17.38)	(19.16)	(31.56)	(37.08)	(30.67)	(31.56)	(30.56)	(30.78)	(32.35)	(29.52)	(36.24)	(30.75)	(40.37)	(29.56)
β^{sp}	0.34 ***	0.31 ***	0.35 ***	0.28 ***	0.30 ***	0.27 ***	0.22 ***	0.25 ***	0.22 ***	0.25 ***	0.35 ***	0.32 ***	0.33 ***	0.32 ***	0.33 ***
	(15.38)	(10.19)	(12.16)	(8.52)	(10.39)	(9.96)	(11.48)	(7.10)	(10.38)	(7.91)	(13.79)	(10.61)	(16.06)	(11.12)	(16.97)
β^{op}		0.09 ***	0.08 ***	0.06 ***	0.06 ***		0.08 ***	0.08 ***	0.07 ***	0.07 ***		0.06 ***	0.06 ***	0.06 ***	0.06 ***
		(6.81)	(6.51)	(3.64)	(3.78)		(10.24)	(9.60)	(7.72)	(8.77)		(10.07)	(10.45)	(11.08)	(8.04)
β^{vix}			0.008 **		0.009 **			0.006		0.009 **			0.011 ***		0.011 ***
			(2.29)		(2.41)			(1.54)		(2.30)			(3.29)		(3.24)
β^{ovx}				−0.021 ***	−0.023 ***				−0.011 ***	−0.011 ***				0.006	−0.002
				(−4.68)	(−4.05)				(−3.50)	(−4.99)				(1.24)	(−0.44)
β^{prem}	−0.30 ***	−0.29 ***	−0.28 ***	−0.29 ***	−0.28 ***	−0.22 ***	−0.22 ***	−0.23 ***	−0.22 ***	−0.22 ***	−0.25 ***	−0.26 ***	−0.24 ***	−0.24 ***	−0.25 ***
	(−8.23)	(−9.08)	(−9.89)	(−8.51)	(−10.48)	(−11.51)	(−11.12)	(−11.46)	(−11.58)	(−11.68)	(−11.48)	(−11.01)	(−10.50)	(−10.94)	(−11.49)
Coeff restrictions	13.69	12.33	15.93	38.61	63.80	24.57	29.52	28.64	28.34	33.94	51.70	88.93	75.62	123.01	69.08

Table 7. *Cont.*

	Bearish Market (τ=0.10)					Normal Market (τ=0.5)					Bullish Market (τ=0.90)				
	1	**2**	**3**	**4**	**5**	**1**	**2**	**3**	**4**	**5**	**1**	**2**	**3**	**4**	**5**
$\beta^{nav}=1$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Goodness of fit															
R^2 adj	0.429	0.448	0.449	0.451	0.453	0.369	0.389	0.389	0.391	0.393	0.394	0.410	0.415	0.410	0.414
(C)															
Regression Estimates															
α	−1.02 ***	−1.01 ***	−1.01 ***	−1.01 ***	−1.01 ***	−0.04 *	−0.04 **	−0.03 *	−0.04 **	−0.04 *	0.91 ***	0.90 ***	0.90 ***	0.89 ***	0.89 ***
	(−30.40)	(−31.24)	(−30.45)	(−31.64)	(−30.41)	(−1.93)	(−2.13)	(−1.65)	(−2.10)	(−1.90)	(27.69)	(28.02)	(27.77)	(28.34)	(27.95)
β^{nav}	0.75 ***	0.73 ***	0.75 ***	0.74 ***	0.75 ***	0.83 ***	0.80 ***	0.82 ***	0.81 ***	0.81 ***	0.86 ***	0.85 ***	0.85 ***	0.85 ***	0.85 ***
	(42.42)	(20.92)	(29.00)	(21.41)	(29.05)	(23.69)	(34.64)	(34.49)	(33.62)	(33.82)	(45.50)	(40.50)	(38.30)	(40.92)	(39.02)
β^{sp}	0.35 ***	0.33 ***	0.30 ***	0.33 ***	0.30 ***	0.24 ***	0.22 ***	0.20 ***	0.23 ***	0.20 ***	0.28 ***	0.26 ***	0.25 ***	0.25 ***	0.25 ***
	(14.26)	(9.90)	(6.16)	(10.63)	(6.17)	(11.88)	(11.63)	(8.19)	(11.34)	(8.18)	(13.47)	(10.50)	(5.18)	(9.96)	(5.39)
β^{op}		0.02 **	0.02 *	0.02	0.02		0.04 ***	0.04 ***	0.04 ***	0.04 ***		0.03 **	0.03 **	0.03 **	0.03 **
		(2.13)	(1.71)	(1.28)	(1.16)		(3.66)	(3.81)	(3.04)	(3.25)		(2.11)	(2.19)	(2.13)	(2.08)
β^{vix}			−0.007		−0.007			−0.005		−0.005			−0.001		−0.001
			(−1.16)		(−1.16)			(−1.60)		(−1.61)			(−0.15)		(−0.09)
β^{ovx}				−0.003	0.000				0.002	0.001				−0.001	−0.001
				(−0.32)	(0.01)				(0.33)	(0.24)				(−0.38)	(−0.31)
β^{prem}	−0.35 ***	−0.35 ***	−0.34 ***	−0.35 ***	−0.34 ***	−0.31 ***	−0.30 ***	−0.31 ***	−0.30 ***	−0.30 ***	−0.41 ***	−0.41 ***	−0.40 ***	−0.40 ***	−0.40 ***
	(−11.49)	(−12.39)	(−11.10)	(−12.50)	(−11.05)	(−14.06)	(−13.77)	(−13.97)	(−13.83)	(−13.83)	(−14.33)	(−13.56)	(−13.00)	(−13.81)	(−13.12)
Coeff restrictions	195.01	59.47	97.36	57.57	97.82	23.86	70.66	61.19	63.55	61.04	51.32	51.42	45.84	51.84	47.69
$\beta^{nav}=1$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Goodness of fit															
R^2 adj	0.398	0.400	0.401	0.400	0.401	0.323	0.328	0.329	0.328	0.328	0.384	0.387	0.387	0.387	0.387

Notes: This table contains the quantile regression estimation results for three selected quantiles $\tau = (0.10,\ 0.5,\ 0.9)$ for the regression defined in Equation (1) excluding the day-of-the-week dummy variables (i.e., $D_{i,t} = 0$ for $1 \le i \le 5$): $\Delta p_t = \alpha + \beta^{nav}\Delta nav_t + \beta^{sp}\Delta sp_t + \beta^{op}\Delta op_t + \beta^{vix}\Delta vix_t + \beta^{ovx}\Delta ovx_t + \beta^{prem} prem_{t-1} + \varepsilon_t$. The t-statistics are in ( ), and the p-values are in [ ]. The restriction imposed on the NAV parameter is tested using the Wald test χ^2 statistic with $\chi^2(1)$ degree of freedom. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Based on Table 8A–C, the coefficients on the interaction terms, representing differential impacts of the variables on Fridays, seem to exhibit stronger patterns in extreme quantiles, particularly for the Qatari and Saudi ETFs. The most notable is the diminished impact of NAV during bullish market phases, which remains significant at 1% for all specifications. Another pattern that only pertains to the Qatari and Saudi ETFs is the increased impact of oil price changes during bull markets for Qatar (across all specifications) and bear markets for Saudi (one exception). On the other hand, the Emirati ETF exhibits unique patterns, including traces of an increased impact of the S&P500 during normal times and a diminished impact of oil during bear markets, although these impacts are not robust across model specifications. Indeed, the differential effect of the lagged premium or discount parameters' estimates retains the same sign as the OLS estimates and remains largely robust across all specifications, countries, and quantiles with only two exceptions—the fifth specification during bear markets for Qatar and the third specification for the Emirates during bull markets.

We turn our attention to the price discovery model as represented by Equation (2). We examine the stability of OLS estimates using the Chow test to check for a potential break due to the COVID-19 pandemic in the same fashion as we did when we considered the price formation model. The results in the bottom of Table 6 show that the Chow test rejects the null of no break in the wake of the pandemic for the Qatari and Saudi ETFs at the 5% and 1% levels, respectively, while no evidence of a break was detected for the Emirati ETF. Anyhow, we estimated the QR using three quantiles (0.10, 0.50, and 0.90) for all ETFs and reported the results in Table 9.

Looking at Table 9, we observe two salient findings: the first is an asymmetric shift in the intercept on Mondays, which is negative during bear markets while being positive during bull markets. Interestingly, no traces are found for the Monday effect during normal market phases. The second finding is more pervasive, confirming that the slope parameters' estimates of the Monday interaction term with lagged premium or discount are significantly larger than Friday's slope parameters for all ETFs, regardless of the prevailing market phase.

Table 8. (**A**) The dummy-augmented QR estimation results for the determinants of ETF's price changes for Qatari ETF. (**B**) The dummy-augmented QR estimation results for the determinants of ETF's price changes for Saudi ETF. (**C**) The dummy-augmented QR estimation results for the determinants of ETF's price changes for Emirati ETF.

	Bearish Market (τ=0.10)					**Normal Market (τ=0.5)**					**Bullish Market (τ=0.90)**				
	1	**2**	**3**	**4**	**5**	**1**	**2**	**3**	**4**	**5**	**1**	**2**	**3**	**4**	**5**
(A)															
Regression Estimates															
α	−1.00 ***	−1.01 ***	−1.01 ***	−1.02 ***	−1.01 ***	−0.07 ***	−0.06 ***	−0.06 ***	−0.06 **	−0.06 ***	0.89 ***	0.89 ***	0.89 ***	0.88 ***	0.89 ***
	(−25.09)	(−27.64)	(−27.41)	(−28.20)	(−28.20)	(−2.90)	(−2.63)	(−2.69)	(−2.50)	(−2.68)	(23.69)	(23.16)	(23.49)	(23.69)	(23.43)
β^{nav}	0.84 ***	0.83 ***	0.84 ***	0.83 ***	0.82 ***	0.77 ***	0.75 ***	0.76 ***	0.75 ***	0.76 ***	0.73 ***	0.72 ***	0.70 ***	0.73 ***	0.72 ***
	(40.60)	(22.48)	(21.22)	(19.51)	(21.91)	(23.37)	(23.81)	(24.01)	(24.04)	(24.02)	(24.96)	(28.37)	(20.88)	(27.17)	(20.90)
β^{sp}	0.26 ***	0.24 ***	0.24 ***	0.24 ***	0.24 ***	0.24 ***	0.21 ***	0.21 ***	0.21 ***	0.22 ***	0.22 ***	0.19 ***	0.22 ***	0.20 ***	0.22 ***
	(8.45)	(6.06)	(5.83)	(5.62)	(5.30)	(10.82)	(10.49)	(10.21)	(10.74)	(10.42)	(6.31)	(7.58)	(6.43)	(7.56)	(6.02)
β^{op}		0.05 ***	0.05 ***	0.04 ***	0.04 **		0.04 ***	0.04 ***	0.04 ***	0.04 ***		0.02	0.02 *	0.03 *	0.03 **
		(4.88)	(5.01)	(3.36)	(2.44)		(2.87)	(2.94)	(2.85)	(2.66)		(1.21)	(1.89)	(1.83)	(1.98)
β^{vix}			0.000		−0.002			0.00		0.00			0.006		0.006
			(0.09)		(−0.40)			(1.13)		(1.10)			(0.85)		(0.86)
β^{ovx}				−0.008	−0.008				0.002	0.002				0.007	0.008
				(−0.95)	(−0.99)				(0.59)	(0.44)				(0.84)	(0.91)
β^{prem}	−0.52 ***	−0.54 ***	−0.54 ***	−0.54 ***	−0.54 ***	−0.39 ***	−0.38 ***	−0.38 ***	−0.37 ***	−0.38 ***	−0.46 ***	−0.47 ***	−0.45 ***	−0.47 ***	−0.47 ***
	(−12.32)	(−15.78)	(−15.50)	(−15.94)	(−15.93)	(−13.54)	(−13.48)	(−13.50)	(−13.38)	(−13.42)	(−16.57)	(−16.59)	(−15.10)	(−16.17)	(−15.16)
α_5	0.15 *	0.19 **	0.088	0.20	0.092	0.10 **	0.07 *	0.08 *	0.05	0.08 *	−0.11	−0.15 *	−0.14	−0.09	−0.09
	(1.67)	(1.97)	(0.94)	(1.39)	(0.74)	(2.49)	(1.71)	(1.90)	(1.27)	(1.71)	(−1.40)	(−1.68)	(−1.27)	(−0.80)	(−0.82)
δ^{nav}	−0.35	−0.04	−0.05	−0.42	−0.13	−0.25	−0.12	−0.19	−0.26	−0.26	−0.61 ***	−0.58 ***	−0.55 ***	−0.56 ***	−0.56 ***
	(−0.20)	(−0.02)	(−0.01)	(−0.38)	(−0.04)	(−0.36)	(−0.48)	(−0.62)	(−0.41)	(−0.40)	(−15.67)	(−15.99)	(−7.60)	(−15.31)	(−13.09)
δ^{sp}	0.07	0.08	0.04	0.08	0.04	0.05	0.04	0.05	0.03	0.03	0.07	−0.02	−0.02	−0.03	−0.05
	(0.88)	(1.01)	(0.12)	(1.10)	(0.09)	(1.10)	(0.89)	(0.95)	(0.64)	(0.50)	(1.28)	(−0.36)	(−0.11)	(−0.57)	(−0.94)
δ^{op}		0.06 *	0.00	−0.02	−0.01		0.01	0.01	0.01	0.01		0.09 ***	0.08 *	0.09 **	0.10 **
		(1.89)	(0.04)	(−0.31)	(−0.13)		(0.49)	(0.72)	(0.33)	(0.50)		(2.82)	(1.68)	(2.21)	(2.27)
δ^{vix}			−0.02		−0.02			0.000		−0.001			0.01		−0.01
			(−0.81)		(−0.48)			(−0.02)		(−0.10)			(0.22)		(−0.42)
δ^{ovx}				−0.02	−0.005				−0.01	−0.01				0.01	0.011
				(−0.58)	(−0.07)				(−0.85)	(−0.76)				(0.72)	(0.66)
δ^{prem}	0.18 ***	0.24 ***	0.18 **	0.24 ***	0.19	0.17 ***	0.19 ***	0.19 ***	0.19 ***	0.20 ***	0.32 ***	0.21 ***	0.22 *	0.19 ***	0.19 **
	(2.66)	(3.30)	(2.21)	(3.69)	(1.47)	(3.49)	(3.43)	(3.45)	(3.62)	(3.59)	(5.33)	(3.48)	(1.93)	(3.05)	(2.36)
Goodness of fit															
R^2 adj	0.389	0.394	0.397	0.395	0.397	0.282	0.287	0.287	0.287	0.287	0.333	0.338	0.338	0.339	0.338
(B)															
Regression Estimates															
α	−0.69 ***	−0.67 ***	−0.70 ***	−0.66 ***	−0.68 ***	0.10 ***	0.10 ***	0.10 ***	0.10 ***	0.10 ***	0.97 ***	0.96 ***	0.96 ***	0.95 ***	0.96 ***
	(−17.87)	(−17.33)	(−17.40)	(−15.99)	(−16.05)	(4.21)	(4.35)	(4.09)	(4.44)	(4.30)	(25.21)	(25.18)	(27.02)	(23.90)	(26.47)
β^{nav}	0.88 ***	0.88 ***	0.85 ***	0.86 ***	0.84 ***	0.87 ***	0.87 ***	0.87 ***	0.86 ***	0.85 ***	0.83 ***	0.79 ***	0.80 ***	0.79 ***	0.80 ***
	(22.40)	(17.61)	(19.98)	(17.53)	(20.10)	(31.86)	(32.13)	(31.26)	(30.41)	(31.40)	(28.06)	(25.81)	(29.20)	(28.78)	(29.45)

Table 8. *Cont.*

	Bearish Market (τ=0.10)					Normal Market (τ=0.5)					Bullish Market (τ=0.90)				
	1	**2**	**3**	**4**	**5**	**1**	**2**	**3**	**4**	**5**	**1**	**2**	**3**	**4**	**5**
β^{sp}	0.31 ***	0.28 ***	0.35 ***	0.26 ***	0.32 ***	0.26 ***	0.22 ***	0.25 ***	0.22 ***	0.25 ***	0.37 ***	0.31 ***	0.32 ***	0.32 ***	0.32 ***
	(12.05)	(6.60)	(14.76)	(7.33)	(11.35)	(8.98)	(10.03)	(6.27)	(8.10)	(7.06)	(18.72)	(9.16)	(18.95)	(7.97)	(18.33)
β^{op}		0.08 ***	0.07 ***	0.06 ***	0.06 ***		0.07 ***	0.07 ***	0.06 ***	0.06 ***		0.06 ***	0.06 ***	0.06 ***	0.06 ***
		(4.81)	(5.08)	(3.53)	(3.35)		(6.39)	(7.01)	(5.77)	(6.94)		(10.14)	(10.45)	(8.70)	(7.67)
β^{vix}			0.011 ***		0.012 **			0.01		0.01			0.008 **		0.008 **
			(3.13)		(2.54)			(1.27)		(1.95)			(2.40)		(2.27)
β^{ovx}				−0.011	−0.013				−0.009 **	−0.010 ***				0.002	0.001
				(−1.38)	(−1.46)				(−2.22)	(−3.20)				(0.31)	(0.18)
β^{prem}	−0.35 ***	−0.33 ***	−0.30 ***	−0.34 ***	−0.32 ***	−0.26 ***	−0.26 ***	−0.26 ***	−0.26 ***	−0.25 ***	−0.27 ***	−0.28 ***	−0.28 ***	−0.28 ***	−0.28 ***
	(−9.84)	(−6.70)	(−9.74)	(−6.46)	(−9.14)	(−11.76)	(−10.71)	(−10.47)	(−10.72)	(−10.77)	(−13.04)	(−11.44)	(−11.18)	(−10.35)	(−10.79)
α_5	0.06	0.02	0.039	0.02	0.049	−0.04	−0.04	−0.04	−0.05	−0.03	−0.18 ***	−0.22 ***	−0.13 *	−0.23 ***	−0.18
	(0.75)	(0.32)	(0.47)	(0.33)	(0.55)	(−0.80)	(−1.02)	(−0.82)	(−1.10)	(−0.62)	(−2.58)	(−3.12)	(−1.91)	(−3.09)	(−1.13)
δ^{nav}	−0.61 **	−0.32	−0.27	−0.88 **	−0.94 ***	−0.95 *	−0.86 **	−0.80 **	−0.64	−0.65	−0.49 ***	−0.25 ***	−0.26 ***	−0.25 ***	−0.26 ***
	(−2.23)	(−1.09)	(−0.90)	(−2.39)	(−2.60)	(−1.95)	(−2.14)	(−1.99)	(−1.54)	(−1.45)	(−4.35)	(−3.15)	(−4.02)	(−3.26)	(−3.27)
δ^{sp}	0.18 ***	0.07	−0.01	0.08	0.08	0.11	0.10	0.09	0.05	0.08	0.02	0.03	0.16 ***	0.02	0.16
	(3.19)	(1.24)	(−0.13)	(1.34)	(0.56)	(1.24)	(1.13)	(0.87)	(0.71)	(0.68)	(0.52)	(0.68)	(4.48)	(0.48)	(1.22)
δ^{op}		0.07 ***	0.08 ***	0.05 **	0.05		0.01	0.02	0.00	0.01		0.01	0.00	0.00	−0.01
		(3.74)	(3.84)	(2.03)	(1.14)		(0.56)	(1.07)	(0.02)	(0.47)		(0.29)	(0.29)	(−0.10)	(−0.22)
δ^{vix}			−0.01		0.00			0.002		0.001			0.03 ***		0.02
			(−1.27)		(0.03)			(0.20)		(0.07)			(3.21)		(0.85)
δ^{ovx}				−0.01	−0.016				−0.01	−0.01				−0.01	−0.010
				(−0.99)	(−1.27)				(−1.63)	(−0.99)				(−0.73)	(−0.48)
δ^{prem}	0.16 ***	0.12 *	0.10 **	0.10 *	0.10 **	0.13 ***	0.13 ***	0.12 **	0.11 **	0.11 **	0.20 ***	0.17 ***	0.22 ***	0.20 ***	0.23 ***
	(3.27)	(1.95)	(2.05)	(1.65)	(2.04)	(2.81)	(2.72)	(2.51)	(2.30)	(2.16)	(3.38)	(3.33)	(4.01)	(3.67)	(3.30)
Goodness of fit															
R^2 adj	0.433	0.452	0.454	0.457	0.459	0.373	0.391	0.392	0.393	0.395	0.401	0.416	0.421	0.416	0.421
(**C**)															
Regression Estimates															
α	−1.03 ***	−1.01 ***	−1.01 ***	−1.01 ***	−1.01 ***	−0.03	−0.02	−0.02	−0.02	−0.02	0.93 ***	0.90 ***	0.91 ***	0.90 ***	0.90 ***
	(−27.31)	(−28.93)	(−28.68)	(−28.16)	(−27.82)	(−1.15)	(−1.09)	(−1.04)	(−1.10)	(−1.05)	(25.49)	(25.65)	(25.93)	(25.65)	(26.11)
β^{nav}	0.75 ***	0.74 ***	0.73 ***	0.75 ***	0.75 ***	0.85 ***	0.82 ***	0.83 ***	0.82 ***	0.83 ***	0.87 ***	0.86 ***	0.85 ***	0.86 ***	0.85 ***
	(40.32)	(21.28)	(22.17)	(19.92)	(20.69)	(28.95)	(36.93)	(35.98)	(36.66)	(35.57)	(46.08)	(42.36)	(41.84)	(42.36)	(41.49)
β^{sp}	0.33 ***	0.32 ***	0.31 ***	0.31 ***	0.30 ***	0.21 ***	0.20 ***	0.19 ***	0.20 ***	0.19 ***	0.28 ***	0.25 ***	0.27 ***	0.26 ***	0.28 ***
	(10.91)	(8.18)	(6.89)	(7.84)	(6.04)	(11.78)	(10.05)	(7.73)	(9.72)	(7.67)	(14.01)	(10.43)	(8.96)	(10.19)	(8.78)
β^{op}		0.03 **	0.03 **	0.03	0.03		0.04 ***	0.04 ***	0.04 ***	0.04 ***		0.03 **	0.02 **	0.02 **	0.03 *
		(2.05)	(1.97)	(1.50)	(1.59)		(3.39)	(3.54)	(2.68)	(2.77)		(2.11)	(2.01)	(1.99)	(1.85)
β^{vix}			−0.002		−0.003			−0.002		−0.002			0.002		0.003
			(−0.35)		(−0.43)			(−0.57)		(−0.56)			(0.44)		(0.54)
β^{ovx}				0.002	0.003				0.000	0.000				−0.001	0.000
				(0.23)	(0.26)				(−0.04)	(−0.01)				(−0.31)	(0.15)
β^{prem}	−0.38 ***	−0.38 ***	−0.39 ***	−0.39 ***	−0.39 ***	−0.35 ***	−0.35 ***	−0.35 ***	−0.35 ***	−0.35 ***	−0.44 ***	−0.42 ***	−0.41 ***	−0.41 ***	−0.41 ***
	(−10.43)	(−12.10)	(−12.17)	(−11.81)	(−11.59)	(−15.15)	(−15.15)	(−15.24)	(−15.08)	(−15.13)	(−14.18)	(−13.22)	(−13.16)	(−13.20)	(−13.34)
α_5	0.06	0.06	−0.079	0.04	−0.056	−0.04	−0.02	−0.071	−0.02	−0.061	−0.06	−0.05	−0.07	−0.09	−0.09
	(0.55)	(0.70)	(−0.61)	(0.44)	(−0.51)	(−0.74)	(−0.38)	(−1.24)	(−0.39)	(−1.01)	(−0.49)	(−0.42)	(−0.66)	(−1.33)	(−1.26)
δ^{nav}	0.79	0.65	0.50	0.45	0.31	0.32	0.19	0.42	0.19	0.37	1.12	1.07	0.77	0.80 **	0.83 **

Table 8. *Cont.*

	Bearish Market (τ=0.10)					Normal Market (τ=0.5)					Bullish Market (τ=0.90)				
	1	**2**	**3**	**4**	**5**	**1**	**2**	**3**	**4**	**5**	**1**	**2**	**3**	**4**	**5**
	(1.06)	(1.06)	(0.59)	(0.90)	(0.64)	(0.54)	(0.41)	(0.77)	(0.38)	(0.67)	(1.45)	(1.10)	(1.59)	(2.42)	(2.50)
δ^{sp}	0.15 **	0.14 *	−0.12	0.15 *	−0.14	0.19 **	0.21 **	0.09	0.21 **	0.10	0.11	0.12	−0.05	0.09	0.05
	(2.03)	(1.87)	(−0.97)	(1.90)	(−0.98)	(2.13)	(2.49)	(0.96)	(2.27)	(0.93)	(0.88)	(0.63)	(−0.09)	(0.89)	(0.38)
δ^{op}		−0.01	−0.08 ***	−0.02	−0.08 ***		0.01	−0.01	0.01	0.00		−0.01	0.02	−0.03	−0.07 *
		(−0.51)	(−3.34)	(−0.65)	(−2.59)		(0.32)	(−0.27)	(0.20)	(0.01)		(−0.14)	(0.16)	(−0.77)	(−1.85)
δ^{vix}			−0.05 **		−0.04 **			−0.02 *		−0.02			−0.03		−0.02 *
			(−2.33)		(−3.40)			(−1.77)		(−1.38)			(−0.91)		(−1.80)
δ^{ovx}				−0.01	−0.007				0.00	0.002				−0.03 ***	−0.024 **
				(−0.51)	(−0.47)				(0.01)	(0.13)				(−2.92)	(−2.27)
δ^{prem}	0.20 ***	0.21 ***	0.23 ***	0.23 ***	0.21 ***	0.18 ***	0.16 ***	0.16 ***	0.16 ***	0.17 ***	0.17 **	0.15 **	0.11	0.17 ***	0.11 *
	(2.60)	(3.22)	(3.51)	(3.50)	(3.20)	(3.23)	(3.43)	(3.77)	(3.41)	(3.87)	(2.12)	(1.96)	(1.12)	(3.17)	(1.94)
Goodness of fit															
R^2 adj	0.403	0.405	0.412	0.405	0.411	0.328	0.333	0.334	0.333	0.333	0.388	0.390	0.392	0.391	0.392

Notes: This table contains the quantile regression estimation results for three selected quantiles $\tau = (0.10,\ 0.5,\ 0.9)$ estimation results for the regression defined in Equation (1) with the Friday dummy variable (i.e., $D_{5,t} = 1$ for $i = 5$ and zero otherwise): $\Delta p_t = \alpha + \beta^{nav}\Delta nav_t + \beta^{sp}\Delta sp_t + \beta^{op}\Delta op_t + \beta^{vix}\Delta vix_t + \beta^{ovx}\Delta ovx_t + \beta^{prem} prem_{t-1} + \alpha_5 D_{5,t} + \delta^{nav}\Delta nav_t \times D_{5,t} + \delta^{sp}\Delta sp_t \times D_{5,t} + \delta^{op}\Delta op_t \times D_{5,t} + \delta^{vix}\Delta vix_t \times D_{5,t} + \delta^{ovx}\Delta ovx_t \times D_{5,t} + \delta^{prem}\Delta prem_{t-1} \times D_{5,t} + \varepsilon_t$. The t-statistics are in ( ), and the p-values are in [ ]. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 9. QR results for ETF price discovery.

	Qatar			Saudi			UAE		
	Bearish Market (τ=0.10)	**Normal Market (τ=0.5)**	**Bullish Market (τ=0.90)**	**Bearish Market (τ=0.10)**	**Normal Market (τ=0.5)**	**Bullish Market (τ=0.90)**	**Bearish Market (τ=0.10)**	**Normal Market (τ=0.5)**	**Bullish Market (τ=0.90)**
Regression Estimates									
θ	−0.11 ***	0.00	0.11 ***	−0.11 ***	0.00	0.10 ***	−0.21 ***	0.01	0.25 ***
	(−12.44)	(−0.18)	(12.11)	(−10.20)	(−0.18)	(9.97)	(−13.97)	(0.76)	(10.87)
θ_1	−1.61 ***	0.02	1.44 ***	−2.08 ***	−0.13	1.34 ***	−1.42 ***	−0.07	1.08 ***
	(−11.91)	(0.28)	(11.06)	(−11.96)	(−1.18)	(12.29)	(−9.49)	(−1.03)	(9.70)
θ_2	−0.94 ***	0.07 *	1.02 ***	−0.94 ***	0.09 *	1.17 ***	−0.79 ***	0.06	0.87 ***
	(−11.14)	(1.68)	(9.41)	(−7.56)	(1.90)	(9.32)	(−8.36)	(1.35)	(9.11)
θ_3	−0.92 ***	0.02	1.05 ***	−0.79 ***	0.02	0.93 ***	−0.80 ***	0.00	0.71 ***
	(−10.72)	(0.60)	(8.95)	(−10.18)	(0.50)	(9.96)	(−10.37)	(0.02)	(7.04)
θ_4	−0.81 ***	0.05	0.93 ***	−0.91 ***	−0.05	0.85 ***	−0.72 ***	0.00	0.81 ***
	(−10.14)	(1.32)	(11.06)	(−10.57)	(−1.04)	(12.30)	(−8.52)	(−0.05)	(7.04)
ϕ	−0.02 *	0.00	0.01 *	0.02 ***	0.00	−0.03 ***	0.01	0.01	0.07 ***
	(−1.88)	(−0.00)	(1.73)	(3.29)	(−0.00)	(−3.39)	(0.63)	(0.80)	(3.46)
ϕ_1	0.42 ***	0.29 ***	0.59 ***	0.56 ***	0.28 **	0.35 ***	0.48 ***	0.19 **	0.19 *
	(4.57)	(3.46)	(6.21)	(8.42)	(2.05)	(3.09)	(5.70)	(2.36)	(1.83)
ϕ_2	0.22 ***	0.03	−0.01	−0.13	−0.03	0.08	0.18 ***	0.06	0.01
	(2.73)	(0.72)	(−0.25)	(−1.25)	(−0.48)	(0.79)	(2.95)	(1.49)	(0.06)
ϕ_3	0.20 ***	0.05	0.34 **	0.03	0.11 ***	0.12 **	0.08	0.06	−0.07
	(2.92)	(1.03)	(2.44)	(0.35)	(2.67)	(1.97)	(1.19)	(1.70)	(−0.48)
ϕ_4	0.19 ***	0.07 *	0.09	0.25 ***	0.14 **	0.28 ***	0.09	0.09 **	0.18 **
	(4.14)	(1.66)	(0.62)	(4.63)	(2.37)	(4.77)	(1.36)	(2.18)	(2.20)
Goodness of fit									
R^2 adj	0.14	0.01	0.12	0.15	0.01	0.13	0.10	0.01	0.07

Notes: This table contains the quantile regression estimation results for three selected quantiles $\tau = (0.10, 0.5, \textit{and}\ 0.9)$ for the regression defined in Equation (2): $\Delta nav_t = \theta + \sum_{i=1}^{4} \theta_i D_{i,t} + \phi prem_{t-1} + \sum_{i=1}^{4} \phi_i prem_{t-1} \times D_{i,t} + \varepsilon_t$. The t-statistics are in ( ). ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

5. Discussion

The results from the price formation model reveal some interesting findings worthy of discussion. First, while the presence of significant intercepts in Table 4 is not unheard of, it implies the availability of arbitrage opportunities. The QR results confirm this finding. Based on Table 7A–C, we can see that the magnitude and statistical significance of the intercepts are larger in absolute terms at extreme quantiles with asymmetric signs—negative during bear markets while being positive during bullish phases. Indeed, such a pattern manifests in this context due to the lack of synchronization between the ETFs and their underlying NAVs. This lack of alignment is mainly caused by the non-overlapping time zones and the difference in trading days between the ETFs and their corresponding GCC markets. However, whether these arbitrage opportunities can be profitably exploited depends on the severity of arbitrage constraints (Al-Nassar 2021). Second, the fact that both estimation techniques (OLS and QR) confirm the absence of a one-to-one co-movement between the ETFs' prices and their underlying fundamental values, as represented by their NAVs, epitomizes the lack of synchronization. Third, by and large, the relatively low correlation between the ETFs' and the S&P500 returns compared to prior studies implies that the GCC ETFs stand out as a promising avenue of diversification for US investors. Fourth, the positive impact that oil returns have on ETF returns suggests that these ETFs are promising candidates to be used as a hedge against oil shocks from the perspective of US investors. Similarly, the incidental finding of a positive and significant parameter on VIX for the Saudi ETF indicates its potential to act as a hedge against the uncertainty of the US market.

Both the OLS and the quantile regression results obtained using the dummy-augmented price formation model in Tables 5 and 8A–C support a regime shift between Friday (on which the GCC markets are closed) and the remaining trading days of the week. This regime shift manifests in a slower adjustment of the ETFs' prices to realign with their underlying NAV on Friday, as shown by the opposite sign on the lagged premiums or discount parameter estimates. However, the "weekend effect" impact is less pronounced for other variables, particularly the S&P500, which exhibits a rather mild weekend effect only for the Emirates ETF in specific quantiles and model specifications. This finding contradicts the explanation by Levy and Lieberman (2013), which suggests that traders in the US market tend to overreact to changes in S&P500 prices when domestic markets are closed.

The impact of the detachment of the ETF prices from the underlying NAVs on the underlying market, presented in Tables 6 and 9 (particularly the median quantile results), completes our understanding of the price discovery. The price discovery takes place in the US market (after the closure of the GCC markets and on Friday when the GCC markets are closed) and predicts the following day's NAV return, albeit with a clear day-of-the-week pattern. The insignificance of Friday's intercept and slope, which is expected given the GCC market closure, implies that the incorporation of the new information by the underlying GCC markets intensifies on the earliest common trading day, Monday. Although the GCC markets open on Sunday, the largest adjustment occurs on Monday, particularly during extreme market phases. This may imply that US-based APs or arbitrageurs largely drive the creation/redemption transactions and/or secondary market arbitrage trades. These trades constitute an important shock transmission channel from the US market to the GCC domestic stock markets (Chari 2023; Filippou et al. 2022). The resultant seasonal effect could be exploited through simple trading rules.

6. Concluding Remarks

In this study, we examine the price formation dynamics in country stock market ETFs tracking three GCC broad market indices. Also, we investigate the extent of price discovery offered by the ETF market by gauging the adjustments of the underlying ETFs' NAVs on the subsequent day to incorporate the new information contained in the ETF's closing prices. We employ a simple extension of the error correction model used by Levy and Lieberman (2013). We expanded the model by including crude oil prices and well-known indicators of uncertainty, viz. VIX and OVX, in addition to the variables used in prior studies, namely, NAV, S&P500, and lagged premium or discount. We also altered the definition of dummy variables of Levy and Lieberman (2013) by including a day-of-the-week dummy to capture the difference in trading days between the US and the GCC markets. By the same token, we respecified the price discovery model proposed by Broman (2016) to include the day-of-the-week dummies. To mitigate the impact of fat tails that manifest in the form of outliers and breaks on our OLS estimates, we use the quantile regression as a robustness check.

The main findings that can be gleaned from the results indicate that while the underlying GCC markets play a dominant role in the pricing of the GCC country ETFs, none of these ETFs seem to move perfectly with their underlying market. This left room for other variables to affect the ETFs' pricing, including the S&P500, the lagged premium, or discount in addition to the crude oil price. The results obtained from the dummy-augmented specification suggest that the strongly significant differential effect of the lagged premium or discount indicates a clear regime shift on Fridays, resulting in a slower adjustment to correct mispricing. The S&P500 returns, however, do not show any meaningfully differing effect on the ETFs' pricing on Fridays, which refutes the overreaction explanation by Levy and Lieberman (2013). The dummy-augmented price discovery model results show that ETFs' daily price changes predict the subsequent day's NAV with a strong seasonal pattern that intensifies on Monday to correct the mispricing that accumulated due to the mismatch between the trading days of the ETFs market and their corresponding underlying GCC home markets. Indeed, while the quantile regression extracts some interesting insights during extreme market conditions, the main conclusion reached using the OLS estimates largely holds.

These results carry significant implications for investors and policymakers. The relatively weaker relationship between the GCC ETFs' returns and the S&P500 and the positive impact of crude oil price changes on the return of these ETFs suggests that these ETFs can potentially offer better diversification benefits compared to their advanced market counterparts, which have a high correlation with the S&P500. Furthermore, the documented seasonal patterns in price discovery can be potentially exploited using trading rules. Moreover, while the price discovery offered by the US market can enhance the pricing efficiency of these ETFs, it constitutes an essential channel of shock transmission from the US market to the GCC market that is exacerbated during extreme market phases. Indeed, macroprudential policymakers in the GCC should pay attention to this shock transmission mechanism to avoid any damaging effects on the stability of their markets by monitoring the price discovery offered by the markets in which ETFs tracking their stock markets are listed. This is more crucial as China approved the first ETFs tracking the Saudi stock market[8], opening another shock transmission channel in addition to the existing US channel.

Indeed, the GCC ETFs offer a unique opportunity to study the impact of the nonoverlapping trading days on ETF price formation and price discovery; therefore, an out-of-sample test for the findings of the present study can be achieved by examining the price formation and price discovery of the newly listed Saudi ETFs in the Chinese market when sufficient data become available. The main caveat of the present study is the sample size. Extending the sample size to study more country ETFs by investigating the effect of differences in trading days due to different holidays between the US or any other market in which the country ETFs are listed and the underlying domestic markets can be a promising future research avenue. Another interesting research direction is investigating the risk-return spillovers among the emerging market ETFs and the US market and their risk and portfolio management implications.

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Notes

1. For details on the recent developments and significant growth in the ETF industry, see Johnson (2023).
2. Arbitrage opportunities also attract non-AP market participants such as high-frequency traders and hedge funds to seize them in the secondary market in transactions that do not involve the creation or redemption of ETF shares (Marshall et al. 2013; Richie et al. 2008).
3. Israeli et al. (2017) find that the increase in the ownership of ETFs in their constituent stocks leads to higher trading costs and disincentivizes efforts to collect firm-specific information, rendering the pricing of the ETF's constituents relatively less informative.
4. When the ETF's price in the secondary market exceeds (falls short of) its NAV, it is said that the ETF trades at a premium (discount). This variable constitutes the error correction term in the model.
5. From 1 January 2022, the UAE shifted its weekend to Saturday and Sunday to align more closely with the global markets (El-Naggar 2021). This change was taken into consideration in the definition of the dummy variables for the UAE ETF. The Friday dummy (the mismatching trading day) for the UAE takes the value 1 on Fridays from the beginning of the sample period until the last Friday in 2021. From the beginning of 2022, Friday's dummy takes the value zero regardless. This change alters the interpretation of the UAE's regression parameters slightly.

[6] The SPDR S&P 500 Trust ETF is the first US-listed ETF, launched in 1993. However, we opted to use the iShares Core S&P 500 ETF in our analysis to maintain consistency with the GCC ETFs that are issued by the same investment company, BlackRock.

[7] The World Health Organization declared the novel coronavirus (COVID-19) outbreak a global pandemic on 11 March 2020. Therefore, we chose this date to be an exogenous break date for the purpose of the Chow test.

[8] https://www.reuters.com/business/finance/china-approves-first-etfs-tracking-saudi-equities-fund-managers-say-2024-06-14/ (accessed on 22 September 2024).

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