Journal of Accounting Literature

Received 2 July 2024
Revised 22 August 2024
Accepted 28 August 2024

On the analysis of time-varying causality between VIX exchange-traded products and VIX futures contracts in high and low volatility regimes

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Abstract

Purpose – The authors analyse the nature of nonlinear long-run causal dynamics between VIX futures and exchange-traded products (ETPs).

Design/methodology/approach – Nonlinear long-run causal relations between daily price movements in ETPs and futures are established through a Markov switching vector error correction model (MS-VECM).

Findings – The authors observe time variation in causality with the volatility of volatility. In particular, demand pressures for VIX ETNs and futures can change in different regimes. The authors observe two regimes where regime 1 is classified as low-mean low-volatility, while regime 2 is classified as high-mean high-volatility. The convergence to the long-run equilibrium in the low-mean low-volatility regime is faster than the high-mean high-volatility regime. The nature of the time varying lead lag relations demonstrates the opportunities for arbitrage.

Originality/value – The linear causal relations between VXX and VIX futures are well established, with leads and lags generally found to be short-lived with arbitrage relations holding. The authors go further to capture the time-varying causal relationships through a Markovian process. The authors establish the nonlinear causal relations between inverse and leveraged products where causal relations are not yet documented.

Keywords Causality, VIX, Exchange-traded products, Markov switching

Paper type Research paper

1. Introduction

The CBOE Volatility Index (VIX) is a popular index that measures the expected volatility of the S&P 500 index over the next 30 days. VIX derivatives were introduced in 2004, and VIX Exchange Traded Products (ETPs) followed in 2009. These ETPs are not productive investments, but instead offer packaged exposure to underlying positions in VIX Futures. They allow investors to trade exposures to VIX Futures and can be used for genuine hedging needs of institutional investors. However, they have also captured the imagination of retail speculators.

The hedging demands associated with these products have driven liquidity to VIX derivatives markets over time. VIX derivatives markets now rival those of SPX and SPY

The authors thank the editors of the journal, Prof Tom Smith, anonymous referees for their helpful comments and suggestions.

This research was funded by the Australian Government through the Australian Research Council (DP230101472).

Journal of Accounting Literature
Vol. 47 No. 5, 2025
pp. 99-109
Emerald Publishing Limited
0737-4607
DOI 10.1108/JAL-07-2024-0147

options as preferred venues for trading volatility (O'Neill and Rajaguru, 2024). VIX Futures have become the dominant market for trading and hedging volatility, futures representing the forward expectation of VIX and predicting the direction of VIX (see Zhang and Zhu, 2006; Lin, 2007; Zhang *et al*., 2010; Konstantinidi and Skiadopoulos, 2011; Shu and Zhang, 2012; Bollen *et al*., 2016; Frijns *et al*., 2016; Dian-Xuan *et al*., 2017; Chen and Tsai, 2017).

VIX ETPs enable retail investors to engage in volatility derivatives strategies that would otherwise be inaccessible. They have contributed to financialization of volatility. This is due to their enabling investors to speculate on stock market volatility, which often leads to taking on excessive risks. Some of the most popular trading strategies have proven to be unsustainable, causing catastrophic losses for retail investors (Whaley, 2013). In particular, a long-exposure to VIX futures indices via ETPs generally (80% of the time) involves daily selling of the nearest maturity contract at a loss, and buying new contracts at a higher price, a strategy ("contango trap").

Similar to O'Neill and Rajaguru (2024), we focus on flagship ETPs including the iPath S&P 500 VIX Short-Term Futures ETN (VXX), ProShares VIX Short-Term Futures ETF (VIXY), Velocity Shares Daily Inverse VIX Short-Term Exchange-Traded Note (XIV), ProShares Short VIX Short-Term Futures ETF (SVXY), VelocityShares Daily 2x VIX Short-Term ETN (TVIX), and ProShares Ultra VIX Short-Term Futures ETF (UVXY). The first two products target the daily return of SPVXSTER index, the second two a -1x (inverse) multiple of this return, and the last two a daily return of 2x (leveraged) multiple.

Institutions might prudently use VXX to hedge their portfolios during periods of high volatility when the futures curve shifts from contango to backwardation, whereas retail investors typically show a buy-and-hold interest in VXX (O'Neill and Rajaguru, 2024).This is not a sustainable buy and hold strategy and it cost investors in VXX well over −97% returns for VXX during 2012 (see Shu and Zang, 2012; Johnson, 2017; Gehricke *et al*., 2018) [1]. VIX ETP strategies involving inverse and leveraged products have also proven to be unsustainable for retail shareholders.

TVIX suffered a liquidity event when Credit-Suisse temporarily suspended the creation of new shares on 21 February 2012. TVIX opened at a 90% premium over its $7.62 net assets per share, but the premium dissipated on March 22–23, 2012, leading to a 30% drop in TVIX over two consecutive days. A more severe liquidity event happened with the collapse of the Velocity Shares Daily Inverse VIX Short-Term exchange-traded note (XIV) in February 2018, known as "Volmageddon." Ideally, institutions would strategically invest in XIV during periods of low volatility and reduce their VXX holdings, but they should exit XIV to prevent losses when the market shifts into backwardation. On 5 February 2018 VIX had a record intraday return spiking 115% spike from 17 to 37% within just a two-hour period (O'Neill and Rajaguru, 2024). In response, to avoid the ETN going to zero the issuer triggered an "acceleration event" signalling the end of the product.

Another unresolved issue highlighted by Volmaggedon is the potential impact of speculative demand for VIX ETPs on market stability, volatility and equitable outcomes for investors, such as retail shareholders whose demands might potential are front-run by market makers. Overall, VIX ETPs are a risky investment that should be avoided by investors who are looking for a sustainable investment. VIX ETPs have a role to play in facilitating tactical hedging requirements of institutional investors. Retail investors who are looking to invest in a sustainable way should avoid speculating on VIX ETPs and instead invest in assets that create real value.

O'Neill and Rajaguru (2024) examined the causal relationships between VIX, VIX ETPs, and VIX Futures across various market conditions. Among the ETPs analysed in their study, VXX offers daily long exposure to a VIX futures index with a 30-day maturity. TVIX provides daily two-times leveraged exposure, while XIV offers daily inverse exposure. Additionally, their study also included the corresponding exchange-traded funds (ETFs): VIXY, UVXY, and SVXY. However, their study assumes that the nature of the causal relationship is invariant across the time. Moreover, analysis of causal behaviour of VIX, VIX derivatives and ETPs needs to capture the regime-switches in VIX. Baba and Sakurai (2011) use a Markov-switching regression techniques, which allows the VIX index to be in one of three states: tranquil, turmoil, or crisis and relate the regime-switching probability to term spreads and other macroeconomic variables. For investors, the findings suggest that they should be aware of the different regime shifts in VIX and regulate their investment strategies accordingly – for strategies to sustainable they need to be dynamic and allow for these regime changes. There is also a potential regulatory concern here about the sustainability of retail speculation in these markets. Markov-switching GARCH models have been utilised to gauge the predictability of high volatility incidents in the S&P 500, to encourage more sustainable and optimised, dynamic long term investment strategy (De la Torre *et al.*, 2021). The implementation of Markov-switching GARCH models has been shown to improve portfolio performance, particularly during periods of high and extreme volatility. Bildirici *et al.* (2022) explored the regime-dependent causal relationships and contagion between VIX and key economic indicators such as oil and gold prices, examining causality across both low and high return regimes and volatility regimes. Moreover, the inclusion of a regime-switching process in pricing models for VIX and S&P 500 options has proven beneficial (Papanicolaou and Sircar, 2014). In a similar vein, regime-switching stochastic volatility models have demonstrated a superior fit for market prices of VIX options compared to the Heston model, thereby enhancing the hedging of VIX options and other volatility derivatives (Goutte *et al.*, 2017). Broader applications involve employing a Markov regime switching method to study short-term sovereign credit default swap (SCDS) spreads. The results indicate that in adverse conditions, investors tend to become more risk-averse and shift their funds to safer assets (Ma *et al.*, 2018). All of these studies suggest that static approaches are often not sustainable, and dynamic strategies which incorporate regime-shifting are more appropriate for volatility markets.

We hypothesise that, similar to VIX Futures, VIX ETPs also precede changes in the VIX itself, a phenomenon described as "the tail wags the dog" (see Bollen *et al.*, 2016).We also explore how various ETPs affect VIX Futures across different volatility environments, including higher and lower volatility regimes, as well as end-of-day effects. To the best of our knowledge, this is the first study which addresses the time varying causal relationship between VIX Futures and VIX ETPs using the regime switching approach. Additionally, we investigate the impact of term structure on lead-lag relationships, particularly how traders in segmented markets might adjust their positions in anticipation of volatility shifts, as evidenced by movements from contango to backwardation in the futures curve [2]. Ultimately participants looking to trade and hedge volatility in VIX product markets in a sustainable way will benefit from a better understanding of price discovery mechanisms particularly in unstable market conditions. In this way, sustainable strategies need to be dynamic and response to different volatility regimes.

This paper is organised as follows: Section 2 provides a description of the VIX product data. Section 3 outlines the methodologies employed and presents the results. The paper concludes with Section 4.

2. VIX product data

We analyse the time series of prices in 6 Exchange-Traded Products (ETPs) against the S&P 500 VIX Futures index which underlies their respective benchmarks. We focus on the same flagship ETPs studied by O'Neill and Rajaguru (2024), being VXX, VIXY, XIV, SVXY, TVIX, and UVXY. Again, the first two products target the daily return of SPVXSTER index, the second two a -1x (inverse) multiple of this return, and the last two a daily return of 2x (leveraged) multiple.

Intraday trade data for the two nearest maturity VIX Futures contracts and the S&P 500 VIX Short-Term Total Return Index (SPVXSTR) were obtained from the Thomson Reuters Tick History (TRTH) database, accessible through the Securities Industry Research Centre of Asia–Pacific (SIRCA) with precision up to the nearest millisecond. Daily trade data for VXX, VIXY, XIV, SXVY, TVIX, and UVYX was sourced from Wharton Research Data Services, covering the trades on the NYSE over the period from each ETP's inception to March 31, 2018.

3. Analysis of causality of price movements

3.1 Unit roots and cointegration

The unit root properties of the log variables in our analysis are examined through the ADF, the DF-GLS, the PP test, and the KPSS test. The results are reported in Table 1 and it shows that all variables are integrated process of order 1 at the 5% level of significance.

Since the variables are I(1), we further investigate the long-term equilibrium relationship among log-transformed variables using the Johansen and Juselius (1990) cointegration testing procedure. This method involves estimating the following pth-order vector autoregression (VAR) process, where p is determined by the Schwarz Criterion (SC).

$$\begin{pmatrix} \ln(SPXSTR_t) \\ \ln(TVIX_t) \\ \ln(VXX_t) \\ \ln(XIV_t) \end{pmatrix} = \mu + \sum_{i=1}^{p} \Pi_i \begin{pmatrix} \ln(SPXSTR_{t-i}) \\ \ln(TVIX_{t-i}) \\ \ln(VXX_{t-i}) \\ \ln(XIV_{t-i}) \end{pmatrix} + \Theta D_t + \varepsilon_t, t = 1, 2, \ldots, T \text{, and}$$

$$\begin{pmatrix} \ln(SPXSTER_t) \\ \ln(VIXY_t) \\ \ln(UVXY_t) \\ \ln(SVXY_t) \end{pmatrix} = \mu + \sum_{i=1}^{p} \Pi_i \begin{pmatrix} \ln(SPXSTER_{t-i}) \\ \ln(VIXY_{t-i}) \\ \ln(UVXY_{t-i}) \\ \ln(SVXY_{t-i}) \end{pmatrix} + \Theta D_t + \varepsilon_t, t = 1, 2, \ldots, T$$

The λ_{trace} statistic and the $\lambda_{\max}$ statistic results reported in Table 2 suggests one cointegrating vector.

Levels	Ln(SPVXSTR)	Ln(TVIX)	Ln(VXX)	LN(XIV)	Ln(VIXY)	Ln(UVXY)	Ln(SVXY)
ADF	−2.07	−2.81	−2.73	−2.66	−1.16	−1.09	−1.04
PP	−2.09	−2.80	−2.62	−2.65	−1.11	−1.07	−1.03
DF-GLS	−0.72	−1.81	−2.21	−1.17	−0.21	−0.81	−0.90
KPSS	84.22***	33.51***	24.67***	20.79***	12.69***	12.85***	13.1***
First differences	**Ln(SPVXSTR)**	**Ln(TVIX)**	**Ln(VXX)**	**LN(XIV)**	**Ln(VIXY)**	**Ln(UVXY)**	**Ln(SVXY)**
ADF	−240.35***	−779.23***	−1239.5***	−1509.4***	−113.8***	−85.4***	−72.3***
PP	−428.66***	−741.99***	−3170.9***	−3337.0***	−114.34***	−126.2***	−133.6***
DF-GLS	−240.33***	−23.39***	−63.18***	−38.18***	−113.1***	−85.3***	−72.3***
KPSS	0.063	0.045	0.038	0.063	0.07	0.09	0.06

Note(s): *, ** and *** denotes the rejection of null at the 10%, 5% and 1% level, respectively
Source(s): Authors' own work

Table 1.
Unit root test results

	Model 1		Model 2	
	Trace statistic	Maximum eigen value statistic	Trace statistic	Maximum eigen value statistic
r = 0	78.76612***	51.62169***	936,160***	70.0304***
r ≤ 1	27.14443	15.29916	23.5856	16.7089
r ≤ 2	11.84527	10.76851	6.87675	6.53306
r ≤ 3	1.076758	1.076758	0.34369	0.34369

Note(s): * and ** denotes the rejection of null at the 5% and 1% respectively
Model 1: Cointegration between ln(SPVXSTR), ln(TVIX), ln(VXX), ln(XIV)
Model 2: Cointegration between ln(SPVXSTR), ln(VIXY), ln(UVXY), and ln(SVXY)
Source(s): Authors' own work

Table 2.
Cointegration test

3.2 Analysis of time varying causality between VIX futures and ETPs in high and low volatility regimes

In this section, we fit the Markov-switching vector error correction model (MS-VECM) for three ETNs and then apply the same model for the corresponding ETFs. The mean, variance and covariance of the residuals, are assumed to be different for regimes. We find that the autoregressive coefficients are statistically invariant across the regimes and hence we estimate the model with regime switching in mean and variance-covariances.

Let s_t be a discrete latent variable that identifies which regime the market is in at time t. While the specific regime at any given time t remains unknown, we can determine the conditional probability of the market being in any particular regime. For instance, if there are two regimes, then $s_t = 1$ corresponds to a low-volatility regime and $s_t = 2$ to a high-volatility regime. Each regime is defined by distinct conditional distributions for the variables involved. We estimate the following model:

$$X_t = \mu(s_t) + \sum_{i=1}^{p} \Phi_i X_{t-i} + \varepsilon_t \text{ for } s_t = 1, 2, \ldots, m,$$

where $X_t = [\mathrm{Ln}(SPXVIXSTR)\ \mathrm{Ln}(TVIX)\ \mathrm{Ln}(VXX)\ \mathrm{Ln}(XIV)]'$,

$\boldsymbol{\mu}(s_t)' = [\,\mu_1(s_t) \quad \mu_2(s_t) \quad \mu_3(s_t)\ \mu_4(s_t)\,]$ is the regime-specific mean, $\varepsilon_t \sim N(0, \Sigma_{s_t})$ is the distribution for the regime-specific residual at time t,

Σ_{s_t} is the regime-specific variance-covariance matrix,

Φ_i is the coefficient matrix for lag i, and

The model is designed such that each regime exhibits distinct mean values and covariance matrices. This regime-shifting approach is based on the premise that the parameters of the VECM process, specifically the intercept and covariances, are contingent upon an latent regime variable, s_t. Both the intercept and variance-covariances are functions of the states in a Markov chain, offering considerable flexibility for modelling time series that experience regime shifts, as noted by Clements and Krolzig (1998).

We employ the estimation procedure developed by Lanne *et al.* (2010) to derive the parameters of the model. If the errors are conditionally normally distributed then we can utilise a maximum likelihood (ML) estimation to concurrently estimate the parameters of the model. If conditional normality fails, then this method produces pseudo-maximum likelihood estimates. We find that errors are normally distributed and hence it is not a series concern for our model.

The optimal lag length and the number of regimes are justified through SC as in Psaradakis and Spagnolo (2003, 2006), Herwartz and Lütkepohl (2011) and Lütkepohl and Netsunajev (2013) [3].

The state variable follows stationary Markov process and is characterised by the transition matrix Π. The entries of the Π matrix are transition probabilities from state i to state j, p_{ij}, where $i,j = 1,2,3, \ldots, m$

The information criteria suggests that the optimal number of regimes is $m = 2$. The regime classification by month shows high-mean high-volatile periods are from August 2011 to November 2011, September 2015 to February 2016 and August 2017 to February 2018. We also show the results of the same model applied with VIXY, UVXY, and SVXY ETFs in place of ETNs VXX, TVIX and XIV, respectively.

The estimated coefficients of long-run equation and the corresponding error correction terms are reported in Table 3 Panel A. The results show that regime 1 is classified as low-mean low-volatile, while regime 2 is classified as high-mean high-volatile. In particular, the volatility in regime 2 is about 25 times larger than regime 1 indicating that the market is unstable in regime 2. The error correction coefficients indicate that markets return to equilibrium more swiftly in the low-mean, low-volatility regime (regime 1) compared to the high-mean, high-volatility regime (regime 2).

Model specific coefficients in Table 3, Panel A demonstrate the time variation in causality with the volatility of volatility. The findings suggest that demand pressures for VIX ETPs and futures can change in different regimes. In particular, Ln(SPVXSTR) responds more sensitively to Ln(VXX) in regime 1 (the coefficient is 1.09) than in regime 2 (the coefficient is 0.71). VXX therefore tends to be more dominant in low volatility (of volatility) regimes, with VIX futures more sensitive to VXX in regime 1 than regime 2. Ln(XIV) exhibits a similar influence in the negative causal domain to Ln(TVIX) in regime. The impact of Ln(TVIX), however, intensifies in regime 2. This may be due to price effects from surges in hedging demand for leveraged products in the face of higher volatility.

The results for ETFs however do not vary materially between regimes 1 and 2. VIXY is consistently dominant in both high and low volatility regimes. Ln(SPVXSTR) responds with roughly the same sensitivity to Ln(VIXY) in regime 1 (the coefficient is 0.98) than in regime 2 (the coefficient is 0.97). Moreover, the coefficients of UVXY and SVXY are substantially lower than TVIX and XIV, respectively, in both regime 1 and 2.

In this section, we further investigate the reliability of the long-run relationships between variables. Comprehensive studies indicate that temporal aggregation and systematic sampling can alter the dynamics of relationships and compromise short-term causal analysis in low-frequency data (Geweke, 1982; Rajaguru, 2004; Rajaguru and Abeysinghe, 2008; Rajaguru *et al.*, 2018). Rajaguru and Abeysinghe (2008) demonstrated that long-term cointegrating relationships remain intact across all levels of aggregation and sampling intervals. Based on these findings, we use high-frequency data to establish long-term relationships through the Vector Error Correction Model (VECM). The causal relationships for all other combinations, standardized by cointegrating equations for each regime, are detailed in Table 3 Panel B. The reverse causality between Ln(SPVXSTR) and Ln(VXX) shows the opposite pattern. SPVXSTR is more dominant in regime 2 (the coefficient is 1.41) and less so in regime 1 (the coefficient is 0.91). Arguably the tail-wags the dog and SPVXSTR is more sensitive to VXX in regime 1 than 2. The causality between Ln(XIV) and Ln(VXX) is very different to that between Ln(XIV) and Ln(SPVXSTR), particularly in regime 1 (the coefficient is 1.02). The causality between Ln(TVIX) and Ln(XIV) also varies substantially between regimes, with coefficient 0.98 in regime 1 and 14.2 in regime 2.

The same is however not true of the corresponding ETFs, SVXY and VIXY, respectively. In fact, in almost all cases for ETFs the causality in regime 1 and 2 do not look notably

Table 3. Regime shifting model estimates

Panel A: Regime specific coefficients – cointegrating vector

	ETNs (29 November 2010 through 15 February 2018)		ETNs (3 October 2011 through 31 March 2018)		ETFs (3 October 2011 through 31 March 2018)		
	Regime 1	Regime 2	Regime 1	Regime 2		Regime 1	Regime 2
μ	7.658449	7.69224	7.40075	9.19638	μ	5.3876	5.486448
Ln(TVIX)	0.037468	0.10821	0.01060	0.25611	Ln(UVXY)	−0.00409	−0.00575
Ln(VXX)	1.087805	0.706911	1.01639	0.22492	Ln(VIXY)	0.97557	0.970747
Ln(XIV)	−0.03815	−0.00758	−0.00459	−0.0244	Ln(SVXY)	−0.00907	−0.0083
σ	0.003646	0.090202	0.01547	0.023741	σ	0.0038	0.04002
ECM (−1)	−0.12	−0.05	−0.13	−0.05	ECM (−1)	−0.18	−0.07

Panel B: Regime specific coefficients – cointegrating vector

ETNs (29 November 2010 through 15 February 2018)			ETFs (3 October 2011 through 31 March 2018)		
	Regime 1	Regime 2		Regime 1	Regime 2
Ln(TVIX) → Ln(SPVXSTR)	0.037468	0.10821	Ln(UVXY) → Ln(SPVXSTR)	−0.00409	−0.00575
Ln(VXX) → Ln(SPVXSTR)	1.087805	0.706911	Ln(VIXY) → Ln(SPVXSTR)	0.97557	0.970747
Ln(XIV) → Ln(SPVXSTR)	−0.03815	−0.00758	Ln(SVXY) → Ln(SPVXSTR)	−0.00907	−0.0083
Ln(SPVXSTR) → Ln(TVIX)	26.68944	9.24129	Ln(SPVXSTR) → Ln(UVXY)	−244.618	−173.822
Ln(VXX) → Ln(TVIX)	−29.0329	−6.53277	Ln(VIXY) → Ln(UVXY)	238.642	138.738
Ln(XIV) → Ln(TVIX)	1.018202	0.070049	Ln(SVXY) → Ln(UVXY)	−2.2182	−1.44289
Ln(SPVXSTR) → Ln(VXX)	0.919282	1.414605	Ln(SPVXSTR) → Ln(VIXY)	1.02504	1.03014
Ln(TVIX) → Ln(VXX)	−0.03444	−0.15307	Ln(UVXY) → Ln(VIXY)	0.00419	0.00593
Ln(XIV) → Ln(VXX)	0.03507	0.01072	Ln(SVXY) → Ln(VIXY)	0.0093	0.00855
Ln(SPVXSTR) → Ln(XIV)	−26.2123	−131.926	Ln(SPVXSTR) → Ln(SVXY)	−110.278	−120.467
Ln(TVIX) → Ln(XIV)	0.982123	14.27573	Ln(UVXY) → Ln(SVXY)	−0.450816	−0.693049
Ln(VXX) → Ln(XIV)	28.51389	93.26003	Ln(VIXY) → Ln(SVXY)	107.584	116.943

Note(s): Table shows Markov Switching VECM Model Estimates of the period. The ETN model is fitted over the period 29 November 2010 through 15 February 2018. The ETF model is fitted over the period 3 October 2011 through 31 March 2018. Regime 1: Low Mean Low Volatility; Regime 2: High Low Mean High Volatility. All estimates are statistically significant at the 1% level of significance. For the robustness, the ETN model is fitted over the period 3 October 2011 through 31 March 2018

Source(s): Authors' own work

different. It is possible that this clear difference between ETNs and ETFs could be due to the promissory note structure of ETNs.

This is an area for future research, and represents a significant gap in the existing literature. ETNs are structured, unsecured products that are issued as senior debt notes, while ETFs represent a stake in an underlying futures positions, providing investments into a fund that directly holds the assets it tracks. The difference in structure for ETNs could break the causal links with ETFs and the SPVXSTR in two ways. Firstly, ETN creation involves issuing new debt to create new units. Unlike ETFs, the creation of units is governed by capital requirements set by bank regulators. An extreme example of this was the pause in TVIX issuance in on February 21, 2012, demand exceeding supply of units and the market price reaching almost 90% above its underlying indicative value. Secondly, for ETNs there is no need for the issuer to strictly hold the assets as a separate pool, nor is there assurance that the issuers will not engage in proprietary trading or hedging activities which might be contrary to interests of note holders. These activities could well extend beyond exposures to VIX derivatives. As a result, an issuer of XIV, for example, need not strictly replicate/hedge -1x SPVXSTR, and their willingness to hedge versus take on balance sheet risk could fluctuate, and could depend on their broader positioning and volatility exposure.

The causal relations between ETFs and ETNs could therefore change in higher volatility regimes, where the ability to create new units is constrained by capital requirements or where tolerance for balance sheet risk of issuers changes.

4. Conclusion

This paper studies causal relations between VIX Short-Term Total Return Index (SPVXSTR) and 6 VIX ETPs, including 1x long ETF and ETN, -1x inverse ETF and ETN, and 2x leveraged ETF and ETN. With the strong growth in VIX futures markets we observe changing causal relations between VIX ETPs and Futures over time.

Cointegration tests reveal unique stable long-run equilibrium relations between VIX ETPs and Futures. Regime shifting models demonstrate the time variation in causation with the volatility of volatility, in particular highlighting different causal relations between ETFs versus ETNs, with causality more stable between high and low volatility regimes for ETFs. In our models, regime 1 is classified as low-mean low-volatile, while regime 2 is classified as high-mean high-volatile, with about 25 times larger volatility than regime 1. Markets return to equilibrium more swiftly regime 1 compared to 2.

We observe time variation in causality with the volatility of volatility. In particular, demand pressures for VIX ETNs and futures can change in different regimes. For example, SPVXSTR sensitive to VXX in regime 1 than regime 2, and XIV is substantially more sensitive to TVIX in regime 2 than 1. On the other hand, we observe very little variation in causality between regimes 1 and 2 for the corresponding ETFs.

It is possible that this clear difference between ETNs and ETFs could be due to the promissory note structure of ETNs which do not demand strict replication/hedging the issuer of TVIX and XIV need strictly hedge 2x and -1x SPVXSTR, respectively. This may be attributable to the stricter replication requirements under ETF structures. In the case of ETNs, market maker hedging risk tolerances may be allowed to vary in different market conditions. Thus, the associated price impact of replication could be varied in higher volatility regimes.

Notes

1. Retail shareholders have also potentially been “front-run” by market-makers, particularly in complex VIX ETP markets. Hill (2013) considers the viability of VIX-based hedging strategies including ETPs, futures and options relative to alternative hedging strategies. Alexander and

Korvilas (2013) discuss VIX ETNs as potentially a valuable source of diversification to non-speculative investors, while at the same time highlighting problems which might include front-running and investors retaining credit risk of issuers which are made more relevant in light of the recent collapse of XIV.

2. Bansal *et al.* (2015) demonstrates that equity volatility serves as a determinant of future Treasury term-structure volatility in terms of level and slope.
3. Information selection criteria are not tabulated here for the sake of brevity. Results are available upon request.

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