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The Dynamic Dependency between a Cryptocurrency ETF and ETFs Representing Conventional Asset Classes

Marcos Velazquez *, Alper Gormus and Nima Vafai

Department of Accounting, Finance, and Energy Business, College of Business, The University of Texas Permian Basin, Odessa, TX 79762, USA; gormus_a@utpb.edu (A.G.); vafai_n@utpb.edu (N.V.)
* Correspondence: velazquez_m@utpb.edu

Abstract: Using daily closing price observations between November 2017 and February 2023, this paper documents how the shocks of a cryptocurrency ETF resonate with ETFs representing traditional asset classes in terms of price and volatility. We find price transmission from the cryptocurrency ETF into the ETFs of several currencies, small-cap equities, and inflation. Risk propagation from the cryptocurrency ETF flows toward ETFs constituted of equities of various sizes, oil prices, high-yield corporate bonds, and inflation. There is scant evidence of transmission from ETFs with underlying conventional assets into the cryptocurrency ETF. The findings bear implications for low-cost risk management strategies.

Keywords: ETF; cryptocurrency; spillover; stock returns; volatility

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1. Introduction

Between September 2014 and April 2023, the price of Bitcoin has grown at a staggering annualized rate of 51%.[1] Yet, such growth has come at considerable peril. The corresponding standard deviation of monthly Bitcoin prices has grown by 45% per year over the same period. As such, Bitcoin and other competing cryptocurrencies have become an attractive, albeit unpredictable, venue for speculation. Thus, the increase in the value and risk associated with Bitcoin is only outpaced by the public's interest in the asset. Average monthly volume has concomitantly grown at an annualized rate of 76%. It would behoove a rational investor to hedge some of the risk associated with longing Bitcoin through diversification.

Exchange-traded funds (ETFs) have become one way to achieve a diversified portfolio (e.g., Huang and Lin 2011; Miralles-Quirós et al. 2019). It is edifying to contextualize the ETF environment since 2014. During the same span in which Bitcoin pricing data are available, the quintessential ETF, SPDR SPY 500, has increased at an annualized rate of 8% and 4% in value and volatility, respectively. The average monthly Sharpe ratio for SPY throughout the period has been 0.03, while that for Bitcoin has been 0.05.[2] Though more modest in its performance, the SPY and other ETFs afford low-cost exposure to a wide array of constituent assets, ranging from commodities, currencies, equities, debt, and traded macroeconomic factors.

This paper addresses the intersection of two of the most significant innovations in finance of the last three decades, ETFs and cryptocurrencies. We document the limitations of a risk-hedging strategy that combines a cryptocurrency ETF with the ETFs of several conventional asset classes, such as equities, bonds, commodities, etc. By finding evidence of price and volatility transmission originating from a cryptocurrency ETF, BITW,[3] this article highlights the shortcomings of an allocation strategy that, on its face, would seem consistent with the paradigm of portfolio diversification. Our findings suggest that there is considerable spillover from the cryptocurrency ETF into the pricing and volatility of ETFs that mimic small capitalization equities, as well as inflation. In addition, there is evidence of level transmission from BITW into ETFs that track key currencies in the global financial landscape: the euro, British pound, and yuan. Volatility passthrough occurring from BITW moves toward funds representing various types of equities by market capitalization, high-yield corporate bonds, and oil. The implication of such interconnections is that the presence of BITW and any of the funds mentioned above would lessen the diversification benefits within a portfolio.

Perhaps just as insightful is the absence of spillover evidence vis-à-vis the cryptocurrency ETF. As such, there is no indication that funds that replicate the performance of firms in the energy sector, precious metals, investment-grade bonds, or the yen correlate with the cryptocurrency fund in either its first or second moments. Unlike those funds with a dynamic conditional correlation relative to the cryptocurrency ETF, such venues would be congenial in an allocation strategy seeking mean-variance efficiency. Furthermore, there is minimal evidence that any of the ETFs representing conventional assets considered in this study convey any information toward BITW.

This study contributes to an already well-established literature on ETF spillover (e.g., Ben-David et al. 2018; Bhattacharya and O'Hara 2018). However, much of that literature explores transmission patterns between the fund and the assets that it reflects. Since ETFs are a conduit for low-cost diversification, this paper addresses a critical gap in the literature: spillover concerning complementary assets.

Another contribution is to the burgeoning field that studies cryptocurrency as an investment (e.g., Ghabri et al. 2022; Rehman and Apergis 2019). However, contributions in that area address the commonality between cryptocurrencies and other assets on an individual basis, such as in Corbet et al. (2018). While instructive, such analysis dismisses the interactions that arise in the scope of a portfolio, which we maintain is a more realistic scenario. That is because the performance of various cryptocurrencies is imperfectly correlated (Zieba et al. 2019; Mensi et al. 2020). In addition, this study reveals the intricacies of the dynamic correlation between cryptocurrencies and conventional asset classes. Even though some of the results herein substantiate the view of Bitcoin as an unsound diversifying agent (e.g., Klein et al. 2018), we find that such is not the case across all conventional asset classes. Moreover, we build upon contributions such as Kurka's (2019) by considering a basket of digital currencies rather than just Bitcoin.

The remainder of this paper is organized as follows. Section 2 provides an overview of the relevant literature. Section 3 describes the data and methods employed in this study. Section 4 presents the results of the analysis. Section 5 discusses the implications of the findings.

2. Related Literature

We classify the pertinent literature into two main strands. First, we delve into the diversification effects of cryptocurrencies in investment portfolios and explore the associated risks of cryptocurrency investments. Second, we present a comprehensive summary of the spillover effects of volatility in cryptocurrency markets, as discussed in the literature. This organizational approach aims to offer a more coherent and structured overview of the subject matter.

2.1. Diversification Effects for Cryptocurrencies in Investment Portfolios

In studying how cryptocurrencies respond to regulation, Shanaev et al. (2020) describe some of the motivations for holding such assets, including the substitution of the money supply, the decentralized enforcement of property rights, tender for illicit activities, and for investment purposes. Cryptocurrencies could serve as alternative investment vehicles to achieve diversification. Indeed, Andrianto and Diputra (2017) note how the inclusion of cryptocurrency into a well-diversified portfolio reduces risk. Shahzad et al. (2019) propose that Bitcoin is, at worst, a weak safe-haven asset relative to equity. Similarly, Anyfantaki et al. (2018) note that the addition of cryptocurrency assets to a more traditional portfolio is beneficial to investors. Corbet et al. (2018) highlight the value of major cryptocurrencies in diversifying one's portfolio, given evidence of limited spillover toward gold, equity, and bond prices.

However, cryptocurrencies are not entirely isolated from other assets. In that sense, exploring the linkages between such alternative investments and more traditional classes is critical. As more investors avail themselves of digital currencies either for speculation or hedging, channels of interdependency arise. For example, Dai et al. (2023) observe that crash risk in eight major cryptocurrencies is linked to ensuring equity crash risk in the form of conditional skewness. Moreover, the crash risk engendered by cryptocurrencies is more relevant than economic policy uncertainty in predicting skewness in equities. Nevertheless, the effect is directional, or at least asymmetrical, as digital currencies are more likely to be transmitters of crashes, and equities are prone to receiving shocks.

Nearly all the existing literature explores the connections between cryptocurrencies and traditional investments from the perspective of a single digital asset or individual holding. However, there is a need to consider exposure to cryptocurrencies from the perspective of a diversified portfolio because of the complexities in the co-movements of single digital currencies discussed above. Zieba et al. (2019) posit that there are benefits to holding multiple digital assets since the price of Bitcoin does not affect and is not affected by the prices of other cryptocurrencies. Mensi et al. (2020) unveil a complex layout of interdependencies resulting in varying portfolio allocations among cryptocurrencies. Moreover, such allocations are contingent upon the economic cycle. Naeem et al. (2022) document how the interconnectedness in volatility between cryptocurrencies changed during the pandemic. Said contribution makes a case for diversification opportunities within the digital currency space made possible by the instability in volatility co-movements. Therefore, examining interdependencies between cryptocurrencies and traditional holdings is not only a sensible measure for risk-averse investors but also warranted, as the topic has been neglected by scholars up to this point.

2.2. Spillover Effects of Volatility

If transmission between cryptocurrencies in aggregate and mainstream assets is to be analyzed, exchange-traded funds (ETFs) provide an ideal vehicle for study. There is already an expansive literature that addresses spillovers related to ETFs. For example, Ben-David et al. (2018) describe how stocks with higher ETF ownership are more volatile and have a more substantial negative autocorrelation in prices. The authors' analysis provides a premise by which to study how ETFs can have spillovers into underlying markets. As demand conditions cause the market price of ETF shares to fluctuate, arbitrage opportunities arise with respect to the fund's constituents. While such a situation is not unique to ETFs, those funds distinguish themselves from alternatives such as mutual funds or futures contracts in that they are continuously traded at low cost. Ben-David et al. (2018) go on to show that shocks from ETFs are nonfundamental in nature, given the reversion in prices for underlying assets. Bhattacharya and O'Hara (2018) document how the same arbitrage channel depicted in Ben-David et al. induces herding behavior, resulting in diminished informational efficiency. Furthermore, Clifford et al. (2014) show that flows into ETFs bear the same motivation as in mutual funds—that is, the search for yield. The lack of evidence on the part of successful market timing associated with ETF flows is additional evidence of not only the plausibility for spillovers (fundamental and otherwise) but also their magnitude. Ghabri et al. (2022) conduct a similar analysis upon oil indices, observing that oil prices predict Bitcoin, while the latter's futures foreshadow fuel indices. However, the directional effects changed and even weakened during the COVID-19 pandemic. The authors note that a dependency between cryptocurrency spots, as well as futures and energy prices, is structural in nature because of the way in which blockchain technology operates. Rehman and Apergis (2019) undertake the same analysis for commodity futures, thereby detecting information spillovers in level and volatility.

Liebi (2020) compiles a literature review of how ETFs interact with other financial markets. Notably, there is evidence of a reciprocal improvement in the liquidity of the fund and its underlying assets, which in turn aids price discovery. However, the liquidity benefit disappears during downturns. Also, when ETFs prognosticate prices, informed traders extract wealth from noise traders. Such a dynamic speaks to the fundamental nature, or lack thereof, of shocks originating in ETFs, particularly in their primary markets. Liebi highlights contributions that imply that nonfundamental shocks, price discovery, and liquidity trading drive volatility in underlying assets. The arbitrage channel described by Ben-David et al. (2018) prompts co-movement with underlying assets, which is exacerbated in high-turnover funds.

For all the attention placed on the ramifications of ETFs in terms of price and volatility transmission, there is a surprising dearth of consideration paid by scholars to assets that are not mimicked by the fund. Such a posture considers only the speculative impetus for trading ETFs while ignoring investors' perpetual need for diversification. Furthermore, no other work has explored how cryptocurrency ETFs, a relatively new class of funds, can project their shocks into complementary assets, such as commodities, currencies, equities, bonds, and traded macroeconomic factors. The closest contribution to our own is that of Pavlova (2021), who studies how the blockchain ETF correlates with the NASDAQ. This paper fills a critical void in the literature as it measures how cryptocurrencies interact with traditional investment vehicles from the viewpoint of a risk-averse investor who values (frictionless) hedging. To that end, we analyze the dynamics of a cryptocurrency ETF in terms of its co-movement with several ETFs representing various asset categories.

3. Data and Methods

3.1. Data

This study uses available daily price observations of 16 different time-series categories spanning from November 2017 to February 2023. Data are collected from the Morningstar database and include the following ETFs:

BITW—Cryptocurrency ETF
XLE-Energy ETF
DBP-Precious Mtl ETF
EROTF—EUR/USD EX ETF
GBBEF—GBP/USD EX ETF
JYNFF-JPY/USD EX ETF
CYB—Yuan/USD EX ETF
IVV—iShares SP500 Index ETF
IMCB—iShares Mid-Cap ETF
ISCB iShares Small-Cap ETF
IAU—iShares Gold ETF
OIL—iPath Crude Oil ETF
USHY—iShares High Yield Corp Bond ETF
LQD—iShares Invmt Grade Corp Bond ETF
JCPI—JPMorgan Inflation Managed
RINF—Proshares Inflation Expectation
BLCRB—Bloomberg Galaxy Crypto Basket

Our research utilizes newly created price, volatility, and transmission models. Such models offer reliable findings concerning time-series interactions, derived from level and variance assessments. Additionally, the type of model used in this study also accounts for both sudden and slow, or "smooth", structural breaks. The presence of structural breaks can profoundly influence the reliability of empirical findings, particularly when employed to examine shocks to other variables.

3.2. Testing for Price Transmission with Permanent Shifts

Detecting price transmission fundamentally involves the use of the past prices of a variable to forecast its future prices. Tests of price transmission focus more on the interaction of levels rather than the volatility of observations. This research applies the price transmission model developed by Nazlioglu et al. (2016, 2019, 2020) and Gormus et al. (2018). The model employed herein is an enhanced version of VAR, incorporating a Fourier approximation that draws upon Gallant's flexible Fourier form (Gallant 1981).

In dealing with financial time-series data, researchers often encounter challenges like structural breaks. Such enduring shocks, identifiable or not, can adversely affect statistical outcomes, leading to erroneous deductions (Ventosa-Santaulària and Vera-Valdés 2008; Enders and Jones 2016). The current literature suggests the use of dummy variables to manage structural breaks. However, said approach assumes that structural breaks are sudden processes (e.g., Perron 1989; Zivot and Andrews 1992; Lee and Strazicich 2003). Yet, a considerable proportion of structural alterations are gradual or "smooth".

Nazlioglu et al. (2016) have incorporated the Fourier approximation into the price transmission model initially proposed by Toda and Yamamoto (1995). The model portrays structural changes as slow processes, without needing prior awareness of the form or number of breaks. Nazlioglu et al. (2016) named such a model the "Fourier-TY" price transmission model. Contrary to the assumption that intercept terms remain constant over time, the Fourier-TY approach constructs a VAR $(p+d)$ model as:

$$\gamma(\mathrm{t}) \cong \gamma_0 + \sum_{k=1}^{n} \gamma_{1k} sin\left(\frac{2\pi kt}{T}\right) + \sum_{k=1}^{n} \gamma_{2k} cos\left(\frac{2\pi kt}{T}\right) \tag{1}$$

In the model, the intercept terms, represented by $\gamma(\mathrm{t})$, account for any structural changes in $y(t)$ and are time-dependent functions. The Fourier approximation is employed to capture structural shifts, which can be a gradual process without any restrictions on the form or number. The approximation can be defined as follows:

$$y_t = \gamma_0 + \sum_{k=1}^{n} \gamma_{1k} sin\left(\frac{2\pi kt}{T}\right) + \sum_{k=1}^{n} \gamma_{2k} cos\left(\frac{2\pi kt}{T}\right) + \Pi_1 y_{t-1} + \cdots + \Pi_{p+d} y_{t-(p+d)} + u_t \tag{2}$$

The null hypothesis in the TY framework, suggesting that there is no price transmission, relies on zero restrictions placed on the p variables ($H_0: \Pi_1 = \cdots = \Pi_p = 0$). The Wald statistic employs the chi-square distribution, with p being the degrees of freedom. To ascertain the best lags for the TY test, as well as the most suitable Fourier frequency in the Fourier TY method, we confine the frequency up to 3 and the lags up to 5. We utilize the Akaike information criterion to pinpoint the optimal frequency and lags. It is important to note that the frequency and lags are not static. The model automatically chooses the optimum frequency and lags.

3.3. Testing for Volatility Transmission with Permanent Shifts

We further evaluate the volatility interactions amongst our datasets by employing a revised version of the Lagrange multiplier (LM) volatility transmission test, developed by Hafner and Herwartz (2006) (referred to as HH). HH constructs a GARCH (1,1) model for the i, j series and subsequently defines:

$$\varepsilon_{it} = \xi_{it}\sqrt{\sigma_{it}^2\left(1 + z_{jt}'\pi\right)},\ z_{jt} = \left(\varepsilon_{jt-1}^2, \sigma_{jt-1}^2\right)' \tag{3}$$

where ξ_{it} are the standardized residuals of series i. ε_{jt}^2 and σ_{jt}^2 are squared disturbance terms and volatility for series j, respectively. The null hypothesis of no volatility transmission ($H_0: \pi = 0$) is tested against the alternative hypothesis of volatility transmission $H_a: \pi \neq 0$). The Lagrange multiplier (LM) component is defined as:

$$\lambda_{LM} = \frac{1}{4T}\left(\sum_{t=1}^{T}\left(\xi_{it}^2 - 1\right)z_{jt}'\right)V(\theta_i)^{-1}\left(\sum_{t=1}^{T}\left(\xi_{it}^2 - 1\right)z_{jt}\right) \tag{4}$$

where

$$V(\theta_i) = \frac{\kappa}{4T}\left(\sum_{t=1}^{T} z_{jt}z'_{jt} - \sum_{t=1}^{T} z_{jt}x'_{it}\left(\sum_{t=1}^{T} x_{it}x'_{it}\right)^{-1}\sum_{t=1}^{T} x_{it}z'_{jt}\right),\ \kappa = \frac{1}{T}\sum_{t=1}^{T}\left(\xi_{it}^2 - 1\right)^2. \quad (5)$$

The issue of structural breaks, earlier identified in price transmission models, persists even in volatility models. The conditional variance of a GARCH model does not account for any structural alterations in its volatility process. Therefore, there is a critical concern when it comes to traditional GARCH models since series affected by structural breaks (whether sudden or gradual) might lead to inaccurate deductions within that framework.

Li and Enders (2018) illustrate how the Fourier approximation can be deployed to manage structural breaks when examining volatility transmission test results. The authors outline the model as follows:

$$\sigma_{it}^2 = \omega_{0i} + \sum_{k=1}^{n}\omega_{1i,k} sin\left(\frac{2\pi k_i t}{T}\right) + \sum_{k=1}^{n}\omega_{2i,k} cos\left(\frac{2\pi k_i t}{T}\right) + \alpha_i\varepsilon_{it-1}^2 + \beta_i\sigma_{it-1}^2. \quad (6)$$

The test statistic in Equation (6) is referred to as Fourier λ_{FM} ($F\lambda_{LM}$). The use of the Fourier approximation does not alter the number of misspecification indicators in z_{jt}, $F\lambda_{LM}$, and thus adheres to an asymptotic chi-square distribution with two degrees of freedom.

4. Results

Tables 1 and 2 provide descriptive statistics and correlations for the time series of ETF prices used in this study. Our tests start with price transmission effects between the cryptocurrency ETF and other markets. It is important to note that such tests strictly look at the ETF category, where asset dynamics can be different from other tradable and nontradable categories. As previously mentioned, price transmission analysis does not convey correlation. The null hypothesis is that the historical prices of one asset cannot predict the future prices of another asset. In this light, rejecting the null hypothesis would indicate a price transmission.

Table 1. Descriptive Statistics.

Series	BITW	BLCRB	XLE	DBP	EROTF	GBBEF	JYNFF	CYB	**IVV**
Mean	20.1280	1084.9100	98.3037	46.3631	41.0477	34.0584	48.8722	29.9366	506.1291
Median	12.6650	771.0100	94.7724	46.8912	41.3227	34.2511	50.3984	29.7475	479.5449
Maximum	68.9529	3870.4180	169.8396	61.3251	46.4527	37.8222	54.2709	32.9806	718.5916
Minimum	3.4900	197.5900	37.3415	35.1676	33.6186	27.5976	35.5649	27.5792	326.1693
Std. Dev.	16.1297	881.7735	28.4409	6.6349	2.6351	1.8942	4.4087	1.5587	109.6747
Skewness	1.1127	1.1597	0.5249	−0.0783	−0.5968	−0.5215	−1.5201	0.3109	0.2812
Kurtosis	3.0105	3.2516	3.0130	1.6936	3.1156	3.0703	4.1193	1.7287	1.6001
Series	IMCB	ISCB	IAU	OIL	USHY	LQD	JCPI	RINF	**VEU**
Mean	67.8241	56.3531	30.6526	20.4434	45.8862	264.8395	60.0997	33.1266	53.5136
Median	63.7275	54.0521	32.4600	18.8798	45.6067	263.9428	59.9656	32.1462	52.4500
Maximum	92.3580	75.8524	39.4600	39.3657	51.9213	303.4092	66.0969	43.0645	65.2800
Minimum	39.9493	32.2135	22.6005	7.1860	36.9505	227.3404	54.4827	24.1844	35.8600
Std. Dev.	12.3117	8.6193	4.6713	6.6719	3.3911	24.9649	3.3905	3.7093	5.5968
Skewness	0.3006	0.3062	−0.2809	0.6880	0.1329	0.0533	0.0839	0.6251	0.1826
Kurtosis	1.7078	2.4092	1.5684	2.8492	1.9197	1.5099	1.6363	2.5309	2.6475

Notes: BITW—Crypto ETF, BLCRB—Bloomberg Crypto Basket, XLE—Energy ETF, DBP—Precious metals ETF, EROTF—euro–U.S. dollar exchange ETF, GBBEF—British pound–U.S. dollar exchange ETF, JYNFF—yen–U.S. dollar exchange ETF, CYB—yuan–U.S. dollar exchange ETF, IVV—iShares SP500 Index ETF, IMCB—iShares Mid-Cap ETF, ISCB—iShares Small-Cap ETF, IAU—iShares Gold ETF, OIL—iPath Crude Oil ETF, USHY—iShares High Yield Corp Bond ETF, LQD—iShares Investment Grade Corp Bond ETF, JCPI—JPMorgan Inflation Managed, RINF—Proshares Inflation Expectation and VEU—Vanguard All World EX-US ETF.

Table 2. Correlations Between Series.

Series	BITW	BLCRB	XLE	DBP	EROTF	GBBEF	JYNFF	CYB	IVV
BITW	1	0.989744	0.139827	0.593641	0.027132	0.384356	−0.16973	0.849088	0.83062
BLCRB	0.989744	1	0.163913	0.547991	0.055944	0.410686	−0.17038	0.845213	0.8072
XLE	0.139827	0.163913	1	−0.08716	−0.56651	−0.39399	−0.85094	0.293981	0.32917
DBP	0.593641	0.547991	−0.08716	1	−0.14891	0.079514	−0.14437	0.699037	0.779742
EROTF	0.027132	0.055944	−0.56651	−0.14891	1	0.865319	0.824849	−0.08367	−0.36346
GBBEF	0.384356	0.410686	−0.39399	0.079514	0.865319	1	0.649006	0.292958	0.024121
JYNFF	−0.16973	−0.170382	−0.85094	−0.14437	0.824849	0.649006	1	−0.32546	−0.47745
CYB	0.849088	0.845213	0.293981	0.699037	−0.08367	0.292958	−0.32546	1	0.878741
IVV	0.83062	0.8072	0.32917	0.779742	−0.36346	0.024121	−0.47745	0.878741	1
IMCB	0.861055	0.84202	0.359677	0.721116	−0.28325	0.116921	−0.43864	0.886318	0.984275
ISCB	0.882781	0.873829	0.30903	0.544224	−0.04313	0.348524	−0.26323	0.825309	0.865875
IAU	0.567898	0.52063	−0.00445	0.983436	−0.30322	−0.06205	−0.26644	0.694582	0.808318
OIL	0.370214	0.382832	0.914162	0.151384	−0.59295	−0.3207	−0.85749	0.532936	0.568098
USHY	0.810241	0.773939	0.033443	0.797545	−0.11629	0.245584	−0.13722	0.791961	0.911696
LQD	0.550955	0.50198	−0.50054	0.800785	0.113693	0.311127	0.296616	0.478313	0.600246
JCPI	0.808031	0.770426	0.094468	0.872324	−0.27236	0.086845	−0.29058	0.838288	0.95609
RINF	0.519135	0.52589	0.84211	0.32389	−0.55761	−0.26467	−0.86183	0.659822	0.71557
VEU	0.808269	0.816519	0.022919	0.459128	0.415093	0.725315	0.139355	0.737848	0.630601

	IMCB	ISCB	IAU	OIL	USHY	LQD	JCPI	RINF	VEU
BITW	0.861055	0.882781	0.567898	0.370214	0.810241	0.550955	0.808031	0.519135	0.808269
BLCRB	0.84202	0.873829	0.52063	0.382832	0.773939	0.50198	0.770426	0.52589	0.816519
XLE	0.359677	0.30903	−0.00445	0.914162	0.033443	−0.50054	0.094468	0.84211	0.022919
DBP	0.721116	0.544224	0.983436	0.151384	0.797545	0.800785	0.872324	0.32389	0.459128
EROTF	−0.28325	−0.043133	−0.30322	−0.59295	−0.11629	0.113693	−0.27236	−0.55761	0.415093
GBBEF	0.116921	0.348524	−0.06205	−0.3207	0.245584	0.311127	0.086845	−0.26467	0.725315
JYNFF	−0.43864	−0.263232	−0.26644	−0.85749	−0.13722	0.296616	−0.29058	−0.86183	0.139355
CYB	0.886318	0.825309	0.694582	0.532936	0.791961	0.478313	0.838288	0.659822	0.737848
IVV	0.984275	0.865875	0.808318	0.568098	0.911696	0.600246	0.95609	0.71557	0.630601
IMCB	1	0.933629	0.734581	0.578579	0.924059	0.571384	0.926918	0.72103	0.723249
ISCB	0.933629	1	0.517638	0.494363	0.872934	0.49901	0.798703	0.628703	0.869016
IAU	0.734581	0.517638	1	0.232219	0.779126	0.757111	0.884601	0.391793	0.366339
OIL	0.578579	0.494363	0.232219	1	0.282281	−0.25509	0.38459	0.929653	0.188336
USHY	0.924059	0.872934	0.779126	0.282281	1	0.811574	0.946948	0.439004	0.748322
LQD	0.571384	0.49901	0.757111	−0.25509	0.811574	1	0.774142	−0.09924	0.532931
JCPI	0.926918	0.798703	0.884601	0.38459	0.946948	0.774142	1	0.532028	0.620271
RINF	0.72103	0.628703	0.391793	0.929653	0.439004	−0.09924	0.532028	1	0.304877
VEU	0.723249	0.869016	0.366339	0.188336	0.748322	0.532931	0.620271	0.304877	1

Notes: BITW—Crypto ETF, BLCRB—Bloomberg Crypto Basket, XLE—Energy ETF, DBP—Precious metals ETF, EROTF—euro–U.S. dollar exchange ETF, GBBEF—British pound–U.S. dollar exchange ETF, JYNFF—yen–U.S. dollar exchange ETF, CYB—yuan–U.S. dollar exchange ETF, IVV—iShares SP500 Index ETF, IMCB—iShares Mid-Cap ETF, ISCB iShares Small-Cap ETF, IAU—iShares Gold ETF, OIL—iPath Crude Oil ETF, USHY—iShares High Yield Corp Bond ETF, LQD—iShares Investment Grade Corp Bond ETF, JCPI—JPMorgan Inflation Managed, RINF—Proshares Inflation Expectation and VEU—Vanguard All World EX-US ETF.

When we look at the price transmission going from the cryptocurrency ETF to other ETFs (Table 3), we see that cryptocurrency market prices have strong potential to predict the price fluctuations of several ETFs. For example, there is evidence that the ETFs corresponding to certain currencies, such as the euro (χ^2 = 5.69, p = 0.02), the British pound (χ^2 = 11.83, p = 0.00), and the yuan (χ^2 = 7.12, p = 0.01), are associated with the movements of the BITW. Similarly, the prices of the small capitalization equity ETF, ISCB, are predetermined by the cryptocurrency ETF (χ^2 = 6.56, p = 0.04). Lastly, an ETF tracking inflation-hedged assets (i.e., RINF) is influenced by BITW (χ^2 = 7.05, p = 0.01). When we look at the reverse direction (price transmission to the cryptocurrency market), we do not find the same results. The only interaction that is observed is the ETF for small-cap stocks having a weak predictive power over the cryptocurrency market (χ^2 = 4.67, p = 0.10).

Table 3. Level (Price) Transmission Between the Cryptocurrency ETF and Other ETFs.

Series	From BITW	*p*-Value	To BITW	*p*-Value
XLE	0.5537	0.4568	0.6035	0.4372
DBP	0.4405	0.5069	0.0043	0.9477
EROTF	5.6909	0.0171	0.0324	0.8572
GBBEF	11.8293	0.0006	1.2365	0.2662
JYNFF	0.1045	0.7465	1.8395	0.1750
CYB	7.1155	0.0076	0.6157	0.4327
IVV	1.0159	0.3135	0.1129	0.7369
IMCB	0.4334	0.5103	0.1284	0.7201
ISCB	6.5586	0.0377	4.6701	0.0968
IAU	0.0028	0.9581	0.0008	0.9781
OIL	2.8416	0.0919	0.4400	0.5071
USHY	0.6638	0.7176	0.7801	0.6770
LQD	0.2230	0.6368	0.0071	0.9330
JCPI	3.4179	0.0645	0.3266	0.5677
RINF	7.0514	0.0079	2.1693	0.1408
VEU	2.6395	0.1042	0.1073	0.7432

Notes: Price transmission is calculated using the Fourier TY approach with one Fourier frequency which is based on Equation (3). Maximum p is set to 5, and optimal p is determined by Akaike information criterion. p-values are calculated based on the bootstrap distribution with 1000 replications following Gormus et al. (2018). VAR(p + d) models are estimated with d equal to 1. Bivariate VAR models include the BITW—Crypto ETF, XLE—Energy ETF, DBP—Precious metals ETF, EROTF—euro–U.S. dollar exchange ETF, GBBEF—British pound–U.S. dollar exchange ETF, JYNFF—yen–U.S. dollar exchange ETF, CYB—yuan–U.S. dollar exchange ETF, IVV—iShares SP500 Index ETF, IMCB—iShares Mid-Cap ETF, ISCB iShares Small-Cap ETF, IAU—iShares Gold ETF, OIL—iPath Crude Oil ETF, USHY—iShares High Yield Corp Bond ETF, LQD—iShares Investment Grade Corp Bond ETF, JCPI—JPMorgan Inflation Managed, RINF—Proshares Inflation Expectation and VEU—Vanguard All World EX-US ETF. The test statistics shown are chi squares.

Such findings can be interpreted in a couple of ways. First, the cryptocurrency markets' ability to predict exchange rates and inflation-hedged assets shows crypto investors do pay close attention to the price movements of the cryptocurrency ETF. In other words, crypto investors move capital from cryptocurrencies toward foreign currency and inflation-hedged assets when they see triggers in the crypto market. However, general foreign exchange and inflation-based investors do not regard alternative assets as an interactable market. Therefore, traders do not move capital into cryptocurrencies regardless of the market movements in foreign currency and inflation-hedged assets. The transmission from the cryptocurrency ETF into that of small-capitalization stocks can be interpreted as investor's underlying preference for holding riskier assets with greater information asymmetries. Fang et al. (2020) comment on the intractability of cryptocurrency returns and how the prices of five major cryptocurrencies are more responsive to investor perceptions than to economic fundamentals. Regardless, the result does not necessarily imply that investors keep their capital in those markets that are characterized by more conventional assets. However, when capital is relocated, our results do not indicate a move toward cryptocurrencies. The mild interaction with the small-cap companies insinuates that some investors who trade in riskier companies could move some capital to crypto, denoting a preference for a risky asset profile.

Following our price transmission tests, we move on to the analysis of volatility transmission. Like price transmission, volatility transmission tests whether the historical characteristics of one asset can predict the future characteristics of another asset. However, the dimension that is predicted here is volatility. In other words, the null hypothesis is that the historical riskiness of one asset cannot predict the future riskiness of another asset. The rejection of this hypothesis suggests a volatility transmission (or spillover).

As Table 4 shows, the cryptocurrency ETF interacts with a larger variety of asset groups from the volatility perspective compared to the level spillover effects depicted in Table 3. For instance, there is volatility transmission to large (χ^2 = 6.20, p = 0.05), medium (χ^2 = 7.81, p = 0.02), and small capitalization ETFs. Also, the volatility of the ETF representing high-yield corporate debt, USHY, is forecast by BITW (χ^2 = 6.56, p = 0.04). Additionally, there is risk spillover from the cryptocurrency ETF into the crude oil ETF (χ^2 = 10.07, p = 0.01). In a result that is reminiscent to the level transmission toward inflation-hedging funds, we find that volatility of BITW forecasts the volatilities of funds that mimic inflation, JCPI (χ^2 = 9.68, p = 0.01) and RINF (χ^2 = 15.99, p = 0.00). In other words, the volatility of the cryptocurrency market provides some predictive power over the volatilities of a wide array of asset groups. Interestingly, the predictive power over the foreign exchange market regarding prices is not observed from the volatility perspective. The result suggests that while there is a directional price interaction, the historically strong price fluctuations in cryptocurrencies do not necessarily predict similar processes in exchange rates. We fail to find any evidence of volatility spillover from any of the ETFs representing conventional asset classes toward BITW.

Table 4. Volatility Transmission Between the Cryptocurrency ETF and Other ETFs.

Series	From BITW	*p*-Value	To BITW	*p*-Value
XLE	5.1499	0.0762	1.3893	0.4992
DBP	1.8460	0.3973	0.0409	0.9798
EROTF	0.4201	0.8105	2.1272	0.3452
BDDEF	2.7900	0.2478	2.4140	0.2991
JYNFF	2.0547	0.3580	1.4759	0.4781
CYB	1.2339	0.5396	0.7364	0.6920
IVV	6.1972	0.0451	0.5364	0.7648
IMCB	7.8131	0.0201	0.4532	0.7973
ISCB	7.8819	0.0194	1.2669	0.5308
IAU	2.8794	0.2370	0.1527	0.9265
OIL	10.0683	0.0065	2.1994	0.3330
USHY	6.5552	0.0377	0.6401	0.7261
LQD	5.8929	0.0525	2.2091	0.3314
JCPI	9.6814	0.0079	0.4635	0.7931
RINF	15.9859	0.0003	1.1277	0.5690
VEU	9.1561	0.0103	0.3578	0.8362

Notes: The volatility transmission Fourier LM test is based on the variance Equation (6) with one Fourier frequency. Test variables include the BITW—Crypto ETF, XLE-Energy ETF, DBP—Precious metals ETF, EROTF—euro–U.S. dollar exchange ETF, GBBEF—British pound–U.S. dollar exchange ETF, JYNFF—yen–U.S. dollar exchange ETF, CYB—yuan–U.S. dollar exchange ETF, IVV—iShares SP500 Index ETF, IMCB—iShares Mid-Cap ETF, ISCB iShares Small-Cap ETF, IAU—iShares Gold ETF, OIL—iPath Crude Oil ETF, USHY—iShares High Yield Corp Bond ETF, LQD—iShares Investment Grade Corp Bond ETF, JCPI—JPMorgan Inflation Managed, RINF—Proshares Inflation Expectation and VEU—Vanguard All World EX-US ETF. The test statistics shown are chi-squares.

Table 4 reveals an asymmetric pattern in the transmission of risk between cryptocurrency markets and all the types of assets addressed in this study. While spillover occurs from the cryptocurrency ETF to the ETFs representing equities, oil, risky debt, and inflation hedging, there is no transmission in the opposite direction. Therefore, one may view risk in the cryptocurrency market as a prelude to risk in stocks, high-yield bonds, energy, and macroeconomic conditions. The implications of such a result are thought provoking. Does volatility in cryptocurrencies cause volatility in such types of investments? Or is the co-movement in volatilities a reflection of a common underlying risk factor? While the answer to those questions is beyond the scope of this paper, we posit that any potential solutions should not only conform with economic theory but also account for the asymmetric nature in the transmission of risk.

In addition to analyzing the interactions between the cryptocurrency ETF and other ETFs, we have analyzed the price and volatility transmission using a cryptocurrency basket. The idea here is to see whether there are differences between the ETF and raw cryptocurrencies in terms of how they interact with ETFs. Referencing our correlation table (Table 2), it is clear that the two variables are highly correlated. As Tables 5 and 6 show, our results are mostly similar, with a few exceptions. Particularly, from a price-transmission perspective (Table 5), we have found evidence of transmission from the basket to mid-cap ETFs (χ^2 = 5.85, p = 0.05), while the transmission to oil disappeared (χ^2 =1.85, p = 0.17).

Such results could indicate that ETF investors are more aligned with diversification into oil (therefore causing the price interaction through trade), where sole crypto investors are not.

Table 5. Level (Price) Transmission Between a Cryptocurrency Basket and ETFs.

Series	From BLCRB	*p*-Value	To BLCRB	*p*-Value
XLE	0.3558	0.5508	1.2391	0.2656
DBP	1.8355	0.1755	0.0357	0.8502
EROTF	11.8177	0.0006	0.2599	0.6102
GBBEF	19.6085	0.0000	0.2887	0.5911
JYNFF	1.7295	0.1885	0.9977	0.3179
CYB	8.2167	0.0042	1.3497	0.2453
IVV	0.1867	0.6657	0.2224	0.6372
IMCB	5.8516	0.0536	3.6674	0.1598
ISCB	8.4038	0.0150	4.8245	0.0896
IAU	0.0182	0.8928	0.0794	0.7782
OIL	1.8470	0.1741	0.9885	0.3201
USHY	0.3868	0.8242	0.2002	0.9047
LQD	1.1034	0.2935	0.0105	0.9185
JCPI	3.7222	0.0537	0.3861	0.5344
RINF	4.0533	0.0441	2.8509	0.0913
VEU	2.2897	0.1302	0.0067	0.9347

Notes: Price transmission is calculated using the Fourier TY approach with one Fourier frequency which is based on Equation (3). Maximum p is set to 5, and optimal p is determined by Akaike information criterion. *p*-values are calculated based on the bootstrap distribution with 1000 replications following Gormus et al. (2018). VAR(p + d) models are estimated with d equal to 1. Bivariate VAR models include the BLCRB—Bloomberg Crypto Basket, XLE—Energy ETF, DBP—Precious metals ETF, EROTF—euro–U.S. dollar exchange ETF, GBBEF—British pound–U.S. dollar exchange ETF, JYNFF—yen–U.S. dollar exchange ETF, CYB—yuan–U.S. dollar exchange ETF, IVV—iShares SP500 Index ETF, IMCB—iShares Mid-Cap ETF, ISCB iShares Small-Cap ETF, IAU—iShares Gold ETF, OIL—iPath Crude Oil ETF, USHY—iShares High Yield Corp Bond ETF, LQD—iShares Investment Grade Corp Bond ETF, JCPI—JPMorgan Inflation Managed, RINF—Proshares Inflation Expectation and VEU—Vanguard All World EX-US ETF. The test statistics shown are chi squares.

Table 6. Volatility Transmission Between a Cryptocurrency Basket and ETFs.

Series	From BLCRB	*p*-Value	To BLCRB	*p*-Value
XLE	9.6475	0.0080	3.1055	0.2117
DBP	3.1039	0.2118	1.3587	0.5070
EROTF	1.2319	0.5401	3.5576	0.1688
BDDEF	3.1444	0.2076	3.5767	0.1672
JYNFF	1.5029	0.4717	1.9975	0.3683
CYB	0.9191	0.6316	1.3456	0.5103
IVV	5.6556	0.0591	1.2711	0.5296
IMCB	6.7906	0.0335	0.9827	0.6118
ISCB	6.8669	0.0323	1.5078	0.4705
IAU	3.0137	0.2216	1.1916	0.5511
OIL	11.4208	0.0033	2.6339	0.2680
USHY	8.2356	0.0163	1.3400	0.5117
LQD	4.2047	0.1222	2.0444	0.3598
JCPI	7.2691	0.0264	1.6605	0.4359
RINF	16.3950	0.0003	1.3666	0.5050
VEU	8.7270	0.0127	0.9453	0.6233

Notes: The volatility transmission Fourier LM test is based on the variance Equation (6) with one Fourier frequency. Test variables include the BLCRB—Bloomberg Crypto Basket, XLE-Energy ETF, DBP—Precious metals ETF, EROTF—euro–U.S. dollar exchange ETF, GBBEF—British pound–U.S. dollar exchange ETF, JYNFF—yen–U.S. dollar exchange ETF, CYB—yuan–U.S. dollar exchange ETF, IVV—iShares SP500 Index ETF, IMCB—iShares Mid-Cap ETF, ISCB iShares Small-Cap ETF, IAU—iShares Gold ETF, OIL—iPath Crude Oil ETF, USHY—iShares High Yield Corp Bond ETF, LQD—iShares Investment Grade Corp Bond ETF, JCPI—JPMorgan Inflation Managed, RINF—Proshares Inflation Expectation and VEU—Vanguard All World EX-US ETF. The test statistics shown are chi-squares.

5. Discussion

In this paper, we have studied how price and volatility movements in a basket of cryptocurrencies manifest themselves upon conventional asset categories. While the existing literature is concerned with transmission between individual assets (Zieba et al. 2019; Naeem et al. 2022; Mensi et al. 2020), we maintain that it is more relevant to examine such an issue through the lens of a well-diversified portfolio with low transaction costs, as is the case with exchange-traded funds. Therefore, we address the issue at hand by augmenting the standard VAR and GARCH models with a time-varying intercept based on a Fourier transformation. The choice in methodology is an enhancement over the traditional approach because it incorporates structural breaks that are otherwise difficult to detect without imposing parametric restrictions into the model.

As such, we have uncovered a set of dynamic relationships between a cryptocurrency ETF, BITW, and several ETFs that track conventional investments. The findings can be summarized as follows. There is a glaring disparity in how shocks are conveyed between BITW and its more established counterparts. While the cryptocurrency ETF is a source of price and volatility spillovers, there is almost no evidence that the ETFs from other asset classes transmit their shocks to BITW. Having established that the dynamic relationship between cryptocurrencies and conventional assets is largely directional in nature, we also encounter that spillover is more common for volatilities than it is for prices. We observe that the asymmetric spillover effects from cryptocurrencies to other ETFs are common. In particular, the small-capitalization and inflation-hedging ETFs are affected by the cryptocurrency ETF in terms of both price and volatility. Nevertheless, the disposition of spillovers is nuanced. The BITW ETF is shown to be a precursor of price shocks corresponding to the ETFs of major currencies: the euro, pound sterling, and the yuan. On the other hand, volatility from BITW goes toward equity ETFs, an ETF tracking crude oil, and another fund that mimics high-yield corporate debt. There is no indication of interdependency between BITW and certain ETFs in either price or volatility, including the ones for energy, precious metals, gold, investment-grade corporate debt, and the yen.

The spillover effects from BITW to the ETFs of several major currencies carries implications for investors as well as scholars. For currency traders, the signals from the cryptocurrency ETF can be implemented as part of an arbitrage strategy. For instance, the correlations between the ETFs for cryptocurrency, the euro, British pound, and yuan suggest that a positive shock in crypto would prompt longing the pound and euro while shorting the yuan. Another application for practitioners is in position hedging. Such an avenue would be advantageous given the difference in volatilities between BITW and such currencies. Notice, from Table 1, that BITW has six, nine, and ten times the volatility of the euro, pound, and yuan, respectively. As such, exposure to cryptocurrencies could be tempered by offsetting investments in lower risk assets. For scholars, there are several questions left to be explored, given the findings of our study. Why are some currencies foreshadowed by BITW while others, such as the yen, are not? Another, perhaps more intriguing, direction is to ascertain why cryptocurrencies would move in the same direction as some fiat currencies. If cryptocurrencies are meant to be a substitute for fiats, more so in times of inflation, then one would expect an inverse relationship, or at least a decoupling between them.

While gold ETFs and currency ETFs might be expected to exhibit similar price and volatility behavior, initial observations reveal a contrasting pattern. Specifically, the BITW ETF does not appear to serve as a harbinger of price shocks for gold ETFs. This phenomenon could be attributed to the historical context of the currency and gold relationship. Before the breakdown of the Bretton Woods system in 1971, currencies were pegged to gold, establishing a direct link between their values. However, after the dissolution of this system, the connection between currencies and gold prices was severed. Despite this detachment, gold has remained consistently recognized as a reliable store of value, particularly during periods of high inflation when currencies tend to depreciate (Booth and Kaen 1979; Booth et al. 1982). Nevertheless, it is worth noting that the theoretical relationship between gold and other currencies may not always hold true after 1971, as demonstrated by studies such as Sjaastad and Scacciavillani (1996) and similar research conducted by Kristoufek and Vosvrda (2016).

The results herein also have ramifications on asset allocation strategies under the Markowitz mean-variance efficiency premise. That is, the shocks stemming from the underlying cryptocurrency market decrease the effectiveness of certain assets in diversifying a portfolio. The conflagration of risk is at its peak among small capitalization stocks. By the same token, combining a diversified cryptocurrency fund with funds consisting of other alternative assets, like gold and precious metals, or high-quality debt, would improve a portfolio's Sharpe ratio. The structure of the dynamic correlations themselves reveals certain features of the cryptocurrency landscape. For example, the presence of spillovers in inflation-hedging ETFs is indicative of how some investors align with one of the main theses of digital currency adoption: lack of discipline on the part of central bankers. The price spillovers toward the ETFs tracking some major currencies show the emerging connections between cryptocurrencies and fiat money. However, it is interesting that such an association does not seem to exist for the yen. The volatility transmission into equity and high-yield debt suggests investor's preferences for risk, implying that such assets are perceived as complementary to each other in terms of asset allocation. In terms of the ongoing debate as to whether cryptocurrencies are a viable diversification asset (e.g., Corbet et al. 2018 vs. Klein et al. 2018), we conclude that the hedging efficacy of such alternative assets is a complex matter and contextual to the composition of a portfolio.

VAR models, such as the "Fourier-TY" price transmission model employed in our study, exhibit several limitations that have been examined in prior research (e.g., Pesaran and Smith 1995; Lütkepohl 2006; Tsay 2013). Such limitations that are pertinent to our research revolve around the assumptions of linearity and normality, as well as the constrained forecasting horizon. VAR models assume data linearity and a normal distribution, and any departure from these assumptions may lead to less accurate results. Additionally, VAR models are generally better suited for short- to medium-term forecasting, as their performance tends to deteriorate when used for long-term predictions because of the cumulative impact of model errors. Despite our model's incorporation of structural break considerations, which is a critical issue in VAR estimations, future researchers may explore the development of models capable of producing more generalized estimates that are effective at longer horizons.

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Notes

1 Based on monthly closing price data found on Yahoo! Finance: Bitcoin USD (BTC-USD) Price History & Historical Data—Yahoo Finance (https://finance.yahoo.com/quote/BTC-USD/history?p=BTC-USD) (accessed on 13 June 2023).

2 Using the yield on U.S. Treasury Securities at 3-month constant maturity, sourced from FRED Economic Data: Market Yield on U.S. Treasury Securities at 3-Month Constant Maturity, Quoted on an Investment Basis (DGS3MO) | FRED | St. Louis Fed (https://fred.stlouisfed.org/series/DGS3MO) (accessed on 13 June 2023).

3 Bitwise 10 Crypto Index Fund: a fund that tracks an index of the 10 most highly valued cryptocurrencies, weighted by market capitalization, and rebalanced monthly.

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