EXAMINING VOLATILITY SPILLOVERS: THE RELATIONSHIP BETWEEN BITCOIN AND U.S. INDUSTRIAL SECTOR

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Abstract. *This research study investigates the volatility spillover effects between Bitcoin and the U.S. Industrial sector, using data from January 2010, June 2019. This research area is significant due to the growing interest in understanding Bitcoin's influence on various financial markets. Notably, prior studies have examined Bitcoin's spillover effects but haven't conclusively determined its predictability in relation to the U.S. Industrial sector. The study employs the Generalized Vector Autoregressive (VAR) Framework, following the approach of Diebold and Yilmaz. This method is grounded in forecast-error variance decompositions derived from Vector Autoregressions (VARs), providing a robust analytical tool for examining inter-market relationships. The findings of this research indicate a limited connection and influence between Bitcoin and the U.S. Industrial sector. Specifically, the study observes an insignificant impact of Bitcoin market volatility on the U.S. Industrial sector. This result is crucial as it contributes to the understanding of Bitcoin's potential as a hedging tool and its effectiveness in managing financial downturns. Furthermore, the study highlights Bitcoin's role in offering significant portfolio diversification and risk hedging benefits, particularly for U.S. domestic and foreign investors.*

Keywords: Bitcoin, U.S. industrial sector, Generalized Vector Autoregressive (VAR) Framework, Volatility spillover, Portfolio diversification

1. Introduction and Literature Review

Financial crises have been a recurring phenomenon throughout the history of financial markets, marked by periods of heightened volatility and notable spillover effects (Reinhart & Rogoff, 2008). In recent times there has been an observable escalation in these patterns of volatility and cross-market spillover. There is need of monitoring these spillovers lies in their potential to serve as early indicators of impending crises and to assess the evolution of ongoing financial turmoil.

The scholarly discourse in finance underscores the imperative of developing refined methods for estimation and risk prognostication. The methods must be free of bias in forecasting the returns of financial assets and in detecting regime shifts within GARCH (Generalized Autoregressive Conditional Heteroskedasticity) dynamics. Notably, volatility co-movements became evident with the onset of global financial integration in the mid-1980s. These co-movements engendered a phenomenon where volatility in one market precipitates effects in another, known as the spillover effect. Pioneering contributions by Engle III, Ito et al. (1988), Mill (1963), and Schneewind (1977) culminated in a methodology to assess returns and volatility relative to other markets, termed 'The Spillover Effect'. Defined by Volosovych, Sørensen, & Kalemli-Ozcan (2010), the spillover effect encapsulates the repercussions of disparate events in a nation's financial market on the economic landscapes of other countries. These effects are inherently globalized, reflecting the interdependence of diverse national economies. Thus, occurrences in one country invariably resonate across the global economic spectrum. Stock market downturns are quintessential catalysts for such spillover effects. In our research, we specifically examine the spillover effect in the context of the US Industrial Sector's response to a potential collapse of the Bitcoin market, exploring the volatility spillover between Bitcoin and this sector.

Financial scholarship extensively documents the historical progression of financial crises and the associated spillover effects across various financial markets. Analysis of the volatility spillover effect can be conducted through unidirectional or multidirectional approaches. Numerous studies have been conducted to investigate these effects. Engle III, Ito et al. (1988) were trailblazers in this domain, examining the volatility spillover between the Yen and U.S. dollar exchange rates. Lin, Engle, and Ito (1994) advanced this field by estimating the spillover effects between U.S. and Japanese stock market volatility, utilizing a VAR model that incorporates short rates and term-structure slopes as variables. The interplay between the bond markets of Germany, the U.S., and the UK was scrutinized by Brooke, Clare, and Lekkos (2000), who discovered that a mix of local and international factors influences the variability of each market's term-structure slopes. The dynamics between exchange rate and stock price volatility across six industrialized nations (U.S., UK, Japan, Germany, France, and Canada) were explored by Kanas and accounting (2000), noting a notable spillover effect from stock prices to exchange rates in all these countries, barring Germany. The intricacies of volatility spillover between the U.S. and Japanese swap markets were analyzed by Toyoshima and Hamori (2012). Additionally, Moon and Yu (2010) employed a GARCH-M model to measure volatility spillover between the U.S. and Chinese stock markets from 1999 to 2007, providing profound insights into the interconnectivity of these two major economies.

In line with these market analyses, the investigation of volatility spillover within the Bitcoin market, in relation to other financial markets, is equally crucial and carries significant relevance. Bitcoin, a leading cryptocurrency, has garnered prime global recognition from institutional entities and widespread media attention worldwide. This has piqued the interest of investors in this novel investment avenue. The burgeoning acceptance of cryptocurrencies has notably impacted the U.S. financial landscape and other markets, prompting a need to examine the contagion effect of Bitcoin, one of the most embraced cryptocurrencies. In contemporary financial discourse, understanding Bitcoin's influence is vital for more accurate portfolio analysis. A potential collapse of the Bitcoin market could precipitate a contagion effect, exacerbating liquidity issues and elevating risk aversion among investors, thereby instigating a decline in other financial market investments.

Recent financial literature delves into Bitcoin's spillover effects with other financial sectors. Symitsi and Chalvatzis (2018) conducted a detailed examination of the return-volatility dynamics and shock spillover between Bitcoin and sectors such as energy and technology. They employed an asymmetric BEKK Generalized Autoregressive Conditional Heteroscedasticity (VAR-BEKKAGARCH) method along with a Vector Autoregression Conditional mean process for measuring returns. Their research uncovered evidence of bidirectional shocks and unidirectional returns, which have profound implications for portfolio management and the understanding of conditional correlations. Their analysis indicates that the volatility spillover from technology companies to Bitcoin is transient, whereas the impact from Bitcoin on technology and energy sectors demonstrates a more enduring nature.

The intricate task of discerning major shifts in Bitcoin’s volatility has seen significant contributions, particularly from Ardia, Bluteau and Rüede (2019). They adeptly utilized a Markov-switching GARCH (MSGARCH) model to analyze alterations in the GARCH volatility dynamics of Bitcoin log-returns. Thies and Molnár (2018) employed a Bayesian change-point method to unearth the underlying causes for structural shifts in Bitcoin’s volatility pattern. Building on this, Ardia et al. (2019) acknowledged the shortcomings in Katsiampa’s (2017) approach and, through a Bayesian framework, posited that the MSGARCH model eclipses the efficacy of single-regime GARCH models, offering superior performance across various GARCH-type models. These models not only elucidate Bitcoin's financial asset characteristics, such as its utility as a hedging instrument and a medium of exchange akin to gold and the dollar, but also underscore its potential in mitigating negative market shocks for risk-averse investors. This is in line with Dyhrberg's (2016) propositions, grounded on an asymmetric GARCH model, that Bitcoin can play a pivotal role in effective risk management. Furthermore, Bitcoin returns appear impervious to positive or negative shocks in other financial markets, underscoring its viability as a strategic tool for hedging against market risk.

The ongoing discourse on Bitcoin's returns and volatility necessitates a critical evaluation of its role in portfolio investment strategies. Briere, Oosterlinck, and Szafarz (2015) were pioneers in assessing Bitcoin's merit within the portfolio optimization process. Their analysis revealed that Bitcoin exhibits minimal correlation with traditional asset classes like bonds, stocks, equities, other currencies, and commodities, thereby positioning it as a significant diversification asset in investment portfolios.

Endorsing this perspective, Briere et al. (2015) advocated for Bitcoin's incorporation into portfolios. Utilizing spanning tests, they argued that despite Bitcoin's heightened volatility, a well-structured portfolio could achieve enhanced diversification by allocating a modest portion (around 3%) of the total investment to Bitcoin. Building upon this, Eisl, Gasser, and Weinmayer (2015) extended Briere et al.'s work, examining the impact of Bitcoin investment on a strategically diversified portfolio through a Conditional Value at Risk (CVaR) framework. This methodology was chosen over the traditional mean-variance approach due to its suitability for handling non-normally distributed returns, characterized by positive skewness and excess kurtosis. Their findings corroborated the potential benefits of including Bitcoin in optimal portfolio investments.

Nevertheless, incorporating Bitcoin into a portfolio could elevate its Conditional Value at Risk (CVaR). This increased risk might be counterbalanced by more favorable risk-return ratios and higher returns. A downturn in the Bitcoin market could intensify investors' risk aversion and liquidity constraints, leading to a broader decline in other financial market investments. Carpenter (2016), using a refined mean-variance framework and back-testing approaches, further substantiated the findings of Briere et al. (2015) and Eisl et al. (2015). Carpenter's research affirmed that Bitcoin could serve as an effective tool for portfolio diversification, potentially enhancing the risk-return ratios of an efficient portfolio.

Examining the interplay between Bitcoin and various financial markets, scholars such as Briere et al. (2015), Carpenter (2016), Baruník, Kočenda, and Vácha (2017), and Qarni, Fatima, Khan, and Shafi (2019) have made substantial contributions. However, a notable gap persists in literature regarding Bitcoin's relationship with the U.S. Industrial sector, a cornerstone of the American economy. Recent developments in both the U.S. Bitcoin sphere and the Industrial sector underscore the importance of exploring their interrelation. This paucity of in-depth research in this area is the driving force behind our study, which aims to delineate the potential portfolio diversification benefits stemming from this relationship. Our research endeavors to bridge this literature gap with two principal goals:

1. Quantifying the volatility spillover effect between Bitcoin and the U.S. Industrial sector.
2. Assessing the directional volatility spillover between these two entities.

This study also delves into the complex dynamics of Bitcoin market volatility spillovers across different periods of price volatility. Given Bitcoin's dual function as both a medium of exchange and a store of value, it garners additional interest for investment portfolios. To fully comprehend Bitcoin's hedging potential and its capacity to weather financial downturns, an analysis of its relationship with the U.S. Industrial sector is essential.

We will conduct this analysis using data spanning from January 4, 2010, to June 28, 2019, employing the Generalized VAR Framework, as proposed by Diebold and Yilmaz (2012), for our empirical investigation. This research holds significant implications for investors, policymakers, and fund managers in the U.S., given Bitcoin's growing prominence in investment strategy formulation. Moreover, there is a keen interest among these stakeholders regarding Bitcoin's volatility impact on the U.S. economy.

This study will benefit U.S. investors in three primary ways, highlighting the low correlation between Bitcoin and the U.S. Industrial sector. Firstly, it will offer empirical evidence of asymmetric volatility spillover. Secondly, it will pinpoint the principal sources (Net transmitters) and primary recipients (Net receivers) of Bitcoin market volatility. Diebold and Yilmaz (2012) have elucidated that positive indices in this context suggest a market acting as a net transmitter of volatility, whereas negative indices indicate a market being a net receiver. Finally, the research will identify the specifics of directional volatility spillover between Bitcoin and the U.S. Industrial sector. In conclusion, this study will reveal how Bitcoin’s non-contagious nature can offer significant portfolio diversification and risk-hedging advantages to both local and international investors in the U.S.

The subsequent section of our research document will delve into the methodology employed, leading to a detailed discussion of the results. The study will conclude with final remarks and suggestions for future research endeavours.

2. Research Methodology

Our study employs the sophisticated Generalized VAR Framework developed by Diebold and Yilmaz (2012) as its methodological backbone. This framework, innovated by Diebold and Yilmaz, introduces a nuanced approach for quantifying volatility spillovers both within and across various asset classes. It leverages forecast-error variance decompositions derived from Vector Autoregressions (VARs), making it a robust tool for tracking trends, cyclical fluctuations, and abrupt changes in individual assets, collective portfolios, and broader asset markets on both local and international scales. This methodology is particularly adept at tracing returns or return volatility spillovers. A key feature of this approach is its invariance to variable ordering in forecast-error variance decompositions, with a specific emphasis on directional spillovers. We will apply this method to our empirical examination of the volatility spillover between Bitcoin and the U.S. Industrial sector. This analysis will span a comprehensive nine-year period, from January 2010 to June 2019, utilizing daily data to gain a detailed understanding of the evolving dynamics between these two entities.

2.1 Definition & measurement of generalized spillover

Generalized VAR Framework estimated directional spillovers using generalized VAR, which eliminates variable-ordering dependence in the estimated results. This methodology will follow the basic approach of a variance disintegration, linked to an N-variable in the Vector Autoregression (Diebold and Yilmaz 2012). Consider a covariance stationary N-variable VAR (p), $x_t = \sum_{i=1}^{p} \Phi_i x_{t-i} + \alpha_t$, where $\alpha \sim (0, \Sigma)$ is a vector of independently and identically distributed disturbances. The moving average representation is $x_t = \sum_{i=0}^{\infty} A_i \alpha_{t-i}$, where the $N \times N$ coefficient matrices A_i obeys the recursion $A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \cdot \cdot \cdot + \Phi_p A_{i-p}$, with A_0 being an $N \times N$ identity matrix and with $A_i = 0$ for $i < 0$.

To understand the system dynamics, the coefficients for moving average or transformations, such as vector decompositions and functions of impulse response are the key components. And to interpret the forecast error variances of each variable into parts that are linked to system shocks, we are relying on variance decompositions. This allow us to assess the fraction of the H step- ahead error variance in forecasting x_i that is due to shocks to x_j, $\forall j \neq i$, for each I . Orthogonal innovations are required to estimate variance decompositions, though our VAR variations will be mutually associated. Based on Cholesky factorization, identification schemes accomplish orthogonality, and the variance disintegrations becomes variable-ordering dependent.

To evade this problem, we extended the work of Koop, Pesaran, and Potter (1996) and Pesaran and Shin (1998), hence KPPS, on generalized VAR framework, which produces ordering invariant variance decompositions. The generalized VAR framework allows correlated shocks, and instead of orthogonalizing them, uses historical distribution of errors to properly account for them. As each variable shock is not orthogonalize, the sum of their contributions for variance forecast error is not necessarily equal to 1.

2.2 Variance shares explanation

In forecasting x_i that are due to shocks to x_j, for i= 1, 2, …, N, the very own variance shares will be used as sections of the H-step-ahead error variances, and in forecasting x_i that are due to the shocks to x_j, for i, j = 1, 2, …, N, such that $i \neq j$, cross variance spill overs as sections of the H-step-ahead variances will be used.

The KPPS H-step-ahead forecast error variance decompositions is represented by : θ gij (H), where H= 1, 2… The equation will take the form:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \sum e j)2}{\sum_{h=0}^{H-1} (e_i' A_h \sum A_h' e i)} \qquad (1)$$

Where;

$\sum$ = variance matrix for error vector α

σ_{ii} = jth equation; error term standard deviation

e_i = selector vector; (1 for ith element, zeros otherwise)

As explained before, in the variance decomposition table, the sum of the elements in each row is not equal to 1: $\sum_{j=i}^{N} \theta_{ij}^{g}(H) \neq 1$. For the calculation of spill over index, each entry of the variance decomposition matrix by the row sum will be normalized, in order to process the available information in the variance disintegration matrix. It is normalized as:

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=i}^{N} \theta_{ij}^{g}(H)} \qquad (2)$$

It should be noted that, by formation, $\sum_{j=i}^{N} \tilde{\theta}_{ij}^{g}(H)$= 1 and $\sum_{ij=1}^{N} \tilde{\theta}_{ij}^{g}(H)$ = N.

2.3 Total spillover measure

To establish the total volatility spillover index, we use the KPPS variance decomposition’s volatility supplement as:

$$S^{g}(H) = \frac{\sum_{\substack{ij=1 \\ i \neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{\sum_{ij=1}^{N} \tilde{\theta}_{ij}^{g}(H)} .100 = \frac{\sum_{\substack{ij=1 \\ i \neq j}}^{N} \tilde{\theta}_{ij}^{g}(H)}{N} .100 \qquad (3)$$

(Diebold and Yilmaz 2012) used this Cholesky factor based KPPS analogy measure, to calculate total volatility spillovers. To measure the contribution of spillover shocks across all classes of assets to forecast error variances, Total spillover index is used. This equation 3 is going to satisfy our desired objective, i.e. measuring the volatility spillover effect between Bitcoin and U.S. industrial sector.

2.4 Directional spillover measure

To comprehend the trajectory of volatility transference among all principal asset categories, the Generalized Vector Autoregression (VAR) framework offers substantial assistance. In light of the invariant nature of variable ordering inherent in the generalized VAR framework, components of the generalized variance decomposition matrix are methodically normalized to ascertain the directional volatility spillover. The directional spillovers acquired by market i from all other markets j, is calculated as:

$$S^{g}_{i.}(H) = \frac{\sum_{\substack{j=1 \\ j\neq i}}^{N} \tilde{\theta}^{g}_{ij}(H)}{\sum_{ij=1}^{N} \tilde{\theta}^{g}_{ij}(H)} .100 = \frac{\sum_{\substack{j=1 \\ j\neq i}}^{N} \tilde{\theta}^{g}_{ij}(H)}{N} .100 \tag{4}$$

We also examine the directional spillovers transferred by market i to all other markets j, using the same method as:

$$S^{g}_{i.}(H) = \frac{\sum_{\substack{j=1 \\ j\neq i}}^{N} \tilde{\theta}^{g}_{ij}(H)}{\sum_{i,j=1}^{N} \tilde{\theta}^{g}_{ij}(H)} .100 = \frac{\sum_{\substack{j=1 \\ j\neq i}}^{N} \tilde{\theta}^{g}_{ij}(H)}{N} .100 \tag{5}$$

To delineate the overall spillover decomposition as emanating from a specific source, the application of the directional spillovers set proves efficacious. The aforementioned formulation will fulfil the intended aim, namely quantifying the directional volatility spillover existing between Bitcoin and the U.S. Industrial sector.

3. Data Analysis and Findings

This study employs an exhaustive dataset that encompasses Bitcoin's daily return information derived from the CoinDesk Bitcoin Price Index (CoinDesk, 2019), coupled with the daily mean value-weighted returns of the U.S. Industrial sector, obtained from Investing's price indices (Investing, 2019). The dataset spans 3,465 observations, covering the period from January 4, 2010, to June 28, 2019. This particular timeframe was chosen for its significance, with the archival data for Bitcoin tracing back to July 30, 2010, thus establishing a lower boundary for our analytical period, given the relatively nascent emergence of the Bitcoin market at that point. Consequently, our examination period commences from 2010, capturing both the stable and volatile stages of Bitcoin and the U.S. Industrial sector, which comprises 54 unique sectors. On days where market activities are not aligned due to holidays, the preceding day's price is utilized, leading to a computed zero return for these non-aligned days. In order to compute the daily volatility of the Bitcoin market, we adopt the approach proposed by Rogers and Satchell (1991), which involves using normalized values of the low, high, and closing prices.

$$\sigma^2 = P_{(h,t)} \left(P_{(h,t)} - P_{(c,t)}\right) + P_{(l,t)} \left(P_{(l,t)} - P_{(c,t)}\right) \tag{6}$$

Where;

P h, t = higher price at day t
P l, t = lower price at day t
P c, t = ending price at day t

3.1 Descriptive Statistics

To calculate the Spillover Asymmetry Measure (SAM), we meticulously segregate each volatility series into its respective positive and negative segments. This segmentation yields a total of eight distinct series for each of the 50 variables scrutinized. The descriptive statistics displayed in Table 1 underscore the prevalence of positive average volatilities for both Bitcoin and the U.S. industrial sector. Critical statistical measures such as the minimum, maximum, mean, and standard deviation underscore a significantly heightened volatility in Bitcoin market prices when juxtaposed with that of the U.S. industrial sector. Enhanced understanding is obtained through the analysis of skewness, kurtosis, and Jarque-Bera statistics for these series. These indicators collectively suggest that all the oscillating series demonstrate heteroskedastic traits and deviate from a normal distribution, signifying the existence of atypical distribution patterns within the dataset.

Table 1 *Descriptive Statistics (US Industrial Sector)*

Sector	Mean	Median	Max.	Min.	S.Dev.	Skewness	Kurtosis	Jarque-Bera
BTC	32.20	2.74	2797.85	0.00	123.5	10.73	170.08	3861455
AGRIC	1.42	0.17	247.75	0.00	5.97	24.98	926.75	1160000
FOOD	0.50	0.08	79.92	0.00	1.78	28.94	1237.2	2080000
SODA	1.38	0.16	272.91	0.00	6.86	26.34	916.18	1140000
BEER	0.67	0.10	34.11	0.00	1.64	7.38	97.26	1238596
SMOKE	0.84	0.12	54.02	0.00	2.39	9.15	137.21	2496645
TOYS	1.19	0.18	68.72	0.00	3.31	9.42	136.06	2457804
FUN	1.17	0.13	80.28	0.00	3.45	9.02	133.60	2365186
BOOKS	1.08	0.14	76.04	0.00	3.21	11.37	209.24	5858538
HSHLD	0.61	0.10	16.73	0.00	1.34	5.05	39.30	193180
CLTHS	1.30	0.18	268.63	0.00	5.67	33.61	1527.7	3170000
HLTH	1.04	0.14	102.01	0.00	3.22	14.25	350.39	16533398
MEDEQ	0.81	0.12	47.75	0.00	2.06	8.12	118.36	1846843
DRUGS	1.30	0.16	51.27	0.00	3.16	5.96	57.66	425981
CHEMS	1.16	0.16	67.40	0.00	3.13	8.63	123.99	2032490
RUBBR	0.90	0.15	45.02	0.00	2.28	7.34	89.71	1052507
TXTLS	1.41	0.19	66.10	0.00	3.72	7.32	82.55	890413
BLDMT	1.18	0.18	70.73	0.00	3.24	8.44	116.22	1783124
CNSTR	1.63	0.22	100.60	0.00	4.13	8.49	137.36	2495801
STEEL	2.00	0.29	114.28	0.00	5.20	8.06	112.37	1663255
FABPR	2.32	0.30	233.78	0.00	7.06	14.65	389.42	20436845
MACH	1.23	0.15	77.62	0.00	3.36	8.87	135.11	2417752
ELCEQ	1.22	0.16	59.91	0.00	3.24	7.77	97.22	1240952
AUTOS	1.40	0.18	72.76	0.00	3.64	7.25	85.85	962642
AERO	0.92	0.13	49.42	0.00	2.38	8.45	119.13	1873928
SHIPS	1.95	0.26	79.21	0.00	4.71	5.63	50.93	329893
GUNS	1.03	0.16	71.91	0.00	3.12	12.20	228.58	7006140
GOLD	4.40	0.61	171.61	0.00	10.43	5.43	48.73	300637

MINES	2.45	0.34	72.25	0.00	5.74	5.36	43.27	236349
COAL	5.67	0.70	421.89	0.00	16.15	9.75	173.18	3992753
OIL	2.76	0.29	162.31	0.00	7.89	8.66	120.23	1911141
UTIL	0.51	0.08	36.60	0.00	1.39	10.85	201.23	5411364
TELCM	0.76	0.12	43.30	0.00	1.85	7.83	117.24	1809286
PERSV	1.15	0.17	88.36	0.00	3.22	12.26	266.03	9496959
BUSSV	0.78	0.10	60.84	0.00	2.19	10.76	211.66	5987840
HARDW	1.11	0.17	49.00	0.00	2.67	6.44	70.94	650732
SOFTW	0.88	0.14	37.33	0.00	2.15	6.66	72.25	676815
CHIPS	0.98	0.14	33.41	0.00	2.25	5.50	49.40	309444
LABEQ	1.03	0.14	55.65	0.00	2.80	8.09	105.42	1463138
PAPER	0.99	0.14	137.36	0.00	4.06	22.89	708.12	67944980
BOXES	1.00	0.14	68.56	0.00	2.77	9.94	174.49	4055858
TRANS	1.06	0.14	36.12	0.00	2.47	5.43	46.19	269891
WHLSL	0.77	0.10	45.02	0.00	1.99	8.17	118.40	1848503
RTAIL	0.80	0.13	35.88	0.00	1.81	6.49	77.89	786127
MEALS	0.64	0.10	29.27	0.00	1.60	7.29	87.03	989824
BANKS	0.92	0.10	113.85	0.00	3.58	15.21	371.59	18614326
INSUR	0.74	0.09	72.59	0.00	2.50	13.68	295.26	11725194
RLEST	1.30	0.16	102.41	0.00	3.94	10.08	177.15	4182452
FIN	1.07	0.12	79.92	0.00	3.51	11.47	199.52	5326909
OTHER	0.84	0.08	75.17	0.00	3.72	12.64	193.56	5028555

Note: At 1% level of significance, all statistics are stationary and round to two decimal places.

3.2 Volatility spillover indices

Table 2 encapsulates the average volatility spillover between Bitcoin and the U.S. Industrial sector over the period from January 4, 2010, to June 28, 2019. Among the various U.S. Industrial sectors analyzed, the Wholesale sector emerges as the most interconnected. This sector exhibits the highest levels of volatility spillover within the selected U.S. Industrial sectors, receiving 95.66% and transmitting 154.42%. In stark contrast, the Bitcoin market demonstrates the lowest volatility spillover within these sectors, receiving a mere 13.81% and transmitting only 1.95%. The extent of volatility spillover from the U.S. Industrial sectors to the Bitcoin market varies, ranging from a minimal 0.03% (from the Beer sector) to a peak of 0.97% (from the Real Estate sector). The computed average volatility spillover between Bitcoin and the U.S. Industrial sector during this period stands at 87.50%.

Following the framework outlined by Diebold and Yilmaz (2012), our analysis highlights both significant and minimal bidirectional spillovers between Bitcoin and the U.S. Industrial sector. Additionally, it is observed that the integration level within the U.S. Industrial sector has evolved over the years. Utilizing the Diebold and Yilmaz (2012) methodology, our findings indicate that the Real Estate sector has been the predominant recipient and source of volatility spillovers throughout the 2010-2019 period, displaying the most pronounced ripple effects with other markets. This relatively low level of correlation and contagion between Bitcoin and the U.S. Industrial sector suggests substantial opportunities for portfolio diversification and risk management for speculative investors in the U.S. market.

Table 2 *Index: Volatility Spillover*

	Bitcoin	**Beer**	**Real Estate**	**Wholesale**	**Merch.**	**From others**
Bitcoin	86.19	0.03	0.97	0.42	0.77	13.81
Beer	0.03	19.77	1.66	2.77	2.07	80.23
Real Estate	0.07	0.37	5.59	3.23	3.53	94.41
Wholesale	0.04	0.51	2.62	4.34	3.51	95.66
Mach	0.04	0.39	2.84	3.57	4.38	95.62
Contribution to others	1.95	26.01	117.75	154.42	149.89	4376.07
Contribution including own	88.14	45.78	123.34	158.76	154.27	87.50

3.3 Total spillover measure: Rolling window analysis

Figure 1 presents a 200-day rolling window analysis that illustrates the evolving dynamics of total volatility spillover between Bitcoin and the U.S. Industrial sector. This figure demonstrates a sensitivity to both domestic and international events, as well as to new announcements. The initial significant surge in spillover between Bitcoin and the U.S. Industrial sector was noted in the latter half of 2011, influenced by the civil unrest in Libya and the consequent disruptions in U.S. financial markets, primarily due to the energy crisis and Euro-zone turmoil. This spillover further intensified as a repercussion of the global stock market downturn, triggered by the U.S. debt ceiling and the escalating Euro-zone crisis in the third quarter of 2011.

A second phase of heightened volatility spillover occurred in May 2012, in response to the deepening Euro-zone crisis. The third spike in volatility spillover between Bitcoin and the U.S. Industrial sector was evident in the latter half of 2013, catalyzed by the U.S. Federal Reserve Board's taper tantrum and the financial crisis in Cyprus. During this period, a notable surge in Bitcoin prices was observed, as the cryptocurrency gained favor among investors amidst the Cyprus crisis. The fourth phase of intensified spillover unfolded throughout 2014, driven by escalating tensions in the Euro-zone, the Crimean crisis, shocks in oil prices, financial stress from these events, and the Russian crisis. Finally, the fifth phase of drastic increase in total spillover was seen between May and August 2015, following the downturns in both the Shanghai and European stock markets. These periods of increased spillover highlight the complex interplay between global events and the volatility relationships between Bitcoin and the U.S. Industrial sector.

The announcement of Brexit on June 23, 2016, and China's Reform Initiative in August 2016 marked the onset of the sixth significant phase of elevated total volatility spillover between Bitcoin and the U.S. Industrial sector. This period was characterized by pronounced responses to various international economic events throughout 2016. However, a notable reduction in the total volatility spillover was observed in 2017, attributed to the relative stability of global financial and industrial markets. In January 2017, fluctuations in volatility were influenced by Donald Trump's inauguration as the 45th President of the United States and the widespread protests that ensued. Additionally, in May 2017, the volatility fluctuations were triggered by a series of global ransomware cyberattacks. The announcement of the U.S. withdrawal from the Paris Climate Agreement in June 2017 also contributed to this instability, reflecting in the financial and industrial sectors. The impact of natural disasters was evident in August 2017, as Hurricanes Irma and Maria significantly affected the United States and the Caribbean, influencing volatility spillovers.

A seventh phase of volatility surges was prompted in August 2018 by financial market uncertainties following the Süddeutsche Zeitung's revelation of 13.4 million documents related to the offshore financial activities of corporate leaders, business magnates, and politicians. The evidence presented indicates a highly reactive nature of volatility spillover between Bitcoin and the U.S. Industrial sector to a multitude of domestic and international events, each with its own distinct dynamics and magnitude of impact.

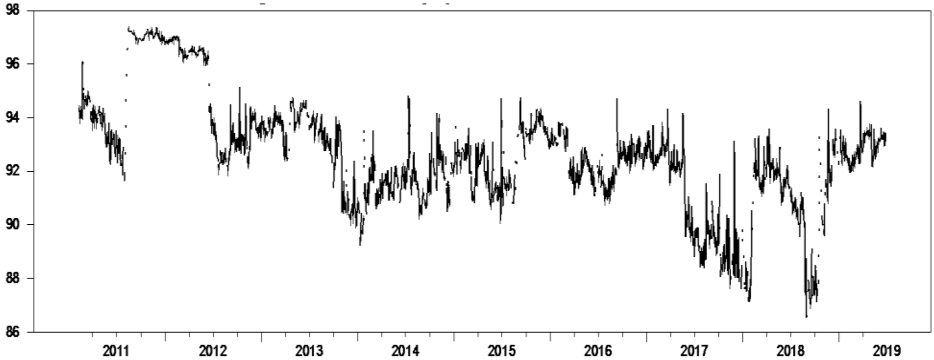


Figure 1 Total Volatility Spillover – U.S. Industrial Sector

3.4 Directional spillover measure

The 200-day rolling window Directional Volatility Spillover Analysis captures the volatility spillover between Bitcoin and the U.S. Industrial sector across both stable and turbulent phases. In times of market upheaval, the spillover from Bitcoin market volatility often surpasses 25%, whereas during tranquil periods, this figure typically remains below 10%. For the U.S. Industrial sector, volatility spillover exceeds 50% during turbulent times and drops below 20% in calmer phases.

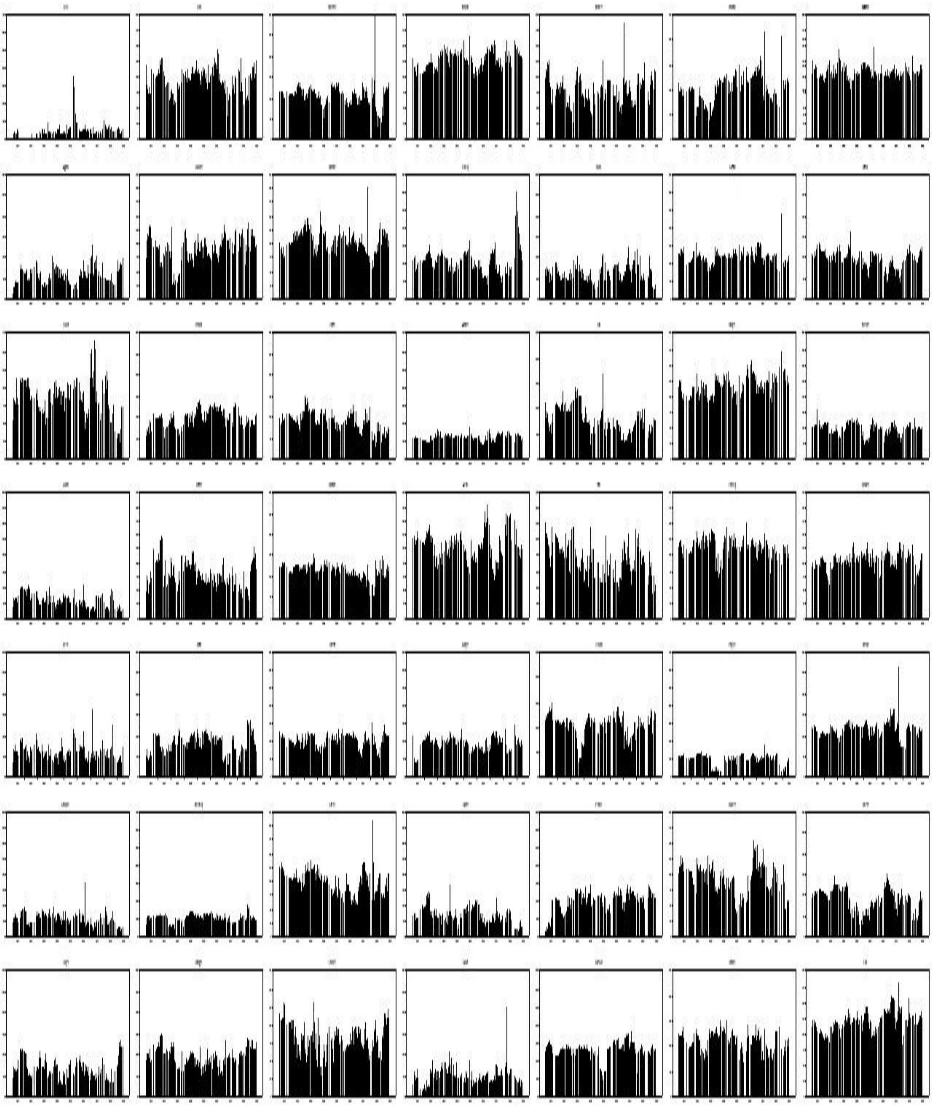
A notable increase in directional volatility spillover from each individual U.S. industry to other sectors was observed from mid-2011 to early 2012, coinciding with the Euro-zone crisis. However, in both halves of 2011, the fallout from the Bitcoin market's directional volatility to the U.S. Industrial sector stayed under 30%. A marked decline in this fallout was seen in the latter half of 2011. Throughout the entire sample period, the directional volatility spillover from the Bitcoin market to the U.S. Industrial sector generally remained below 30%, with occasional spikes.

In the latter part of 2013, significant increases in directional volatility were noted in the U.S. Beer and Real Estate sectors, affecting other industrial sectors. Conversely, during the latter half of 2014, directional shifts in the Wholesale and Merchandising sectors were less prone to cause spillover in other U.S. industries. Notably, on August 24, 2015, coinciding with the European stock market crash, the U.S. Wholesale sector emerged as a major transmitter of volatility across other U.S. Industrial sectors. Furthermore, following the UK's Brexit announcement on June 23, 2016, and China's reform initiative in August 2016, the U.S. merchandising and beer sectors became prominent sources of volatility within the broader U.S. Industrial landscape.

The study reveals dynamic and non-static patterns in the time-varying directional volatility interplay between Bitcoin and the U.S. Industrial sector. In periods of market instability, Bitcoin's market volatility has been observed to escalate to as much as 35%, while in more stable times, it recedes to below 10%. However, the U.S. Industrial sector consistently demonstrates greater volatility than Bitcoin, irrespective of the market's state. Specifically, during turbulent phases, volatility spillover in U.S. industrial sectors often surpasses 40%, but dips below 20% in tranquil periods. Particularly, the U.S. Real Estate and Wholesale sectors exhibited volatility spillover exceeding 50%, reacting notably to global financial events. The U.S. wholesale sector experienced heightened volatility during the 2011 Eurozone crisis more than any other U.S. industrial sector. Nonetheless, across the sample period, Bitcoin consistently showed the least amount of volatility spillover compared to other U.S. industrial sectors.

Significant events such as the U.S. Federal Reserve Board's taper tantrum and the Cyprus financial crisis in 2013, along with the June 2016 Brexit announcement and China's August 2016 reform initiative, have notably influenced volatility in the U.S. Beer and Real Estate sectors, making them major recipients of volatility spillovers.

This research underlines a low level of correlation and contagion between Bitcoin and the U.S. Industrial sector, emphasizing Bitcoin's relevance in U.S. investment strategies and portfolio diversification. It addresses the potential role of Bitcoin as an alternative investment for U.S. investors and investigates the asymmetric and directional volatility spillover effects between Bitcoin and the U.S. industrial sector. Consistent with the findings of Qarni et al. (2019), the results suggest that fluctuations in the Bitcoin market have a minimal impact on other U.S. financial markets. Consequently, U.S. investors may consider Bitcoin as a viable alternative investment tool in their portfolios. For those involved in portfolio management and market analysis, incorporating Bitcoin can offer an additional hedging mechanism and aid in more informed decision-making. Risk-averse investors might also find Bitcoin valuable for anticipating market downturns. Echoing Dyhrberg's (2016) conclusions, Bitcoin, with its dual characteristics as both a currency and a commodity, emerges as a significant instrument for risk assessment, gauging market sentiment, and enhancing portfolio management strategies.



4. Conclusion, Recommendations, and Future Directions

The primary aim of this research is to explore the predictability of volatility spillover between Bitcoin and the U.S. Industrial sector. The findings, utilizing the Diebold and Yilmaz (2012) spillover index and the spillover asymmetry measure developed by Baruník et al. (2017), indicate a minimal level of correlation and contagion, alongside asymmetric volatility spillover, between Bitcoin and the U.S. Industrial sector. The analysis also identifies a reduction in the interconnectedness and mutual influence of the U.S. Industrial sector, which appears to be influenced by the presence and dynamics of the Bitcoin markets.

This study further reveals the presence of asymmetric volatility spillover between Bitcoin and the U.S. Industrial sector. This asymmetry is characterized by transient periods of spillover, which hold significant implications for both investors and policymakers in the U.S. The meteoric rise of Bitcoin, coupled with escalating investor confidence, has been a key driver of its rapid expansion. Historical patterns suggest that rapid increases in value are often followed by equally swift declines. This phenomenon is evident in Bitcoin's trajectory, where, despite a steep fall from its peak of around $19,800 to $8,000 per coin, it continued to exhibit a downward trend over time.

Despite these concerning trends, the turmoil in the Bitcoin market is anticipated to exert minimal impact on the U.S. Industrial sector. One of the primary reasons for this non-catastrophic influence of Bitcoin's fluctuations on other financial markets is the growing acceptance and integration of cryptocurrencies. This diversification into various cryptocurrencies could potentially capture a broader share of assets from leveraged investors, mitigating the concentrated risk associated with reliance on a single cryptocurrency like Bitcoin.

In summarizing the key findings, it is deduced that Bitcoin, with its escalating popularity and increased tradability, is poised to potentially influence the U.S. Industrial sector significantly in the foreseeable future. The relationship between Bitcoin and the U.S. Industrial sector is influenced by the dynamic nature of global financial markets, thereby underscoring Bitcoin's market sensitivity to various international economic events. This research offers valuable insights for investors, policymakers, and fund managers in the U.S., particularly those viewing Bitcoin as a crucial component in crafting investment strategies and concerned about its volatility impact on the U.S. economy. The minimal correlation and contagion between Bitcoin and the U.S. Industrial sector can be leveraged, exploiting Bitcoin's hedging potential. The findings indicate that Bitcoin is largely uncorrelated with the U.S. Industrial sector, suggesting that U.S. investors can simultaneously invest in both, mitigating risk and diversifying their portfolios. A limitation of this research is its focus solely on the U.S. Industrial sector, constrained by data availability.

For future research avenues, scholars and analysts might consider several promising directions. These include exploring the integration and spillover dynamics between other cryptocurrencies and global financial markets, investigating the volatility spillover effects between Bitcoin and industrial sectors outside the U.S., and conducting micro-level spillover analyses encompassing a broader range of cryptocurrencies, Chinese industrial sectors, foreign exchange pairs, alternative investment options, and other fixed income securities. These areas offer fertile ground for further academic inquiry and practical application.

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