Global Economic Policy Uncertainty and Ethereum Price

--A Time-Series Analysis from 2015 to 2022

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Abstract

This research paper explores the relationship between the global economic policy uncertainty index (GEPU) and Ethereum price. By employing the Hodrick-Prescott Filter Decomposition, the price of Ethereum is decomposed into a trend component, which reflects the increasingly wide usage, and the cyclical component, which shows its character as a safe haven asset and a speculative financial asset. By examining the relationship between the GEPU and the cyclical component of Ethereum, I find that GEPU Granger causes cyclical Ethereum, and they have a cointegration relationship. Their error correction models also demonstrate that cyclical Ethereum responds in the short-run to changes in GEPU and deviations from long-run equilibrium. The dynamics make the cyclical Ethereum converge towards their long-run equilibrium relationship.

Keywords- *Ethereum; global economic uncertainty; cryptocurrency; Granger causality; cointegration; error correction*

1. INTRODUCTION

Cryptocurrencies such as bitcoin and Ethereum are considered developing substitutes for gold and the US dollar to be a neonatal safety asset due to its decentralized characteristics. Different from bitcoin, which is designed to have a maximum quantity of 21 million, making its price inclined to increase, Ethereum does not have a maximum quantity, which means the price of Ethereum is more reflective of the authentic value of digital currencies. This study examines the relationship between global economic policy uncertainty (GEPU) and digital currencies utilizing Ethereum (ETH) as a representative to demonstrate its safe-haven characteristics.

Besides its character as a safe haven under uncertainty, ETH has been increasingly widely accepted as a digital payment tool around the world thanks to its relatively low transaction costs ([1]Blau, 2017; [2]Kristoufek, 2015). However, cryptocurrencies are not guaranteed by a central bank, and hence are more volatile. Its high volatility also creates certain demand for speculation in the financial market, which is related to global economic uncertainty as well. To study how global economic turmoil affects the price of ETH, we need to decompose ETH into two components, the one reflecting actual use as a payment method on an e-commerce platform, and the other one component as a safe haven and speculative financial asset. The latter is directly impacted by global economic uncertainty.

The development of ETH is similar to bitcoin but with a lag. Meanwhile, the price of ETH seems to be relatively more stable than bitcoin due to its unlimited quantity design, a foundation for blockchain technology and less trading volume.

Since its initial launch, ETH has experienced several important phases and protocol upgrades (Fig. 1). In 2016, US$50 million of DAO (decentralized autonomous organization) tokens are stolen by an unknown hacker. This event arouses a wide discussion of whether ETH should perform a contentious "hard fork" to reappropriate the affected funds. As a result, the network splits into two blockchains: ETH with the theft reversed and ETH Classic which continued on the original chain.

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G. Vilas Bhau et al. (Eds.): MSEA 2022, ACSR 101, pp. 90–94, 2023.
https://doi.org/10.2991/978-94-6463-042-8_15

2017 is a fruitful year for ETH, as the Enterprise ETH Alliance (EEA) is formed and soon developed to include 150 enterprise members such as ConsenSys, CME Group, Cornell University, Toyota, Samsung, Microsoft, Intel, JP Morgan, Merck, Deloitte and so on. The price of ETH surges to over US$1000 accordingly. As bitcoin reaches a periodic peak of market value and trading volume in December 2017, regulations start to be strict in many countries and currency exchanges. Consequently, the cryptocurrency bubble bursts in January 2018 and ETH falls back to around US$110 for several years until the covid-19 pandemic sparks global economic turmoil and investment sentiment toward cryptocurrencies that should have revived. Thus, ETH reaches a new all-time high of US$4600 with other digital currencies.

The referendum on Britain's exit from the European Union (EU) is a major uncertainty since 2014. In 2016, global uncertainty is driven by the Brexit vote and the US presidential election, pushing up the GEPU index to a periodic high. After cooling off in 2017, the GEPU index rises again in 2018 thanks to the trade tension between China and the United States and has been the major theme before the covid-19 takes the headline.

This study contributes to the literature by examining the relationship between GEPU and ETH since most prior research focuses on the causal link or relationship between GEPU and bitcoin and generally evaluates cryptocurrencies as a whole without decomposition. As cryptocurrencies present various characteristics, this paper focuses on ETH instead of bitcoin to avoid bitcoin's natural value accumulation due to its 21 million limited quantity and creatively decomposes ETH into a trend component and a cyclical component. While the trend component is largely driven by the acceptable level of ETH as a payment, the cyclical component is a reasonable reflection of the demand for a safe haven and speculation and is directly linked to GEPU. While previous studies do not find a Granger causality nor a cointegration relationship between cryptocurrency and GEPU, my results show that GEPU does Granger cause the cyclical component of ETH (ETH cyclical), and they have a cointegration relationship that will be converged after short-term deviations.

2. Literature Review

2.1. Literature

Prior research mainly concentrates on the relationship between United States economic uncertainty and the price of bitcoin ([3]Dyhrberg, 2016; [5]Bouri, Molnar et al. 2017; [6]Al-Khazali et al. (2018); [7]P. Wang et al. (2020)). Several researchers demonstrate that GEPU has an impact on the price of bitcoin ([8]Bouoiyour and Selmi (2016); [9]Demir et al. (2018)). [8]Bouoiyour and Selmi (2016) find they move in the same direction. But [10]Qin et al. (2021) find both positive and negative relationships between GEPU and cryptocurrencies. [11]Khan et. al (2021) leverage the rolling window method and discover both positive and negative bidirectional causalities between GEPU and bitcoin price across various subsamples. The relationship between GEPU and bitcoin volatility is also a popular topic ([12]Conrad et al. (2018); [13]Yu (2019); [14]Fang et al. (2019); [15]Walther et al. (2019)). Regarding the hedging character, [16]Corbet et al. (2018) and [17]Aslanidis et al. (2019) discover a decorrelation relationship between cryptocurrencies and traditional financial assets. [4]Bouri, Gupta, et al. (2017) examine whether hedging against GEPU is a character of cryptocurrency. [5]Bouri, Azzi, and Dyhrberg (2017) reveal the haven feature of cryptocurrencies. Several scholars also try to forecast the prices of cryptocurrencies. [15]Walther et al. (2019) use a mixed data sampling approach.

2.2. Contributions

The past literature generally evaluates the relationship between GEPU and the entire cryptocurrency. Even though some researchers divide data into subgroups based on structural breaks, it does not decompose based on the different characteristics of cryptocurrencies. As a result, whether GEPU has a positive or negative impact on bitcoin and ETH prices remains undecided. Also, the Granger causality relationship is unsettled among researchers and sensitive to subsamples. The major reason is that cryptocurrencies such as bitcoin and ETH possess various features, and not all the features are influenced similarly by GEPU. Therefore, instead of using a conventional method, this study employs the Hodrick-Prescott filter decomposition method to decompose ETH into a trend component, which mainly reflects the increasingly wide acceptance of cryptocurrencies, and a cyclical component, which is the transitory component that should be highly affected by GEPU. From Table 1 & Fig. 3, the 12-month rolling correlation between GEPU and ETH cyclical has a higher mean and median but lower standard deviation, and hence a more stable correlation than that of GEPU and ETH trend. The correlation between GEPU and ETH cyclical is mostly negative, while the GEPU & ETH trend correlation is spreading widely in both positive and negative zones.

TABLE 1. GEPU & ETH Cyclical/Trend Rolling Correlation

Variables	*Mean*	*Median*	*s.d.*	*Skewness*	*Kurtosis*
GEPU_ETH Cyclical_Corr	-0.37	-0.47	0.36	1.08	3.16
GEPU_ETH Trend_Corr	-0.26	-0.40	0.53	0.38	1.68

This study contributes to the literature in the following aspects. First, most previous studies use bitcoin price as a proxy for cryptocurrency price. But bitcoin has a limited quantity of 21 million, which makes bitcoin gradually more difficult and more costly to mine. Hence, bitcoin naturally has increased value due to its higher cost. But very few past papers consider this issue. This paper selects ETH to represent cryptocurrencies, as ETH is the second-largest cryptocurrency but with indefinite quantity, and hence with constant basic cost. Besides, the ETH foundation is the base of many blockchain technologies, which makes it more stable, and less speculative with higher real value than bitcoin. Therefore an evaluation of GEPU and ETH can be a good indication of the entire crypto ecosystem as a reflection of GEPU.

3. Data and Method

3.1. Data

This paper employs monthly data of the Global Economic Policy Uncertainty Index, which is a GDP-weighted average of national EPU indices for 20 countries, and the price of ETH from September 2015 to January 2022. It covers almost the entire period of ETH history. The GEPU monitors global economic and policy events and changes that have stirred global economic and financial turmoil, e.g. Eurozone debt crisis, Brexit, the US elections, the US fiscal cliff, the US-China trade war, important meetings of Chinese government, the covid-19 pandemic, and the slowdown of major economies etc. All these events exacerbate economic uncertainty and have tremendous influence on financial markets and ordinary people's daily lives. During this period, though cryptocurrencies greatly gain acceptance in the conventional system and market, ETH experiences 2017 peak and 2018 bubble burst, as well as 2021 peak and 2022 adjustment, which has almost two full cycles.

TABLE 2. Summary Statistics

Variables	*Mean*	*s.d.*	*Skewness*	*Kurtosis*	*J-B*
ETH	666.67	1075.86	2.14	6.65	101.69***
ETH cyclical	8.22e-11	371.18	1.62	8.10	123.26***
GEPU	217.24	67.85	0.72	3.21	6.74**

a. Note. J-B=Jarque-Bera; ***1% significance **5% significance

Table 2 summarizes the basic characteristics of GEPU and ETH. ETH has a higher standard deviation. Both GEPU and ETH are skewed to the right. Both data series have kurtosis values higher than 3 implying they both have a thin "bell" distribution with high peaks.

3.2. Empirical Method

I use the Hodrick-Prescott filter decomposition method to decompose ETH into two components. One is the trend component, and the other is the cyclical or transitory component (Fig. 2).

The trend component represents the increasing wide usage and acceptance of cryptocurrencies, which is similar to bitcoin and other digital currencies. More and more banks, market exchanges and companies start to use and invest in cryptocurrencies. Major cryptocurrencies are accepted as payment methods by several famous e-commerce companies such as PayPal, eBay, Alibaba Taobao and so on. All of these lead to a rise in popularity and usage by the public. However, this trend is irrelevant to GEPU. The GEPU index does not cause an increase in currency's intrinsic value. As a result, including the trend component may distort the relationship between GEPU and ETH. The rest belongs to the cyclical or transitory component, which is the residual of the trend component extraction. We see that the cyclical component oscillates around zero and does not have an upward sloping trend. It has a mean very close to zero, and much lower standard deviation and smaller skewness than ETH. This component displays the characteristics of a substitute for safe-haven assets like gold and a speculative financial asset, both of which are highly affected by GEPU.

I use several unit root tests, augmented Dickey-Fuller test, Phillips-Perron test and Kwiatkowski-Phillips_Schmidt-Shin test (KPSS) to examine whether the data series are stationary. From Table 3, ETH is not stationary at the level but stationary at the first difference. But both GEPU and ETH cyclical components are stationary at the level. This allows us to apply the cointegration model to examine causality between GEPU and ETH cyclical components.

TABLE 3. Unit Root Tests

Variable	*Level*			*First Difference*		
	ADF	*PP*	*KPSS*	*ADF*	*PP*	*KPSS*
ETH	0.7966	0.8095	0.2200	0.0000***	0.0000***	0.0710***
ETH cyclical	0.0081***	0.0042***	0.0501***	0.0000***	0.0000***	0.0821***
GEPU	0.0462**	0.0493**	0.1120**	0.0001***	0.0001***	0.1550**

Note ***1% significance **5% significance

Based on Akaike Criterion (AIC) and Schwarz Criterion (SIC), lag 1 or 2 periods are the best respectively. Thus, I conduct the Granger Causality test with a lag of 1 and 2 periods. The full sample demonstrates that GEPU Granger causes ETH price both lagging 1 and 2 periods but not vice versa. That means

GEPU does have a causal link with the ETH cyclical component and leads in one to two periods.

TABLE 4. GRANGER CAUSALITY TESTS

	H0: GEPU does not Granger cause ETH cyclical		*H0: ETH cyclical does not Granger cause GEPU*	
	Statistics	*p-value*	*Statistics*	*p-value*
Lag 1	4.05337	0.0478**	0.03988	0.8423
Lag 2	2.49051	0.0902*	0.06065	0.9412

Note **5% significance *10% significance

I continue to examine their cointegration relationship to see whether they have a long-term equilibrium by employing the Engle-Granger model and Johansen System Cointegration test. We reject the null hypothesis that series are not cointegrated at the 5% significance using Engle-Granger Model and find one cointegration at the 5% significance level with Johansen Cointegration Test. That suggests GEPU and ETH have a long-run cointegration relationship. I also explore the coefficients of GEPU lagging one and two periods and they are both negative and significant at a 1% level as well. That implies GEPU negatively impacts ETH cyclical, which is different from most prior research.

$$ETH\ Cyclical = 419.35 - 1.81{*}GEPU \quad (1)$$

$$(3.20^{**})\ (-3.14^{**})$$

$$R\text{-}square = 0.17$$

TABLE 5. THE COINTEGRATION TEST

Null hypothesis	*Trace Value*	*Max eigenvalue*	*0.05 Critical Value*	*p-values*
r=0	18.65196	0.139722	15.49471	0.0161**
r=1	7.514968	0.096567	3.841466	0.0061***

Note ***1% significance **5% significance

To examine the short-term dynamics between the two data series, I use the error correction model and find that the coefficients of the error correction model are one negative and less than 1 and one positive, which shows the ETH cyclical component responds in the short-run to changes in GEPU, and deviations from long-run equilibrium. The dynamics make the ETH cyclical component converge towards its long-run equilibrium.

TABLE 6. ERROR CORRECTION MODEL

Dependent Variable	*Independent Variable(s)*					
	CointEq1	*D(GEPU(-1))*	*D(GEPU(-2))*	*D(ETH Cyc(-1))*	*D(ETH Cyc(-2))*	*Constant*
D(ETH Cyclical)	-0.82**	-0.30	-0.28	0.22*	-0.18	-5.92
D(GEPU)	0.02	-0.32**	0.01	-0.01	-0.02	2.82

Note *10% significance **5% significance

4. CONCLUSION

This research studies the relationship between GEPU and ETH price by decomposing ETH into trend and cyclical components and extracting the cyclical component and abandoning the irrelevant trend component. In this way, I find results different from previous literature and provide an improved explanation. Without distortion from the trend component, GEPU Granger causes ETH, which differs from prior research conclusions. Besides, GEPU and ETH cyclical have a stable long-run negative cointegration relationship, which is also different from previous studies and most scholars' expectations, as most research concludes that GEPU and ETH have a positive relationship. The relationship between GEPU and ETH may be disturbed by the trend component, of which the upward-sloping trend dominates. When ETH cyclical does not have a trend, it responds negatively to GEPU and its lagging terms. That means that cryptocurrencies may react ahead of the market like stocks and other financial assets, when global economic uncertainty escalates, the news may have been priced in and the ETH cyclical component reverses accordingly. The error correction model demonstrates that the ETH cyclical component responds in the short-run to changes in GEPU and deviations from their long-run equilibrium. The dynamics make the ETH cyclical component converge towards its long-run equilibrium.

4.1. *Figures and Tables*

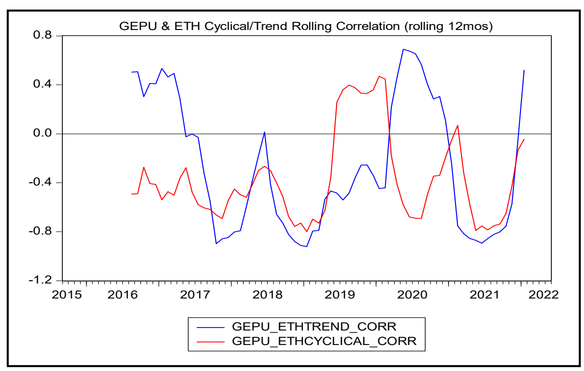

Figure 1. Global Economic Uncertainty & Ethereum Price

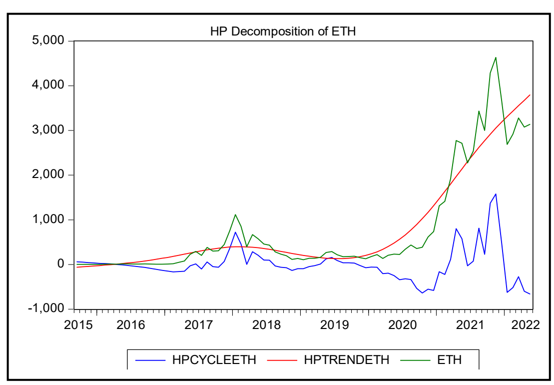

Figure 2. Hodrick-Prescott Decomposition of Ethereum Price

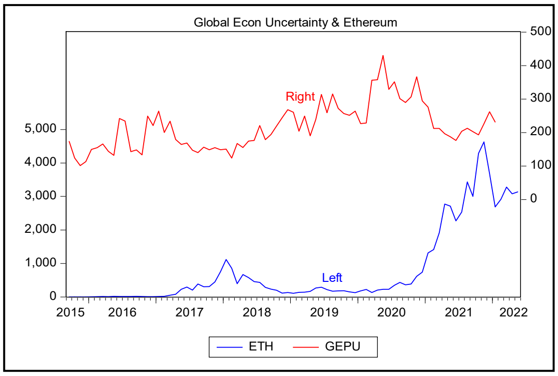

Figure 3. GEPU & ETH Cyclical/Trend Rolling Correlation

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