FinTech

Article

Examining the Drivers and Economic and Social Impacts of Cryptocurrency Adoption

Yongsheng Guo *, Ezaddin Yousef and Mirza Muhammad Naseer

International Business School, Teesside University, Middlesbrough TS1 3BX, UK; e.yousef@tees.ac.uk (E.Y.); m.naseer@tees.ac.uk (M.M.N.)
* Correspondence: y.guo@tees.ac.uk; Tel.: +44-1642-342834

Abstract: This study investigates the key drivers and the economic and social impacts of cryptocurrency adoption. Based on panel data across 37 countries from 2020 to 2023, this research examines the interplay between cryptocurrency adoption and technology development, monetary policies, and economic and social development. Employing a mixed-methods approach, the research incorporates panel data analysis across multiple countries to explore correlations and causal relationships between these variables. The study found that technology development, measured by the Network Readiness Index (NRI) enables cryptocurrency adoption. Economic conditions measured by higher national inflation rates and monetary policy indicators, including lower interest and exchange rates are the key drivers for cryptocurrency adoption. The empirical findings reveal that cryptocurrency adoption has negative relationships with economic development measured by the GDP growth rate, unemployment rate, and social development represented by the governance quality corruption index. It implies that cryptocurrency is used as a virtual anchor (digital gold) for national inflation. Findings reveal how network readiness, economic conditions, and monetary policies contribute to fostering cryptocurrency adoption, while resulting in impacts on economic growth, labour markets, and governance. The research contributes to the literature by integrating technological, economic, and governance perspectives to elucidate the role of cryptocurrency in reshaping the global economic and social systems.

Keywords: cryptocurrency; inflation; monetary policies; GDP growth; governance quality

JEL Classification: C12; E4; O4

Academic Editors: Nikiforos T. Laopodis and Eleftheria Kostika

Received: 15 December 2024
Revised: 21 January 2025
Accepted: 22 January 2025
Published: 25 January 2025

Citation: Guo, Y.; Yousef, E.; Naseer, M.M. Examining the Drivers and Economic and Social Impacts of Cryptocurrency Adoption. *FinTech* **2025**, *4*, 5. https://doi.org/10.3390/fintech4010005

1. Introduction

The development of cryptocurrencies has undergone significant evolution [1,2], driven by technological advancements [3] and increased adoption across countries. Blockchain technology remains the backbone of cryptocurrencies, enabling features like immutability, decentralisation, and transparency [4]. The integration of blockchain into financial systems highlights its potential to improve transactional efficiency and foster financial inclusion [5,6]. Cryptocurrency adoption has emerged as a transformative element in global financial ecosystems [7], influencing various aspects of economic development [8]. Its potential to enhance financial inclusion, foster innovation, and streamline cross-border transactions highlights its role in shaping modern economies [9–11].

The adoption of cryptocurrencies and their interplay with national inflation has garnered increasing academic interest due to their disruptive potential in financial systems [12–15]. Specifically, cryptocurrencies, often seen as a hedge against inflation, have found popularity in countries with unstable fiat currencies [16,17]. Cryptocurrencies are often criticised for their price volatility [3,18], which can hinder their utility as a reliable store of value or medium of exchange. This volatility poses risks for economies heavily reliant on digital currencies for development [19,20].

Moreover, issues like fraud, cyberattacks, and insufficient consumer protection mechanisms [1,21] can undermine trust in cryptocurrencies, limiting their adoption and economic impact. Last but not least, energy-intensive mining processes associated with cryptocurrencies like Bitcoin raise environmental sustainability questions [22], particularly in developing economies with limited energy resources [7].

The studies investigate the drivers of cryptocurrency adoption, focusing on the interplay between technology development [16,17], economic conditions [14,23], monetary policies [24–26], non-crypto investors [27] and perceived corruption [28]. Technology development is evaluated using the Network Readiness Index (NRI), which captures a nation's capacity to leverage technology for growth and innovation. Economic conditions are represented by the national inflation rate (INF) and Economic Freedom Index (EFI), highlighting the role of macroeconomic stability in fostering or hindering cryptocurrency adoption. Monetary policy indicators, including the interest rate (INT) and exchange rate (EXR), are analysed to understand their influence on the decision to adopt decentralised digital currencies as alternatives or complements to traditional financial systems. Moreover, this study examines the impact of cryptocurrency adoption on economic and social development [12,14], focusing on key indicators such as the economic growth rate (GDP), unemployment rate (UEMP), and governance quality as represented by the corruption index (CORR).

This study aims to provide insights into how technological preparedness, economic pressures, and monetary dynamics shape the adoption trajectory of cryptocurrencies globally, and to offer a better understanding of the role of cryptocurrency in macroeconomic performance and societal governance. It reveals the advantages of cryptocurrencies in fostering economic opportunities while highlighting the challenges of potential economic and governance risks. By bridging the gap between cryptocurrency adoption and broader developmental outcomes, this study contributes to the growing body of knowledge on financial technology and proposes practical implications for policymakers, investors, and technology developers in navigating the evolving cryptocurrency landscape.

The rest of this paper is designed to provide a critical review of existing studies on cryptocurrency adoption, and economic and social development. The Theoretical Framework and Hypotheses are derived based on identified research gaps. The Research Methodology Section explains the data sources, variables, and econometric models used to examine the relationships between cryptocurrency adoption and developmental indicators. The Results and Discussion Section presents the findings, offering detailed interpretations and comparisons with existing literature. Finally, the Conclusion and Policy Implications Section summarises the study's contributions, suggests practical applications, and highlights avenues for future research.

2. Literature Review

2.1. Drivers of Cryptocurrency Adoption

Among others, technological development, national economic conditions, and monetary policies are the main drivers of cryptocurrency adoption. The role of technology in cryptocurrency adoption is critical, as digital currencies are inherently technological innovations [16,17]. The study [29] uses a mixed-methods approach to explore factors influencing the adoption of sustainable cryptocurrencies and investment barriers. It provides insights for investors, policymakers, and industry managers, emphasising the importance of regulatory support, customer trust, and sustainability in promoting cryptocurrency adoption [29]. Other studies show that countries with robust internet penetration, advanced mobile networks, and high rates of digital literacy are more likely to see higher cryptocurrency adoption rates [30]. Moreover, the rapid evolution of blockchain applications, including decentralised finance (DeFi) and non-fungible tokens (NFTs), has further driven adoption [31].

Economic conditions often act as a catalyst for cryptocurrency adoption [32], particularly in regions with high inflation or volatile currencies [33,34]. For instance, studies demonstrate that individuals and businesses in countries with unstable fiat currencies turn to cryptocurrencies as a store of value or medium of exchange to hedge against economic uncertainty [35]. Inflation rates have a significant impact, as seen in nations like Venezuela and Zimbabwe, where hyperinflation led to a surge in cryptocurrency use [36].

Additionally, economic growth indicators such as GDP per capita influence adoption, with higher-income countries showing greater investment in cryptocurrencies as speculative assets. The study [37] utilised Fuzzy-set Qualitative Comparative Analysis an inductive approach whereby causal factors are obtained from prior studies to explore their complex interdependency. It first analyses a larger sample of 101 countries (without cultural values) and further investigates the cultural aspects and their roles in 43 countries. The result shows that social factors and financial development are the central factors for cryptocurrency adoption. Monetary policies, including interest rates and exchange rate stability [38], significantly shape cryptocurrency adoption. Low or negative interest rates reduce the opportunity cost of holding cryptocurrencies, thereby encouraging adoption [39,40]. Similarly, exchange rate volatility incentivises individuals and corporations to adopt cryptocurrencies as a means of preserving value and facilitating cross-border transactions without the risks associated with fluctuating fiat currencies [41]. Regulatory clarity in monetary policies also plays a crucial role; permissive environments foster adoption, while restrictive measures, such as outright bans, hinder it [42].

2.2. Effects of Cryptocurrency Adoption

Cryptocurrency adoption has sparked significant debate among researchers [19,21] and policymakers regarding its effects on macroeconomic indicators and social structures. Cryptocurrencies contribute to economic growth by facilitating financial inclusion, reducing transaction costs, and promoting cross-border trade [43]. Blockchain technology, which underpins cryptocurrencies, enhances financial efficiency and transparency, thus encouraging economic activity [30]. For example, decentralised finance (DeFi) platforms allow small- and medium-sized enterprises (SMEs) to access funding in regions where traditional banking systems are underdeveloped.

Studies highlight a positive correlation between cryptocurrency adoption and GDP growth, particularly in emerging markets. Ref. [1] emphasises the role of cryptocurrencies in increasing remittance inflows, which are crucial for economic development in low-income countries. However, critics argue that speculative trading and market volatility could overshadow these benefits, leading to financial instability.

Cryptocurrencies have implications for social development, particularly governance quality and corruption. Blockchain's transparency and immutability make it a valuable tool for combating corruption by ensuring accountability in public financial management [42]. Countries with high levels of corruption often experience increased cryptocurrency adoption as citizens seek alternatives to circumvent corrupt financial systems [35].

Despite these benefits, the anonymity provided by some cryptocurrencies can also enable illicit activities, undermining governance and legal systems. Research by [36] highlights a dual impact: while blockchain fosters transparency, unregulated cryptocurrency markets may facilitate tax evasion and money laundering. Addressing these challenges requires robust regulatory frameworks that balance innovation with accountability.

2.3. Research Gaps

Despite extensive studies on the drivers and effects of cryptocurrency adoption, several gaps remain [19,20]. Firstly, although the literature extensively covers individual drivers, integrated models that examine the interplay between technology, economic conditions, and monetary policies are limited. Secondly, while the impact of inflation is well documented in hyperinflationary economies, more research is needed on stable monetary systems. Thirdly, the long-term effects of cryptocurrency on economic growth and the role of cryptocurrencies in enhancing governance quality calls for nuanced studies on international contexts.

The adoption of cryptocurrencies is a multifaceted phenomenon driven by technological advancements, economic conditions, and monetary policies. Understanding these drivers offers valuable insights for policymakers, businesses, and technology developers, aiming to harness the potential of digital currencies. Future research should adopt a multidisciplinary approach to address existing gaps and provide a holistic view of cryptocurrency adoption dynamics.

The adoption of cryptocurrencies has significant implications for inflation management, economic growth, and social development. While they offer innovative solutions for financial inclusion and governance, challenges such as volatility and regulatory concerns persist. A comprehensive understanding of these dynamics is essential for maximising the benefits of cryptocurrency adoption while mitigating associated risks.

2.4. Theoretical Framework and Hypotheses

This study introduces the multiple-currency model for cryptocurrency where cryptocurrencies coexist or compete with traditional fiat currencies catering for different functions [44]. For example, multiple currencies provide diverse financial tools, enabling access for underserved populations without access to traditional banking systems [1]. A diverse currency ecosystem promotes innovation in payment technologies, transaction efficiencies, and financial products [30].

This study argues that cryptocurrencies can be used as a nominal anchor [45], which suggests that the value of a currency should be tied to a stable measure or "anchor" to maintain price stability and control inflation [46,47]. For example, Bitcoin has been proposed as a potential nominal anchor in a decentralised monetary system [36] because of its fixed supply (capped at 21 million coins), and in environments where fiat currencies are unreliable [35].

Based on the multiple-currency model and nominal anchor theory, this study builds a theoretical framework for cryptocurrency adoption. Factors such as technological development, monetary policies and economic conditions influence the adoption of cryptocurrency. Moreover, cryptocurrency adoption affects national economic and social development. Therefore, this study proposes the following hypotheses:

H1. *Cryptocurrency adoption has positive relationships with technology development, monetary policies and economic conditions;*

H2. *Cryptocurrency adoption has positive relationships with economic growth, labour market and social development.*

3. Research Methodology

3.1. Data and Variables

This study employs a quantitative research design using panel data analysis to investigate the drivers and impacts of cryptocurrency adoption. The data spans 37 countries from 2020 to 2023, covering diverse economic, social, and governance contexts. The dependent variable of the study is the cryptocurrency adoption rate (CAR) measured by the Crypto Adoption Index. Chainalysis produces annual reports known as the Crypto Adoption Index, which aims to measure and track cryptocurrency adoption levels in different countries. The index is based on a comprehensive analysis of blockchain transactions. The global Crypto Adoption Index ranks countries on a scale of 0–1. The closer the score is to 1, the higher the rank [48].

The dependent variables are GDP, INF, UNEMP, EXR, NRI, INTR, CORR, and EFI. GDP is calculated as the total market value of all goods and services produced within a country in a specific year, serving as a key indicator of economic health. To adjust for inflation effects, GDP is often expressed in constant U.S. dollars. INF is quantified through the annual percentage change in the Consumer Price Index, which tracks the cost-of-living adjustments. UNEMP is defined as the proportion of the labour force that is unemployed but actively seeking work. EXR denotes the rate at which a country's currency can be exchanged for the U.S. dollar (USD), reflecting the relative stability of the national currency. NRI measures a country's capability to adopt and utilise digital technologies, including cryptocurrencies. It evaluates aspects such as ICT infrastructure, affordability, digital skills, and usage, with higher scores indicating better readiness for digital advancements and cryptocurrency integration (detailed methodology available at https://networkreadinessindex.org/ accessed on 2 September 2024). Figure 1 illustrates the main pillars of the NRI. INTR is represented by the central bank's policy rate or the short-term interest rate, which influences the cost of borrowing and returns on savings, thereby impacting investment choices and financial behaviour including the uptake of cryptocurrencies. CPI, published by Transparency International, gauges the perceived levels of public sector corruption in a country. Higher corruption may encourage the use of cryptocurrencies to circumvent traditional financial systems seen as corrupt. EFI issued by the Heritage Foundation, evaluates economic freedom within a country, considering elements like property rights, government integrity, and regulatory efficiency. Elevated levels of economic freedom typically correlate with more developed financial markets and greater receptiveness to innovations such as cryptocurrencies.

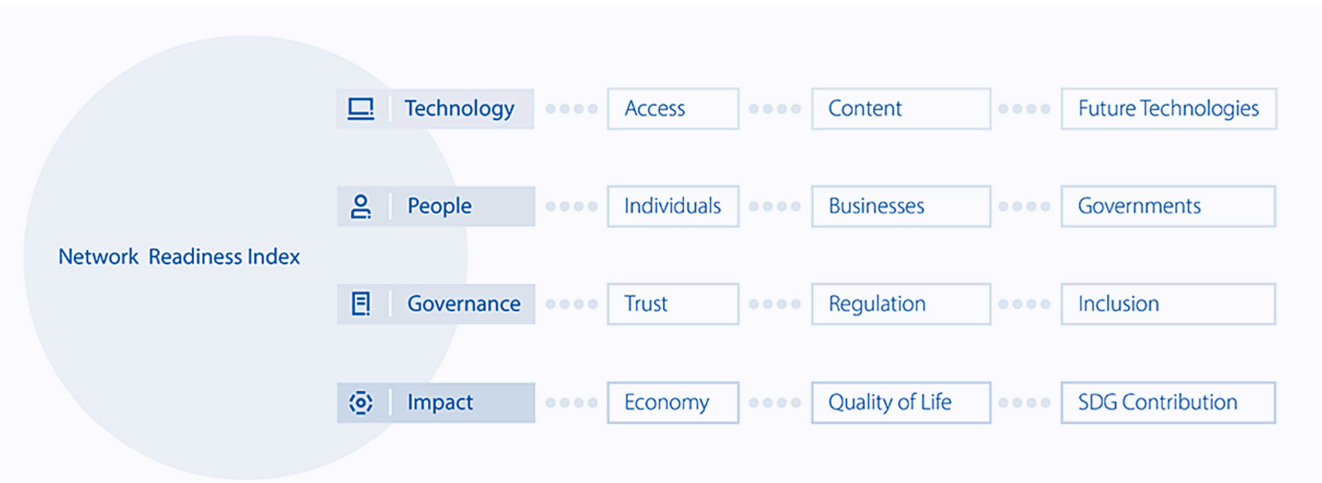

Figure 1. Pillars of Network Readiness Index (NRI)—source [49].

3.2. Empirical Strategy

Panel data methodology is chosen for its ability to capture both cross-sectional and time-series variations, allowing for robust modelling of the relationships among variables [50]. Based on the theoretical framework hypotheses are derived from literature. The research model below illustrates the relationship between cryptocurrency adoption with technology development, monetary policies, and economic conditions.

$$CAR_{i,t} = A\ X\ (NRI)_{i,t}{}^{a1} X\ (INTR)_{i,t}{}^{a2} X\ (EXR)_{i,t}{}^{a3} X(EF1)_{i,t}{}^{a4} \quad (1)$$

Moreover, the dependent variables and relationships might be dynamic and evolve over time. Equation (2) shows dynamic models.

$$\frac{dCARi_t}{dt} = f\left(CAR_{i(t-n)},\ NRI_{it}, INTR_{it}, EXR_{it}, EFI_t\right) \quad (2)$$

where CAR is the cryptocurrency adoption rate; NRI is the Network Readiness Index; INTR is the National Central Bank interest rate; EXR is the exchange rate; and EFI is the Economic Freedom Index.

Moreover, cryptocurrency adoption may have relationships with economic and social development.

$$CAR_{i,t} = A\ X\ (INF)_{i,t}{}^{5a} X\ (GDP)_{i,t}{}^{a6} X\ (UNEMP)_{i,t}{}^{a7} X(CORR)_{i,t}{}^{a8} \quad (3)$$

Moreover, the dependent variables and relationships might be dynamic and evolve over time. Equation (2) shows dynamic models.

$$\frac{dCARi_t}{dt} = f\left(CAR_{i(t-n)},\ INF_{it}, GDP_{it}, UNEMP_{it}, CORR_{it}\right) \quad (4)$$

where CAR is the cryptocurrency adoption rate; INF is the national annual inflation rate, representing economic development; GDP is the gross domestic product growth rate, representing economic development; UNEMP is the national unemployment rate, representing social development; and CORR is the corruption index of the quality of governance represents social development.

The study uses secondary data obtained from international databases, including those of the World Bank, IMF, and Transparency International, over a period from 2020 to 2023.

Table 1 shows the variables and data sources.

Table 1. Variables and data source.

Variables	Indicator Name	Definition	Data Source
CAR	Cryptocurrency Adoption Rate	Global Crypto Adoption Index	Chain analysis, data are available at https://www.chainalysis.com/blog/2023-global-crypto-adoption-index (accessed on 10 October 2023)
NRI	Network Readiness Index	Network Readiness Index	Data are available at https://networkreadinessindex.org (accessed on 10 October 2024)
INTR	Interest Rate	National Central Bank Interest rate	International Monetary Fund (IMF) Database

Table 1. *Cont.*

Variables	Indicator Name	Definition	Data Source
EXR	Exchange Rate	EXR is the exchange rate (nominal), which represents the value at which the currency of a specific country can be exchanged for the United States Dollar (USD)	International Monetary Fund (IMF) Database
EFI	Economic Freedom	The impact of liberty and free markets around the globe	The Heritage Foundation's Index of Economic Freedom
INF	Inflation Rate	Consumer Prices Index (CPI)	International Monetary Fund (IMF) Database
GDP	Gross Domestic Product	Gross domestic product (current US $)	World Bank national accounts data, and OECD National Accounts data files
UNEMP	Unemployment Rate	The International Labour Organisation's (ILO) unemployment rate	https://stats.oecd.org (accessed on 10 October 2024)
CORR	Corruption Index	CORR perceives levels of public sector corruption, score 0 (highly corrupt) to 100 (very clean)	https://www.transparency.org (accessed on 10 October 2024)

To examine the relationships among key variables, a comprehensive approach includes pairwise correlations, cross-sectional dependence tests, regression tests, and causality tests are used in this study.

The Pearson correlation coefficient [51] is computed to find the pairwise correlations among variables.

$$\varrho(X,Y) = Cov(X,Y)/\sigma X\sigma Y$$

where $\varrho(X,Y)$ is the Pearson correlation coefficient; Cov (X, Y) is the covariance between variables X and Y; σX and σY are the standard deviations of X and Y, respectively.

To find if the observations are interdependent or correlated, a cross-sectional dependence test is conducted. The Breusch–Pagan LM test [52] is conducted to assess heteroscedasticity. To examine cross-sectional dependence, the Pesaran-scaled LM test [53] is employed to ensure the independence of observations. The Bias-Corrected Scaled LM test is applied to mitigate finite-sample bias [54]. The Pesaran CD test is used to explore cross-sectional dependence [55], which ensures the robustness of detecting dependencies among different cross-sectional units.

In the Breusch–Pagan LM test,

$$\mathrm{LM} = \mathrm{nR}^2$$

where

LM: the test statistic;

n: the number of observations;

R^2: the R-squared from the regression.

In the Pesaran-scaled LM test,

$$\mathrm{LM} = \frac{\mathrm{N}}{\mathrm{N}-1}\frac{\mathrm{T}(\mathrm{T}-1)}{4}\frac{\mathrm{R}^2}{1-\mathrm{R}^2}$$

where

LM: the test statistic;
N: the number of cross-sectional units;
T: the number of time periods;
R^2: the R-squared from the auxiliary regression.

In the Bias-Corrected Scaled LM Test,

$$\mathrm{LM_{BC}} = \mathrm{LM} / \left(1 - \frac{2}{\mathrm{T}}\right)$$

where

$\mathrm{LM_{BC}}$: the Bias-Corrected LM test statistic;
LM: The original LM test statistic;
T: the number of time periods.

In the Pesaran CD test,

$$\mathrm{CD} = \mathrm{N}(\mathrm{LM}/\mathrm{N})$$

where

CD: the Pesaran CD test statistic;
LM: the test statistic from the Pesaran-scaled LM test;
N is the number of cross-sectional units.

Ordinary Least Squares (OLS) is used in the Baseline Regression, estimating the parameters in linear regression models. The coefficients derived from OLS provide the magnitude and direction of the relationship [56]. R^2 shows the Goodness-of-Fit measuring the proportion of variance in the dependent variable explained by the independent variables [57].

Feasible Generalised Least Squares (FGLS) is an econometric estimation technique used to address issues of heteroskedasticity and autocorrelation in regression models. FGLS provides more efficient and unbiased parameter estimates under heteroskedasticity or autocorrelation [56]. The technique of Panel-Corrected Standard Errors (PCSEs) is an econometric method developed by [58] to address issues of heteroskedasticity and cross-sectional dependence in panel data regression models. PCSEs adjust the standard errors of regression coefficients to ensure valid statistical inference when the error structure exhibits contemporaneous correlation and heteroskedasticity across panel units. The Generalised Method of Moments (GMM) is a widely used econometric estimation technique [59], which is particularly suitable for models that involve endogeneity, heteroskedasticity, or when the researcher has a set of moment conditions derived from economic theory. It has become a standard tool for dynamic panel data models, time-series analysis, and instrumental variable regressions [60].

The pairwise Dumitrescu–Hurlin panel causality test is employed to identify the causal relationships [61]. The Wald Statistic WStat is used to check the existence of causality in panel data:

$$W_{Stat} = \frac{T(N-1)}{N(T-1)} \left(\sum_{i=1}^{N} \sum_{t=1}^{T} \check{\varepsilon}_{it}^2 \right)$$

where

$\mathrm{W_{Stat:}}$ the Wald Statistic;
T: the number of time periods;
N: the number of cross-sectional units;
$\check{\varepsilon}_{it}$: the residuals from the pooled regression.

4. Findings and Discussion

4.1. Summary Statistics

Table 2 provides descriptive statistics for the variables, summarising their central tendencies and variations based on a dataset of 148 observations. The cryptocurrency adoption rate (CAR) has a mean of 0.11 with a standard deviation of 0.137, and the maximum adoption is 0.93, reflecting an uneven distribution of digital currency penetration. The dataset demonstrates diverse economic, social, and technological contexts across observations. There is significant variability in interest and exchange rates, inflation, and governance quality suggesting heterogeneity among the entities studied.

Table 2. Descriptive statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
CAR	148	0.110	0.137	0.000	0.931
GDP	148	1.914	4.822	−11.20	16.30
INF	148	4.862	4.142	−1.20	19.70
UNEMP	148	6.322	2.983	2.000	17.60
EXR	148	24.129	62.851	0.630	375.0
NRI	148	67.707	8.745	46.26	82.75
INTR	148	2.350	2.783	−0.75	16.00
CORR	148	64.98	15.679	26.00	90.00
EFI	148	71.816	6.193	53.80	84.20

The table provides descriptive statistics for the study variables. CAR is the cryptocurrency adoption rate, GDP is the gross domestic product, INF is inflation, UNEMP is the unemployment rate, EXR is the exchange rate, NRI is the Network Readiness Index, INTR is interest rates, CORR is the corruption index, and EFI is the economic freedom.

Table 3 provides a correlation matrix showing the relationships between variables of interest. Each entry represents the Pearson correlation coefficient ranging from −1 to 1. The weak but notable correlation between cryptocurrency adoption (CAR) and inflation (INF) suggests that inflationary environments may drive individuals toward alternative financial systems like cryptocurrencies. Strong correlations between the Network Readiness Index (NRI) and governance indicators (CORR and EFI) highlight the critical role of technological infrastructure in promoting better governance and economic freedom. The positive relationship between inflation (INF) and interest rates (INTR) underscores the interplay between monetary policy and price stability.

Table 3. Matrix of correlations.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) CAR	1.000								
(2) GDP	−0.142	1.000							
(3) INF	0.147	0.248	1.000						
(4) UNEMP	−0.063	−0.122	−0.091	1.000					
(5) EXR	−0.030	−0.003	0.236	−0.115	1.000				
(6) NRI	0.110	−0.007	−0.356	−0.422	−0.257	1.000			
(7) INTR	0.077	0.082	0.675	−0.174	0.360	−0.377	1.000		
(8) CORR	−0.098	−0.049	−0.279	−0.354	−0.333	0.880	−0.348	1.000	
(9) EFI	−0.096	0.055	−0.170	−0.389	−0.232	0.674	−0.336	0.788	1.000

The table provides a correlation matrix for the study variables. CAR is the cryptocurrency adoption rate, GDP is the gross domestic product, INF is inflation, UNEMP is the unemployment rate, EXR is the exchange rate, NRI is the Network Readiness Index, INTR is interest rates, CORR is the corruption index, and EFI is the economic freedom.

4.2. Cross-Sectional Dependence and Slope Heterogeneity Test

Table 4 reports the results from multiple tests for cross-sectional dependence among variables by using Breusch–Pagan LM, Pesaran Scaled LM, Bias-Corrected Scaled LM, and Pesaran CD tests. These tests determine whether variables exhibit dependence across cross-sectional units (countries) in panel data. The null hypothesis (H0H_0H0) for all tests is that there is no cross-sectional dependence. All tests indicate substantial cross-sectional dependence for most variables, implying that global or regional factors play a significant role in shaping the variables under study. This finding supports the need for econometric techniques, such as cross-sectional dependence-adjusted models or spatial econometrics, to account for these correlations in further analyses. In particular, the Pesaran CD test, suitable for both small time periods and cross-sections, generally confirms the presence of cross-sectional dependence, although some variables, such as CORR (1.307) and EFI (10.086), show weaker dependence compared to others.

Table 4. Cross-sectional dependence tests and slope heterogeneity.

Variables	Breusch–Pagan LM	Pesaran Scaled LM	Bias-Corrected Scaled LM	Pesaran CD
CAR	2223.08 ***	42.66 ***	36.50 ***	46.71 ***
GDP	2125.31 ***	39.98 ***	33.82 ***	45.41 ***
INF	2277.10 ***	44.144 ***	37.978 ***	47.525 ***
UNEMP	1687.028 ***	27.976 ***	21.809 ***	38.767 ***
EXR	1543.961 ***	32.028 ***	25.862 ***	16.086 ***
NRI	1896.972 ***	33.728 ***	27.562 ***	38.964 ***
INTR	1974.971 ***	41.784 ***	30.731 ***	12.448 ***
CORR	1452.287 ***	21.544 ***	15.377 ***	1.307
EFI	1396.961 ***	20.028 ***	13.862 ***	10.086 ***
Testing for slope heterogeneity [62]. H0: slope coefficients are homogenous.				
Delta	−7.795			
p_value	0.000			

The table presents cross-sectional dependence using four different tests and slope heterogeneity using Pesaran and Yamagata (2008) tests [62]. The null hypothesis (H0) for cross-sectional dependence is that underlying variables are independent across different sections while for slope heterogeneity it is slope coefficients are homogenous. Asterisks indicate statistical significance at the 10% one-star, 5% two-star, and 1% three-star levels, respectively. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.3. Baseline Regression

Table 5 presents results from multiple Ordinary Least Squares (OLS) regression models, testing the effects of several independent variables. The results show that Inflation (INF), GDP, technological readiness (NRI), exchange rates (EXR), and governance quality (CORR) emerge as significant drivers of cryptocurrency adoption. Unemployment (UNEMP), interest rates (INTR), and economic freedom (EFI) show limited or no significant effects. It highlights the importance of technological infrastructure in facilitating cryptocurrency usage and the impact of inflation, exchange rates, and governance on shaping adoption patterns.

Table 6 presents the result from three econometric models Feasible Generalised Least Squares (FGLS), Panel-Corrected Standard Errors (PCSEs), and Generalised Method of Moments (GMM) to analyse the relationships between the dependent variable (likely cryptocurrency adoption rate (CAR)) and several independent variables. The lagged cryptocurrency adoption rate in the GMM model has a significant negative relationship (coefficient = −0.518; $p < 0.01$), showing that a high past adoption rate is associated with a reduction in current adoption growth, potentially due to market saturation or diminishing marginal adoption effects. Inflation (INF) is positive and significant across all models (coefficients: 0.018 in FGLS test, 0.017 in PCSE test, and 0.008 in GMM test), which means that higher inflation rates drive cryptocurrency adoption, supporting its role as a hedge against fiat currency instability.

Table 5. Baseline regression.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
GDP	−0.004 * (0.002)								−0.008 *** (0.002)
INF		0.005 * (0.003)							0.013 *** (0.003)
UNEMP			−0.003 (0.004)						0.001 (0.004)
EXR				−0.002 (0.001)					−0.005 ** (0.001)
NRI					0.002 (0.001)				0.018 *** (0.003)
INTR						0.004 (0.004)			−0.002 (0.005)
CORR							−0.001 (0.001)		−0.010 *** (0.002)
EFI								−0.002 (0.002)	0.001 (0.003)
Constant	0.118 *** (0.012)	0.087 *** (0.017)	0.128 *** (0.026)	0.112 *** (0.012)	−0.006 (0.088)	0.101 *** (0.015)	0.166 *** (0.048)	0.262 ** (0.131)	−0.572 *** (0.213)
Observations	148	148	148	148	148	148	148	148	148
R-squared	0.020	0.022	0.004	0.001	0.012	0.006	0.010	0.009	0.327

This table contains estimates of baseline regression models. The dependent variable is CAR (cryptocurrency adoption rate), GDP is the gross domestic product, INF is inflation, UNEMP is the unemployment rate, EXR is the exchange rate, NRI is the Network Readiness Index, INTR is interest rates, CORR is the corruption index, and EFI is economic freedom. All estimations include OLS. Under the coefficients in the parentheses () standard errors are shown. Statistical significance is indicated by asterisks at the * (10%), ** (5%), and *** (1%).

Table 6. Results using FGLS, PCSEs, and GMM.

	(1)	(2)	(3)
Variables	**FGLS**	**PCSEs**	**GMM**
L.CAR			−0.518 *** (0.044)
INF	0.018 *** (0.003)	0.017 *** (0.001)	0.008 ** (0.003)
CORR	−0.006 *** (0.001)	−0.007 *** (0.002)	−0.022 *** (0.004)
NRI	0.015 *** (0.002)	0.018 *** (0.005)	0.023 ** (0.010)
INTR	−0.017 *** (0.006)	−0.021 *** (0.006)	−0.018 *** (0.005)
EFI	−0.005 ** (0.002)	−0.006 *** (0.002)	−0.007 ** (0.003)
UNEMP	−0.002 (0.004)	−0.007 *** (0.002)	−0.005 (0.010)
GDP	−0.005 * (0.003)	−0.006 *** (0.002)	−0.006 * (0.003)
EXR	−0.004 (0.003)	−0.002 (0.003)	−0.001 (0.001)
Constant	−0.240 (0.195)	−0.144 (0.223)	0.067 (0.454)
Observations	148	148	148
R-squared		0.766	
Wald chi2	102.45	734.98	275.70
Prob > chi2	0.000	0.000	0.000

Table 6. *Cont.*

	(1)	(2)	(3)
Variables	**FGLS**	**PCSEs**	**GMM**
AR2			0.768
Sargan			0.396

This table contains estimates of long-run co-integration analysis models. The dependent variable is CAR (cryptocurrency adoption rate), GDP is the gross domestic product, INF is inflation, UNEMP is the unemployment rate, EXR is the exchange rate, NRI is the Network Readiness Index, INTR is interest rates, CORR is the corruption index, and EFI is economic freedom. Estimations include FGLS, PCSE, and GMM. Under the coefficients in the parentheses () standard errors are shown. Statistical significance is indicated by asterisks at the * (10%), ** (5%), and *** (1%).

The Network Readiness Index (NRI) is positive and significant across all models, indicating that technological development strongly promotes cryptocurrency adoption. Interest Rate (INTR) shows negative and significant across all models, which means that higher interest rates discourage cryptocurrency adoption, possibly because traditional savings instruments become more attractive. The Economic Freedom Index (EFI) is negative and significant across all models. It means greater economic freedom reduces cryptocurrency adoption, suggesting that cryptocurrencies thrive more in restrictive environments. exchange rate (EXR) is not significant, indicating limited direct effects on cryptocurrency adoption.

The economic growth rate (GDP) is negative and significant in all models, which reveals that higher GDP levels are associated with reduced cryptocurrency adoption. Maybe stable economies rely less on alternative financial tools, and cryptocurrency is widely used in less-developed nations. The unemployment rate (UNEMP) has mixed results as it may have varying impacts on cryptocurrency adoption depending on model specification. The corruption index (CORR) is negative and significant across all models, showing that higher governance quality is associated with reduced cryptocurrency adoption; possibly, cryptocurrency is widely used in corrupt nations.

4.4. Granger Causality Tests

Table 7 illustrates the results of Granger causality tests conducted between various economic, social, and technological variables. The relationship between cryptocurrency adoption rate (CAR) and inflation (INF) is bidirectional, with stronger evidence that CAR influences inflation, possibly by increasing speculative or transactional demand in high-inflation economies. No predictive relationship is observed between corruption levels and cryptocurrency adoption. Technology development predicts cryptocurrency adoption, reflecting the importance of digital infrastructure. Cryptocurrency adoption predicts economic freedom, possibly by influencing financial innovation or liberalisation.

Table 7. Pairwise Granger causality tests.

X → Y Test (F, *p*)	**Y → X Test (F, *p*)**	**Direction**
CORR → CAR: (0.074, 0.786)	CAR → CORR: (1.550, 0.216)	Uni-directional
EFI → CAR: (0.235, 0.629)	CAR → EFI: (8.070, 0.005)	Uni-directional
EXR → CAR: (0.127, 0.723)	CAR → EXR: (0.231, 0.632)	Uni-directional
GDP → CAR: (13.149, 0.000)	CAR → GDP: (7.261, 0.008)	Bi-directional
INF → CAR: (3.777, 0.055)	CAR → INF: (10.725, 0.001)	Bi-directional
INTR → CAR: (1.845, 0.177)	CAR → INTR: (0.184, 0.669)	No
NRI → CAR: (3.962, 0.049)	CAR → NRI: (2.289, 0.133)	Uni-directional
UNEMP → CAR: (0.006, 0.939)	CAR → UNEMP: (0.098, 0.754)	No
EFI → CORR: (1.137, 0.289)	CORR → EFI: (9.976, 0.002)	Uni-directional
EXR → CORR: (1.804, 0.182)	CORR → EXR: (0.001, 0.974)	No

Table 7. *Cont.*

X → Y Test (F, *p*)	Y → X Test (F, *p*)	Direction
GDP → CORR: (0.050, 0.824)	CORR → GDP: (3.330, 0.071)	Uni-directional
INF → CORR: (10.204, 0.002)	CORR → INF: (0.988, 0.322)	Uni-directional
INTR → CORR: (2.951, 0.089)	CORR → INTR: (2.559, 0.113)	Uni-directional
NRI → CORR: (0.000, 0.988)	CORR → NRI: (5.098, 0.026)	Uni-directional
UNEMP → CORR: (2.256, 0.136)	CORR → UNEMP: (0.598, 0.441)	No
EXR → EFI: (2.098, 0.150)	EFI → EXR: (0.097, 0.756)	No
GDP → EFI: (3.128, 0.080)	EFI → GDP: (1.044, 0.309)	Uni-directional
INF → EFI: (2.220, 0.139)	EFI → INF: (32.592, 0.000)	Uni-directional
INTR → EFI: (0.892, 0.347)	EFI → INTR: (38.784, 0.000)	Uni-directional
NRI → EFI: (3.365, 0.069)	EFI → NRI: (4.524, 0.036)	Bi-directional
UNEMP → EFI: (0.361, 0.549)	EFI → UNEMP: (2.779, 0.098)	No
GDP → EXR: (0.237, 0.627)	EXR → GDP: (0.279, 0.598)	No
INF → EXR: (6.509, 0.012)	EXR → INF: (4.872, 0.029)	Bi-directional
INTR → EXR: (2.817, 0.096)	EXR → INTR: (25.935, 0.000)	Uni-directional
NRI → EXR: (0.015, 0.904)	EXR → NRI: (0.197, 0.658)	No
UNEMP → EXR: (0.362, 0.549)	EXR → UNEMP: (0.179, 0.673)	No
INF → GDP: (38.903, 0.000)	GDP → INF: (47.989, 0.000)	Bi-directional
INTR → GDP: (37.933, 0.000)	GDP → INTR: (25.004, 0.000)	Bi-directional
NRI → GDP: (64.697, 0.000)	GDP → NRI: (1.688, 0.197)	Uni-directional
UNEMP → GDP: (8.406, 0.005)	GDP → UNEMP: (1.313, 0.254)	Uni-directional
INTR → INF: (0.716, 0.399)	INF → INTR: (10.532, 0.002)	Uni-directional
NRI → INF: (7.949, 0.006)	INF → NRI: (57.435, 0.000)	Bi-directional
UNEMP → INF: (1.791, 0.184)	INF → UNEMP: (4.263, 0.041)	Uni-directional
UNEMP → INTR: (0.259, 0.612)	INTR → UNEMP: (3.727, 0.056)	Uni-directional

This table contains estimates of Granger causality tests. CAR is the cryptocurrency adoption rate, GDP is the gross domestic product, INF is inflation, UNEMP is the unemployment rate, EXR is the exchange rate, NRI is the Network Readiness Index, INTR is interest rates, CORR is the corruption index, and EFI is economic freedom. After the variable pair in parentheses (), the first value is f-stat, and the second value following the comma is the *p*-value.

The bidirectional causality suggests that GDP growth fosters cryptocurrency adoption, and adoption might influence economic output, possibly through financial innovation. No significant Granger causality is observed between CAR and unemployment (UNEMP) or exchange rate (EXR) in either direction.

In addition, the results show that corruption drives inflation but not vice versa. Inflation impacts technological readiness, and vice versa, reflecting economic interdependencies. GDP and inflation mutually influence each other, which is consistent with macroeconomic theory. Economic freedom and technological readiness reinforce each other. Interest rates and GDP growth interact closely, consistent with monetary policy theory.

4.5. Discussion

The finding that inflation significantly drives cryptocurrency adoption aligns with prior studies. Studies [27] suggest that sophisticated investors are more inclined to invest in assets that serve as hedges against economic downturns, including scenarios characterised by high future inflation. High inflation erodes the value of fiat currencies, pushing individuals toward cryptocurrencies as a hedge. For example, studies on hyperinflationary economies, such as Venezuela and Zimbabwe, demonstrate how cryptocurrencies like Bitcoin offer an alternative store of value and medium of exchange when traditional currencies collapse [35,36]. It implies that cryptocurrencies act as "digital gold", reinforcing their utility as a store of value in times of economic instability [39]. This supports theories of money that highlight the importance of scarcity and stability for value retention.

The negative relationship between corruption and cryptocurrency adoption contrasts with some studies suggesting that cryptocurrencies are often used in highly corrupt environments to circumvent opaque traditional financial systems. However, lower adoption in less corrupt environments might reflect trust in existing institutions and regulatory clarity [30,42]. It suggests that cryptocurrencies are used in corruptive systems and as a speculative asset and therefore improved governance may reduce the perceived need for decentralised alternatives.

The positive association between technological readiness and cryptocurrency adoption is consistent with studies emphasising the role of digital infrastructure in facilitating blockchain use. Advanced technological ecosystems lower barriers to entry for adopting decentralised systems and integrating them into economic activities [1]. This finding reinforces the innovation diffusion theory, which posits that the adoption of new technologies depends on access to infrastructure and societal readiness.

The negative effect of interest rates on cryptocurrency adoption mirrors findings where low or negative interest rates reduce the opportunity cost of holding cryptocurrencies, making them more attractive relative to fiat savings [39]. This aligns with monetary substitution theories, where individuals shift to alternative currencies when traditional instruments offer lower returns.

Lower economic freedom and higher corruption drive cryptocurrency adoption, underscoring its appeal in restrictive environments. This finding supports studies showing higher adoption rates in developing nations with limited financial access [63]. This supports financial innovation theory, which highlights the disruptive potential of decentralised systems.

The finding that inflation Granger causes cryptocurrency adoption aligns with prior research highlighting the role of economic instability. Cryptocurrencies serve as a hedge in high-inflation environments, particularly in economies with unstable fiat currencies, such as Venezuela and Zimbabwe [36]. This finding supports the view that individuals and businesses increasingly turn to decentralised assets to preserve value during monetary crises [35]. This reinforces monetary substitution theory, where agents opt for alternative currencies when the domestic currency loses purchasing power.

The positive causality from GDP to CAR may reflect the role of economic activity in driving innovation and investment in cryptocurrencies. Wealthier economies tend to have greater resources and infrastructure to support technological adoption [1]. Conversely, the feedback effect (CAR impacts GDP) suggests that cryptocurrencies can spur economic activity by enabling financial inclusion and reducing transaction costs [39]. This relationship underscores financial innovation theory, which posits that digital currencies foster economic activity by creating alternative financial ecosystems.

The finding that technological readiness predicts CAR aligns with literature emphasising the importance of digital infrastructure for cryptocurrency adoption. NRI captures a country's capacity to leverage ICT (Information and Communication Technology), which is critical for enabling blockchain-based systems [30]. This supports the innovation diffusion theory, which highlights that access to technology and digital literacy are prerequisites for adopting disruptive financial technologies.

The mutual relationship between CAR and GDP suggests that cryptocurrency adoption not only depends on economic conditions but also contributes to economic growth. Previous studies indicate that cryptocurrencies facilitate cross-border trade, lower remittance costs, and provide financial tools for unbanked populations, thereby fostering economic expansion [42].

The influence of CAR on EFI reflects cryptocurrencies' potential to liberalise economies. By reducing dependence on traditional financial systems, cryptocurrencies promote individual financial autonomy and stimulate regulatory changes [63]. These findings align with institutional economics theory, which suggests that technological innovations like cryptocurrencies can drive institutional reform and economic liberalisation.

The observed mutual causality among inflation, GDP, and governance quality (CORR) reflects the complex interdependence of economic and institutional factors. Inflation and GDP are tightly linked through monetary policy and economic cycles, while governance quality mediates the effectiveness of these policies [38].

The role of governance (CORR) is particularly nuanced. On the one hand, lower corruption improves financial stability, reducing the need for alternative systems like cryptocurrencies. On the other hand, weak governance in some contexts drives adoption by undermining trust in traditional systems [42]. This supports the theory of economic institutionalism, which posits that institutional quality determines economic outcomes and shapes the adoption of disruptive innovations.

5. Conclusions

5.1. Summary

This study examined cryptocurrency adoption's key drivers and impacts across 37 countries from 2020 to 2023. This study found that inflation emerged as a critical driver of cryptocurrency adoption, particularly in economies with volatile fiat currencies. This supports the view of cryptocurrencies as a hedge against inflation [36]. The Network Readiness Index (NRI) significantly influences adoption, highlighting the necessity of digital infrastructure and technological ecosystems [30]. Lower interest rates (INTRs) encourage adoption, while higher GDP is associated with reduced adoption, reflecting the influence of economic stability and monetary policy on adoption patterns [39].

Moreover, cryptocurrencies not only respond to but also impact GDP and economic freedom (EFI), creating feedback loops that promote financial inclusion and economic liberalisation [42]. Lower corruption levels (CORR) correlate with reduced cryptocurrency adoption, possibly due to increased trust in traditional financial systems [63]. Furthermore, this study found that inflation, GDP, and governance are interconnected, influencing both cryptocurrency adoption and broader economic conditions. This highlights the complex interplay between economic and institutional dynamics in shaping financial innovation.

5.2. Theoretical Implications

Cryptocurrencies act as an alternative monetary system, especially in inflationary environments. This supports the Monetary Substitution Theory that economic instability pushes individuals and institutions toward decentralised currencies [33,35].

Technological readiness (NRI) is critical for the adoption of disruptive innovations like cryptocurrencies, which has implications for innovation diffusion theory. Policymakers must focus on enhancing digital infrastructure to maximise the benefits of these technologies [30].

The feedback effects between cryptocurrency adoption and governance quality reinforce the role of institutional frameworks in facilitating or hindering adoption, which supports the institutional economics theory. Cryptocurrencies can promote financial liberalisation in restrictive environments but require robust governance to prevent misuse [42].

5.3. Policy Recommendations

This study suggests that policymakers should first focus on reducing corruption and increasing transparency to improve trust in traditional financial systems while enabling regulated cryptocurrency adoption. Secondly, investments in technology readiness are essential to leverage the economic benefits of cryptocurrencies. Developing countries should prioritise digital literacy and ICT infrastructure. Thirdly, regulatory frameworks should aim to mitigate the risks of cryptocurrency misuse without stifling innovation. Clear guidelines on taxation, anti-money laundering (AML), and investor protection are critical.

Finally, countries facing high inflation should explore the integration of cryptocurrencies into their monetary systems while addressing underlying economic instability.

5.4. Limitations and Future Research Directions

While this research offers valuable insights into the drivers and impacts of cryptocurrency adoption, several limitations need to be acknowledged to contextualise the findings and guide future studies.

The study uses data spanning 2020–2023, but comprehensive, reliable, and consistent data on cryptocurrency adoption are only available from the late 2010s. This temporal limitation may affect the robustness of the findings, particularly in the early years when adoption rates were negligible. The dataset includes 37 countries, which may not represent the global diversity in economic, technological, and governance conditions. The exclusion of countries with nascent cryptocurrency markets or limited data availability may introduce selection bias.

Despite efforts to address endogeneity using dynamic models (e.g., GMM), the study cannot entirely rule out omitted variable bias, particularly in complex relationships such as CAR and governance quality (CORR) [39]. While Granger causality tests suggest predictive relationships, they do not imply true causality. For example, the bidirectional relationships between CAR and GDP may reflect simultaneous influences rather than clear causal pathways [35].

Although governance quality (CORR) and economic freedom (EFI) were included as proxies for social development, other dimensions such as income inequality, education, or gender equality were not explored. These could provide a broader perspective on the societal implications of cryptocurrency adoption [1].

The cryptocurrency ecosystem is rapidly evolving, with the emergence of stablecoins, decentralised finance (DeFi), and central bank digital currencies (CBDCs). These innovations were not fully accounted for in the analysis, potentially limiting their applicability to current market dynamics [30].

The study does not account for cultural or behavioural drivers of cryptocurrency adoption, such as trust in technology or societal attitudes toward financial innovation. These factors could significantly influence adoption rates and require qualitative or survey-based research to understand fully [63].

This study treats all cryptocurrencies as a homogeneous group, which simplifies the analysis but does not account for the distinct characteristics of different cryptocurrencies. Variations in technology, market acceptance, and regulatory treatment among cryptocurrencies like Bitcoin and Ethereum versus smaller digital currencies could influence adoption rates and economic impacts differently. This approach may limit the generalizability of our findings across the diverse landscape of digital currencies. Future research should consider differentiating cryptocurrencies by their unique attributes and market positions to provide a more nuanced understanding of their adoption and impacts.

Future research may expand the dataset, integrating qualitative methods, and incorporating emerging trends such as DeFi and CBDCs, which provides a more comprehensive understanding of the dynamics and implications of cryptocurrencies in global economies. The long-term effects of cryptocurrency adoption on economic growth, governance, and inequality could be conducted in future studies. Sector-specific analysis might be another future research opportunity, for example, examining how cryptocurrencies impact remittances or cross-border trade.

Author Contributions: Conceptualization: Y.G.; data collection: E.Y.; data analysis: M.M.N. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: The study was approved by the Ethics Committee of Teesside University.

Informed Consent Statement: Not applicable.

Data Availability Statement: Research data will be shared if required.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Almeida, J.; Gonçalves, T.C. A Decade of Cryptocurrency Investment Literature: A Cluster-Based Systematic Analysis. *Int. J. Financ. Stud.* **2023**, *11*, 71. [CrossRef]
2. García-Corral, F.J.; Cordero-García, J.A.; de Pablo-Valenciano, J.; Uribe-Toril, J. A bibliometric review of cryptocurrencies: How have they grown? *Financ. Innov.* **2022**, *8*, 2. [CrossRef] [PubMed]
3. Aslam, F.; Memon, B.A.; Hunjra, A.I.; Bouri, E. The dynamics of market efficiency of major cryptocurrencies. *Glob. Financ. J.* **2023**, *58*, 100899. [CrossRef]
4. Nakamoto, S. Bitcoin: A Peer-to-Peer Electronic Cash System. (White Paper). 2008. Available online: https://www.klausnordby.com/bitcoin/Bitcoin_Whitepaper_Document_HD.pdf (accessed on 2 September 2024).
5. Viviana, A.C.; Kamin, S.; Zampolli, F. Central bank digital currencies (CBDCs) in Latin America and the Caribbean. *Lat. Am. J. Cent. Bank.* **2024**, 100140. [CrossRef]
6. Viviana, A.C.; Kamin, S.; Zampolli, F. Central bank digital currencies (CBDCs) in Latin America and the Caribbean. 2022. Bank for International Settlements. Available online: https://www.bis.org/publ/work989.htm (accessed on 8 May 2023).
7. Li, Z.; Meng, Q. Time and frequency connectedness and portfolio diversification between cryptocurrencies and renewable energy stock markets during COVID-19. *N. Am. J. Econ. Financ.* **2022**, *59*, 101565. [CrossRef]
8. Au, A. Cryptocurrencies and the promise of individual economic sovereignty in an age of digitalization: A critical appraisal. *Sociol. Rev.* **2022**, *71*, 992–1011. [CrossRef]
9. Bogusz, C.I.; Laurell, C.; Sandström, C. Tracking the Digital Evolution of Entrepreneurial Finance: The Interplay Between Crowdfunding, Blockchain Technologies, Cryptocurrencies, and Initial Coin Offerings. *IEEE Trans. Eng. Manag.* **2020**, *67*, 1099–1108. [CrossRef]
10. Abdelkaoui, F.; Sidaoui, A.; Nasser, F.; Bouzidi, M. Cryptocurrency and Macroeconomic Dynamics: Case of 10 Asian Economies. *South Asian J. Macroecon. Public Financ.* **2024**, *13*, 100–126. [CrossRef]
11. Sadraoui, T.; Nasr, A.; Mgadmi, N. Studding relationship between bitcoin, exchange rate and financial development: A panel data analysis. *Int. J. Manag. Financ. Account.* **2021**, *13*, 232–252. [CrossRef]
12. Conlon, T.; Corbet, S.; McGee, R.J. Inflation and cryptocurrencies revisited: A time-scale analysis. *Econ. Lett.* **2021**, *206*, 109996. [CrossRef]
13. Elsayed, A.H.; Sousa, R.M. International monetary policy and cryptocurrency markets: Dynamic and spillover effects. *Eur. J. Financ.* **2024**, *30*, 1855–1875. [CrossRef]
14. Vo, A.; Chapman, T.A.; Lee, Y.-S. Examining Bitcoin and Economic Determinants: An Evolutionary Perspective. *J. Comput. Inf. Syst.* **2022**, *62*, 572–586. [CrossRef]
15. Bouri, E.; Lucey, B.; Roubaud, D. Cryptocurrencies and the downside risk in equity investments. *Financ. Res. Lett.* **2020**, *33*, 101211. [CrossRef]
16. Bhimani, A.; Hausken, K.; Arif, S. Do national development factors affect cryptocurrency adoption? *Technol. Forecast. Soc. Change* **2022**, *181*, 121739. [CrossRef]
17. Huynh, T.L.D.; Shahbaz, M.; Nasir, M.A.; Ullah, S. Financial modelling, risk management of energy instruments and the role of cryptocurrencies. *Ann. Oper. Res.* **2022**, *313*, 47–75. [CrossRef]
18. Bouri, E.; Gabauer, D.; Gupta, R.; Tiwari, A.K. Volatility connectedness of major cryptocurrencies: The role of investor happiness. *J. Behav. Exp. Financ.* **2021**, *30*, 100463. [CrossRef]
19. Angerer, M.; Hoffmann, C.H.; Neitzert, F.; Kraus, S. Objective and subjective risks of investing into cryptocurrencies. *Financ. Res. Lett.* **2021**, *40*, 101737. [CrossRef]
20. Corbet, S.; Lucey, B.; Urquhart, A.; Yarovaya, L. Cryptocurrencies as a financial asset: A systematic analysis. *Int. Rev. Financ. Anal.* **2019**, *62*, 182–199. [CrossRef]
21. Li, R.; Li, S.; Yuan, D.; Zhu, H. Investor attention and cryptocurrency: Evidence from wavelet-based quantile Granger causality analysis. *Res. Int. Bus. Financ.* **2021**, *56*, 101389. [CrossRef]
22. Alonso, S.L.; Jorge-Vázquez, J.; Echarte Fernández, M.Á.; Reier Forradellas, R.F. Cryptocurrency Mining from an Economic and Environmental Perspective. Analysis of the Most and Least Sustainable Countries. *Energies* **2021**, *14*, 4254. [CrossRef]

23. Hsu, S.-H.; Sheu, C.; Yoon, J. Risk spillovers between cryptocurrencies and traditional currencies and gold under different global economic conditions. *N. Am. J. Econ. Financ.* **2021**, *57*, 101443. [CrossRef]
24. Mnif, E.; Jarboui, A.; Mouakhar, K. How the cryptocurrency market has performed during COVID 19? A multifractal analysis. *Financ. Res. Lett.* **2020**, *36*, 101647. [CrossRef] [PubMed]
25. Papadamou, S.; Kyriazis, N.A.; Tzeremes, P.G. Non-linear causal linkages of EPU and gold with major cryptocurrencies during bull and bear markets. *N. Am. J. Econ. Financ.* **2021**, *56*, 101343. [CrossRef]
26. Kyriazis, N.; Papadamou, S.; Corbet, S. A systematic review of the bubble dynamics of cryptocurrency prices. *Res. Int. Bus. Financ.* **2020**, *54*, 101254. [CrossRef]
27. Colombo, J.A.; Yarovaya, L. Are crypto and non-crypto investors alike? Evidence from a comprehensive survey in Brazil. *Technol. Soc.* **2024**, *76*, 102468. [CrossRef]
28. Alnasaa, M.; Gueorguiev, N.; Honda, J.; Imamoglu, E.; Mauro, P.; Primus, K.; Rozhkov, D. Crypto-assets, corruption, and capital controls: Cross-country correlations. *Econ. Lett.* **2022**, *215*, 110492. [CrossRef]
29. Drăgan, G.B.; Ben Arfi, W.; Tiberius, V.; Ammari, A.; Khvatova, T. Navigating the green wave: Understanding behavioral antecedents of sustainable cryptocurrency investment. *Technol. Forecast. Soc. Change* **2025**, *210*, 123909. [CrossRef]
30. Mikhaylov, A. Understanding the risks associated with wallets, depository services, trading, lending, and borrowing in the crypto space. *J. Infrastruct. Policy Dev.* **2023**, *7*, 2223. [CrossRef]
31. Corbet, S.; Goodell, J.W.; Günay, S. What drives DeFi prices? Investigating the effects of investor attention. *Financ. Res. Lett.* **2022**, *48*, 102883. [CrossRef]
32. Jiang, Y.; Wu, L.; Tian, G.; Nie, H. Do cryptocurrencies hedge against EPU and the equity market volatility during COVID-19?—New evidence from quantile coherency analysis. *J. Int. Financ. Mark. Inst. Money* **2021**, *72*, 101324. [CrossRef]
33. Benigno, P. Monetary Policy in a World of Cryptocurrencies. *J. Eur. Econ. Assoc.* **2023**, *21*, 1363–1396. [CrossRef]
34. Haq, I.U.; Maneengam, A.; Chupradit, S.; Suksatan, W.; Huo, C. Economic Policy Uncertainty and Cryptocurrency Market as a Risk Management Avenue: A Systematic Review. *Risks* **2021**, *9*, 163. [CrossRef]
35. Yermack, D. Chapter 2—Is Bitcoin a Real Currency? An Economic Appraisal. In *Handbook of Digital Currency*, 2nd ed.; Lee Kuo Chuen, D., Ed.; Academic Press: San Diego, CA, USA, 2024; pp. 29–40. [CrossRef]
36. Bouri, E.; Jalkh, N. Spillovers of joint volatility-skewness-kurtosis of major cryptocurrencies and their determinants. *Int. Rev. Financ. Anal.* **2023**, *90*, 102915. [CrossRef]
37. Nguyen, L.T.M.; Nguyen, P.T. Determinants of cryptocurrency and decentralized finance adoption—A configurational exploration. *Technol. Forecast. Soc. Chang.* **2024**, *201*, 123244. [CrossRef]
38. Benigno, P.; Schilling, L.M.; Uhlig, H. Cryptocurrencies, currency competition, and the impossible trinity. *J. Int. Econ.* **2022**, *136*, 103601. [CrossRef]
39. Cheah, E.-T.; Mishra, T.; Parhi, M.; Zhang, Z. Long Memory Interdependency and Inefficiency in Bitcoin Markets. *Econ. Lett.* **2018**, *167*, 18–25. [CrossRef]
40. Zhang, S.; Gregoriou, A. Cryptocurrencies in portfolios: Return–liquidity trade-off around China forbidding initial coin offerings. *Appl. Econ. Lett.* **2021**, *28*, 1036–1040. [CrossRef]
41. Bespalova, O.; Appendino, M.; Bhattacharya, R.; Clevy Aguilar, J.F.; Geng, N.; Komatsuzaki, T.; Lesniak, J.; Lian, W.; Marcelino, S.; Villafuerte, M.; et al. Crypto assets and CBDCs in Latin America and the Caribbean: Opportunities and risks. *Lat. Am. J. Cent. Bank.* **2024**, 100157, *in press*. [CrossRef]
42. OECD. *OECD Economic Outlook, Volume 2023 Issue 2*; OECD: Paris, France, 2023.
43. Yue, Y.; Li, X.; Zhang, D.; Wang, S. How cryptocurrency affects economy? A network analysis using bibliometric methods. *Int. Rev. Financ. Anal.* **2021**, *77*, 101869. [CrossRef]
44. Zhang, Z.J. Cryptopricing: Whence comes the value for cryptocurrencies and NFTs? *Int. J. Res. Mark.* **2023**, *40*, 22–29. [CrossRef]
45. Mishkin, F. *Money, Banking and Financial Markets*; New Horizons: Paris, France, 2007.
46. Wang, P.; Zhang, H.; Yang, C.; Guo, Y. Time and frequency dynamics of connectedness and hedging performance in global stock markets: Bitcoin versus conventional hedges. *Res. Int. Bus. Financ.* **2021**, *58*, 101479. [CrossRef]
47. Shen, D.; Urquhart, A.; Wang, P. A three-factor pricing model for cryptocurrencies. *Financ. Res. Lett.* **2020**, *34*, 101248. [CrossRef]
48. Chainalysis. *The Chainalysis 2023 Geography of Cryptocurrency Report*; Chainalysis: New York, NY, USA, 2023.
49. NRI. *Network Readiness Index 2024*; Portulans Institute: Washington, DC, USA, 2024.
50. Hsiao, C. *Analysis of Panel Data*; Cambridge University Press: Cambridge, UK, 2022.
51. Pearson, K. Notes on regression and inheritance in the case of two parents. *Proc. R. Soc. Lond.* **1895**, *58*, 240–242.
52. Breusch, T.S.; Pagan, A.R. A Simple Test for Heteroscedasticity and Random Coefficient Variation. *Econometrica* **1979**, *47*, 1287–1294. [CrossRef]
53. Pesaran, M.H. General diagnostic tests for cross section dependence in panels. Cambridge Working Papers. *Economics* **2004**, *1240*, 1.

54. Baltagi, B.H.; Feng, Q.; Kao, C. A Lagrange Multiplier test for cross-sectional dependence in a fixed effects panel data model. *J. Econom.* **2012**, *170*, 164–177. [CrossRef]
55. Pesaran, M.H. A simple panel unit root test in the presence of cross-section dependence. *J. Appl. Econom.* **2007**, *22*, 265–312. [CrossRef]
56. Wooldridge, J.M.; Wadud, M.; Lye, J. *Introductory Econometrics: Asia Pacific Edition with Online Study Tools 12 Months*; Cengage AU: Molbourne, Australia, 2016.
57. Gujarati, D.N. *Basic Econometrics*; McGraw-Hill: New York, NY, USA, 2009.
58. Beck, N.; Katz, J.N. What To Do (and Not to Do) with Time-Series Cross-Section Data. *Am. Political Sci. Rev.* **1995**, *89*, 634–647. [CrossRef]
59. Hansen, L.P. Large Sample Properties of Generalized Method of Moments Estimators. *Econometrica* **1982**, *50*, 1029–1054. [CrossRef]
60. Arellano, M.; Bond, S. Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations. *Rev. Econ. Stud.* **1991**, *58*, 277–297. [CrossRef]
61. Dumitrescu, E.-I.; Hurlin, C. Testing for Granger non-causality in heterogeneous panels. *Econ. Model.* **2012**, *29*, 1450–1460. [CrossRef]
62. Hashem Pesaran, M.; Yamagata, T. Testing slope homogeneity in large panels. *J. Econom.* **2008**, *142*, 50–93. [CrossRef]
63. Murugappan, M.; Nair, R.; Krishnan, S. Global Market Perceptions of Cryptocurrency and the Use of Cryptocurrency by Consumers: A Pilot Study. *J. Theor. Appl. Electron. Commer. Res.* **2023**, *18*, 1955–1970. [CrossRef]