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Do national development factors affect cryptocurrency adoption?

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ABSTRACT

The adoption of cryptocurrencies is uneven across businesses, industries, and countries. Different forces drive cryptocurrency adoption (CA) dependent on the national level of development. We empirically assess the relationship between certain macro-national developmental indicators and cryptocurrency deployment across 137 countries. Linear regressions determine specific associations with cryptocurrency adoption. We report that CA correlates positively and in decreasing order with Education, the Human Development Index, the Network Readiness Index, the Gini index, Democracy, Regulatory Quality, and Gross Domestic Product, and negatively and in decreasing order with Control of Corruption, the Corruption Perception Index, and the Economic Freedom Index. We draw on our findings to point to policy implications tied to the usage of cryptocurrencies and blockchain technologies more widely and identify further research possibilities.

JEL Classification Numbers: C5, O

1. Introduction

Technological innovations impact organizations and countries differently (Wang et al., 2020). Cryptocurrency blockchain technologies adoptions are no different. But research in this area of innovation has tended to be prescriptive and theoretical focusing primarily on blockchain and cryptocurrency technical attributes with little scholarship undertaken on what drives differences across nations (Bhimani et al., 2021; Kouhizadeh et al., 2021; Schlecht et al., 2021). It is known that many developmental issues influence the adoption of cryptocurrency and blockchain systems in both developing and advanced economies (Behnke and Janssen, 2020; Bodkhe et al., 2020; Laroiya et al., 2020; Sinha et al., 2020; Stockburger et al., 2021). In relation to nations being receptive to cryptocurrency deployment, the focus has been on the potential costs and benefits offered by permissionless systems in different settings. But as Saiedi et al. (2021, p. 354) note: “While theoretical papers are emerging, discussing why cryptocurrencies, or digital currencies in general, may be adopted by individuals or businesses, there is a scarcity of global empirical studies on drivers of their adoption.” Our aim is to point to macro-national developmental indicators that influence cryptocurrency adoption (CA) across economies.

We recognise there are different theoretical foundations as to the process of technology adoption and its role in economic development. Theorists have advanced different perspectives including the work of Dixit and Pindyck (1994), Mansfield (1993), and Tornatzky et al. (1990) and others (Fan et al., 2018). We draw more explicitly on the economic growth and long run economic development arguments posited by Acemoglu (2009). Our interest lies in development factors affecting CA across nations. In reporting on factors which find positive or negative association with national developmental indicators, we contribute to policy decision making by identifying the strength of impact of different developmental indicators which are context-specific within different nations. We draw on data relating to 137 countries to ensure the comprehensiveness of our findings which have relevance to policy decision making. Aside from the practical implications of our findings, we advance academic research by widening the diversity of factors, both economic and societal, which impact CA. Scholars will benefit from our results in being able to extend the baseline research we have produced to other regional and economic contexts. The methodology we adopt will also prove useful in analyses tied to cryptocurrency and blockchain systems usage in other domains and point to further additional relationships with other independent variables and dependent variables.

The rest of this paper is structured as follows. In Section 2 we identify some costs and benefits of cryptocurrency adoption as indicated by differing country deployment experiences. In Section 3, we discuss national development factors affecting cryptocurrency technology

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adoption decisions in developed and developing economies. In Section 4, we model cryptocurrency adoption and empirically assess the model in Section 5. We thereafter discuss and present limitations and identify areas for future research in Section 6. Section 7 concludes the paper.

2. Cryptocurrency adoption and experiences

Much has been documented on the ascent of the fourth industrial revolution. Artificial intelligence, information communication and technology, the internet of things and blockchains rest at the core of this fourth revolution. In respect to the latter, PwC (2020) predicts that blockchains will boost global GDP by US$1.76 trillion by 2030. Asia is expected to benefit the most from blockchains. Chinese bureaucrats place blockchains as one of the country's their top five priority expecting the potential net benefit in China to be US$440bn (versus US$407bn for the USA). Other countries including Germany, Japan, the UK, India, and France will see estimated returns exceeding US$50bn (PwC, 2020). At the enterprise level, across several developed nations, a majority of senior industrialists seem to be making blockchain systems a top priority for their organizations (Deloitte, 2020).

A major UNCTAD (2021) study (2021, p. 6) on blockchain usage notes that governments of developing countries "…should seek to strengthen their innovation systems to strategically position themselves to benefit from this new wave of technological change." In this light, Domjan et al., (2021, p. xi)) states that: "There is a growing realization all over the world, but especially in developing countries, that there is a set of problems linked to trust, verification and value transfer that could be solved with blockchain technology". Cryptocurrency adoption (CA) resting on blockchain logic can enable readier access to digital financial products and offer services at a lower cost increasing financial inclusion and connecting local populations to broader global markets (Aysan, 2020; Schuetz and Venkatesh, 2020). In developed nations, enterprises have been open to CA. For instance, firms such Tesla has accepted Bitcoin on-and-off for car payments (Hussain and Balu, 2021) and all goods and services can in principle be priced in Bitcoin (Frankenfield, 2021). Institutionally, there is also growing interest in cryptocurrencies for speculative, investment, store of value, and payment purposes. An International Finance Corporation study (IFC, 2017) reflected on how CA can promote "… greater financial inclusion and improve productivity" in developing economies.

Other economic benefits of CA viewed as relevant to developing countries include the protection of ownership rights, verifiable identity systems and the containment of corruption potential (Pisa and Juden, 2017). But the lack of standardization of transactional systems, weakness of governance institutions, high upfront installation costs, systems expertise and energy consumption issues are challenges affecting CA (Chang et al., 2020; Uddin et al., 2021). Bitcoin represents the first mobilisation of blockchain mechanics. Bitcoin is premised on the notion of a blockchain being a distributed ledger system which produces secure tamper-proof records. The elimination of third parties, immutability, transparency and decentralization enable a wide variety of applications for blockchain based systems of control (Iansiti and Lakhani, 2017). The high levels of privacy and anonymity allows for contracts execution more economically, rapidly and efficiently relative to contemporary systems relying on mechanical or human input (Angelis and Da Silva, 2019). But there are hurdles including high installation costs, operational skills requirements, systems changeover hurdles and regulatory constraints. A key point of significance is that blockchains may be permissioned or permissionless. Permissioned blockchains are used by centralized authorities in various forms (Allen et al., 2020; Kiff et al., 2020) whereas permissionless systems, with their protocol designs and processes of validation and mining transactions, ordinarily require crypto asset issuance. Nakamoto (2008) described a permissionless blockchain as exemplified by Bitcoin. While technical factors pervade cryptocurrency operations, CA entails dimensions of industrial capacity, regulatory environment, expertise availability as well as social and cultural influences (Hughes et al., 2019). Cryptocurrencies use specifically and blockchain systems deployment generally can be complex and entail a variety of issues that are tied to macro-level national factors. This represents the focus of our interest in this paper. We elaborate on this in the next section.

3. Developmental factors affecting cryptocurrency adoption

The question of whether information technologies generally show differential penetration and speed trajectories across developing and developed economies remains open due to absorptive capacity being influenced by a wide range of factors tied to level of national development (Keller, 2004; Niebel, 2018; Steinmueller, 2001). In this respect, we look at macro-level developmental indicators which impact technology adoption of which cryptocurrency deployment is a case. The literature on digital technology adoption at the country level is vast. Reference has been made to leapfrog possibilities, whereby processes in the accumulation of fixed investments and human capabilities can be sidestepped permitting developing nations to evolve faster as they can bypass having to disinvest prior structural institutions. Additionally, developing nations become more and more disconnected and less dependent on advanced country technical systems, have access to more knowledge and benefit as the costs of newer technologies decrease (Tchamyou et al., 2019). Venkatesh et al. (2003) brings together much of this literature in terms of perceptions of adopters and technology acceptance. Datta (2011) compliments this perspective with Rogers (1983) technology diffusion theory. In relation to macro level national contingent factors which enable or obstruct digital technology adoption at the national level, the prior literature points to technology support mechanisms (Kirkman et al., 2002) which include four distinct elements: economic context, policy and the legislative environment, society with a focus on education and training and access as per infrastructure capabilities. Economic conditions relate to the degree to which a technology may become integrated into the economic activity of a country. Policy focused issues relate to the overall business and economic climate of a country taking account of the level of competition permitted in terms of start-ups, technology development subsidies, privatization, and national legislative policies. Society-based elements include education and training. Access entails telecommunications and information infrastructure availability. Fong (2009) extends the literature analysis of factors relevant to conditions that may enable "technological leapfrogging" to include human capabilities, governance controls, institutional capacity and readiness, inequality indicators. The prior literature combined with Sen (2001) identification of democracy and human development in enabling the national development of technological advances leads us to focus on the following factors as impacting cryptocurrency adoption decisions: the legal environment, governance structure, democracy variables, human development, GDP, income inequality, education, economic freedom, and network readiness. We elaborate below on each of these and their relevance to cryptocurrency adoption decisions.

3.1. The legal environment

Not only has the legality status of cryptocurrency been under scrutiny but it has been long accepted that cryptocurrency would only survive and spur in countries with receptive regulatory environments. While the future of cryptocurrency is uncertain in most countries, other applications of blockchain including identity management, execution of smart contracts, supply chain routing and integrity are seeing growing usage. The legality status of blockchain is currently being debated at national levels primarily in reference to its use in financial and investment sectors. While a few countries have introduced regulations to support the implementation and use of the cryptocurrency, some countries have outrightly banned it and others have restricted its use in banking. Wright and De Filippi (2015) recognize the development of a new body of law to administer self-executed smart contracts and decentralized organizational structure while controlling for illicit activities. Cryptocurrencies have also been seen as enabling the replacement of tax havens (Marian, 2013), usage for money laundering (Barone and Masciandaro, 2019) and been associated with anonymity that encourages their use in digital black markets. Considering the challenge of taxing and regulating cryptocurrencies some of these exchanges have relocated to countries with friendlier or non-existent asset investment legal structures (Molloy, 2019). Akins et al. (2014) speak to the lack of federal income tax laws on virtual economy elements and propose a range of solutions. Switzerland, the UK, Estonia, Gibraltar and Malta have been identified as leaders towards the development of friendly yet secure regulation system (Suciu et al., 2019). Blockchain Alliance founded in 2015 has been actively working to conduct educational programs for around 700 law enforcement officers and regulators from more than 35 countries and include over 100 blockchain companies along with regulatory agencies including US, Europol and Interpol and authorities in Europe, Latin America, Africa, Asia, and Australia (Dewey, 2019). India plans to introduce laws to limit private cryptocurrencies and introduce a framework for the creation of an official central bank digital currency. Turkey has banned the use of crypto assets in payment services (Finextra, 2021) just as China continues to carry nationwide crackdowns against cryptocurrency mining shutting down more than 90% of its bitcoin mining capacity (Global Times, 2021). The ban on cryptocurrency however does not negate the benefit of the underlying technology via other applications. While India is exploring its potential benefits in smart contracts, the Blockchain Service Network (BSN) launched by China in 2020 seeks to enable enterprises to access, build and adopt blockchain for economic growth (Ozden, 2021).

3.2. Governance standards

The use of E-governance has long been debated to improve the governance systems through increased transparency, removing information asymmetry, minimizing delays and protecting against data theft (Banerjee et al., 2020; Halachmi and Greiling, 2013). The benefit offered by cryptocurrency including its temper free record keeping, decentralization and elimination of intermediaries makes it a cutting-edge anti-corruption technology for governance systems. Research is being conducted to assess these benefits of cryptocurrencies as well as central bank digital currencies to deal with issues of funds embezzlement and illicit activities especially in developing countries (Sanka and Cheung, 2019; Zbinden and Kondova, 2019). Government efficiency has been known to hasten technology adoption by lowering production costs, uncertainty imposed by corruption and protection of property rights (Galang, 2012; Murphy et al., 1991). Luo (2005) investigates the effects of corruption on innovative activity from the perspective of organizational theory. In this regard a firm will innovate or adopt new technology depending on the ease of the alternatives available. In the case of cryptocurrency, since it provides an audit trail and makes counterfeiting almost impossible, corrupt intermediaries may see it as a threat and discourage CA.

Cryptocurrency may be adopted as a solution to the corruption emanating from poor governance which has been a major cause of poverty in developing economies. Resnick (2020) studies the tax compliance behaviour of informal workers and concludes that the compliance is higher when the route of accountability between tax collector and payer is shorter. This can be achieved using cryptocurrency which eliminates intermediaries and offers higher level of trust in the system. On the other hand it has been argued that in well governed states the cost of replacing already established systems can exceed any benefits realized and so poorly governed states may make a fast paced shift to adopt cryptocurrency to address issues of legitimate transactions and to enhance transparency (Chan et al., 2008). Reducing corruption may be a priority for some emerging economies to facilitate global exchanges, economic development, and aid receipt.

3.3. Democracy level

Democracy is seen to reduce digital divide by promoting innovation and rapid technology adoption (Gao et al., 2017; Milner, 2006). Blockchain based solutions confer more power to citizens by reducing information asymmetries via decentralized voting, identity management, e-governance and e-democracy processes. Aysan et al. (2019) find that price volatility and returns of Bitcoin are positively and negatively, respectively, related to geopolitical risks. They suggest that Bitcoin can be a hedging tool against geopolitical risks. Moreover, since cryptocurrencies cannot be counterfeited, they are the perfect solution to the problems of decentralization and poor governance in many democracies.

Tellman et al. (2021) highlight how decentralization of land regulation has left the system fractured. The informal urbanization of Mexico City at the hands of intermediaries and politicians had led to the exploitation of informal settlers. Boret et al. (2021) also confirm that decentralization of local expenditure could help lower poverty. But decentralization requires either trust in the local government or robust system which makes misappropriation impossible. Cryptocurrencies address these problems and so it is not only more likely to be adopted by democratic countries but is also further strengthen them.

3.4. Human development

The human development index is a composite measure of life expectancy, education and per capita income. Asongu and Le Roux (2017) show how information communication and technology could be used for human development in sub–Saharan Africa. Technological advancements have been shown to play a role in gender empowerment (Crittenden et al., 2019), providing access to healthcare (McGhin et al., 2019) and identity management (Kuperberg, 2019). Healthcare can realize the benefits of blockchain in various regards. It can revolutionize drug discovery and development process with better data availability, ability to carry out analytical procedures, optimizing the efficiency of the Internet of Healthy Things, safeguarding internet-connected medical equipment and combating counterfeit medicines (Clauson et al., 2018). Pharmaceutical companies on average lose $200 billion to counterfeit drugs annually. The World Health Organization has identified the worth of black market of medicine at $75 billion. Blockchain enabled traceability, auditability and secure databases for storing and accessing drug trial data can assist in reducing falsified medication extensively (Arsene, 2019). The storing of a patient's data on blockchain network giving him or her the right to share it with can enable faster sharing of information, help eliminate data corruption and the illegal selling of data (Hughes et al., 2018)

Blockchain enabled identification can lead to certain benefits tied to human development. The World Food Program for instance, successfully deployed blockchain for its refugee program in Jordan. Various other countries are using blockchains to facilitate human development including Ghana which is using blockchain to resolve land disputes and India where the government think tank is working to use the technology in land titling and electronic health records (Nayyar, 2018). Smith and Floro (2020) highlight the significance of migration and remittance flows in reducing food insecurity especially in low- and middle-income countries. Such economies can multiply these benefits using blockchain. Apart from ensuring traceability, transparency, reducing cost through elimination of intermediaries, blockchain based solutions including cryptocurrency also has the potential to minimize bureaucracy and promote coordination amongst donors to ensure the best deployment of resources (Galen et al., 2018; Pisa and Juden, 2017). Cryptocurrencies also boost economic activity by including the unbanked into the financial system and empowering entrepreneurs to receive payments in more currencies.

3.5. GDP level

According to the growth principle technological transformation leads to an increase in GDP through an increase in capita per person which motivates savings and investment. Comin and Hobijn (2003) further support this claim by showing that the rate of adoption of technology in early stages of life cycle is largely determined by level of economic development of a country. While technology is a major determinant of economic growth a country's GDP per capita would influence technology adoption. Developing countries while most of them are highly indebted, face high inflation and low GDP would prioritize basic needs of the public over technology adoption owed to the high upfront implementation cost and investment in research and development of blockchain based application including cryptocurrency. Since cryptocurrency skills are still a niche market, the developers and network engineers are costly in terms of salaries (Davies, 2019). Organizations can be faced with the burden of hiring staff including compliance and legal personnel who understand the technology and can work in coordination with system developers and financial regulators. Another cost of implementation is that of energy consumption. Proof of work cryptocurrency require huge amount of energy, the Digiconomist's Bitcoin Energy Consumption Index estimated that one Bitcoin transaction takes 1544 kWh to complete (Gonzalez, 2021). This poses a hurdle for CA particularly in developing countries with high-cost energy sources.

3.6. Income inequality

Technology adoption in emerging economies has been slower as compared to developed economies given the cost of adoption and complementary factors like human capital (Comin and Mestieri, 2018; De Gregorio, 2018). The technology can create jobs for technical people while eliminating certain jobs worsening social and income inequalities. Analysing the opposite causation of that assessed in the current article, technological change can also reduce income inequality (Adrián et al., 2019; Tchamyou et al., 2018) in that many start-up companies like are able to be launched (Kshetri, 2017). Income inequality can have a cause-and-effect relation on cryptocurrency and ultimately the adoption of blockchain. It can motivate countries with high inequality to adopt cryptocurrencies to address the prevailing level of inequality. With lower transaction costs, financial inclusion and property rights security, and various income inequality issues, cryptocurrency adoption is regarded in some nations enable increased financial participation by the poor. Cryptocurrencies may confer greater economic participation since anyone with a smart phone and internet can become part of the global economy. Blockchain micro lending apps deployed in Southeast Asia have enabled 1.7 billion unbanked people in the world to build an auditable credit history. A digital currency created by the Venezuelan government has been deployed to assist citizens to be shielded from fiat currency devaluation (Carter, 2020).

3.7. Education level

Countries ranking higher in education level attainment can be expected to adopt cryptocurrency faster in the light of technical skills and knowledge presence (Li et al., 2019; Riddell and Song, 2017). Equally, the deployment impact of cryptocurrency can be extremely high in developing nations depending on skills level (Shapiro and Mandelman, 2021). Aside from pedagogical implications, blockchain systems can allow the issuance of decentralized degree certificates and checks on the authenticity of existing degree awards (Raimundo and Rosário, 2021). Cryptocurrency usage can open up possibilities for smart contracts to be used as financial literacy and educational attainment can enhance the understanding of cryptocurrency based systems including the wider deployment of blockchains.

3.8. Economic freedom

Economic freedom includes the right to control one's labour and property. Since economic freedom is a measure of regulatory efficiency, financial freedom, and rule of law amongst other factors it could be closely linked to cryptocurrency adoption the success of which also relies on the aforementioned factors. Cryptocurrencies can help advance the core tenets of economic freedom including property rights, lack of reliance on central authorities, privacy and equality of opportunity (Gulker, 2017). They can eliminate the need of intermediaries and provide opportunities to participate in the global economy where segments of the populations lack verifiable identity modalities or have no access to banking services.

3.9. Network readiness

The Network Readiness Index measures the ability of the country to exploit the advantages offered by information communication and technology. Network readiness is closely tied to cryptocurrency adoption since it measures the preparedness of an economy in relation to the presence of infrastructure and skills required for technology adoption. It could provide guidelines to policy makers and ICT (Information and Communication Technology) stakeholders to collaborate and promote ICT development (Malisuwan et al., 2016).

The various factors to assess the impact on cryptocurrency adoption decisions discussed above are summarized in Table 2.

4. Model development and sample selection

Based on our above discussion based on what developmental factors impact CA, we present a model in this section with C as a dependent variable tied to the ten independent variables. These are democracy D, education E, Gini index G, GDP per capita GDP, human development HDI, corruption perception index CPI, regulatory quality RQ, control of corruption CC, economic freedom index EF and network readiness index N. Our model is as follows:

$$C = a_1D + a_2E + a_3G + a_4GDP + a_5HDI + a_6CPI + a_7RQ + a_8CC + a_9EF + a_{10}N \tag{1}$$

Table 3 shows indices for democracy, education, income inequality, GDP per capita, human development, corruption perception, regulatory quality, control of corruption, economic freedom, and network readiness. The global crypto adoption index C, ranks countries on a scale of 0-1. The closer the score is to 1, the higher the rank (Chinalysis, 2020). The democracy index ranks 167 countries (Economic Intelligence Unit, 2019) scaled from 0 to 10. The education index and human development index rank 189 countries (Human Development Report, 2019) scaled from 0 to 1. The Gini index for income inequality ranks countries on a scale of 0 to 100 (World Bank, 2018) where a higher number means more inequality, the GDP per capita ranks countries according to their purchasing power parity (World Bank, 2019a). The corruption perception index CPI ranks 180 countries on a scale of 0 to 100 (Transparency International, 2019), where 0 specifies maximum perception of corruption and 100 specifies minimum perception of corruption. The regulatory quality index RQ and control of corruption CC scaled from 0 to 100 are a part of world wide governance indicators which rank over 200 countries (World Bank, 2019b). High numbers express high regulatory quality index RQ and high control of corruption CC. The economic freedom index EF ranks 184 countries (Heritage Foundation, 2019) scaled from 0 to 100 and the network readiness index N ranks 121 economies based on their performarnce across 60 variables (Portulans Institute, 2019). A high number means more economic freedom EF.

Table 3 shows the index values for 137 countries. For missing numbers, we apply the average numbers of the neighbouring countries as an approximation criterion. Afghanistan's Gini Index is assumed to be the average of Kazakhstan, Kyrgyzstan, and Tajikistan. Azerbaijan's Gini Index is estimated using its 2013 Gini index. The missing Gini Indices of Saudi Arabia, Kuwait, Bahrain, Qatar, and Oman are assumed to be the average of United Arab Emirates, Jordan, Iran, Qatar, and Yemen. Brunei's Gini and democracy index is assumed to be the same as UAE. Cambodia's Gini index is estimated using its 2013's Gini index. Hong Kong's control of corruption, regulatory quality, education, and Gini index is assumed to be the same as China's. Iraq economic freedom index is assumed to be the same as Iran's. Jamaica Gini index is estimated using its 2013 index. Maldives democracy index is based on its 2018 government restriction index. New Zealand's missing Gini Index is assumed to be the same as Australia's. Missing education index of Saudi Arabia is assumed to be the average of United Arab Emirates, Jordan, Iran, Qatar, and Yemen. Trinidad and Tobago's Gini index is assumed to be the same as Venezuela's. Uzbekistan's Gini index is estimated using the average of Kazakhstan, Kyrgyzstan, and Tajikistan. Venezuela's Gini Index is assumed to be the average of Brazil and Colombia. Yemen's economic freedom index assumed to be the average of Saudi Arabia and Oman. The network readiness index of Afghanistan is assumed to be the average of Kazakhstan, Kyrgyzstan, and Tajikistan. Network readiness index of Angola and Democratic Republic of Congo is assumed to be the average of Namibia and Zambia. Network readiness index of Benin, Togo and Burkina Faso is assumed to be same as that of Nigeria. The network readiness index of Bolivia is assumed to be the average of Argentina, Brazil, and Chile. Brunei's network readiness index is assumed to be the same as UAE's. Cape Verde's network readiness index is assumed to be the same as Senegal's. Chad's network readiness index is assumed to be the average of Nigeria and Cameroon. Gabon's network readiness index is assumed to be the average of Cameroon and Congo. Haiti's network readiness index is assumed to be the average of Jamaica and Dominican Republic. Iraq's network readiness index is assumed to be the same as Iran's. Network readiness index of Maldives is assumed to be the average of Sri Lanka and India. Montenegro's network readiness index is assumed to be the average of Croatia, Bosnia and Herzegovina, Serbia, and Albania. Myanmar's network readiness index is assumed to be the average of India and Bangladesh. Nicaragua's network readiness index is assumed to be the average of Costa Rica and Honduras. Papua New Guinea's network readiness index is assumed to be the average of Australia and Indonesia. Sudan's network readiness index is assumed to be the average of Chad and Egypt. Sweden's network readiness index is assumed to be the average of Norway and Finland. Uzbekistan's network readiness index is assumed to be the average of Kazakhstan, Kyrgyzstan, and Tajikistan.

Table 2
Summary of variables and their effects.

	Independent variables	Variable names	Positive effect	Negative effect
1	Democracy	*D*	Will foster CA since the idea behind the technology is to have a decentralized model of the economy	
2	Education	*E*	Will encourage CA	
3	Inequality, measured with the Gini index	*G*		Cryptocurrencies are suspected to decrease inequality by giving equal opportunity to rich and poor to enter contracts
4	GDP per capita	*GDP*	The higher the GDP, the more available resources for the country to experiment with new technology	
5	Human development index	*HDI*	Supply chain uses (medical and aid disbursement) identity management by developing a database for citizens and identifying refugees and other non-residents	
6	Corruption perception index	*CPI*		Corrupt government may resist adoption
7,8	World governance indicators	*RQ*, *CC*	Regulatory Quality and control over corruption would encourage CA	
9	Economic Freedom Index	*EF*	Economic Freedom would encourage CA	
10	Network Readiness Index	*N*	Network Readiness would accelerate CA	

5. Correlation analysis and regression analysis

5.1. Correlation

Table 1 demonstrates the Pearson Correlation between cryptocurrency adoption *C*, Democracy *D*, Education *E*, Gini Index *G*, Gross Domestic Product *GDP*, Human Development Index *HDI*, Corruption Perception Index *CPI*, Regulatory Quality *RQ*, Control of Corruption *CC*, Economic Freedom Index *EF* and Network Readiness Index *N*. Cryptocurrency adoption *C* has the strongest correlation with education *E*

Table 1
Matrix of correlation.

Variables	C	D	E	G	GDP	HDI	CPI	RQ	CC	EF	N
C	1.000	0.051	0.189	0.118	0.005	0.140	-0.007	0.050	-0.005	-0.062	0.140
D	0.051	1.000	0.599	-0.083	0.503	0.617	0.701	0.755	0.709	0.554	0.641
E	0.189	0.599	1.000	-0.381	0.701	0.952	0.719	0.776	0.711	0.584	0.840
G	0.118	-0.083	-0.381	1.000	-0.479	-0.426	-0.375	-0.332	-0.342	-0.328	-0.475
GDP	0.005	0.503	0.701	-0.479	1.000	0.804	0.820	0.765	0.778	0.701	0.855
HDI	0.140	0.617	0.952	-0.426	0.804	1.000	0.774	0.816	0.756	0.653	0.901
CPI	-0.007	0.701	0.719	-0.375	0.820	0.774	1.000	0.872	0.962	0.780	0.847
RQ	0.050	0.755	0.776	-0.332	0.765	0.816	0.872	1.000	0.901	0.817	0.853
CC	-0.005	0.709	0.711	-0.342	0.778	0.756	0.962	0.901	1.000	0.729	0.818
EF	-0.062	0.554	0.584	-0.328	0.701	0.653	0.780	0.817	0.729	1.000	0.711
N	0.140	0.641	0.840	-0.475	0.855	0.901	0.847	0.853	0.818	0.711	1.000

Table 3
Variables data for 137 countries.

Country	C	CC	RQ	D	EF	HDI	E	G	CPI	GDP	N
Afghanistan	0	6.73	10.10	2.85	51.5	0.511	0.414	29.7	16	2542.853	41.77
Albania	0.01	33.17	63.94	5.89	66.5	0.795	0.746	33.2	35	14534.109	46.57
Algeria	0	29.33	7.69	4.01	46.2	0.748	0.672	27.6	35	11894.859	35.3
Angola	0.016	13.94	16.35	3.72	50.6	0.581	0.5	51.3	26	7346.304	29.77
Argentina	0.174	53.37	33.65	7.02	52.2	0.845	0.855	41.4	45	22997	51.27
Armenia	0.021	50.00	63.46	5.54	67.7	0.776	0.74	34.4	42	14176.871	49.84
Australia	0.21	94.23	98.56	9.09	80.9	0.944	0.924	34.4	77	52712.423	74.8
Austria	0.087	90.87	91.35	8.29	72	0.922	0.865	29.7	77	58684.546	74.36
Azerbaijan	0.008	19.71	43.75	2.75	65.4	0.756	0.711	33.7	30	15075.895	47.74
Bahrain	0.009	56.73	67.79	2.55	66.4	0.852	0.769	30.5	42	51948.07	58.73
Bangladesh	0.118	16.35	15.38	5.88	55.6	0.632	0.529	32.4	26	5330.045	34.48
Benin	0.039	42.79	37.50	5.09	55.3	0.545	0.478	47.8	41	3422.706	28.22
Belarus	0.241	53.85	32.21	2.88	57.9	0.823	0.838	25.2	45	19984.356	50.34
Belgium	0.125	91.35	87.50	7.64	67.3	0.931	0.902	27.4	75	54265.288	72.62
Bolivia	0.082	25.96	12.50	4.84	42.3	0.718	0.695	42.2	31	9064.103	53.24
Bosnia and Herzegovina	0.042	30.29	47.12	4.86	61.9	0.78	0.711	33	36	15627.11	42.72
Botswana	0.016	75.48	65.87	7.81	69.5	0.735	0.676	53.3	61	18571.806	34.85
Brazil	0.338	42.31	48.08	6.86	51.9	0.765	0.694	53.9	35	15454.34	51.07
Brunei Darussalam	0.003	78.37	73.08	2.76	65.1	0.838	0.702	32.5	60	61032.097	65.45
Bulgaria	0.073	50.48	71.15	7.03	69	0.816	0.779	40.4	43	24333.46	54.77
Burkina Faso	0.006	49.52	37.02	4.04	59.4	0.452	0.312	35.3	40	2282.256	28.22
Cameroon	0.085	11.06	19.23	2.85	77.7	0.563	0.547	46.6	25	3801.233	25.94
Canada	0.196	93.27	95.67	9.22	63.1	0.929	0.894	33.8	77	51481.186	74.72
Cape Verde	0	79.81	44.71	7.78	57.8	0.665	0.562	42.4	58	7470.874	33.67
Chad	0	5.77	11.06	1.61	49.9	0.398	0.288	43.3	20	1654.192	27.08
Chile	0.147	83.17	84.13	8.08	75.4	0.851	0.81	44.4	67	24969.159	57.38
China	0.672	43.27	42.79	2.26	58.4	0.761	0.657	38.5	41	16659.476	57.63
Colombia	0.444	48.08	66.35	7.13	67.3	0.767	0.682	50.4	37	15344.56	48.77
Cambodia	0.04	9.62	30.29	3.53	52.4	0.594	0.484	36	20	4832.715	32.29
Congo, Dem. Rep.	0.02	3.37	5.29	1.13	50.3	0.48	0.496	42.1	18	1129.689	29.77
Costa Rica	0.052	75.96	68.75	8.13	65.3	0.81	0.726	48	56	20962.399	54.59
Croatia	0.054	60.10	72.12	6.57	61.4	0.851	0.805	30.4	47	29925.367	56.75
Cyprus	0.067	71.63	80.77	7.59	68.1	0.887	0.827	31.4	58	42236.155	61.57
Czech Republic	0.114	68.75	86.54	7.69	73.7	0.9	0.89	24.9	56	42668.037	65.09
Denmark	0.042	97.60	92.31	9.22	76.7	0.94	0.92	28.7	87	60378.899	81.08
Dominican Republic	0.083	25.00	52.40	6.54	61	0.756	0.666	43.7	28	19897.824	42.59
Ecuador	0.157	34.62	19.71	6.33	46.9	0.759	0.702	45.4	38	11923.998	41.98
Egypt	0.074	27.88	18.75	3.06	52.5	0.707	0.618	31.5	35	12445.206	38.58
EL Salvador	0.09	32.69	56.25	6.15	61.8	0.673	0.555	38.6	34	9146.495	37.27
Estonia	0.13	90.38	92.79	7.9	76.6	0.892	0.882	30.4	74	38479.757	69.3
Ethiopia	0.009	39.90	16.83	3.44	53.6	0.485	0.341	35	37	2752.7	23.37
Finland	0.085	99.04	97.60	9.25	74.9	0.938	0.927	27.4	86	50791.483	80.34
France	0.208	88.94	90.87	8.12	63.8	0.901	0.817	31.6	69	49696.096	73.42
Gabon	0.003	17.79	14.42	3.61	56.3	0.703	0.65	38	31	16271.87	27.86
Georgia	0.17	74.04	82.69	5.42	75.9	0.812	0.862	36.4	56	15612.859	48.81
Germany	0.147	95.19	96.15	8.68	73.5	0.947	0.943	31.9	80	56226.224	78.23
Ghana	0.18	52.40	50.48	6.63	57.5	0.611	0.563	43.5	41	5688.213	37.07
Greece	0.084	56.25	70.67	7.43	57.7	0.888	0.849	34.4	48	30916.551	57.07
Guatemala	0.039	18.75	44.23	5.26	62.6	0.663	0.519	48.3	26	8486.94	36.07
Haiti	0.006	8.17	8.65	4.57	52.7	0.51	0.456	41.1	18	3028.311	44.06
Honduras	0.013	23.08	34.13	5.42	60.2	0.634	0.499	52.1	26	5955.318	35.88
Hong Kong	0.202	43.27	42.79	6.02	90.2	0.949	0.657	38.5	76	62266.872	68.14
Hungary	0.041	57.69	72.60	6.63	65	0.854	0.821	30.6	44	34327.386	59.95
Iceland	0.01	92.79	89.90	9.58	77.1	0.949	0.926	26.8	78	60419.215	71.94
India	0.395	47.60	48.56	6.9	55.2	0.645	0.555	37.8	41	6991.81	44.81
Indonesia	0.151	37.98	51.44	6.48	65.8	0.718	0.65	39	40	12482.807	46.15
Iran	0.092	14.90	6.73	2.38	51.1	0.783	0.756	40.8	26	12858.061	43.66
Iraq	0.005	8.65	9.62	3.74	51.1	0.674	0.557	29.5	20	11378.737	43.66
Ireland	0.071	89.42	93.27	9.24	80.5	0.955	0.922	32.8	74	91812.025	73.29
Israel	0.033	78.85	87.02	7.86	72.8	0.919	0.883	39	60	41785.561	70.86
Italy	0.109	62.02	76.92	7.52	62.2	0.892	0.793	35.9	53	44217.623	63.21
Jamaica	0.038	54.33	62.02	6.96	68.6	0.734	0.689	45.5	43	10990.537	45.52
Japan	0.065	89.90	88.46	7.99	72.1	0.919	0.851	32.9	73	43710.261	76.17
Jordan	0.033	60.58	57.21	3.93	66.5	0.729	0.667	33.7	48	10530.381	46.97
Kazakhstan	0.072	43.75	61.06	2.94	65.4	0.825	0.83	27.5	34	27292.246	50.68
Kenya	0.645	24.52	41.35	5.18	55.1	0.601	0.534	40.8	28	4984.57	38.19
Kuwait	0.021	50.96	57.69	3.93	60.8	0.806	0.638	30.5	40	46017.841	53.39
Kyrgyzstan	0.008	17.31	38.46	4.89	62.3	0.697	0.73	27.7	30	5515.665	39.72
Laos	0	13.46	23.56	2.14	57.4	0.613	0.481	36.4	29	8164.694	31.88
Latvia	0.204	68.27	83.65	7.49	70.4	0.866	0.883	35.6	56	32076.082	59.31
Lebanon	0.013	12.02	36.54	4.36	51.1	0.744	0.604	31.8	28	15166.989	41.44
Lithuania	0.144	74.52	83.17	7.5	74.2	0.882	0.898	37.3	60	38703.911	64.13
Luxembourg	0.025	98.08	95.19	8.81	75.9	0.916	0.806	34.9	80	120490.76	77.46
Madagascar	0.018	15.87	22.60	5.64	56.6	0.528	0.486	42.6	24	1692.139	22.73

(continued on next page)

Table 3 (*continued*)

Country	C	CC	RQ	D	EF	HDI	E	G	CPI	GDP	N
Malawi	0.004	24.04	24.52	5.5	51.4	0.483	0.47	44.7	31	1003.658	22.9
Malaysia	0.192	62.50	73.56	7.16	74	0.81	0.726	41	53	29042.99	63.76
Maldives	0.006	46.15	34.62	8.2	53.2	0.74	0.573	31.3	29	29073.294	43.62
Mali	0.023	26.92	29.81	4.92	58.1	0.434	0.286	33	29	2493.659	24.29
Malta	0.048	61.54	77.40	7.95	68.6	0.895	0.825	29.2	54	47468.474	66.94
Mauritius	0.059	63.94	79.33	8.22	73	0.804	0.736	36.8	52	23818.571	53.4
Mexico	0.135	22.60	59.62	6.09	64.7	0.779	0.703	45.4	29	20795.81	51.44
Moldova	0.04	29.81	55.77	5.75	59.1	0.75	0.711	25.7	32	13440.458	48.93
Mongolia	0	37.50	53.85	6.5	55.4	0.737	0.736	32.7	35	12558.483	39.91
Montenergo	0.06	55.29	65.38	5.65	60.5	0.829	0.803	39	45	22446.939	49.92
Morocco	0.127	45.67	46.15	5.1	62.9	0.686	0.569	39.5	41	8180.157	41.38
Mozambique	0.061	23.56	23.08	3.65	48.6	0.456	0.395	54	26	1301.686	22.07
Myanmar	0.003	28.85	21.63	3.55	53.6	0.583	0.464	30.7	29	5053.608	39.65
Nambia	0.021	65.87	50.96	6.43	58.7	0.646	0.584	59.1	52	10299.512	33.34
Nepal	0.049	27.40	24.04	5.28	53.8	0.602	0.521	32.8	34	4142.178	32.96
Netherlands	0.183	96.63	98.08	9.01	76.8	0.944	0.914	28.5	82	59516.936	81.78
New Zealand	0.075	100.00	99.04	9.26	84.4	0.931	0.926	34.4	87	43689.071	73.97
Nicaragua	0.02	12.50	25.00	3.55	57.7	0.66	0.573	46.2	22	5651.147	45.24
Nigeria	0.459	12.98	17.79	4.12	57.3	0.539	0.499	43	26	5352.672	28.22
Norway	0.072	97.12	97.12	9.87	73	0.957	0.93	27	84	65904.563	81.3
Oman	0.008	67.31	64.42	3.06	61	0.813	0.718	30.5	52	30653.98	52.87
Pakistan	0.272	21.15	27.40	4.25	55	0.557	0.402	33.5	32	5203.809	33.38
Panama	0.094	30.77	64.90	7.05	67.2	0.815	0.7	49.2	36	32975.955	46.96
Paraguay	0.015	22.12	46.63	6.24	61.8	0.728	0.638	46.2	28	13021.816	40.55
Peru	0.242	36.54	71.63	6.6	67.8	0.777	0.74	42.8	36	13327.718	45.68
Philippines	0.262	31.25	55.29	6.64	63.8	0.718	0.678	44.4	34	9356.442	47.7
Poland	0.137	71.15	81.25	6.62	67.8	0.88	0.869	29.7	58	34624.263	61.46
Popua New Guinea	0.001	16.83	32.69	6.03	58.4	0.555	0.439	41.9	28	4022.466	60.48
Portugal	0.126	77.40	77.88	8.03	65.3	0.864	0.768	33.8	62	36400.144	65.56
Qatar	0.01	79.33	74.04	3.19	72.6	0.848	0.659	30.5	62	95107.743	63.73
Serbia	0.073	37.02	60.10	6.41	63.9	0.806	0.783	36.2	39	19026.994	53.65
Romania	0.112	51.44	67.31	6.49	68.6	0.828	0.765	36	44	31243.656	55.47
Russia	0.931	21.63	36.06	3.11	58.9	0.824	0.823	37.5	28	28450.207	54.98
Rwanda	0.049	70.67	58.17	3.16	71.1	0.543	0.458	43.7	53	2362.728	39.97
Saudi Arabia	0.036	62.98	51.92	1.93	60.7	0.854	0.802	30.5	53	49216.192	56.49
Senegal	0.029	59.13	50.00	5.81	56.3	0.512	0.345	40.3	45	3503.619	33.67
Singapore	0.102	99.52	100.00	6.02	89.4	0.938	0.844	0.452	85	102573.465	82.13
Slovakia	0.143	64.42	79.81	7.17	65	0.86	0.826	25.2	50	34137.419	61.95
Slovenia	0.133	80.29	80.29	7.5	65.5	0.917	0.91	24.2	60	40879.323	66.89
South Africa	0.526	59.62	61.54	7.24	58.3	0.709	0.724	63	44	12961.702	47.38
Spain	0.138	73.56	81.73	8.18	65.7	0.904	0.831	34.7	62	42608.816	68.01
Sri Lanka	0.053	44.23	47.60	6.27	56.4	#N/A	0.746	39.8	38	13622.869	42.42
Sudan	0.003	7.69	3.85	2.7	47.7	0.51	0.345	34.2	16	4310.324	32.83
Sweden	0.117	98.56	96.63	9.39	75.2	0.945	0.918	28.8	85	55324.383	80.82
Switzerland	0.08	96.15	94.71	9.03	81.9	0.955	0.9	32.7	85	74744.585	81.08
Tajikistan	0	9.13	12.02	1.93	55.6	0.668	0.682	34	25	3543.752	34.9
Tanzania	0.081	40.87	27.88	5.16	60.2	0.529	0.429	40.5	37	2840.653	30.73
Thailand	0.365	39.42	60.58	6.32	68.3	0.777	0.682	36.4	36	19233.878	51.54
Togo	0.06	25.48	25.96	3.3	50.3	0.515	0.517	43.1	29	2210.976	28.22
Trinidad and Tobago	0.025	49.04	49.52	7.16	57	0.796	0.728	52.15	40	26920.092	49.29
Tunisia	0.014	52.88	35.58	6.72	55.4	0.74	0.661	32.8	43	11074.953	42.04
Turkey	0.174	44.71	54.81	4.09	64.6	0.82	0.731	41.9	39	29723.533	53.75
Uganda	0.079	11.54	37.98	5.02	59.7	0.544	0.523	42.8	28	2689.091	29.7
Ukraine	1	26.44	42.31	5.9	52.3	0.779	0.799	26.1	30	13442.094	48.91
United Arab Emirates	0.056	83.65	78.37	2.76	77.6	0.89	0.802	32.5	71	63589.803	65.45
United Kingdom	0.333	93.75	93.75	8.52	78.9	0.932	0.928	34.8	77	48603.041	77.73
United States	0.627	84.62	88.94	7.96	76.8	0.926	0.9	41.4	69	65253.518	80.32
Uzbekistan	0.013	14.42	12.98	2.01	53.3	0.72	0.729	29.7	25	7382.387	41.77
Venezuela	0.799	4.33	0.48	2.88	25.9	0.711	0.7	52.15	16	7344.079	34.14
Vietnam	0.443	34.13	41.83	3.08	55.3	0.704	0.63	35.7	37	10535.168	49.57
Yemen	0.005	1.92	4.33	1.95	60.85	0.47	0.35	36.7	15	2056.586	12.33
Zambia	0.051	28.37	31.25	5.09	53.6	0.584	0.557	57.1	34	3526.397	26.2
Zimbawe	0	10.10	6.25	3.16	40.4	0.571	0.587	44.3	24	2869.348	22.09

which shows the importance of having prerequisite knowledge to operate the technology before its adoption. Network readiness also has a high correlation which again points towards the preparedness of an economy to the adoption of technology. The high correlation of CA *C* with human development *HDI* shows the willingness of economies investing highly in human welfare to continue facilitating their residents by upgrading their technology. It also shows an economy's willingness to adopt cryptocurrency to encourage financial inclusion and accelerate efforts towards identity management. A moderate correlation with the Gini index suggests that cryptocurrency could help lessen the income inequality by giving more opportunities to everyone alike. Weaker correlation exists with democracy, GDP per capita and regulatory quality. The corruption perception index *CPI*, control of corruption *CC* and economic freedom index *EF* exhibit a negative correlation which shows that countries with poor governance and economic structures would hinder the adoption of technology. Overall, the ten variables show a weak correlation with CA which could be attributed to the newness of the phenomenon and missing indicators which could affect the adoption.

5.2. Regression analysis

We regress cryptocurrency adoption C as the dependent variable and ten other independent variables with the regression line in Eq. (1). The hypothesis to be tested is whether a statistically significant linear relationship exists between the independent variables on the right hand side, i.e. $D,E,G,GDP,HDI,CPI,RQ,CC,EF,N$ in Eq. (1), and the one dependent variable on the left hand side, i.e. cryptocurrency adoption C. The null hypothesis is that no statistically significant linear relationship exists, i.e. that the slope of the regression line is zero.

The first regression equation,

$$C = 0.004D + 0.099 \tag{2}$$

tests for the relation of cryptocurrency adoption C as the dependent variable and democracy D as the independent variable. Table 4a exhibits the results of the regression

The second regression equation,

$$C = -0.008D + 0.262E - 0.011 \tag{3}$$

with cryptocurrency adoption C as the dependent variable, and democracy D and education E as the independent variables yields the results shown in Table 4b.

For the next regression equation,

$$C = -0.013D + 0.399E + 0.005G - 0.273 \tag{4}$$

democracy D, education E and Gini Index G are chosen as the independent variables with cryptocurrency adoption C as the dependent variable. The results are demonstrated in Table 4c.

For the next regression equation,

$$C = -0.01D + 0.472E + 0.004G + 0GDP - 0.278 \tag{5}$$

we add GDP per capita GDP as the independent variable in addition to democracy D, education E and Gini index G, where $0GDP$ means the number 0 multiplied with GDP (and analogously below). Cryptocurrency adoption C is the dependent variable. The results of the regression are shown in Eq. (5) and Table 4d.

For the regression equation

$$\mathrm{C} = -0.01\mathrm{D} + 0.491\mathrm{E} + 0.004\mathrm{G} + 0\mathrm{GDP} - 0.029\mathrm{HDI} - 0.27 \tag{6}$$

Cryptocurrency adoption C is the dependent variable, and democracy D, education E, Gini index G, GDP per capita GDP and the human development index HDI are the independent variables. The results are shown in Table 4e.

For the regression equation

$$C = -0.004D + 0.527E + 0.004G + 0GDP - 0.051HDI - 0.002CPI - 0.244 \tag{7}$$

Cryptocurrency adoption C is the dependent variable, and democracy D, education E, Gini index G, GDP per capita GDP, human development index HDI and corruption perception index CPI are the independent variables. The results are demonstrated in Table 4f.

For the regression equation

$$C = -0.004D + 0.529E + 0.004G + 0GDP - 0.047HDI - 0.002CPI + 0RQ - 0.247 \tag{8}$$

we add one of the world governance indicators regulatory quality RQ as the independent variable along with democracy D, education E, Gini index G, GDP per capita GDP, human development index HDI and corruption perception index CPI. Cryptocurrency adoption C is the dependent variable. Table 4g shows the results.

For the regression equation

$$C = -0.004D + 0.533E + 0.004G + 0GDP - 0.06HDI - 0.001CPI + 0RQ - 0.001CC - 0.259 \tag{9}$$

we add another world governance indicator control of corruption CC along with other regulatory quality RQ, democracy D, education E, Gini index G, GDP per capita GDP, human development index HDI and corruption perception index CPI as the independent variables. Cryptocurrency adoption C is the dependent variable. Table 4h shows the results.

The regression equation

$$C = -0.008D + 0.454E + 0.004G + 0GDP - 0.036HDI + 0.002CPI + 0.002RQ - 0.003CC - 0.005EF - 0.031 \tag{10}$$

tests for the relation of cryptocurrency adoption C as the dependent variable and control of corruption CC, regulatory quality RQ, democracy D, education E, Gini index G, GDP per capita GDP, human development index HDI, corruption perception index CPI and economic freedom index EF as the independent variables. The results are demonstrated in Table 4i.

The last regression,

$$C = -0.01D + 0.461E + 0.005G + 0GDP - 0.381HDI + 0CPI + 0.001RQ - 0.002CC - 0.004EF + 0.007N - 0.083 \tag{11}$$

has all the 10 independent variables, namely control of corruption CC, regulatory quality RQ, democracy D, education E, Gini index G, GDP per capita GDP, human development index HDI, corruption perception index CPI, economic freedom index EF and network readiness index N. Cryptocurrency adoption C is the dependent variable. The results of this regression are shown in Table 4j.

5.3. Structural equation modeling

To address the problem of multicollinearity among the variables, we use Eq (12) to run the structural equation model. The results are shown in Table 5a.

Next, we apply the variance inflation factor (VIF) test to address the problem of multicollinearity. The results are shown in Table 5b.

A variance inflation factor (VIF) of more than 10 means high covariance. We drop the variables with a VIF of 10 or more to produce

Table 4a

C	Coef.	St.Err.	*t*-value	*P*-value	[95% Conf	Interval]	Sig
D	.004	.007	0.59	.555	-.01	.018	
Constant	.099	.043	2.30	.023	.014	.185	**
Mean dependent var	0.123	SD dependent var	0.177				
R-squared	0.003	Number of obs.	137.000				
F-test	0.350	Prob > F	0.555				
Akaike crit. (AIC)	-82.427	Bayesian crit. (BIC)	-76.587				

*** $p<.01$, ** $p<.05$, * $p<.1$

Table 4b

C	Coef.	St.Err.	*t*-value	*P*-value	[95% Conf	Interval]	Sig
D	-.008	.009	-0.92	.36	-.025	.009	
E	.262	.112	2.34	.021	.041	.484	**
Constant	-.011	.064	-0.18	.858	-.137	.114	
Mean dependent var	0.123	SD dependent var	0.177				
R-squared	0.042	Number of obs.	137.000				
F-test	2.917	Prob > F	0.058				
Akaike crit. (AIC)	-85.911	Bayesian crit. (BIC)	-77.151				

*** p<.01, ** p<.05, * p<.1.

Table 4c

C	Coef.	St.Err.	*t*-value	*P*-value	[95% Conf	Interval]	Sig
D	-.013	.009	-1.46	.147	-.03	.004	
E	.399	.12	3.31	.001	.161	.637	***
G	.005	.002	2.73	.007	.001	.009	***
Constant	-.273	.114	-2.39	.018	-.5	-.047	**
Mean dependent var	0.123	SD dependent var	0.177				
R-squared	0.092	Number of obs.	137.000				
F-test	4.515	Prob > F	0.005				
Akaike crit. (AIC)	-91.358	Bayesian crit. (BIC)	-79.679				

*** p<.01, ** p<.05, * p<.1

Table 4d

C	Coef.	St.Err.	*t*-value	*P*-value	[95% Conf	Interval]	Sig
D	-.01	.009	-1.16	.246	-.028	.007	
E	.472	.136	3.46	.001	.202	.741	***
G	.004	.002	2.13	.035	0	.008	**
GDP	0	0	-1.14	.255	0	0	
Constant	-.278	.114	-2.43	.016	-.504	-.052	**
Mean dependent var	0.123	SD dependent var	0.177				
R-squared	0.101	Number of obs.	137.000				
F-test	3.721	Prob > F	0.007				
Akaike crit. (AIC)	-90.711	Bayesian crit. (BIC)	-76.111				

*** p<.01, ** p<.05, * p<.1.

Table 4e

C	Coef.	St.Err.	*t*-value	*P*-value	[95% Conf	Interval]	Sig
D	-.01	.009	-1.14	.257	-.028	.008	
E	.491	.308	1.59	.114	-.119	1.1	
G	.004	.002	2.12	.036	0	.008	**
GDP	0	0	-0.89	.375	0	0	
HDI	-.029	.428	-0.07	.946	-.876	.818	
Constant	-.27	.16	-1.69	.094	-.587	.047	*
Mean dependent var	0.123	SD dependent var	0.177				
R-squared	0.101	Number of obs.	137.000				
F-test	2.956	Prob > F	0.015				
Akaike crit. (AIC)	-88.715	Bayesian crit. (BIC)	-71.196				

*** p<.01, ** p<.05, * p<.1.

the results shown in Table 5c.

To examine the difference between cryptocurrency adoption of developing and developed countries we introduce a dummy variable where 0 denotes developing and 1 denotes developed country. Economies in transition are categorized as developing countries for our analysis (United Nations, 2020). Applying the Generalized Method of Moments, we get the results shown in Table 5d.

6. Discussion, limitations and future research

Our analysis focuses on developmental indicators which are associated with receptivity to cryptocurrency adoption. The value of such an investigation is that this sheds light on what policy makers may focus on given the specific mix of developmental elements prevailing in their country context. We identify dimensions used by developmental economists encompassing the following: Education, the Human Development Index, the Network Readiness Index, the Gini index, Democracy, Regulatory Quality, and Gross Domestic Product, Control of Corruption, the Corruption Perception Index, and the Economic Freedom Index. These have been used in the prior literature in relation to aiding policy decision making capacity. While it must be borne in mind that a multitude of factors that are developmental in nature can impact technological operationalisation, we are able to focus on ones that are at the core of the discourse on development and national growth (Acemoglu, 2009).

Table 4f

C	Coef.	St.Err.	*t*-value	*P*-value	[95% Conf	Interval]	Sig
D	-.004	.01	-0.39	.694	-.025	.017	
E	.527	.309	1.70	.091	-.085	1.14	*
G	.004	.002	2.01	.046	0	.008	**
GDP	0	0	-0.12	.904	0	0	
HDI	-.051	.428	-0.12	.906	-.898	.796	
CPI	-.002	.002	-1.13	.263	-.005	.001	
Constant	-.244	.162	-1.51	.135	-.564	.077	
Mean dependent var	0.123	SD dependent var	0.177				
R-squared	0.110	Number of obs.	137.000				
F-test	2.679	Prob > F	0.017				
Akaike crit. (AIC)	-88.043	Bayesian crit. (BIC)	-67.603				

*** p<.01, ** p<.05, * p<.1.

Table 4g

C	Coef.	St.Err.	*t*-value	*P*-value	[95% Conf	Interval]	Sig
D	-.004	.011	-0.33	.743	-.026	.019	
E	.529	.312	1.70	.092	-.087	1.146	*
G	.004	.002	2.01	.047	0	.008	**
GDP	0	0	-0.11	.911	0	0	
HDI	-.047	.432	-0.11	.914	-.901	.807	
CPI	-.002	.002	-0.97	.334	-.006	.002	
RQ	0	.001	-0.09	.928	-.003	.002	
Constant	-.247	.168	-1.48	.142	-.579	.084	
Mean dependent var	0.123	SD dependent var	0.177				
R-squared	0.110	Number of obs.	137.000				
F-test	2.280	Prob > F	0.032				
Akaike crit. (AIC)	-86.052	Bayesian crit. (BIC)	-62.692				

*** p<.01, ** p<.05, * p<.1.

Table 4h

C	Coef.	St.Err.	*t*-value	*P*-value	[95% Conf	Interval]	Sig
D	-.004	.011	-0.36	.722	-.027	.018	
E	.533	.313	1.70	.091	-.086	1.151	*
G	.004	.002	2.02	.046	0	.008	**
GDP	0	0	-0.16	.877	0	0	
HDI	-.06	.434	-0.14	.89	-.919	.799	
CPI	-.001	.003	-0.20	.844	-.007	.006	
RQ	0	.001	0.13	.896	-.003	.003	
CC	-.001	.002	-0.45	.652	-.005	.003	
Constant	-.259	.17	-1.52	.13	-.595	.078	
Mean dependent var	0.123	SD dependent var	0.177				
R-squared	0.112	Number of obs.	137.000				
F-test	2.008	Prob > F	0.050				
Akaike crit. (AIC)	-84.270	Bayesian crit. (BIC)	-57.990				

*** p<.01, ** p<.05, * p<.1.

Table 4i

C	Coef.	St.Err.	*t*-value	*P*-value	[95% Conf	Interval]	Sig
D	-.008	.012	-0.71	.479	-.031	.015	
E	.454	.314	1.44	.151	-.168	1.076	
G	.004	.002	2.04	.044	0	.008	**
GDP	0	0	-0.15	.881	0	0	
HDI	-.036	.432	-0.08	.933	-.891	.818	
CPI	.002	.004	0.63	.532	-.005	.01	
RQ	.002	.002	1.12	.265	-.002	.006	
CC	-.003	.002	-1.15	.251	-.008	.002	
EF	-.005	.003	-1.64	.104	-.011	.001	
Constant	-.031	.219	-0.14	.887	-.464	.402	
Mean dependent var	0.123	SD dependent var	0.177				
R-squared	0.130	Number of obs.	137.000				
F-test	2.106	Prob > F	0.034				
Akaike crit. (AIC)	-85.131	Bayesian crit. (BIC)	-55.931				

*** p<.01, ** p<.05, * p<.1.

Table 4j

C	Coef.	St.Err.	*t*-value	*P*-value	[95% Conf	Interval]	Sig
D	-.01	.011	-0.86	.39	-.032	.013	
E	.461	.307	1.50	.135	-.145	1.068	
G	.005	.002	2.59	.011	.001	.009	**
GDP	0	0	-0.87	.389	0	0	
HDI	-.381	.44	-0.87	.387	-1.251	.488	
CPI	0	.004	0.02	.988	-.007	.007	
RQ	.001	.002	0.49	.628	-.003	.005	
CC	-.002	.002	-0.75	.453	-.007	.003	
EF	-.004	.003	-1.38	.171	-.01	.002	
N	.007	.003	2.73	.007	.002	.012	***
Constant	-.083	.214	-0.39	.698	-.507	.341	
Mean dependent var	0.123	SD dependent var	0.177				
R-squared	0.179	Number of obs.	137.000				
F-test	2.739	Prob > F	0.004				
Akaike crit. (AIC)	-91.022	Bayesian crit. (BIC)	-58.902				

*** p<.01, ** p<.05, * p<.1.

Table 5a

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.126531	0.013716	9.224905	0.0000
D01	-0.003673	0.042764	-0.085890	0.9317
E	-0.086316	0.070650	-1.221735	0.2242
G	-0.000873	0.015564	-0.056082	0.9554
GDP	0.054042	0.025296	2.136415	0.0346
HDI	-0.109080	0.153001	-0.712939	0.4772
CPI	-0.068999	0.086857	-0.794396	0.4285
RQ	0.001372	0.039106	0.035072	0.9721
CC	0.020227	0.047306	0.427574	0.6697
EF	-0.130129	0.095207	-1.366796	0.1742
NRI_N_	0.050520	0.009063	5.574554	0.0000
R-squared	0.307580	Mean dependent var	0.124917	
Adjusted R-squared	0.250824	S.D. dependent var	0.179187	
S.E. of regression	0.155095	Akaike info criterion	-0.810472	
Sum squared resid	2.934646	Schwarz criterion	-0.571420	
Log likelihood	64.89637	Hannan-Quinn criter.	-0.713330	
F-statistic	5.419367	Durbin-Watson stat	1.410849	
Prob(F-statistic)	0.000001	Wald F-statistic	4.554540	
Prob(Wald F-statistic)	0.000017			

Table 5b

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	Coefficient	Uncentered	Centered
Variable	Variance	VIF	VIF
C	0.000188	2.549144	NA
D01	0.001829	5.627426	5.516651
E	0.004991	9.885991	9.844882
G	0.000242	2.148895	2.108662
GDP	0.000640	20.08664	20.07377
HDI	0.023409	24.96239	24.76446
CPI	0.007544	31.93340	31.70992
RQ	0.001529	15.53631	15.29007
CC	0.002238	24.33405	24.26090
EF	0.009064	4.774838	4.766566
NRI_N_	8.21E-05	3.931500	2.774592

Decision makers and policy makers may appeal to data on these aggregate pointers which we suggest find positive or negative association. Little doubt exists that future studies will fine tune the data in investigating regions of the world, on different industry sectors and perhaps diversifying the methodology. Our study represents a first attempt to link cryptocurrency adoption vis-a-vis developmental parameters widely seen as tied to technology advances and economic growth at a macro-level. We have also argued, based on the recent literature, that cryptocurrency adoption can mobilise wider blockchain development and deployment in different country contexts.

Table 5c

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	Coefficient	Uncentered	Centered
Variable	Variance	VIF	VIF
C	0.000181	2.103516	NA
D01	0.001467	3.888581	3.596100
E	0.002430	3.579578	3.506021
G	0.000195	1.426829	1.423180
GDP	0.000236	6.207288	5.990930
CC	0.000456	4.076784	3.809033
EF	0.013486	5.055519	4.788807
NRI_N_	7.96E-05	4.013473	2.425047

Table 5d

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Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.111976	0.017531	6.387205	0.0000
D01	-0.052858	0.066005	-0.800823	0.4248
E	-0.104014	0.046199	-2.251443	0.0261
G	0.008052	0.020584	0.391190	0.6963
GDP	0.042451	0.018048	2.352138	0.0203
CC	0.023221	0.025184	0.922052	0.3583
EF	-0.209819	0.087854	-2.388282	0.0184
N	0.046454	0.009339	4.974008	0.0000
DUM	-0.001032	0.034562	-0.029857	0.9762
R-squared	0.273853	Mean dependent var	0.125864	
Adjusted R-squared	0.226624	S.D. dependent var	0.179536	
S.E. of regression	0.157887	Sum squared resid	3.066171	
Durbin-Watson stat	1.480161	J-statistic	11.97323	
Instrument rank	13	Prob(J-statistic)	0.017551	

We report that, on regressing all the 10 variables together, GDP per capita *GDP* and corruption perception index *CPI* retains zero coefficient which shows that it does not affect the decision to adopt cryptocurrency in any way. The negative coefficient of the economic freedom index *EF*, democracy *D* and control of corruption *CC* and human development index *HDI* indicates that countries with liberal economic and regulatory laws, transparent governance systems and high human development may already have robust infrastructure in place and the cost of replacing those will be much greater than the potential benefits offered by cryptocurrency. The statistically significant relation with the Gini index *G* imply that greater income inequality is a motivator in adopting cryptocurrency to address the problem. The statistically significant relation with education *E* and network readiness index *N* is consistent with our expectation for them being the prerequisites for cryptocurrency adoption.

The *p*-values for control of corruption *CC*, regulatory quality *RQ* and corruption perception index *CPI* are too high as shown in Table 4j. This may be due to strong correlation among the three variables as these three are indicators of governance quality. Table 4e-j shows that the human development index *HDI* also gives a very high *p*-value. The *p*-value for democracy *D* is quite high, i.e., 0.55 in the simple linear regression with one independent variable. It declines to its lowest of 0.147 when education *E* and the Gini index *G* are introduced as shown in Table 4c and increases to as high as 0.743 in Table 4g. The *p*-values for most independent variables are quite high. The highest *p*-value of education *E* is 0.151 but it drops to a low of 0.001 in Table 4d. The Gini index *G* and network readiness index *N* show the lowest *p*-values of all the variables.

We repeated the regression adding variables in a different sequence. The results shown in Appendix 1 support the results of our prior regressions where we get at most education *E*, Gini index *G* and network readiness index *N* as the only statistically significant variables in any regression.

In our third set of regression analysis demonstrated in Appendix 2 we started by regressing all 10 independent variables and kept removing the variable with the highest *p*-value in subsequent regressions. This provided five statistically significant variables at most, i.e., education *E*, control of corruption *CC*, Gini index *G*, economic freedom index *EF* and the network readiness index *N*. Next, we undertook a country wise analysis excluding multicollinearity and addressing issue of endogeneity. We report a statistically significant relation with education *E*, GDP per capita *GDP*, economic freedom *EF* and network readiness *N*. However, the statistical insignificance of our dummy variable suggests that CA may not be country sensitive. Future research may conduct multi-group analysis after removing multicollinearity. Endogeneity issues that surface in studies like ours also may be addressed by researchers.

The statistical insignificance of most variables in our results could be attributed to the newness of the phenomenon and the limited understanding of its impact. Our cost benefit analysis reveals that newly industrialized economies from a wider pool of emerging economies, especially the ones with greater income inequality (Gini index) and possessing prerequisite infrastructure shown by the statistical significance of education and network readiness, will adopt cryptocurrency at a growing pace while economies with robust legal systems may be averse to the idea of wider adoption.

One limitation is the supplementation of missing numbers by using the average numbers of the neighbouring countries as an approximation criterion. That approximation is often viable but must be qualified. For example, assuming that Afghanistan's network readiness index *N* is the average of Kazakhstan, Kyrgyzstan and Tajikistan may be problematic given that Kazakhstan's index N is moderately high at 50.68. However, the estimated number for Afghanistan, 41.77, may not be unreasonable (see Serbian, 2021 on cryptocurrency mining in Afghanistan). Future research may apply other clustering methods as approximation criteria.

One potential limitation is whether the independent variables used in our study are necessarily independent, and whether the dependent variable can be independent. For example, a higher Human Development Index HDI may cause decreasing income inequality which could be a consequence of CA. More generally, causes and effects could be reversed. It is also possible that the independent variables may exist prior to or simultaneously with CA, which may support the notion that they are independent. Future research may address issues around independent/dependent variable linkages and other factors which might affect CA decisions. Future research may also consider analyses such as path analysis to statistically assess the direction of relationships, especially those that are statistically significant.

7. Conclusion

We developed a model to analyze factors in developed and developing economies which may accelerate or hinder the adoption of cryptocurrency and point to blockchain technology deployment as a consequence. The ten factors used in our study are drawn from prior studies addressing issues of technology adoption and their impact on nations at different degrees of development. Our results suggest that cryptocurrency usage can vary across nations given country specific factors tied to the level of economic development. Country based adoption decisions are guided by various factors outside simple technical issues or commercial value impact assessments. While current research has mainly focused on technical aspects of cryptocurrency deployment, a need exists to further research wider level developmental factors which our study results point to.

The study results are of value to both policy makers and researchers. Our results confirm, like other broader studies on Information and Communication Technology, that differentials across developing and developed countries impact CA (cryptocurrency adoption) in relation to macro-national developmental factors. We report a positive relationship with educational level, the Human Development Index, the extent of network readiness, the Gini index magnitude, the level of democracy, the extent of regulatory effectiveness and the Gross Domestic Product. These are clear indicators that leapfrogging is a possibility if national decision makers focus on initiatives and investments that enhance these factors. Further, the results provide a basis for prioritising economic and social programs of focus for governments. We report also that the Corruption Perception Index and the Economic Freedom Index are inversely associated with CA. This further enhances the policy prioritisation perspective offered to policy makers. Policy makers in emerging economies may benefit from the results presented here by assessing those associations in the 137 countries which bear relevance to their nation or region where similarities to developmental indices we have explored are in place. The factors outlined may have a cause effect relationship which are country specific, and which create particularity in terms of cryptocurrency adoption. Such a focus directs decision makers to elements of governance, human development and inequality indicators that may be prioritized. As in developed countries, CA may be a precursor to wider blockchain technology-based platforms becoming operationalised.

Regression Results
Results from Structural Equation Modelling.

Declaration of Competing Interest

The authors declare no competing interests.

Funding

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Data availability

The article contains no associated data. All data generated or analysed during this study is included in this published article.

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Appendix 1

Second set of regressions.
Linear regression

C	Coef.	St.Err.	*t*-value	*p*-value	[95% Conf	Interval]	Sig
D	.004	.007	.59	.555	-.01	.018	
Constant	.099	.043	2.30	.023	.014	.185	**
Mean dependent var	0.123	SD dependent var	0.177				
R-squared	0.003	Number of obs.	137.000				
F-test	0.350	Prob > F	0.555				
Akaike crit. (AIC)	-82.427	Bayesian crit. (BIC)	-76.587				
*** p<.01, ** p<.05, * p<.1							

Linear regression

C	Coef.	St.Err.	*t*-value	*p*-value	[95% Conf	Interval]	Sig
D	-.008	.009	-0.92	.36	-.025	.009	
E	.262	.112	2.34	.021	.041	.484	**
Constant	-.011	.064	-0.18	.858	-.137	.114	
Mean dependent var	0.123	SD dependent var	0.177				
R-squared	0.042	Number of obs.	137.000				
F-test	2.917	Prob > F	0.058				
Akaike crit. (AIC)	-85.911	Bayesian crit. (BIC)	-77.151				
**** p<.01, ** p<.05, * p<.1*							

Linear regression

C	Coef.	St.Err.	*t*-value	*p*-value	[95% Conf	Interval]	Sig
D	-.005	.009	-0.62	.533	-.022	.012	
E	.421	.136	3.10	.002	.153	.69	***
GDP	0	0	-2.02	.045	0	0	**
Constant	-.09	.074	-1.22	.226	-.236	.056	
Mean dependent var	0.123	SD dependent var	0.177				
R-squared	0.070	Number of obs.	137.000				
F-test	3.355	Prob > F	0.021				
Akaike crit. (AIC)	-88.068	Bayesian crit. (BIC)	-76.388				
**** p<.01, ** p<.05, * p<.1*							

Linear regression

C	Coef.	St.Err.	*t*-value	*p*-value	[95% Conf	Interval]	Sig
D	-.005	.009	-0.59	.556	-.022	.012	
E	.478	.312	1.53	.128	-.139	1.095	
GDP	0	0	-1.46	.146	0	0	
HDI	-.088	.433	-0.20	.84	-.944	.769	
Constant	-.068	.13	-0.52	.603	-.326	.19	
Mean dependent var	0.123	SD dependent var	0.177				
R-squared	0.071	Number of obs.	137.000				
F-test	2.509	Prob > F	0.045				
Akaike crit. (AIC)	-86.110	Bayesian crit. (BIC)	-71.510				
**** p<.01, ** p<.05, * p<.1*							

Linear regression

C	Coef.	St.Err.	*t*-value	*p*-value	[95% Conf	Interval]	Sig
D	.002	.01	0.15	.877	-.019	.022	
E	.521	.313	1.66	.098	-.098	1.14	*
GDP	0	0	-0.46	.65	0	0	
HDI	-.11	.432	-0.25	.8	-.964	.745	
CPI	-.002	.002	-1.29	.2	-.006	.001	
Constant	-.048	.131	-0.37	.714	-.307	.211	
Mean dependent var	0.123	SD dependent var	0.177				

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R-squared	0.082	Number of obs.	137.000
F-test	2.348	Prob > F	0.044
Akaike crit. (AIC)	-85.831	Bayesian crit. (BIC)	-68.311
**** p<.01, ** p<.05, * p<.1*			

Linear regression

C	Coef.	St.Err.	*t*-value	*p*-value	[95% Conf	Interval]	Sig
D	.002	.01	0.21	.837	-.018	.023	
E	.528	.315	1.68	.096	-.095	1.15	*
GDP	0	0	-0.47	.638	0	0	
HDI	-.112	.434	-0.26	.796	-.97	.746	
CPI	-.001	.003	-0.36	.719	-.007	.005	
CC	-.001	.002	-0.38	.706	-.005	.003	
Constant	-.063	.137	-0.46	.648	-.334	.208	
Mean dependent var	0.123	SD dependent var	0.177				
R-squared	0.083	Number of obs.	137.000				
F-test	1.968	Prob > F	0.075				
Akaike crit. (AIC)	-83.982	Bayesian crit. (BIC)	-63.543				
**** p<.01, ** p<.05, * p<.1*							

Linear regression

C	Coef.	St.Err.	*t*-value	*p*-value	[95% Conf	Interval]	Sig
D	.002	.011	0.16	.874	-.02	.024	
E	.526	.316	1.66	.099	-.1	1.152	*
GDP	0	0	-0.48	.634	0	0	
HDI	-.117	.438	-0.27	.791	-.984	.751	
CPI	-.001	.003	-0.34	.733	-.008	.005	
CC	-.001	.002	-0.37	.709	-.005	.004	
RQ	0	.002	0.09	.932	-.003	.003	
Constant	-.061	.14	-0.43	.667	-.338	.217	
Mean dependent var	0.123	SD dependent var	0.177				
R-squared	0.083	Number of obs.	137.000				
F-test	1.675	Prob > F	0.121				
Akaike crit. (AIC)	-81.990	Bayesian crit. (BIC)	-58.630				
**** p<.01, ** p<.05, * p<.1*							

Linear regression

C	Coef.	St.Err.	*t*-value	*p*-value	[95% Conf	Interval]	Sig
D	-.004	.011	-0.36	.722	-.027	.018	
E	.533	.313	1.70	.091	-.086	1.151	*
GDP	0	0	-0.16	.877	0	0	
HDI	-.06	.434	-0.14	.89	-.919	.799	
CPI	-.001	.003	-0.20	.844	-.007	.006	
CC	-.001	.002	-0.45	.652	-.005	.003	
RQ	0	.001	0.13	.896	-.003	.003	
G	.004	.002	2.02	.046	0	.008	**
Constant	-.259	.17	-1.52	.13	-.595	.078	
Mean dependent var	0.123	SD dependent var	0.177				
R-squared	0.112	Number of obs.	137.000				
F-test	2.008	Prob > F	0.050				
Akaike crit. (AIC)	-84.270	Bayesian crit. (BIC)	-57.990				
**** p<.01, ** p<.05, * p<.1*							

Linear regression

C	Coef.	St.Err.	*t*-value	*p*-value	[95% Conf	Interval]	Sig
D	-.008	.012	-0.71	.479	-.031	.015	
E	.454	.314	1.44	.151	-.168	1.076	
GDP	0	0	-0.15	.881	0	0	
HDI	-.036	.432	-0.08	.933	-.891	.818	
CPI	.002	.004	0.63	.532	-.005	.01	

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CC	-.003	.002	-1.15	.251	-.008	.002	
RQ	.002	.002	1.12	.265	-.002	.006	
G	.004	.002	2.04	.044	0	.008	**
EF	-.005	.003	-1.64	.104	-.011	.001	
Constant	-.031	.219	-0.14	.887	-.464	.402	
Mean dependent var	0.123	SD dependent var	0.177				
R-squared	0.130	Number of obs.	137.000				
F-test	2.106	Prob > F	0.034				
Akaike crit. (AIC)	-85.131	Bayesian crit. (BIC)	-55.931				

**** p<.01, ** p<.05, * p<.1*

Linear regression

C	Coef.	St.Err.	*t*-value	*p*-value	[95% Conf	Interval]	Sig
D	-.01	.011	-0.86	.39	-.032	.013	
E	.461	.307	1.50	.135	-.145	1.068	
GDP	0	0	-0.87	.389	0	0	
HDI	-.381	.44	-0.87	.387	-1.251	.488	
CPI	0	.004	0.02	.988	-.007	.007	
CC	-.002	.002	-0.75	.453	-.007	.003	
RQ	.001	.002	0.49	.628	-.003	.005	
G	.005	.002	2.59	.011	.001	.009	**
EF	-.004	.003	-1.38	.171	-.01	.002	
N	.007	.003	2.73	.007	.002	.012	***
Constant	-.083	.214	-0.39	.698	-.507	.341	
Mean dependent var	0.123	SD dependent var	0.177				
R-squared	0.179	Number of obs.	137.000				
F-test	2.739	Prob > F	0.004				
Akaike crit. (AIC)	-91.022	Bayesian crit. (BIC)	-58.902				

**** p<.01, ** p<.05, * p<.1*

Appendix 2

Third set of regressions

Linear regression

C	Coef.	St.Err.	*t*-value	*p*-value	[95% Conf	Interval]	Sig
D	-.01	.011	-0.86	.39	-.032	.013	
E	.461	.307	1.50	.135	-.145	1.068	
GDP	0	0	-0.87	.389	0	0	
HDI	-.381	.44	-0.87	.387	-1.251	.488	
CPI	0	.004	0.02	.988	-.007	.007	
CC	-.002	.002	-0.75	.453	-.007	.003	
RQ	.001	.002	0.49	.628	-.003	.005	
G	.005	.002	2.59	.011	.001	.009	**
EF	-.004	.003	-1.38	.171	-.01	.002	
N	.007	.003	2.73	.007	.002	.012	***
Constant	-.083	.214	-0.39	.698	-.507	.341	
Mean dependent var	0.123	SD dependent var	0.177				
R-squared	0.179	Number of obs.	137.000				
F-test	2.739	Prob > F	0.004				
Akaike crit. (AIC)	-91.022	Bayesian crit. (BIC)	-58.902				

**** p<.01, ** p<.05, * p<.1*

Linear regression

C	Coef.	St.Err.	*t*-value	*p*-value	[95% Conf	Interval]	Sig
D	-.01	.011	-0.89	.373	-.031	.012	
E	.462	.304	1.52	.131	-.14	1.063	
GDP	0	0	-0.89	.377	0	0	
HDI	-.382	.437	-0.87	.383	-1.246	.482	
CC	-.002	.001	-1.44	.153	-.004	.001	
RQ	.001	.002	0.53	.594	-.002	.004	
G	.005	.002	2.60	.01	.001	.009	**

(*continued on next page*)

(*continued*)

EF	-.004	.003	-1.58	.116	-.009	.001	
N	.007	.003	2.82	.006	.002	.012	***
Constant	-.084	.211	-0.40	.692	-.501	.333	
Mean dependent var	0.123	SD dependent var	0.177				
R-squared	0.179	Number of obs.	137.000				
F-test	3.068	Prob > F	0.002				
Akaike crit. (AIC)	-93.022	Bayesian crit. (BIC)	-63.822				
**** p<.01, ** p<.05, * p<.1*							

Linear regression

C	Coef.	St.Err.	*t*-value	*p*-value	[95% Conf	Interval]	Sig
D	-.008	.01	-0.77	.445	-.028	.012	
E	.479	.301	1.59	.115	-.118	1.076	
GDP	0	0	-0.93	.353	0	0	
HDI	-.373	.435	-0.86	.392	-1.234	.487	
CC	-.001	.001	-1.36	.175	-.004	.001	
G	.005	.002	2.63	.009	.001	.009	***
EF	-.003	.002	-1.53	.128	-.008	.001	
N	.007	.003	2.94	.004	.002	.012	***
Constant	-.137	.185	-0.74	.461	-.504	.23	
Mean dependent var	0.123	SD dependent var	0.177				
R-squared	0.177	Number of obs.	137.000				
F-test	3.435	Prob > F	0.001				
Akaike crit. (AIC)	-94.713	Bayesian crit. (BIC)	-68.434				
**** p<.01, ** p<.05, * p<.1*							

Linear regression

C	Coef.	St.Err.	*t*-value	*p*-value	[95% Conf	Interval]	Sig
E	.48	.301	1.60	.113	-.115	1.076	
GDP	0	0	-0.78	.436	0	0	
HDI	-.399	.433	-0.92	.359	-1.256	.458	
CC	-.002	.001	-1.84	.068	-.004	0	*
G	.005	.002	2.52	.013	.001	.009	**
EF	-.004	.002	-1.61	.111	-.008	.001	
N	.007	.002	2.86	.005	.002	.012	***
Constant	-.112	.182	-0.61	.541	-.472	.248	
Mean dependent var	0.123	SD dependent var	0.177				
R-squared	0.173	Number of obs.	137.000				
F-test	3.854	Prob > F	0.001				
Akaike crit. (AIC)	-96.088	Bayesian crit. (BIC)	-72.728				
**** p<.01, ** p<.05, * p<.1*							

Linear regression

C	Coef.	St.Err.	*t*-value	*p*-value	[95% Conf	Interval]	Sig
E	.56	.283	1.98	.05	0	1.119	*
HDI	-.519	.404	-1.29	.201	-1.319	.28	
CC	-.002	.001	-2.08	.039	-.004	0	**
G	.005	.002	2.72	.007	.001	.009	***
EF	-.004	.002	-1.73	.086	-.008	.001	*
N	.006	.002	2.75	.007	.002	.011	***
Constant	-.061	.17	-0.36	.72	-.397	.275	
Mean dependent var	0.123	SD dependent var	0.177				
R-squared	0.169	Number of obs.	137.000				
F-test	4.408	Prob > F	0.000				
Akaike crit. (AIC)	-97.442	Bayesian crit. (BIC)	-77.002				
**** p<.01, ** p<.05, * p<.1*							

Linear regression

C	Coef.	St.Err.	*t*-value	*p*-value	[95% Conf	Interval]	Sig
E	.257	.158	1.63	.105	-.055	.57	
CC	-.002	.001	-2.06	.041	-.004	0	**
G	.005	.002	2.78	.006	.002	.009	***
EF	-.004	.002	-1.90	.06	-.008	0	*
N	.005	.002	2.43	.017	.001	.009	**
Constant	-.157	.153	-1.03	.307	-.459	.146	
Mean dependent var	0.123	SD dependent var	0.177				
R-squared	0.158	Number of obs.	137.000				
F-test	4.934	Prob > F	0.000				
Akaike crit. (AIC)	-97.711	Bayesian crit. (BIC)	-80.191				
**** p<.01, ** p<.05, * p<.1*							

Linear regression

C	Coef.	St.Err.	*t*-value	*p*-value	[95% Conf	Interval]	Sig
E	.277	.159	1.74	.084	-.037	.592	*
CC	-.003	.001	-2.94	.004	-.004	-.001	***
G	.005	.002	2.78	.006	.002	.009	***
N	.004	.002	2.00	.048	0	.008	**
Constant	-.347	.117	-2.98	.003	-.578	-.117	***
Mean dependent var	0.123	SD dependent var	0.177				
R-squared	0.135	Number of obs.	137.000				
F-test	5.164	Prob > F	0.001				
Akaike crit. (AIC)	-95.990	Bayesian crit. (BIC)	-81.390				
**** p<.01, ** p<.05, * p<.1*							

Linear regression

C	Coef.	St.Err.	*t*-value	*p*-value	[95% Conf	Interval]	Sig
CC	-.002	.001	-2.79	.006	-.004	-.001	***
G	.006	.002	2.82	.006	.002	.009	***
N	.006	.002	3.88	0	.003	.01	***
Constant	-.276	.11	-2.51	.013	-.494	-.059	**
Mean dependent var	0.123	SD dependent var	0.177				
R-squared	0.115	Number of obs.	137.000				
F-test	5.784	Prob > F	0.001				
Akaike crit. (AIC)	-94.873	Bayesian crit. (BIC)	-83.193				
**** p<.01, ** p<.05, * p<.1*							

Linear regression

C	Coef.	St.Err.	*t*-value	*p*-value	[95% Conf	Interval]	Sig
CC	-.002	.001	-2.48	.014	-.004	0	**
N	.005	.002	2.99	.003	.002	.008	***
Constant	.001	.051	0.01	.992	-.1	.101	
Mean dependent var	0.123	SD dependent var	0.177				
R-squared	0.063	Number of obs.	137.000				
F-test	4.479	Prob > F	0.013				
Akaike crit. (AIC)	-88.937	Bayesian crit. (BIC)	-80.177				
**** p<.01, ** p<.05, * p<.1*							

Linear regression

C	Coef.	St.Err.	*t*-value	*p*-value	[95% Conf	Interval]	Sig
N	.001	.001	1.64	.103	0	.003	
Constant	.049	.048	1.02	.311	-.046	.143	
Mean dependent var	0.123	SD dependent var	0.177				

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R-squared	0.020	Number of obs.	137.000
F-test	2.691	Prob > F	0.103
Akaike crit. (AIC)	-84.777	Bayesian crit. (BIC)	-78.937

*** $p<.01$, ** $p<.05$, * $p<.1$

References

Acemoglu, D., 2009. Introduction to modern economic growth. Introduction to Modern Economic Growth. Princeton University Press. https://doi.org/10.1111/j.1475-4932.2011.00816.x.

Adrián Risso, W., Sánchez Carrera, E.J, 2019. On the impact of innovation and inequality in economic growth. Economics of Innovation and New Technology 28 (1), 64–81. https://doi.org/10.1080/10438599.2018.1429534.

Akins, B.W., Chapman, J.L., Gordon, J.M., 2014. A Whole New World: Income Tax Considerations of the Bitcoin Economy. Pittsburgh Tax Review 12 (1), 24–56. https://doi.org/10.5195/taxreview.2014.32.

Allen, S., Capkun, S., Eyal, I., Fanti Giulia, Ford, B., Grimmelmann, J., Kostiainen, K. (2020). *Design choices for central bank digital currency: Policy and technical considerations* (No. NBER Working Paper 27634). Retrieved from https://www.brookings.edu/research/design-choices-for-central-bank-digital-currency-policy-and-technical-considerations/.

Angelis, J., Ribeiro da Silva, E, 2019. Blockchain adoption: A value driver perspective. Business Horizons 62 (3), 307–314. https://doi.org/10.1016/j.bushor.2018.12.001.

Arsene, C. (2019). The Global "Blockchain in Healthcare" Report: the 2019 ultimate guide for every executive - Healthcare Weekly. Retrieved November 24, 2019, from https://healthcareweekly.com/blockchain-in-healthcare-guide/.

Asongu, S.A., Le Roux, S., 2017. Enhancing ICT for inclusive human development in Sub-Saharan Africa. Technological Forecasting and Social Change 118, 44–54. https://doi.org/10.1016/j.techfore.2017.01.026.

Aysan, A.F., Sadriu, B., Topuz, H., 2020. Blockchain Futures in Cryptocurrencies, Trade and Finance: A Preliminary Assessment. Buletin Ekonomi Moneter Dan Perbankan 23 (4), 525–542. https://doi.org/10.21098/BEMP.V23I4.1240.

Aysan, A.F., Demir, E., Gozgor, G., Lau, C.K.M., 2019. Effects of the geopolitical risks on Bitcoin returns and volatility. In: Research in International Business and Finance, 47, pp. 511–518. https://doi.org/10.1016/J.RIBAF.2018.09.011.

Banerjee, A., Duflo, E., Imbert, C., Mathew, S., Pande, R., 2020. E-governance, Accountability, and Leakage in Public Programs: Experimental Evidence from a Financial Management Reform in India. American Economic Journal: Applied Economics 12 (4), 39–72. https://doi.org/10.1257/app.20180302

Bank, W. (2018). Gini index (World Bank estimate) | Data. Retrieved June 9, 2021, from https://data.worldbank.org/indicator/SI.POV.GINI.

Bank, W. (2019a). GDP per capita (current US$) | Data. Retrieved June 9, 2021, from https://data.worldbank.org/indicator/NY.GDP.PCAP.CD.

Bank, W. (2019b). Worldwide Governance Indicators | DataBank. Retrieved June 9, 2021, from https://databank.worldbank.org/source/worldwide-governance-indicators.

Barone, R., Masciandaro, D., 2019. Cryptocurrency or usury? Crime and alternative money laundering techniques. European Journal of Law and Economics 47 (2), 233–254. https://doi.org/10.1007/s10657-019-09609-6.

Behnke, K., Janssen, M.F.W.H.A., 2020. Boundary conditions for traceability in food supply chains using blockchain technology. International Journal of Information Management 52. https://doi.org/10.1016/j.ijinfomgt.2019.05.025.

Bhimani, A., Hausken, K., Arif, S., 2021. Blockchain Technology Adoption Decisions: Developed vs. Developing Economies. Information for Efficient Decision Making, pp. 91–113. https://doi.org/10.1142/9789811220470_0003. World scientific.

Bodkhe, U., Tanwar, S., Parekh, K., Khanpara, P., Tyagi, S., Kumar, N., Alazab, M., 2020. Blockchain for Industry 4.0: A comprehensive review, 8. IEEE Access, pp. 79764–79800. https://doi.org/10.1109/ACCESS.2020.2988579.

Boret, N., Gawande, K., & Kobb, D. P. (2021). Can decentralization lower poverty? Cambodia's Commune and Sangkat Fund. *World Development, 146*, 105548. https://doi.org/10.1016/J.WORLDDEV.2021.105548.

Carter, T. (2020). How Blockchain can Address Wealth Inequality - Thomas Carter..

Chan, C.M., Isobe, T., Makino, S., 2008. Which country matters? Institutional development and foreign affiliate performance. Strategic Management Journal 29 (11), 1179–1205. https://doi.org/10.1002/smj.705.

Chang, V., Baudier, P., Zhang, H., Xu, Q., Zhang, J., Arami, M., 2020. How Blockchain can impact financial services – The overview, challenges and recommendations from expert interviewees. Technological Forecasting and Social Change 158. https://doi.org/10.1016/j.techfore.2020.120166.

Chinalysis. (2020.). Chainalysis Blog | The 2020 Global Crypto Adoption Index: Cryptocurrency is a Global Phenomenon. Retrieved June 26, 2021, from https://blog.chainalysis.com/reports/2020-global-cryptocurrency-adoption-index-2020.

Clauson, K. A., Breeden, E. A., Davidson, C., & Mackey, T. K. (2018). Leveraging Blockchain Technology to Enhance Supply Chain Management in Healthcare: *Blockchain in Healthcare Today*, 1(0). https://doi.org/10.30953/bhty.v1.20.

Comin, D., & Hobijn, B. (2003). *Cross-Country Technology Adoption: Making the Theories Face the Facts Cross-Country Technology Adoption: Making the Theories Face the Facts.*.

Comin, D., Mestieri, M., 2018. If technology has arrived everywhere, why has income diverged? American Economic Journal: Macroeconomics 10 (3), 137–178. https://doi.org/10.1257/mac.20150175.

Crittenden, V.L., Crittenden, W.F., Ajjan, H., 2019. Empowering women micro-entrepreneurs in emerging economies: The role of information communications technology. Journal of Business Research 98, 191–203. https://doi.org/10.1016/j.jbusres.2019.01.045.

Datta, P., 2011. A preliminary study of ecommerce adoption in developing countries. Information Systems Journal 21 (1), 3–32. https://doi.org/10.1111/J.1365-2575.2009.00344.X.

Davies, A., 2019. How Much Does It Cost to Build a Blockchain Project? DevTeam.Space. Retrieved from. https://www.devteam.space/blog/how-much-does-it-cost-to-build-a-blockchain-project/.

De Gregorio, J., 2018. Productivity in Emerging-Market Economies: Slowdown or Stagnation? SSRN Electronic Journal. https://doi.org/10.2139/ssrn.3268918.

Deloitte, 2020. 51 Critical Blockchain Statistics: 2021 Data Analysis & Market Share - Financesonline. com. Retrieved June 26, 2021, from. https://financesonline.com/blockchain-statistics/.

Dewey, J. (2019). Blockchain & Cryptocurrency Regulation. *Global Legal Group Ltd.* Retrieved from https://www.acc.com/sites/default/files/resources/vl/membersonly/Article/1489775_1.pdf.

Dixit, R.K., Pindyck, R.S., 1994. Investment under Uncertainty. Princeton University Press. Retrieved from. https://press.princeton.edu/books/hardcover/9780691034102/investment-under-uncertainty.

Domjan, P., Serkin, G., Thomas, B., Toshack, J., 2021. Introducing Blockchain: Tomorrow's Railroads. Chain Reaction 1–8. https://doi.org/10.1007/978-3-030-51784-7_1.

Finextra. (2021, May). Crypto regulation : whether you fear it or embrace it, crypto is bound to stay. Retrieved July 4, 2021, from https://www.finextra.com/blogposting/20394/crypto-regulation–whether-you-fear-it-or-embrace-it-crypto-is-bound-to-stay.

Finkelstein Shapiro, A., Mandelman, F.S, 2021. Digital adoption, automation, and labor markets in developing countries. Journal of Development Economics 151. https://doi.org/10.1016/J.JDEVECO.2021.102656.

Fong, M.W., 2009. Technology Leapfrogging for Developing Countries. IGI Global. https://doi.org/10.4018/978-1-60566-026-4.CH591 https://services.igi-global.com/resolvedoi/resolve.aspx?doi=10.4018/978-1-60566-026-4.ch591.

Heritage Foundation, (2019). Index of Economic Freedom: Promoting Economic Opportunity and Prosperity by Country. Retrieved June 9, 2021.

Frankenfield, J. (2021). Lightning Network Definition. Retrieved January 2, 2022, from https://www.investopedia.com/terms/l/lightning-network.asp.

Galang, R.M.N., 2012. Government efficiency and international technology adoption: The spread of electronic ticketing among airlines. Journal of International Business Studies 43 (7), 631–654. https://doi.org/10.1057/jibs.2012.20.

Galen, D., Boucherle, L., Davis, R., Do, N., El-Baz, B., Wharton, K., & Lee, J. (2018.). Blockchain for Social Impact - Moving Beyond the Hype *in collaboration with RippleWorks.*.

Gao, Y., Zang, L., Roth, A., Wang, P., 2017. Does democracy cause innovation? An empirical test of the popper hypothesis. Research Policy 46 (7), 1272–1283. https://doi.org/10.1016/j.respol.2017.05.014.

Global Times, 2021. China to shut down over 90% of its Bitcoin mining capacity after local bans. Global Times. Retrieved July 4, 2021, from. https://www.globaltimes.cn/page/202106/1226598.shtml.

Gulker, M. (2017.). Blockchain: Innovating Our Way to Economic Freedom?, AIER. Retrieved from https://www.aier.org/research/blockchain-innovating-our-way-to-economic-freedom-2/.

Gonzalez, O. (2021). Here's how much electricity it takes to mine Bitcoin and why people are worried - CNET. Retrieved January 9, 2022, from https://www.cnet.com/personal-finance/crypto/heres-how-much-electricity-it-takes-to-mine-bitcoin-and-why-people-are-worried/.

Halachmi, A., Greiling, D., 2013. Transparency, E-government, and accountability: Some issues and considerations. Public Performance and Management Review 36 (4), 562–584. https://doi.org/10.2753/PMR1530-9576360404.

Hughes, A., Park, A., Kietzmann, J., Archer-Brown, C., 2018. Beyond Bitcoin: What blockchain and distributed ledger technologies mean for firms. Business Horizons 62 (3), 273–281. https://doi.org/10.1016/j.bushor.2019.01.002.

Hughes, L., Dwivedi, Y.K., Misra, S.K., Rana, N.P., Raghavan, V., Akella, V., 2019. Blockchain research, practice and policy: Applications, benefits, limitations, emerging research themes and research agenda. International Journal of Information Management 49, 114–129. https://doi.org/10.1016/j.ijinfomgt.2019.02.005.

Hussain, N. Z., & Balu, N. (2021). Tesla will "most likely" restart accepting bitcoin as payments, says Musk. Retrieved January 1, 2022, from https://www.reuters.com/business/autos-transportation/tesla-will-most-likely-restart-accepting-bitcoin-payments-says-musk-2021-07-21/.

Iansiti, M., & Lakhani, K. R. (2017). The Truth About Blockchain. Retrieved from https://enterprisersproject.com/sites/default/files/the_truth_about_blockchain.pdf.

IFC. (2017). Blockchain in Financial Services in Emerging Markets Part I: Current Trends. Retrieved March 21, 2022, from https://www.ifc.org/wps/wcm/connect/a3559b7c-19b7-4f8d-94be-30d1cf7e172b/EMCompass+Note+43+FINAL+8-21.pdf?MOD=AJPERES&CVID=lU51Cxz.

Keller, W., 2004. International Technology Diffusion. Journal of Economic Literature 42 (3), 752–782. https://doi.org/10.1257/0022051042177685.

Kiff, J., Alwazir, J., Davidovic, S., Farias, A., Khan, A., Khiaonarong, T., & Zhou, P. (2020). A Survey of Research on Retail Central Bank Digital Currency. Retrieved January 1, 2022, from https://www.imf.org/en/Publications/WP/Issues/2020/06/26/A-Survey-of-Research-on-Retail-Central-Bank-Digital-Currency-49517.

Kirkman, G.S., Osorio, C.A., Sachs, J.D., 2002. The Networked Readiness Index: Measuring the Preparedness of Nations for the Networked World. Global Information Technology Report. Retrieved from. https://www.researchgate.net/publication/241169294_The_Networked_Readiness_Index_Measuring_the_Preparedness_of_Nations_for_the_Networked_World.

Kouhizadeh, M., Saberi, S., Sarkis, J., 2021. Blockchain technology and the sustainable supply chain: Theoretically exploring adoption barriers. International Journal of Production Economics 231, 107831. https://doi.org/10.1016/j.ijpe.2020.107831.

Kshetri, N. (2017). Potential roles of blockchain in fighting poverty and reducing financial exclusion in the global south. https://doi.org/10.1080/1097198X.2017.1391370, 20(4), 201–204. https://doi.org/10.1080/1097198X.2017.1391370.

Kuperberg, M., 2019. Blockchain-Based Identity Management: A Survey From the Enterprise and Ecosystem Perspective. IEEE Transactions on Engineering Management. https://doi.org/10.1109/TEM.2019.2926471.

Laroiya, C., Saxena, D., Komalavalli, C., 2020. Applications of Blockchain Technology. Handbook of Research on Blockchain Technology. Elsevier, pp. 213–243. https://doi.org/10.1016/b978-0-12-819816-2.00009-5.

Li, H., Huang, D., Ma, Q., Qi, W., Li, H., 2019. Factors Influencing the Technology Adoption Behaviours of Litchi Farmers in China. Sustainability 2020 Vol. 12. https://doi.org/10.3390/SU12010271. Page 271*12*(1), 271.

Luo, Y., 2005. An Organizational Perspective of Corruption. Management and Organization Review 1 (01), 119–154. https://doi.org/10.1111/j.1740-8784.2004.00006.x.

Malisuwan, S., Kaewphanuekrungsi, W., Tiamnara, N., Suriyakrai, N., 2016. Thailand's Position in the Network Readiness Index (NRI): Analysis and Recommendations. Journal of Economics, Business and Management 4. Retrieved from. http://www.joebm.com/vol4/426-B040.pdf.

Mansfield, E., Mansfield, E., 1993. The Economics of technical change. Edward Elgar Publishing. Retrieved from. https://www.e-elgar.com/shop/gbp/the-economics-of-technical-change-9781852787837.html.

Marian, O. (2013). Are Cryptocurrencies Super Tax Havens. *Michigan Law Review First Impressions*, 112. Retrieved from https://heinonline.org/HOL/Page?handle=hein.journals/mlro112&id=38&div=&collection=.

McGhin, T., Choo, K.K.R., Liu, C.Z., He, D., 2019. Blockchain in healthcare applications: Research challenges and opportunities. Journal of Network and Computer Applications. https://doi.org/10.1016/j.jnca.2019.02.027. Academic Press.

Milner, H.V., 2006. The Digital Divide The Role of Political Institutions in Technology Diffusion. Comparative Political Studies 39 (2), 176–199. https://doi.org/10.1177/0010414005282983.

Molloy, B. (2019). Taxing the Blockchain: How Cryptocurrencies Thwart International Tax Policy. Retrieved from https://www..

Murphy, K.M., Shleifer, A., Vishny, R.W., 1991. The Allocation of Talent: Implications for Growth. The Quarterly Journal of Economics 106 (2), 503. https://doi.org/10.2307/2937945.

Nakamoto, S. (2008). Bitcoin: A Peer-to-Peer Electronic Cash System. Retrieved from www.bitcoin.org.

Nations, U. (2020). World Economic Situation and Prospects 2020..

Nayyar, S., 2018. Blockchain technology for human development: Not so fast? | Human Development Reports.

Niebel, Thomas, 2018. ICT and economic growth – Comparing developing, emerging and developed countries. World Development 104, 197–211. https://doi.org/10.1016/J.WORLDDEV.2017.11.024. C.

Ozden, O. (2021, April). What China's Blockchain Network Means for the World - CoinDesk. Retrieved July 18, 2021, from https://www.coindesk.com/what-chinas-blockchain-services-network-means-for-the-world.

Pisa, M., & Juden, M. (2017). *Blockchain and Economic Development: Hype vs. Reality*..

Institute, Portulans, 2019. Network Readiness Index. Retrieved June 9, 2021, from. https://networkreadinessindex.org/.

PwC. (2020, October 13). Blockchain technologies could boost the global economy US $1.76 trillion by 2030. Retrieved July 4, 2021, from https://www.pwc.com/gx/en/news-room/press-releases/2020/blockchain-boost-global-economy-track-trace-trust.html.

Raimundo, R., Rosário, A., 2021. Blockchain System in the Higher Education. European Journal of Investigation in Health, Psychology and Education 2021 11 (1), 276–293. https://doi.org/10.3390/EJIHPE11010021. Vol. 11276–293.

Report, H. D. (2019). Human Development Reports. Retrieved June 9, 2021, from http://hdr.undp.org/en/indicators/103706.

Resnick, D. (2020). Taxing Informality: Compliance and Policy Preferences in Urban Zambia. https://doi.org/10.1080/00220388.2020.1841171, 57(7), 1063–1085.

Riddell, W.C., Song, X., 2017. The Role of Education in Technology Use and Adoption: Evidence from the Canadian Workplace and Employee Survey. ILR Review 70 (5), 1219–1253. https://doi.org/10.1177/0019793916687719.

Rogers, E.M., 1983. Diffusion of Innovations, 3rd ed. The Free Press, New York, NY, USA. Retrieved from. https://www.scirp.org/(S(lz5mqp453edsnp55rrgjct55))/reference/ReferencesPapers.aspx?ReferenceID=1786060.

Saiedi, E., Broström, A., Ruiz, F., 2021. Global drivers of cryptocurrency infrastructure adoption. Small Business Economics 57 (1), 353–406. https://doi.org/10.1007/S11187-019-00309-8, 2020 57:1.

Sanka, A.I., Cheung, R.C., 2019. Blockchain: Panacea for Corrupt Practices in Developing Countries. In: *2019 2nd International Conference of the* IEEE Nigeria Computer Chapter, NigeriaComputConf 2019. Institute of Electrical and Electronics Engineers Inc. https://doi.org/10.1109/NigeriaComputConf45974.2019.8949626.

Schlecht, L., Schneider, S., Buchwald, A., 2021. The prospective value creation potential of Blockchain in business models: A delphi study. Technological Forecasting and Social Change 166, 120601. https://doi.org/10.1016/j.techfore.2021.120601.

Schuetz, S., Venkatesh, V., 2020. Blockchain, adoption, and financial inclusion in India: Research opportunities. International Journal of Information Management 52, 101936. https://doi.org/10.1016/j.ijinfomgt.2019.04.009.

Sen, A., 2001. *Employment, Technology, and Development*. Some Policy Issues. Oxford University Press, New Delhi and Oxford.

Serbian, G. (2021). After Taliban seizes power, cryptocurrency miners flee Afghanistan. Retrieved January 1, 2022, from https://olhardigital.com.br/2021/08/30/pro/taleba-mineradores-criptomoedas-afeganistao/.

Sinha, A., Sengupta, T., Saha, T., 2020. Technology policy and environmental quality at crossroads: Designing SDG policies for select Asia Pacific countries. Technological Forecasting and Social Change 161, 120317. https://doi.org/10.1016/J.TECHFORE.2020.120317.

Smith, M. D., & Floro, M. S. (2020). The Effects of Domestic and International Remittances on Food Insecurity in Low- and Middle-Income Countries. Https://Doi.Org/10.1080/00220388.2020.1849619, 57(7), 1198–1220. .

Steinmueller, W.E., 2001. ICTs and the possibilities for leapfrogging by developing countries. International Labour Review 140 (2).

Stockburger, L., Kokosioulis, G., Mukkamala, A., Mukkamala, R.R., Avital, M., 2021. Blockchain-Enabled Decentralized Identify Management: The Case of Self-Sovereign Identity in Public Transportation. Blockchain: Research and Applications 100014. https://doi.org/10.1016/j.bcra.2021.100014.

Suciu, C.M., Nasulea, C., Nasulea, D.F., 2019. Towards developing a friendlier regulatory framework for blockchain-based businesses. Theoretical and Applied Economics. Special Issue 15–24. *XXVI*Retrieved from. https://www.researchgate.net/publication/335755763_Towards_developing_a_friendlier_regulatory_framework_for_blockchain-based_businesses.

Tchamyou, V.S., Erreygers, G., Cassimon, D., 2018. Inequality, ICT and financial access in Africa. Technological Forecasting and Social Change 139, 169–184. https://doi.org/10.1016/j.techfore.2018.11.004.

Tchamyou, V.S., Erreygers, G., Cassimon, D., 2019. Inequality, ICT and financial access in Africa. Technological Forecasting and Social Change 139, 169–184. https://doi.org/10.1016/J.TECHFORE.2018.11.004.

Tellman, B., Eakin, H., Janssen, M.A., de Alba, F., Turner, B.L., 2021. The role of institutional entrepreneurs and informal land transactions in Mexico City's urban expansion. World Development 140, 105374. https://doi.org/10.1016/J.WORLDDEV.2020.105374.

Tornatzky, L.G., Fleischer, M., Chakrabarti, A.K., 1990. The processes of technological innovation. Lexington Books, Lexington Mass. Retrieved from. https://www.worldcat.org/title/processes-of-technological-innovation/oclc/20669819.

Transparency International. (2019). 2019 - CPI - Transparency.org. Retrieved June 9, 2021, from https://www.transparency.org/en/cpi/2019/index/nzl.

Uddin, M.A., Stranieri, A., Gondal, I., Balasubramanian, V., 2021. A Survey on the Adoption of Blockchain in IoT: Challenges and Solutions. Blockchain: Research and Applications 100006. https://doi.org/10.1016/j.bcra.2021.100006.

UNCTAD, (2021) Harnessing blockchain for sustainable development:prospects and challenges. Paper presented at the United Nations Commission on Science and Technology for Development Inter-sessional Panel 2020-202118-22 January 2021 Geneva, Switzerland.

Unit, E. I. (2019). EIU Democracy Index 2019 - World Democracy Report. Retrieved from http://www.eiu.com/topic/democracy-index/.

Venkatesh, V., Morris, M.G., Davis, G.B., Davis, F.D., 2003. User acceptance of information technology: Toward a unified view. MIS Quarterly: Management Information Systems 27 (3), 425–478. https://doi.org/10.2307/30036540.

Wang, L., Luo, G.li, Sari, A., Shao, X.F., 2020. What nurtures fourth industrial revolution? An investigation of economic and social determinants of technological innovation in

advanced economies. Technological Forecasting and Social Change 161, 120305. https://doi.org/10.1016/J.TECHFORE.2020.120305.
Wright, A., De Filippi, P., 2015. Decentralized Blockchain Technology and the Rise of Lex Cryptographia. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.2580664.
Zbinden, F., Kondova, G., 2019. Economic Development in Mexico and the Role of Blockchain by Fabian Zbinden, Galia Kondova. SSRN. *Advances in Economics and Business* 7 (1), 55–64. Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3515206.

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