INSTITUTO
UNIVERSITÁRIO
DE LISBOA

Will Cryptocurrencies help alleviate recessions?

Nuno Miguel da Costa Justo Baptista

Master in Economics

Supervisor:
PhD Alexandra Ferreira Lopes, Assistant Professor,
ISCTE Business School

Co-Supervisor:
PhD Luís Filipe Martins Assistant, Professor with Habilitation,
ISCTE Business School

November, 2020

Department of Economics / Department of Political Economy

Will Cryptocurrencies help alleviate recessions?

Nuno Miguel da Costa Justo Baptista

Master in Economics

Supervisor:
PhD Alexandra Ferreira Lopes, Assistant Professor,
ISCTE Business School

Co-Supervisor:
PhD Luís Filipe Martins Assistant, Professor with Habilitation,
ISCTE Business School

November, 2020

Acknowledgements

While writing this dissertation I faced many adversities trying to study a new field of relation between cryptocurrencies and economic crisis. However, I have received enormous support from my thesis supervisor and co-supervisor. That being said I must thank my supervisor Prof. Alexandra Ferreira-Lopes and my co-supervisor Prof. Luís Filipe Martins of the ISCTE Business School from Department of Economics for the endless support and willingness to help and contribute to this dissertation. I am grateful that I got to work and get to know better my supervisors, their expertise's on the matter was undoubtedly a huge help during the writing of this thesis. I would also like to thank ISCTE Business School for being such a friendly and providing community during this process.

Furthermore, I would like to thank my friends and family for their continuous support during this writing.

The year of 2020 was faced with challenges and I'm glad all the people mentioned above were close to me helping me on this goal.

Resumo

O objetivo desta tese é procurar encontrar e explicar os efeitos das criptomoedas no ciclo económico e compreender se este novo método de transação de bens e outros valores pode ou não aliviar o ciclo de futuras recessões económicas, facilitando a recuperação da economia para o seu estado de equilíbrio e possibilitando a sua expansão de novo.

Para tal, foram usadas variáveis de rendimento/retorno em algumas criptomoedas e outras variáveis referentes à normal atividade das mesmas, como rácios entre volume de transações e total quantidade no mercado.

Adicionalmente, e para melhorar o modelo, adicionámos variáveis que representam alternativas de investimento às criptomoedas, desde moedas oficiais como o Euro da Zona Euro, o Dólar dos Estados Unidos da América, a Libra do Reino Unido, o Iene Japonês e o Yuan Chinês, e outras variáveis relativas ao mercado como os retornos do S&P500, do Ouro e da Prata, as taxas de juro de referência de bancos centrais de vários países e o valor do mercado bolsista de cada país.

Utilizando modelos Logit para dados em painel, com particular ênfase em modelos Logit de Efeitos Fixos, podemos analisar como se alteram as variáveis ao longo do tempo e por país e como afetam o nosso modelo geral, sendo que o modelo é composto por uma variável dependente binária (dummy) que nos permite analisar as duas situações de interesse: expansão versus recessão.

Construímos esta tese à volta de cinco criptomoedas, Bitcoin, Litecoin, Eosio, Ripple e Ethereum, com dados de 38 países, todos de 2007 a 2019. Concluímos que algumas criptomoedas podem ter um impacto nas futuras recessões económicas, como o Ripple que fornece transações baratas e rápidas, o Ethereum que pode fornecer quantidades infinitas das suas moedas para ajudar a impulsionar uma expansão e a Bitcoin que pode ser usada como um porto seguro para proteger e diversificar o risco na carteira de investidores.

Palavras-Chave: Bitcoin, Ethereum, Eosio, Litecoin, Ripple, criptomoedas, mercado financeiro, recessões e expansões económicas, dados em painel, modelo Logit.

JEL Codes: C23, E32.

Abstract

The objective of this dissertation is to assess and explain the effects of cryptocurrencies on the business cycle and to understand whether this new method of transaction of goods and other values, may or may not ease the cycle of future economic recessions, facilitating the recovery of the economy to its equilibrium state and re-enabling its expansion.

To achieve this goal we used the returns for some selected cryptocurrencies and other variables referring to their normal activity as ratios between volume of transactions and total amount in the market.

In addition and to improve the model, we added variables that represent alternatives to cryptocurrencies, from an investing point of view. Official currencies such as the Eurozone Euro, the United States Dollar, the United Kingdom Pound, the Japanese Yen, and the Chinese Yuan, and others market-related variables such as the returns of the S&P500, Gold and Silver, the reference interest rates of central banks of various countries and the stock market value of each country.

Using Logit models for panel data, with a particular emphasis on Fixed Effects Logit models, we can analyze how the variables vary over time for each country and how they affect our general model, which is composed of a binary dependent variable (dummy) that allows us to analyze both situations of interest: expansion versus recession.

We built this work around five cryptocurrencies, Bitcoin, Litecoin, Eosio, Ripple and Ethereum, with data from 38 countries, all from 2007 to 2019. We concluded that some cryptocurrencies can have an impact on future economic recessions, such as Ripple, which provides cheap and fast transactions, Ethereum, which can provide an infinite supply of its coins to help drive an expansion and Bitcoin, which can be used as a safe haven to protect and diverse risk on investors portfolio.

Keywords: Bitcoin, Ethereum, Eosio, Litecoin, Ripple, crypto-currencies, financial market, economic recessions and expansions, panel data, Logit model.

JEL Codes: C23, E32.

Table of Contents

List of Tables

1. Introduction

This thesis aims to study and verify the impact of various macroeconomic and finance variables on the business cycle and in particular to determine whether cryptocurrencies can or not explain the development of an economic recovery or recession. We will be using the following cryptocurrencies as our crypto variables - Bitcoin (BTC), Litecoin (LTC), Ethereum (ETH), Ripple (XRP), and EOSIO (EOS). We choose these variables based on their importance in the market. For instance, Bitcoin is generally seen as a measure of holding value and trading for goods in some markets, whereas Ripple is used with a different view and purpose such as a currency exchange system. However, all the cryptocurrencies aim to the same goal, which is to ease and help in the transfer of goods, hence the usage of them all.

In addition, our database includes 38 countries, which we will mention later on, with data from 2007 to 2019.

We believe this study offers and interesting and refreshing contribution to the role of cryptocurrencys in the business cycle.

We use panel data-type models (Fixed Effects), to estimate one model where we aimed to study the effects of our variables on the main variable, our dependent variable, the GDP Business Cycle (GDPCYCLE). This is a dummy variable that takes the value of one whenever there is an expansion. Therefore, our model of interest is a Logit panel data fixed effects model.

We concluded that some cryptocurrencies can have an impact on future economic recessions, such as Ripple, which provides cheap and fast transactions, Ethereum, which can provide an infinite supply of its coins to help drive an expansion and Bitcoin, which can be used as a safe haven to protect and diverse risk on investors portfolio.

This dissertation has the following structure. In section 2 we will be reviewing the previous literature that is relevant to this work. Section 3 will provide an explanation of our Empirical Methodology by describing the variables of our model. Then on section 4 we describe the Methodology. Section 5 includes the results and our analysis of them. Section 6 is the conclusion.

2. Literature Review

2.1. Cryptocurrencies as Currencies or Assets?

According to Weber (2014), Bitcoin faces a legitimacy issue that currencies do not, since a government backs them. Bitcoin aims to gain trust by having its community trusting an intangible technological system, however the system is not 100% safe nor fully understood. The anonymity aspect of this coin also raises questions and other risks. Weber ends by concluding that Bitcoin relies more on fiat currency than the already working systems. Bitcoin is regarded as a decentralized currency, however Gervais *et al.* (2014) conclude that this is not the case, since the cryptocurrency is hosted by many centralized services and its developers maintain control in case of emergencies on the platform. Yermack (2015) studies the obstacles Bitcoin faced to become a real currency, reaching the conclusion that as of now, the biggest obstacle it faced was its own volatility that pushes away consumers and works more like a speculative investment. Also, for Bitcoin to ever become a real currency it would have to be recognized internationally like so. Cryptocurrencies are generally unregulated and lack policies regarding their use. Nabilou *et al.* (2020) indicate that cryptocurrencies are not the first non-governmental money to ever be created, and like before, policies and more government control is expected to happen.

Poon *et al.* (2016) studied the amount of process and storage space needed for all world transaction to go through a Blockchain system and opposed it to the traditional system. The results were incredible, suggesting that Blockchain technology would use 24GB every 10 minutes while traditional systems would need 133MB. He concluded that the amount of processing required could lead to a centralization of processes within the Bitcoin's blockchain technology. Umeh (2018) brought to attention the use of blockchain technology and other security and communication innovations. Just like any enabling technology the blockchain will impact future technology that will emerge.

A suggested use of cryptocurrencies is its use as a way of diversifying portfolios. Dyhrberg (2016) analyzes Bitcoin's capabilities of being the digital gold, by comparing it to the classic financial assets, markets and gold, concluding that bitcoin can in fact be used to minimize risk against the FTSE Index. Corbet *et al.* (2018) conducted a paper where they aimed to study the relationship between classic financial assets and cryptocurrencies. They concluded that cryptocurrencies do have a role in an investor portfolio, since they are so disconnected from the other financial assets and highly connected between themselves. About the risks and factors that drive the evolution of cryptocurrency returns, Liu *et al.* (2020) concluded that cryptocurrency markets mostly respond to momentum and investors attention. Bradbury (2020) states that while Bitcoin could be an exciting digital option during an economic crisis, its lack the backing that a fiat currency has, and its volatility, might be a big obstacle for general consumers to opt for it.

2.2. Cryptocurrencies and the Business Cycle

Although the first cryptocurrency – Bitcoin -, was only invented in 2008, and only emerged to a wider use many years later, the literature available about cryptocurrencies is somehow wide. However, finding relevant papers about the relationship between cryptocurrencies and business cycles is a challenge, since the literature is very scarce. The two most related papers about this topic are from Caton (2018) and Kliber *et al.* (2019).

Caton (2018) analyzes the influence of monetary stability on the overall global economy. The author starts by pointing out the two types of money that cryptocurrencies can assume, specifically Money and Near Money. Money is the generic and widely used way of transactions, as we know it, while Near Money are high liquidity level assets. This is extremely important, as cryptocurrencies are not globally accepted as official currency. The author analyzes previous crises and their determinants, such as the increase in money demand or the increase in savings and assets investments. These are important to understand the role that cryptocurrencies may play in a crisis.

Additionally, the author compares “traditional” monetary policy rules with the type of policy rules that cryptocurrencies can assume. The k- percent rule sets a positive and constant growth rate of the money stock. The money stock is affected massively during a crisis. Cryptocurrencies in general also allow for a policy similar to the k-percent rule. However, some allow this policy to release a certain amount of currency with a maxed cap, meaning that once all the currency is released, no more can be created, such as the Bitcoin, while others allow for endless currency release. The author gives these examples in order to claim that continually improved monetary policies implemented on blockchain based cryptocurrencies may provide economic stability and offset the negative effects of a crisis. Since crisis are offsets on the demand for money, cryptocurrencies may provide a way to obtain money, by buying and selling them. If these are backed by assets, liquidity may even be higher and help even more on certain economic recessions. Canton finishes by stating that there is a huge potential on monetizing illiquid assets using the blockchain.

According to a paper by Kliber *et al.* (2019), under different market conditions, most importantly depending on the Bitcoin price in local currency, Bitcoin can assume three different positions, such as a safe haven, hedge, or a diversifier. The authors analyze different markets such as Japan, Venezuela, China, Estonia, and Sweden, by obtaining the data of local stock markets from 2014 to 2017 and building a dynamic correlation model between the stock prices and the bitcoin prices.

At a first glance, when compared to the USD exchange rate, all markets show evidence of receiving Bitcoin as a weak hedge. However, a specific analysis within each country and its local currency, show completely different results. Bitcoin is then a safe haven in Venezuela, a diversifier in China and Japan and a weak hedge in Sweden and Estonia. The authors conclude that not only is important to understand the role of the Bitcoin in different markets, but dynamic risk management policies should be adopted, in accordance to the different markets and their local currency. The authors also point out that there is a need for international policies and regulation on these virtual assets, in order to achieve lower volatility.

2.3. Australia and Venezuela and Cryptocurrencies' Use

We now analyze two countries in different economic situations, where cryptocurrencies, namely Bitcoin, have proven to be very beneficial and helpful to its users – Venezuela and Australia.

An article written in *The Economist* on April 3rd 2018, studies the current political and economic situation in Venezuela and explains why Venezuelans are mining so much bitcoin. Venezuela lives an economic crisis where their local currency, the Venezuelan Bolivar, is decreasing its value when compared to currencies like the USD or the EUR. Right now, the exchange rate is around 9.98700 VEF to 1 USD. This was not always the case. The inflation and political problems lead the country to this state. In the article is explained how all these conditions created a country that was capable and wiling to mine bitcoin. Venezuelans still hold money and assets, however, this are now not worth as much as before. One would expect that the overall decrease in assets value would lead to a considerable consumer prices decrease as well, namely on general goods. However, these goods did not lower their price, since a big part came from imports to the country, who were reduced massively. Therefore, mining bitcoin provided the Venezuelans with a valuable asset to exchange for USD or local currency in order to acquire goods and assets. Those who did own the capital to import the machinery needed (around 2000 USD for the cheapest hardware at the time) found themselves a great source of income. As of 2016, there was a reduction in the price of electricity in Venezuela, which is the biggest cost of mining bitcoin. This condition enabled Venezuela to be one of the few countries where mining bitcoin can be profitable. However, the article sadly finishes on President Nicolás Maduro plans and actions to stop the overall crypto mining, as he dislikes such activity. Many mining equipment were seized and the miners face energy theft accusations.

On the other side, some countries are adopting cryptocurrency and helping its acceptance. One country in this situation is Australia, as analyzed by Darryn Pollock in an article written in the *Cointelegraph* on April 15th, 2018. Pollock states that the Australian government is actively focused on becoming cryptocurrency friendly, by creating rules and policies who do not aim to control or damage the virtual coins/assets and at the same time, allow these to enter the country and develop within it. An example is the end of the double tax rule that was previously introduced on crypto markets. Australia believes that these policies will help disrupt the bubble rumors that chases cryptocurrencies, as regulations like this can help reduce the short-term inflation of these currencies, who are usually caused not only but also by the mass adoption and hype. A big concern that might appear with such acceptance of cryptocurrencies, concerns financial markets stability, but Australia has plans to register an official exchange rate, which along with other policies, would ensure some level of stability within the market. In addition, a new division was created to watch and learn more on cryptocurrencies. This division is specially observing Initial Coin Offerings (ICO) and working on making sure that these are legal and fraud free. The next step would be to accept cryptocurrencies as a payment method (legal tender), which is exactly what Australia did, by accepting Bitcoin, making it the second country ever to do so after Japan. When asked on how the industries would accept these changes, the article states that overall, most industries accepted cryptocurrency and the new policies.

3. Empirical Methodology

3.1. Data

In this section we will detail our database. In brackets in bold, we put the acronym of the variable, as used in the database.

We have taken quarterly Real GDP *per capita*, calculated with the expenditure approach, from the Organization for Cooperation and Economic Development (OECD)'s website.[1] The sample ranges from the 1st quarter of 2007 until the 2nd quarter of 2019 (2007:Q1-2019:Q2). Data is seasonally adjusted and all the values extracted are in US Dollars and adjusted for Purchasing Power Parity (PPP). We have taken data for the following 38 countries: Australia, Austria, Belgium, Bulgaria, Canada, Chile, Costa Rica, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Korea, Latvia, Lithuania, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Romania, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, United Kingdom, and United States. We also gathered data from two economic zones (consolidated): the Euro area (19 countries) and the European Union (28 countries). Bulgaria, Costa Rica, and Romania are not OECD countries but their data is available in the database.

3.2. Variables

In this section we will detail our variables, dependent and independent.

3.2.1. Dependent Variable

In this section we will explain the construction of our dependent variable (**GDP_CYCLE**), which is based on Gross Domestic Product (GDP).

Our aim with the data mentioned is to calculate the business cycle (or output gap) of each one of these economies. With this purpose, we calculated in STATA, potential (or trend) GDP using the Hodrick-Prescott filter, which is the most commonly used filter to calculate the trend.

[1] www.OECD.org, most precisely from www.stats.oecd.org.

The smoothing parameter (λ) usually used for quarterly data is 1600, so this is the value that we have used. After we get the trend or potential GDP, we subtract it from the original GDP time-series and obtained the business cycle (or output gap). A negative output gap is an indication that the economy is below potential GDP and a positive output indicates that the economy is above potential GDP.

We then construct a dummy variable, which takes the value 0 if the output gap is negative and 1 if the output gap is positive. A dummy variable is useful in a regression, in order to isolate the presence of a given effect that is expected to cause a variation on the outcome and allowing us to better understand it. The next step was to convert this dummy variable from a quarterly time series to a monthly based one. In order to do that, we assume that if in a given quarter the value for this variable was 1 or 0, then the months compressed within that quarter would assume the same value. For example, if in the first quarter of a given year the dummy variable is 1, then the months of January, February, and March will assume the same value of 1. This allowed us to move from the original time series, with a range of 50 quarters (Quarter 1 of 2007 to Quarter 3 of 2019), to a new time series starting on January 2007 until September 2019. This new series is made of 155 observations *per* country.

3.2.2. Independent Variables

In this section we will explain the construction of our independent variables.

3.2.2.1. Countries Specific Shocks

We took yearly data from the database of Laeven and Valencia (2008, 2013, 2018) ranging from 1970 to 2018 and comprising many countries, from which we selected and extracted the 38 countries that we are analyzing. The data contains four variables (Crisis (**Crisis**), which comprises at least one of the following three, Banking Crisis (**Banking**), Currency Crisis (**Currency**), and Sovereign Debt Crisis (**SovDebt**) with value 1 when one of the previous crisis is present and 0 otherwise.

Our aim was to build four variables that would allow us to verify if a given country was experiencing one or more types of crisis in a given year, use them as dummy variables, and isolate specific country shocks. We also transform this variable into a monthly variable, so in any year that we had the value 1, all the months in that year had the value 1, and 0 otherwise.

3.2.2.2. **Cryptocurrencies Monthly Returns**

We have taken multiple cryptocurrencies data, regarding its daily closing price, in order to build a variable that represents the monthly average return for each of the chosen cryptocurrencies **(ACRONYM OF THE CRYPTOCURRENCY_Returns**, for each cryptocurreny). The data was taken from Investing.com website.[2] We chose to work with Bitcoin (BTC), Litecoin (LTC), Ethereum (ETH), Ripple (XRP), and EOSIO (EOS), which have a substantial weight in the cryptocurrencies market. All the cryptocurrencies data had a time frame ending in May of 2019. However, each had a different starting point in our database. For instance, BTC and LTC both started in April of 2013, while XRP started in August 2013, ETH started in August 2015, and lastly EOS in July of 2017.

We then had the challenge to make these variables compatible with the rest of the variables we will be using in the database, which are presented in a monthly basis. To achieve this, we calculated monthly return averages from all of the previous mentioned cryptocurrencies, by using the following formula: $\left(\frac{Closing\ Price\ Month - Closing\ Price\ of\ Previous\ Month}{Closing\ price\ of\ Previous\ Month}\right)$.

At this stage, we had a percentage value for each month in our database, which on its own has a time frame from January 2007 to September 2019. All the months that we didn't collect data to were left blank.

3.2.2.3. **Exchanged Volume/Market Cap**

[2] www.INVESTING.org, most precisely from www.investing.com/crypto/BITCOIN/historical-data www.investing.com/crypto/LITECOIN/historical-data , www.investing.com/crypto/RIPPLE/historical-data , www.investing.com/crypto/EOS/historical-data , www.investing.com/crypto/EOS/historical-data.

In order to measure the relative amount of a given cryptocurrency that is being exchanged on a given day, we used a ratio of Exchanged Volume/Market Cap, since the Exchanged Volume represents the value in U.S. Dollars that is being traded and the Market Cap is the total amount.

The data was converted from a daily format to monthly, by computing a monthly average from the daily data.

This variable (**ACRONYM OF THE CRYPTOCURRENCY _EVMC**, for each cryptocurrency) was taken for each of the previous mentioned cryptocurrencies, with a time frame from December 2013 to May 2019 for BTC, XRP, and LTC. The other two cryptocurrencies had different starting points, even though experiencing the same May 2019 ending date. ETH started on August 2015 and EOS on July 2017.

The data for the Market Cap and Exchanged Volume for all the cryptocurrencies was taken from the CoinMarketCap website[3].

3.2.2.4. Stock Market Index for each Country

Since we will be studying the performance of cryptocurrencies and comparing them to other financial assets, another important variable will be the stock market index for each country on our database (**Stock_Index**). We collected monthly data from January 2007 to September 2019, regarding each country in our database. We gathered the data from the Organization for Cooperation and Economic Development (OECD)'s website.[4]

Lastly, the data for Costa Rica, Romania, and Lithuania had to be gathered separately, since it didn't feature in the mentioned database. This data was extracted for the time period mentioned before, from Investing.com website.[5]

Monthly Return on S&P500

[3] www.coinsmarketcap.org, most precisely from www.coinsmarketcap.com/currencies.
[4] www.OECD.org, most precisely from www.data.oecd.org.
[5] www.INVESTING.com, most precisely from www.investing.com/indices/.

Another important variable to our model was the S&P500 (SP500), most specifically its returns, since it is regarded as one of the benchmarks for the U.S. Stock market, due to its historical returns and composition of the 500 large-cap companies from the U.S. Additionally, the US stock market is also regarded as a safe haven relative to other countries' financial markets.

We started with the daily (except weekends) closing values of the S&P500. Next, we focused on the closing price of each month, allowing us to use the same approach as with the cryptocurrencies returns, in order to determine its monthly return. Data were taken from the World Development Indicators[6], covering data from February 2009 to January 2019.

3.2.2.5. **Central Banks Interest Rates**

Another important variable to our model is the reference rate of the Central Bank of each country in our database (**Cbir**), since this variable allows us to verify at each point in time how easy/hard it is for companies and families to borrow money. Monthly data was obtained from the Bank for International Settlements[7] covering the period between January 2007 to September 2019.

Effective Federal Funds Rate

We then gathered the effective federal funds rate, on a daily basis, with a time frame from April 2009 to March 2019, from the Federal Reserve [8]. This variable (**EFFR**) allows us, on yet another interest rate to add to our model, which is the overnight loans interest rate of the US market, usually a benchmark market for investors. As mentioned, this series was taken on a daily format and therefore needed to be converted to a monthly basis in order to join our database. To achieve this, a monthly average of the rates was computed.

[6] World Development Indicators, most precisely from https://databank.worldbank.org.
[7] www.bis.org, most precisely from https://www.bis.org/statistics/.
[8] www.fed.org, most precisely from https://fred.stlouisfed.org.

3.2.2.6. **Gold Fixing Price**

The price of gold is a sign of the current state of the economy, since a usual behavior from investors is to invest in gold when the economy is facing a recession, on an effort to protect their capital from inflation and potential crisis. Therefore, the price of gold (**GoldF**) is a very relevant variable to add to our model. The data for the price was obtained on a daily format from February 2009 to January 2019. Since it initially had daily values, we considered the closing price of each month when computing the monthly returns. The valuation of gold is done daily at 10:30 AM by the London Bullion Market Association (LBMA) and the data was obtained from FRED website [9].

3.2.2.7. **Silver Fixing Price**

The reasons behind the importance of the price of silver (**SilverF**) are the same as for the price of gold, although, historically, the price of silver has proven to be more stable then the price of gold, mostly due to its industrial use, lacking in the case of gold. Therefore, it is also a good asset to consider in our model, since investors can diversify between the two metals. We have also calculated the monthly returns. The silver fixing price is announced at noon, London time, also by the LBMA. The data we used was gathered from the FRED website [10].

3.2.2.8. **Effective Exchange Rates of Certain Currencies**

Our dataset also comprises the effective exchange rate for five currencies: the Euro (**EUR**), the U.S. Dollar (**USD**), the Pound Sterling (**GBP**), the Japanese Yen (**IENE**), and the Chinese Yuan (**RMB**). These are the most important currencies in the International Monetary System, and quite often used as a safe haven or as a financial asset. Values for the Euro were taken from the European Central Bank (ECB) website[11], the values for the U.S. Dollar were taken from

[9] www.fed.org, most precisely from https://fred.stlouisfed.org.
[10] www.fred.org, most precisely from https://fred.stlouisfed.org.
[11] www.ecb.europa.eu, most precisely from https://www.ecb.europa.eu/stats/.

The Federal Reserve[12], the values for the Pound sterling extracted from the Bank of England website[13], and the Japanese Yen and Chinese Yuan rates were obtained from the FRED website[14].

They are important to our model when we consider their monthly returns, so we can compare them to the cryptocurrencies. The data on the nominal effective exchange rates was obtained with a time frame starting on January 2009 to May 2019. Since we compiled daily values, in order to comply with our database, the next step on all five currencies was to compute the monthly average returns, by adding all the daily returns.

4. Methodology

In this section we explain the econometric models and methods used in this dissertation. For further notice, it should be mentioned that all our data and estimation was processed using the software Stata. The commands are presented in brackets after the mentioned procedures in the text.

We started by organizing our data on a panel data format (xtset found on **Table 1,** xtsum) and obtained all the respective descriptive statistics for our variables (**Table 2**) , such as averages, standard deviation and other useful information, by country and year. This was an important step to give us a quick insight on the data we were about to study and analyze, offering us a better understanding of how our panel data was built and what to expect of each variable. It also allowed us to detect any errors and mistakes that might have been present so far on our database.

Table 1 - The Panel Data Database

xtset CountryID MMYY				
panel variable:	CountryID	(strongly	balanced)	
time variable:	MMYY, Jan	07 to Sep	19, but with	gaps
delta:	1 day			

[12] www.federalreserve.gov, most precisely from https://www.federalreserve.gov/releases/.
[13] www.bankofenglag.co.uk, most precisely from https://www.bankofengland.co.uk/boeapps/database/.
[14] www.fred.org, most precisely from https://fred.stlouisfed.org.

Table 2 - Descriptive Statistics

Variable Name	Mean	Std. Err.	[95% Conf.	Interval]
Cbir	.0055756	.0007632	.0040768	.0070743
Stock_Index	471.5822	84.01678	306.5834	636.5811
GDPCYCLE	.1595395	.0148627	.1303509	.1887281
BTC_RETURNS	.0256269	.0110508	.0039245	.0473292
ETH_RETURNS	-.0593511	.0146231	-.088069	-.0306331
EOS_RETURNS	.1395852	.0268893	.0867778	.1923926
XRP_RETURNS	.1438878	.0298674	.0852317	.2025438
LTC_RETURNS	.0420881	.01653	.0096252	.0745511
BTC_EVMC	.0491793	.0007532	.0477002	.0506585
ETH_EVMC	.0772628	.0026985	.0719632	.0825624
EOS_EVMC	.1573429	.0042594	.1489779	.1657079
XRP_EVMC	.029901	.0005249	.0288701	.0309319
LTC_EVMC	.1217341	.0035524	.1147577	.1287105
EFFR	1.811701	.0164695	1.779357	1.844045
SP500	.0023438	.0015341	-.000669	.0053566
GoldF	.0122778	.0021382	.0080786	.0164769
SilverF	.0006153	.0013998	-.0021337	.0033643
EUR	-.0016494	.0003017	-.0022419	-.0010569
USD	.0027501	.000561	.0016484	.0038518
POUNDUK	.0010213	.000477	.0000845	.0019581
IENE	.0036792	.0004641	.0027678	.0045907
YUAN	.0001984	.0004615	-.000708	.0011048

In the next step we analyzed whether our data was stationary or not. For this, we used a Unit Root test (xtunitroot). Our data analysis included two tests, Im–Pesaran–Shin (xtunitroot ips) tests and Fisher-type tests (xtunitroot fisher). Our data proved to be stationary, allowing us to proceed with our econometric approach as planned.

Afterwards, we searched for the fittest model for our study. To do this, we combined multiple combinations of variables that revealed to be statistically significant, looking for the model (xtlogit) that offered the best significance and fit.

We considered a significance level of 0.10 (p=0.10), eliminating any coefficient whose pvalue of the t-test was above that. The final model was a fixed effects "xtlogit GDPCYCLE BTC_EVMC ETH_EVMC XRP_RETURNS XRP_EVMC EFFR YUAN Cbir SP500 GoldF USD" as found on **Table 4 in Section 5 (Results) below**.

Finally we choose between Random-Effects (FE, xtlogit ,re) model (Table 4 in Section 5) and a Fixed-Effects (FE, xtlogit ,fe) model in order to estimate the type of individual effects that best fits our data.

Resourcing to the Hausman Specification Test (**Table 6 in Section 5**), we concluded that the model that best fits our data was the Fixed-Effects model, since we rejected the H0 in this test, providing evidence in favor of Fixed-type individual Effects.

We didn't differentiate the use of cryptocurrencies on our models and our goal was to achieve the most complete and significant model, while including there as many of the initial cryptocurrencies as possible.

Additionally, we obtained the estimated pairwise Correlation coefficients (**Table 3**) to verify and acknowledge the levels of covariance between our independent variables. The results were the expected ones and no correlation was high enough to invalidate the use of any variable on our model.

Table 3 - Correlations

	Cbir	Stock_~x	BTC_RE~S	ETH_RE~S	EOS_RE~S	XRP_RE~S	LTC_RE~S	BTC_EVMC
Cbir	1.0000							
Stock_Index	0.5152	1.0000						
BTC_RETURNS	-0.0112	0.0085	1.0000					
ETH_RETURNS	-0.0054	0.0051	0.8379	1.0000				
EOS_RETURNS	-0.0076	0.0081	0.7851	0.8273	1.0000			
XRP_RETURNS	-0.0026	0.0055	0.5395	0.6857	0.6884	1.0000		
LTC_RETURNS	-0.0064	0.0070	0.7766	0.8067	0.7712	0.8621	1.0000	
BTC_EVMC	0.0124	-0.0066	-0.2905	0.0085	-0.1042	-0.0066	0.0801	1.0000
ETH_EVMC	0.0154	-0.0089	-0.3538	-0.1069	-0.2435	-0.1350	-0.1061	0.9128
EOS_EVMC	0.0151	-0.0091	-0.3712	-0.0434	-0.2150	-0.1421	-0.1284	0.9276
XRP_EVMC	0.0065	-0.0003	0.1633	0.3729	0.3523	0.7500	0.6641	0.4425
LTC_EVMC	0.0132	-0.0070	-0.2440	-0.0381	-0.1431	0.0158	0.0801	0.9293
SP500	-0.0087	0.0043	0.2863	-0.0105	0.0936	0.0911	0.2304	-0.3200
EFFR	0.0175	-0.0121	-0.5770	-0.3362	-0.4900	-0.3404	-0.4418	0.6478
GoldF	0.0127	-0.0064	-0.1250	-0.0036	0.0144	0.0319	0.0812	0.6926
SilverF	0.0085	-0.0030	-0.0437	0.2573	0.0774	0.1207	0.1297	0.7028
EUR	-0.0034	0.0020	0.1554	0.0962	0.2674	0.0998	0.0298	-0.2139
USD	-0.0066	0.0009	0.0281	0.0329	-0.1554	-0.1229	-0.1588	-0.5841
POUNDUK	0.0050	-0.0004	-0.1949	-0.3145	-0.0318	-0.2051	-0.1999	0.3814
IENE	0.0042	-0.0034	-0.4681	-0.5813	-0.4074	-0.4658	-0.3249	0.4851
YUAN	0.0017	-0.0009	0.0219	0.1735	0.0097	0.1223	0.3191	0.4520

	ETH_EVMC	EOS_EVMC	XRP_EVMC	LTC_EVMC	SP500	EFFR	GoldF	SilverF	EUR	USD	POUNDUK
ETH_EVMC	1.0000										
EOS_EVMC	0.9679	1.0000									
XRP_EVMC	0.3727	0.3163	1.0000								
LTC_EVMC	0.9631	0.9027	0.5063	1.0000							
SP500	-0.4447	-0.4757	-0.1505	-0.3570	1.0000						
EFFR	0.8056	0.7810	0.0481	0.6864	-0.4388	1.0000					
GoldF	0.7361	0.6608	0.3308	0.7699	-0.1531	0.4974	1.0000				
SilverF	0.7369	0.7413	0.3882	0.7397	-0.5723	0.3939	0.6897	1.0000			
EUR	-0.2459	-0.1986	-0.1401	-0.2216	-0.0092	-0.1831	-0.2641	-0.3665	1.0000		
USD	-0.5943	-0.5340	-0.3627	-0.6461	0.0922	-0.2735	-0.5707	-0.3924	-0.2871	1.0000	
POUNDUK	0.5052	0.3886	-0.0197	0.5005	-0.0945	0.3552	0.6327	0.3699	-0.0374	-0.6871	1.0000
IENE	0.4386	0.3958	-0.1729	0.4698	-0.0373	0.3844	0.3968	0.0604	0.0669	-0.4492	0.5371
YUAN	0.3581	0.3362	0.5120	0.4131	-0.0180	0.0223	0.2466	0.3680	-0.5732	0.0530	-0.0699

	IENE	YUAN
IENE	1.0000	
YUAN	-0.0149	1.0000

In the end, we reached the following final equation model that we estimated to study our research question:

$$GDPCYCLE = \alpha + \beta1*BTC\_EVMC + \beta2*ETH\_EVMC + \beta3*XRP\_RETURNS + \beta4*XRP\_EVMC + \beta5*EFFR + \beta6*YUAN + \beta7*CBIR + \beta8*SP500 + \beta9*GoldF + \beta10*USD + Et, \quad (1)$$

where Et is the model's error term that includes the individual fixed-effects and β's are the coefficients associated to each variable.

As one might notice, not all variables were included in this final model. This is a result of the lack of significance found on the remaining of the variables when each joined the model, during its build-up. The end result is a model where all variables are within the 10% significance level for its t-test we set in the beginning of the model build.

For further details about this approach, please see Peng et al. (2002).

5. Results

To interpret the results and answer the research question, we estimated the model presented in equation (1) using the mentioned software on the methodology chapter. The results can be found below on Table 4. Here in the text, p.p. can be read as percentage points.

The results provided below include all variables that were found to be significant, since we dropped all the non-significant variables, as mentioned before.

Table 4 - Results of the Fixed Effects Logit Model

GDPCYCLE	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
BTC_EVMC	-53.29642	10.78241	-4.94	0.000	-74.42955	-32.16329
ETH_EVMC	23.32399	3.234245	7.21	0.000	16.98499	29.66299
XRP_RETURNS	-.2588178	.1414479	-1.83	0.067	-.5360506	.0184151
XRP_EVMC	21.7425	11.46494	1.90	0.058	-.7283749	44.21337
EFFR	-1.37014	.2423848	-5.65	0.000	-1.845205	-.8950742
YUAN	-14.04475	7.922316	-1.77	0.076	-29.5722	1.482706
Cbir	-123.265	23.98997	-5.14	0.000	-170.2845	-76.24555
SP500	2.777348	1.235128	2.25	0.025	.3565419	5.198154
GoldF	4.611898	1.617479	2.85	0.004	1.441698	7.782099
USD	9.858128	5.221013	1.89	0.059	-.3748688	20.09112

The coefficient of BTC_EVMC is negative, which indicates that a higher quantity of exchanged Bitcoin coins on the market represents a decrease on the probability of an actual positive state of the economy, therefore, more quantity on the market can be seen as inducing negative economic periods, like recessions or crisis.

More specifically, our model shows that an increase of one p.p. of BTC_EVMC causes a decrease of 53296.42% on our odds ratio of GDPCYCLE (ratio of probability of expansion over the probability of recession), decreasing the chance of success and being on an expansion.

The coefficient of ETH_EVMC is positive 23.32399, meaning that unlike BTC_EVMC, a higher quantity of Ethereum transitioned on the market is a sign that we are likelier to be in an expansion.

This might be explained by the fact that Ethereum and Bitcoin are quite different in terms of use and existence. For instance, Ethereum might be used as a way of transferring value like bitcoin, but its decentralized platform also enables its users to use it for much more, like contracts and other. Also, ETH network's is faster than BTC's.

Other explanation to the positive coefficient of this variable can be the fact that prices on ETH have always been lower than BTC's.

Most specifically, ETH_EVMC's coefficient is positive 23.32399, which means that an increase of 1 unit on the ratio of Ether's Exchanged Value/Market Cap will result in an increase of 23323.99% on the odd change of GDPCYCLE, meaning that we increase the chance of success, therefore, we are likelier to be in an expansion.

Next, we analyze the coefficient of XRP_RETURNS.

Ripple is an interesting cryptocurrency due to its aim within the cryptocurrency network. Ripple aims to offer rapid and little cost transactions. To show how different Ripple works, some banks even use its payment system. For comparison, Ripple works more like SWIFT (the international money service) than an ordinary cryptocurrency.

Considering all that, the coefficient is negative 0.2588 approximately meaning that an increase of one p.p. of XRP_RETURNS represents a decrease in 25.88% of the chance of success on our odds ratio for the dependent variable GDPCYCLE, therefore, being and indicator of a negative economic state.

After stating the previous conclusion, one would expect that a lower Ripple price, would enable the network to work with more users since it's cheaper to use, and would expect XRP_EVMC coefficient's to be positive.

That is exactly what happens on our model. XRP_EVMC coefficient is positive 21.7425. A positive economic state (expansions) has more transactions happening compared to a negative one, therefore we expected this result on this specific variable.

The coefficient means that an increase in one unit on our XRP_EVMC ratio, increases our odds ratio of success of GDPCYCLE by 21742.5%, placing us on a positive economic path.

As stated in the variables section, we added some control variables that are already studied such as the Countries interest rates (CBIR) and the Effective Federal Funds Rate, in order to not only test the model, but also compare them to cryptocurrency variables.

On that note, we expected EFFR coefficients to be negative, since an increase in the Fed funds rate usually slows down the economy. This is a usual sign of a negative economic path.

On our model, EFFR's coefficient is negative 1.37, which means that every time the FED increases the rate by 1%, our odds ratio of success on our dependent variable decrease by 137%.

The same thing applies for the analysis of the Cbir (Country Interest Rates) result on our model. Its coefficient is negative, as expected since an increase in countries' interest rates is generally a sign that the country is entering a negative economic path, that is by forcing the rates to be higher, lending less money and slowing down the overall economy. The coefficient is negative 123.267, showing us that Country Interest rates have a huge impact on the countries' economic situation.

This result shows us that every time the interest rates are increased by 1%, the country has a 123265% increase in the chance of the odds ratio of unsuccess for our dependent variable, meaning that's super likely to be entering an economic crisis.

Our next control variable is the returns on the widely used S&P500 index.

This index is used as a benchmark for many financial and economical situations, making it a great add to our model. As we know, when the economy is growing so is the S&P500 index, since an expansion is usually related to better financial results for the companies present in the index. The presented model shows just that, a positive coefficient for the S&P500 returns variable (SP500), meaning that every time the S&P500 returns grow 1%, the odds ratio (chance) of success on our variable, manning the chance of the current economic path being a positive growing one, increases by 2777% approximately.

In order to improve the model we also added a commodity that is often linked and compared to many cryptocurrencies, mainly bitcoin due to its behavior. This commodity is Gold or in this specific cases, the returns on Gold.

Gold represents so much for the world's economy and investor options. Usually investors tend to opt and purchase gold in times with increasing inflation, since gold is an actual material with production uses and limited supply, it generally hold its value better than general FIAT money currency.

The historical trend of gold prices is an uptrend, which is expected since the general stock market and economic trend is an uptrend, caused by inflation and money printing in general. Therefore, gold is usually considered a "safe haven" for investors looking to secure their portfolio against possible economic downturns and depressions.

Looking at our model below, GoldF has a positive coefficient of approximately 4.611 which means that for every 1% increase in gold investment returns the chance of success for our main variable GDP_CYCLE increases by 4611%, helping the economy follow its positive growing path.

At last our model also includes two currencies, the Chinese Yuan (Renminbi) and the United States of America Dollar USD.

We suspected our model needed to include currencies since not only does it allow for further comparison but also since the aim of many cryptocurrencies is to be used as a coin, replacing the functions of other currencies and therefore looking to be considered one. Also, the general consumer looks at cryptocurrency as other forms of currency making it a must on our model.

Following this, we started by analyzing the results of YUAN. This variable measures the effective exchange rate of the Chinese currency.

On our model Yuan has a negative coefficient which was expected. Given their consumption habits, China is the number one exporting country in the world and when the world experiences an overall and global expansion, China tends to export more due to that. However, an increase in Yuan's value, means that other countries won't buy from China, since it's now more expensive to do so, with the appreciation of China's currency, opposed to the value of the buying countries currency.

That coefficient of negative 14.04475 means that every increase of YUAN's Effective exchange rate by 1% decreases our chances of success on GDP_CYCLE by 14044.75% (therefore, increases our chances of experiencing an economic depression).

On the other hand, our other observed currency USD behaves completely different to the previous mentioned currency, experiencing a positive coefficient. This result was also expected, since the United States of America are of huge global importance due to their financial market and consumer market as well.

Also, the USD has for many years been a benchmark for other countries in terms of currency values and other economic factors due to their massive global presence and importance.

Therefore, an increase in USD effective exchange rates is a direct result of the USA's economic health and strength.

Looking at our model the variable USD has a positive coefficient of approximately 9.858 meaning that for every 1% increase in USD effective exchange rate our dependent variable chances of success are increased by 9858% moving us towards a positive expansion situation.

Table 5 - Results of the Random Effects Logit Model

GDPCYCLE	Coef.	Std. Err.	z	P>z	[95% Conf.	Interval]
BTC_EVMC	-54.93125	10.66899	-5.15	0.000	-75.84209	-34.02041
ETH_EVMC	23.26291	3.213637	7.24	0.000	16.96429	29.56152
XRP_RETURNS	-.2535255	.1403237	-1.81	0.071	-.5285549	.021504
XRP_EVMC	22.82421	11.37374	2.01	0.045	.5320812	45.11633
EFFR	-1.365376	.239467	-5.70	0.000	-1.834723	-.8960293
YUAN	-14.22088	7.80804	-1.82	0.069	-29.52436	1.082597
Cbir	-19.82048	10.34292	-1.92	0.055	-40.09223	.4512667
SP500	2.964271	1.222413	2.42	0.015	.5683866	5.360156
GoldF	4.42213	1.599294	2.77	0.006	1.287571	7.556689
USD	9.11836	5.160237	1.77	0.077	-.9955184	19.23224
_cons	.9452706	.1909945	4.95	0.000	.5709281	1.319613
/lnsig2u	-.1976662	.3479398			-.8796158	.4842833
sigma_u	.9058939	.1575983			.6441602	1.273975
rho	.1996451	.0555962			.112001	.3303585

Table 6 - Results from the Hausman Test for Random Effects.

	Coefficients (b) fixed	---- (B) random	(b-B) Difference	sqrt(diag(V_b V_B)) S.E.
BTC_EVMC	-53.29642	54.93125	1.634832	1.559807
ETH_EVMC	23.32399	23.26291	.0610827	.3645212
XRP_RETURNS	-.2588178	.2535255	-.0052923	.0177979
XRP_EVMC	21.7425	22.82421	-1.081712	1.443204
EFFR	-1.37014	1.365376	-.0047637	.0374959
YUAN	-14.04475	14.22088	.1761318	1.340746
Cbir	-123.265	19.82048	-103.4445	21.64584
SP500	2.777348	2.964271	-.1869233	.1767717
GoldF	4.611898	4.42213	.1897681	.2418597
USD	9.858128	9.11836	.7397679	.79431

b = consistent under Ho and Ha; obtained from xtlogit

B = inconsistent under Ha, efficient under Ho; obtained from xtlogit

Test: Ho: difference in coefficients not systematic

chi2(10) = (b-B)'[(V_b-V_B)^(-1)](b-B)

= 43.72

Prob>chi2 = 0.0000

(V_b-V_B is not positive definite)

6. Conclusion

In this dissertation, we analyze the effects of cryptocurrencies on the business cycle, namely the likelihood of being in an expansion or a recession, and compare it to other variables that can also be used as a store of value. We built this work around five cryptocurrencies, Bitcoin, Litecoin, Eosio, Ripple and Ethereum. We used data and estimated our model using a panel data Logit model with Fixed Effects. The model estimated in this work provided us with results and insights that are fairly new to the studies of cryptocurrencies, allowing us to develop an interesting overview on this subject.

The results provided by our model allowed us to the following conclusions.

As expected, we have several positive coefficients for many variables linked to the business cycle, such as the returns on S&P500, Gold and USD. An expansion is linked with a S&P500's growth since the companies included in this index are experiencing growing profits and therefore increasing its overall index value. USD is also positive as it should, since it reflects the state of one of the world's biggest economies, the United States of America. An increase in the USD value shows that the importance of the US economy in the world is enlarged. Then we have Gold returns, which have historically been known as a haven for investors. This is made possible due to the constant uptrend Gold faces, since it is backed by its own rarity and value.

We can now analyze the expected negative coefficient variables, which are the EFFR, YUAN and Cbir. For instance, Effective Federal Funds Rate are expected to have a negative sign since the Fed increasing this rate means that banks won't borrow as much money and therefore the economy will slow down. The Chinese Yuan was also expected to be negative, since China is the number one exporting country and an increase of their currency value would make it harder and more expensive for other countries to buy from them, therefore, resulting in a decrease in the Chinese exportation. Since China's GDP is largely influenced by their exporting activities, their monetary policies and central banks are controlling its currency in order for the country to keep exporting. The last one, Country interest rates are known to be high during crisis and low during economic expansion. This is explained by the willingness to offer capital by the banks. During a crisis, banks are looking for a bigger payout on their capital therefore increasing the rates, whilst during an expansion, the bank can easily invest their capital and expect a lower return, since the economic situation suggests a safe period for this operation.

Having explained and concluded on these control variables, we now analyze our variables related to cryptocurrencies. As we know, we started with 10 crypto related variables, however, do to their statistical significance and availability of data, our final model is composed by 4.

To start, we will analyze BTC_EVMC, ETH_EVMC and XRP_EVMC due to their common nature. Both coefficients for ETH_EVMC and XRP_EVMC are positive while BTC_EVMC is negative, suggesting that during an expansion the use of Ethereum and Ripple is beneficial to its user and to the overall economy. With respect to Ripple, this happens due to the nature of this cryptocurrency goal within the market which is not to be a currency but a payment settling service, where the goal is not to have ripple increasing its value, but to be used more and more.

Ethereum is however a good one to compare to Bitcoin since they both aim to be a new currency with more and more value. Ethereum while being similar as Bitcoin offers one main difference that make it more similar to real FIAT currency, which is the fact that it does not have a limited supply set by their creators, while bitcoin does have a supply maximum value of 21 million coins. This is the difference that allows the amount of Ethereum on the market to have a positive impact on expansion that the amount of Bitcoin on the market at first glance can't.

Ethereum should then, over time, see its value following the overall economy state (growing when the economy grows).

Since Bitcoin has a capped amount, analysts suggest that Bitcoin should be considered a commodity and not a currency, since it behaves like gold in terms of value depending on scarcity and economical panic within investors, which after conducting this study we fully agree as the similarities can be observed. At least for now, while no country or organization accepts and declares Bitcoin as global official currency, Bitcoin should be seen as a commodity.

At last, Ripple's returns show a negative coefficient since its value is basically the cost of a service to use their digital transaction process. This means that their value is seen increasing during an expansion, which is expectable since consumers have more purchasing power, and decreasing during an economic crisis. That could mean that Ripple values follow the economic situation and overall value over time, meaning that people can resort to the use of Ripple to transfer goods and value during an economic crisis with as much ease as during an expansion or at least, with more ease than other conventional methods. Also, Ripple has a negative relationship between its market use and value, suggesting that during crisis its value will be lower, and its increase in use on the market will lead us to an expansion.

In conclusion, there are some cryptocurrencies that we estimate to have an impact on future economic crisis, helping countries return to a positive economic state. Ripple for instance provides an easy and cheap method to enable transaction even during a crisis, Ethereum provides and infinite amount of coins that can be used during a crisis to also lead us to an expansion, just like real currency.

Bitcoin can also help investors on future crisis, by acting as a safe haven since it has a limited supply and the more coins in the market available at a given time, the less value it has, meaning investors can hold onto their Bitcoin in order to protect their portfolio during recessions.

For further research and work, it would be interesting to analyze on weather Bitcoin behaves like a commodity during future crisis or its lack of fundamental value like gold should bring its value down. It would also be interesting to analyze how the emerging of this cryptocurrencies and their technology such as Blockchain can improve the standard Banking methods and build trust whiten the consumer.

References

1. Bradbury, D. (2020), "Is Bitcoin the answer in a financial crisis?", *The Balance*, 24 April: https://www.thebalance.com/is-bitcoin-the-answer-in-a-financial-crisis-391275
2. Caton, J. (2018). "Cryptoliquidity: The Blockchain and Monetary Stability." *AIER Sound Money Project Working Paper Working Paper No. 2018–15*.
3. Corbet, S., Meegan, A., Larkin, C., Lucey, B., & Yarovaya, L. (2018). Exploring the Dynamic Relationships between Cryptocurrencies and Other Financial Assets. *Economics Letters*, 165: 28–34. https://doi.org/10.1016/j.econlet.2018.01.004
4. Dyhrberg, A. H. (2016). Hedging capabilities of bitcoin. Is it the virtual gold? *Finance Research Letters,* 16: 139–144. https://doi.org/10.1016/j.frl.2015.10.025.
5. Gervais, A., Karame, G. O., Capkun, V., & Capkun, S. (2014). Is Bitcoin a Decentralized Currency? *IEEE Security & Privacy*, 12(3), 54–60. https://doi.org/10.1109/MSP.2014.49
6. Joseph, P., & Dryja, T. (2016), "The Bitcoin Lightning Network: Scalable Off-Chain Instant Payments", https://lightning.network/lightning-network-paper.pdf
7. Kliber, A., Marszałek, P., Musiałkowska, I., & Świerczyńska, K. (2019). "Bitcoin: Safe heaven, hedge or diversifier? Perception of bitcoin in the context of a country's economic situation —A stochastic volatility approach". *Physica A,* 524: 246-257.
8. Laeven, L. and Valencia, F. (2008). Systemic Banking Crises Database: A New Database. *IMF Working Papers 08/224*. Washington, D.C.: International Monetary Fund.
9. Laeven, L. and Valencia, F. (2013). Systemic Banking Crises Database. *IMF Economic Review*, 61(2), 225-270.
10. Laeven, L. and Valencia, F. (2018). Systemic Banking Crises Revisited. *IMF Working Papers 18/206*. Washington, D.C.: International Monetary Fund.
11. Liu, Y., & Tsyvinski, A. (2020). Risks and Returns of Cryptocurrency. *The Review of Financial Studies*. https://doi.org/10.1093/rfs/hhaa113
12. Nabilou, H., & Prüm, A. (2019). Ignorance, Debt, and Cryptocurrencies: The Old and the New in the Law and Economics of Concurrent Currencies. *Journal of Financial Regulation*, 5(1), 29–63. https://doi.org/10.1093/jfr/fjz002
13. Peng, C.-Y. J., Lee, K. L., & Ingersoll, G. M. (2002). An Introduction to Logistic Regression Analysis and Reporting. *The Journal of Educational Research*, 96(1), 3–

14.:
https://www.researchgate.net/publication/242579096_An_Introduction_to_Logistic_Regression_Analysis_and_Reporting
14. Pollock, D. (2018), "How Australia is Becoming a Cryptocurrency Continent: Markets, Regulation, and Plans", *CoinTelegraph*, 15 April: https://cointelegraph.com/news/how-australia-is-becoming-a-cryptocurrency-continent-markets-regulations-and-plans
15. The Economist (2018), "Why are Venezuelans Mining so Much Bitcoin?" 3 April: https://www.economist.com/theeconomist-explains/2018/04/03/why-are-venezuelans-mining-so-much-bitcoin
16. Umeh, J. (2018). Beyond Bitcoin and the Blockchain. *ITNOW*, 60(3), 48–49. https://doi.org/10.1093/itnow/bwy077
17. Weber, B. (2014). Bitcoin and the legitimacy crisis of money. *Cambridge Journal of Economics*, 40(1), 17–41. https://doi.org/10.1093/cje/beu067
18. Yermack, D. (2015). Is Bitcoin a Real Currency? An Economic Appraisal. *Handbook of Digital Currency*, 31–43. https://doi.org/10.1016/B978-0-12-802117-0.00002-3.