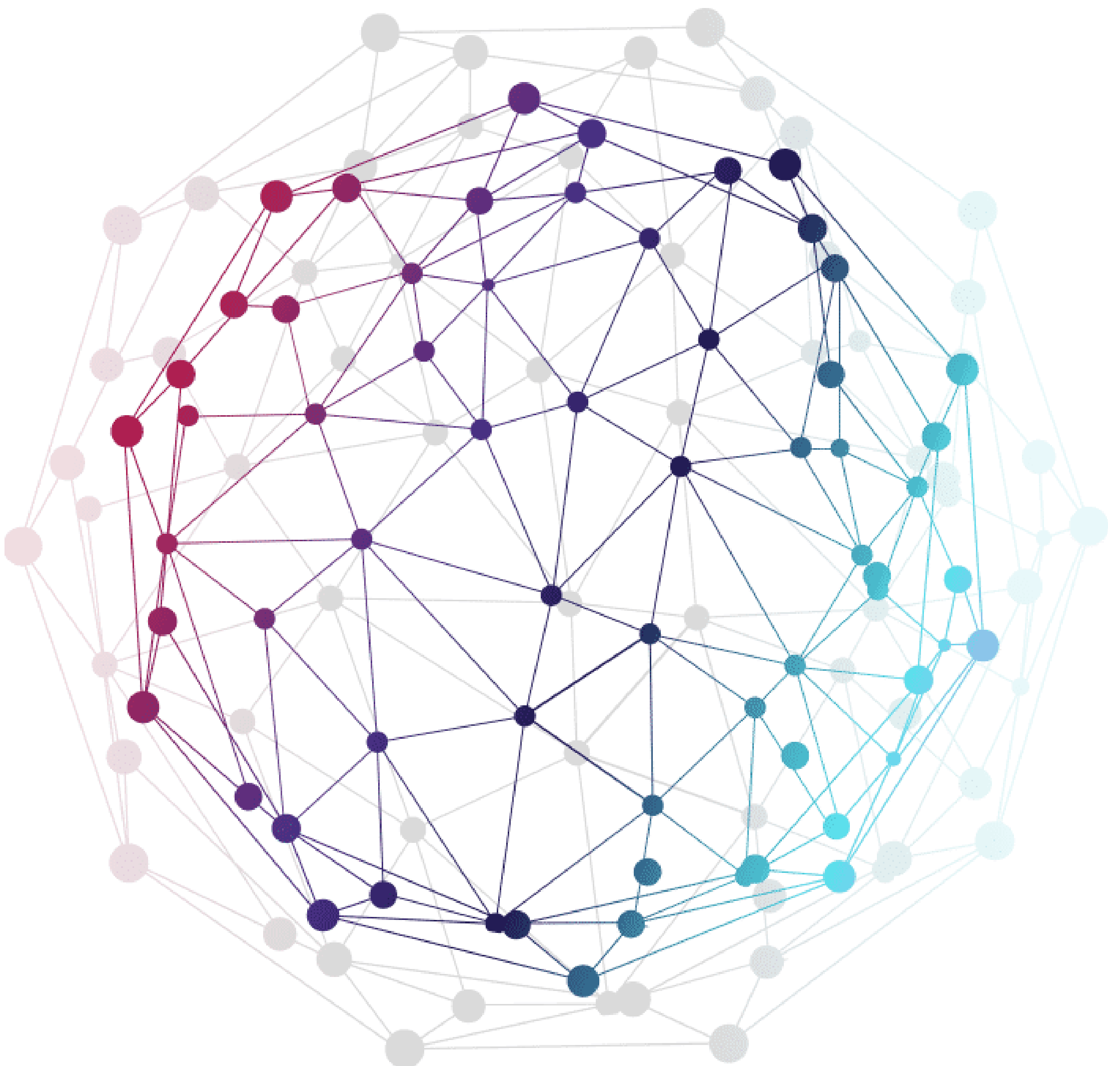
Master Thesis U.S.E.

Blockchain consensus mechanisms and price volatilities



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Abstract

Cryptocurrencies show extreme and persistent volatilities. This makes cryptocurrencies less useful as a medium of exchange and more risky as an investment. This research looks into the effect of a cryptocurrency's consensus mechanism on its price volatility. Numerous theories suggest that high volatilities are an equilibrium outcome of the Proof of Work consensus mechanism. This research aims to test this empirically. By doing a Random Effects regression on a panel data set it is found that a coin's consensus mechanism indeed influences its price volatility. Coins using Delegated Proof of Stake and Nominated Proof of Stake have statistically significant lower average volatilities than coins using Proof of Work. Coins using RandomX have marginally statistically significant higher average volatilities than coins using Proof of Work. No significant relationship is found for coins using Proof of Stake or Scrypt.

1. Introduction

This paper aims to go deeper into cryptocurrency price volatilities and whether they are influenced by the coin's consensus mechanism. Cryptocurrencies do show extreme and persistent volatility (Chu, Chan, Nadarajah, & Osterrieder, 2017). High volatilities decreases the usability of cryptocurrencies as a medium of exchange. The more volatile a coin is the less usable it becomes as a payment method (Baur, Bühler, Bick, & Bonorden, 2015). High volatilities also increase the risks of investing in cryptocurrencies. Understanding the reasons that contribute to a cryptocurrency's volatility is important for cryptocurrency investors, coin creators and society as a whole. With this information investors can better manage their risk and portfolio. Coin creators can select the right consensus mechanism for their coin that aligns with their goals. Society benefits, because some consensus mechanisms are shown to be less environmentally wasteful than others, while they also might be more stable.

Cryptocurrencies are defined as digital currencies which are secured by cryptography. Often these cryptocurrencies are decentralized, which means they are not controlled by a central entity (Frankenfield, 2022). To record transactions without a central authority blockchain technology is used. A blockchain is a publicly available decentralized digital ledger which records transactions across the network (Saleh, 2021). Members of the network update and store the blockchain and are rewarded for this. These members are called *validators*. The usefulness of the blockchain depends on validators agreeing on its contents. (Saleh, 2021) This is called *consensus* and the way in which consensus is reached between validators is called the *consensus mechanism*.

There are many ways in which validators can reach consensus, the most popular being a Proof of Work (PoW) model. In a PoW consensus mechanism validators have computers compete to be the one to update the ledger. PoW is very computational heavy and can require huge amounts of energy to function. Bitcoin, the biggest cryptocurrency, uses a PoW consensus mechanism. The annual energy consumption used for mining Bitcoin is comparable to that of Argentina (Digiconomist, 2022).

Proof of Stake (PoS) is the most popular alternative to a PoW consensus mechanism. PoS is a more sustainable alternative to PoW, because it does not require the computational race that PoW requires in order to update the blockchain.

This research aims to give an empirical answer to whether cryptocurrency volatility is influenced by a coin's consensus mechanism. Theories suggest that these high volatilities might be the equilibrium outcome of the Proof of Work (PoW) consensus mechanism and that the Proof of Stake (PoS) consensus mechanism might have a more stable equilibrium (Alsabah and Capponi, 2020; Hinzen et al., 2019; Saleh, 2021). This research aims to test this theory, include other consensus mechanisms, and give an empirical answer to the following research question:
'Does a cryptocurrency's consensus mechanism impact its price volatility?'

By using cryptocurrency price data of 16 different coins sourced from Kaggle, Kraken and Coingecko, I am able to perform an econometric regression of volatility on consensus mechanisms. The consensus mechanisms included in this research are: PoS, PoW, Delegated PoS (DPoS), Nominated PoS (NPoS), Scrypt PoW and RandomX PoW. The workings of these consensus mechanisms are explained in chapter 2.

This paper relates to a number of studies that look into cryptocurrency volatilities. As mentioned before, the equilibrium outcome of the PoW consensus mechanism might lead to high price volatilities. This can be concluded from two studies. One study theorizes that this unstable equilibrium is inherent to the PoW consensus mechanism (Hinzen, John, & Saleh, 2019). They theorize that an increase in transactions, leads to an increase in fees, which leads to more validators entering the network. More validators entering the network makes it harder to reach consensus, which can cause payment delays. These payment delays decrease the demand for the network, which decreases transactions. The other study finds that the price of Bitcoin is positively correlated with the hash rate, so volatilities in the hash rate will be correlated with volatilities in the price (Alsabah & Capponi, 2020). The hash rate is the total amount of computational power spend on mining. The full deduction on how these mechanisms lead to high price volatilities is given in chapter 3.

Finally, one study theorizes that PoS might lead to a more stable equilibrium than PoW (Saleh, 2021). Validators in PoS networks are motivated to reach consensus quickly, so payment delays are less likely to happen.

Of course, volatility is affected by more than the coin’s consensus mechanism. A study finds that the size of a coin (for example in terms of market cap), its momentum and trading volume can be used to predict future returns (Liu, Tsyvinski, & Wu, Common Risk Factors in Cryptocurrency, 2022). A different research looks into the numerous macroeconomic factors impacting cryptocurrency price volatility (Walther, Klein, & Bouri, 2019). Another study finds the effect of Covid-19 panic on the volatility of cryptocurrencies (Umar & Gubareva, 2020). Liquidity can also influence volatility. If a market is illiquid, it is hard for buyers and sellers to buy and sell at the market price. This can cause big price jumps and crashes. These are factors that need to be controlled for in the regression.

This research aims to test whether it is true that PoW has a more unstable equilibrium than PoS and other consensus mechanisms. As laid out above an econometric regression will be performed with a coin’s volatility as a dependent variable and the different consensus mechanisms and control variables as independent variables.

In the next chapter, some background information is given on the different consensus mechanisms included in this research. Chapter 3 contains a deeper dive into the literature and an in depth overview of how an unstable equilibrium for PoW coins might be reached. This chapter will also go over different ways to calculate volatility and the option chosen in this research. In chapter 4 an overview will be given of the data used and where it was sourced from. In this chapter the selection of control variables will also be motivated and the methodology explained. In chapter 5 the results of this research are presented. In chapter 6 the findings are discussed and a conclusion is presented.

2. Background information

There are many different consensus mechanisms cryptocurrencies can utilize to update the blockchain. The workings of these consensus mechanisms can differ largely, but they all revolve around reaching consensus. The most popular choices are PoW and PoS, these were mentioned briefly in the introduction. In this chapter the workings of the consensus mechanisms included in this research are explained. In total this research includes 6 consensus mechanisms.

As mentioned in the introduction, a Proof of Work (PoW) model has validators compete with each other to be the one to add the next block to the blockchain. They compete by having computers solve complex puzzles, which can get increasingly complex. The first to get the right answer gets to update the blockchain and is rewarded for this. This process is called mining. (Hinzen, John, & Saleh, 2019)

Proof of Stake (PoS) does not have validators compete with each other. PoS gives a random validator the power to update the blockchain, for which this validator will be rewarded. To ensure that validators are incentivized to update the ledger correctly, they must stake their coin. This means that they have a holding in the coin which they cannot access for a given amount of time. If a validator decides to update the ledger incorrectly, this will lead to a loss in value for the coin and thus the validator. (Saleh, 2021)

Delegated PoS (DPoS) is very similar to PoS as the name suggests. In a Delegated PoS consensus algorithm stakeholders can vote for delegates who update the blockchain on their behalf, instead of updating the blockchain themselves like in a PoS consensus mechanism. It is in the delegates best interest to be efficient and honest, otherwise they get voted out (Binance Academy, 2021). The biggest cryptocurrency utilizing DPoS included in this research is Tron.

Nominated PoS (NPoS) is also very similar to the PoS consensus mechanism and even more similar to the Delegated PoS consensus mechanism. Nominated PoS is a Proof of Stake system where *nominators* nominate validators, just like in the Delegated PoS model. NPoS differs from DPoS in that with NPoS nominators back their nominated validators with their stake. They do this as a token of faith, in that the validator is trustworthy. Nominators are subject to loss if they nominate a bad validator (Polkadot, 2022). Currently, the biggest NPoS coin by market cap is Polkadot (CoinMarketCap, 2022).

Scrypt PoW in turn is very similar to PoW. It works in the same way as a PoW consensus mechanism, only mining as a validator on a Scrypt PoW blockchain is more memory intensive. This makes Scrypt PoW coins more costly to attack and thus more secure (Garg, 2021). Currently, the biggest Scrypt PoW coin by market cap is Dogecoin (CoinMarketCap, 2022).

RandomX PoW is similar to PoW and Scrypt PoW. The goal of RandomX is to discourage the use of specialized hardware. It does this by using random code execution in combination with numerous memory-hard techniques. This decreases the efficiency advantage of special mining hardware. RandomX was created to keep mining decentralized (tevador, 2019). Currently, the biggest coin utilizing RandomX is Monero (CoinMarketCap, 2022).

3. Literature review

Some research has already been done on the topic of cryptocurrency consensus mechanisms and cryptocurrency price volatilities. One research claims that the limited adoption of certain cryptocurrencies like Bitcoin is due to a flaw in the PoW blockchain (Hinzen, John, & Saleh, 2019). PoW works by having computers solve a complex puzzle to update the blockchain. The puzzle difficulty is a parameter that can change over time. This is done so the time between block creation remains roughly equal. The more *miners* (computers that try to solve these puzzles) come online, the more difficult the puzzle will become. This however, poses an artificial supply constraint. This research theorizes that this supply constraint leads to limited adoption of the coin. (Hinzen, John, & Saleh, 2019)

Due to this artificial supply constraint an increase in transactions leads to an increase in fees. Although, the time between blocks will remain roughly equal, network delays can still occur. A network delay can be defined as the time it takes for information to travel across the network. Network delays can cause problems for the network. If a validator, Validator A, solves the puzzle and proposes a new block at a certain height, other validators may still be looking to add a new block at the same height, because the information that Validator A has updated the blockchain is not yet known by everybody. There is a chance that a different validator, Validator B, also finds a valid block, before knowing that Validator A already proposed a valid block. Now Validator A and B perceive 2 different blockchains, this is called a fork. When a fork arises, the blockchain needs a certain number of consecutive blocks where no multiple blocks are proposed at the same height to return to consensus. Payments cannot be made during a fork. This can cause delays in payment confirmation times which turns users away from the network. (Hinzen, John, & Saleh, 2019)

Summarized, when transactions increase, fees increase and when fees increase this attracts more validators to enter the network. When more validators are online, the chances of a fork happening are higher, which increases payment delays. Payment delays drive users away from the network and this decreases transactions again.

Other research finds that Bitcoin’s price is positively correlated to the hash rate. The hash rate is the total amount of computational power spend on mining. The higher the hash rate the more computers are competing to update the blockchain. This research also found that mining tends to move towards centralization, where the biggest players invest the most and drive smaller players out of the market. These big players do this by investing in R&D, which usually leads to an increase in their hash rate. This means that volatilities in Bitcoin’s hash rate are correlated with volatilities in Bitcoin’s price. (Alsabah & Capponi, 2020)

These findings are in line with the research done on the equilibrium outcome of PoW blockchains. As mentioned, an increase in transactions leads to an increase in fees, which leads to an increase in the number of validators (Hinzen, John, & Saleh, 2019). Transaction volume is correlated with price, because when more transactions happen, more people need to own the coin. It also means that more validators will come online. If more validators come online, the hash rate will be higher. So it is logical that price and hash rate are positively correlated. A higher coin price on itself can also cause more validators to come online. Validators are paid in the network’s native coin (Alsabah & Capponi, 2020). This means that if the coin rises in value compared to a fiat currency, becoming a validator becomes more profitable and thus more attractive.

The limited adoption problem also relates to prices. For example, if demand and transactions for Bitcoin increases, its price will increase. The increase in transactions will lead to higher fees, because the time between blocks remains equal. Higher prices and fees will attract more validators to come online. When more validators are online the chances of a fork happening are higher and thus payment delays will worsen. This will drive users away from the network, leading to a decrease in price and fees. In equilibrium only users that are insensitive to payment delays remain (Hinzen, John, & Saleh, 2019).

This equilibrium is likely unstable. Forks have a positive probability of occurring and happen randomly. The more validators that are online the higher this probability becomes. Because forks happen randomly, there might be periods with little forks occurring. In these periods, demand and prices are higher than in periods where many forks occur. This randomness can cause price swings even in equilibrium.

PoS is seen as the biggest alternative to PoW. This is mainly because the PoW miners require an exorbitant amount of energy to operate. PoS is a lot friendlier to the environment, because it does not need computers to solve puzzles to update the block. As explained in the background section, PoS reaches consensus by randomly assigning a stakeholder to update the blockchain. Theories suggest that PoS also leads to consensus and is thus a good alternative to PoW (Saleh, 2021). Saleh (2021) also finds that PoS may lead to a more stable equilibrium than the equilibrium reached by PoW blockchains.

When a fork happens on a PoS blockchain stakeholders can ‘bet’ their coins on the valid block. If they choose the wrong block, they lose their bet (consensus, 2019). Saleh (2021) showed that in a well-functioning PoS blockchain, validators will follow a strategy that will lead to consensus being reached fast. As validators in a PoS blockchain are also stakeholders, they want to maximize the value of their coin holdings. Coins become more valuable as they are more easily exchanged, fast consensus is the basis for this. This will motivate validators to reach consensus quickly and vote on the right block, meaning forks will be resolved quickly.

There are different ways of calculating volatility. One study looks into the volatility of stablecoins (Grobys, Junttila, Kolari, & Sapkota, 2021). Stablecoins are cryptocurrencies which value is pegged or tied to another currency (Hayes, 2022). This study uses the following formula to calculate realized annual volatility:

$$\sigma_{i,t} = \sqrt{T}\sqrt{(\ln\left(\frac{HIGH_{i,t}}{CLOSE_{i,t}}\right) * \ln\left(\frac{HIGH_{i,t}}{OPEN_{i,t}}\right) + \ln\left(\frac{LOW_{i,t}}{CLOSE_{i,t}}\right) * \ln\left(\frac{LOW_{i,t}}{OPEN_{i,t}}\right))}$$

Where $OPEN_{i,t}$, $HIGH_{i,t}$, $LOW_{i,t}$ and $CLOSE_{i,t}$ represent the opening, highest, lowest and closing price of cryptocurrency i on day t. $T = 365$, because cryptocurrencies are traded 24/7. $\sigma_{i,t}$ denotes the realized annualized volatility of cryptocurrency i on day t. This method of calculating volatility is based on a different study that proves that this calculation provides unbiased results (Rogers & Satchell, 1991). This study mentions that a stock’s price can be expressed as exp $(\sigma B_t + ct)$, where B_t is a standard Brownian motion, σ is the unknown volatility and c is an unknown constant. If someone knows all the historic prices of the stock the standard deviation can be calculated from the quadratic variation. In reality someone only observes a stock’s price as a series of spaced times, for example hourly prices. The estimator used by Hayes(2022) is shown to be an unbiased estimator of volatility (Rogers & Satchell, 1991).

Another research measures realized volatility as the sum of the daily squared log returns from the month before (Liu & Tsyvinski, Risks and Returns of Cryptocurrency, 2018). The returns are calculated using the corresponding price data. Another way of modelling cryptocurrency volatility is by using different GARCH models (Chu, Chan, Nadarajah, & Osterrieder, 2017).

As mentioned in the introduction, a coin's volatility is influenced by more than that coin's consensus mechanism. A study looking into the macroeconomic factors influencing cryptocurrency volatility finds that Global Real Economic Activity (GREA), the Global Financial Stress Index (FSI) and the Chinese Economic Policy Uncertainty index (CEPU) can be used to forecast cryptocurrency volatility (Walther, Klein, & Bouri, 2019). This study uses a GARCH-MIDAS framework to forecast the cryptocurrency volatilities. The effect of CEPU on cryptocurrency volatility is confirmed by another study, which finds that CEPU is negatively correlated with volatility (Yen & Cheng, 2021). This can be explained by low uncertainty leading to investors having high trust in their fiat currencies, which decreases demand for cryptocurrencies. Furthermore when taking the effects of Covid-19 on cryptocurrency volatility into account, it is found that Covid-19 panic is positively correlated with cryptocurrency volatility (Umar & Gubareva, 2020). This research uses wavelet analyses to find coherence between moves of Covid-19 panic and cryptocurrency volatilities.

Research finds that size, momentum and volume all can be used in predicting cryptocurrency returns (Liu, Tsyvinski, & Wu, Common Risk Factors in Cryptocurrency, 2022). This is relevant because returns are related to volatility. For size the research finds that the coin's market cap, price and maximum price are statistically significant in predicting returns. For momentum the study finds that past weeks returns predict future returns. For volume only the coin's price multiplied by the daily trading volume is statistically significant in predicting returns. Liquidity is another factor that can influence volatility. Illiquid markets make it hard for buyers and sellers to buy and sell at market price. Research finds that a coin's price multiplied by the daily trading volume can successfully predict future returns. (Liu, Tsyvinski, & Wu, Common Risk Factors in Cryptocurrency, 2022).

Controlling for other influences of volatility is necessary to achieve unbiased results.

4. Data and methodology

In this chapter an explanation is given on how the research question will be answered and what data is used in this research. This research aims to give an empirical answer to the question whether or not different cryptocurrency consensus mechanisms lead to different price volatilities. To do this panel data on cryptocurrency daily price data is used. There are thousands of cryptocurrencies and not all can or should be included in this research. In this research the top 30 biggest cryptocurrencies by market cap on 06/07/2021 are included (CoinMarketCap, 2021). Most cryptocurrency price data included in this research runs until this date, so these were the biggest coins at that time. Adding more coins causes problems, because random influences that are hard to control for likely have a bigger effect on smaller coins than bigger coins. This is because bigger coins have a more diverse group of owners and well-established markets, making it harder to manipulate. Data availability also poses a problem when including more coins. Using the 30 biggest cryptocurrencies should provide enough data to make meaningful inferences on cryptocurrency's consensus mechanisms and their volatilities.

Stablecoins have been excluded from this research. The value of a stablecoin is relatively stable, because its value is often tied or pegged to a fiat currency. Therefore, including stablecoins in the regression is unnecessary and might distort results. Coins which use their own unique consensus mechanism or a combination of different consensus mechanisms, are excluded. This is done to keep the scope of this research on the more prominent consensus mechanisms which are used by numerous coins.

Most cryptocurrency daily price data is sourced from Kaggle (Rajkumar, 2021). Some coins are not included in the Kaggle dataset, for these coins Kraken and CoinGecko is used. For these coins the daily opening, highest, lowest and closing prices are sourced from Kraken (Kraken, 2022). This data is supplemented by the coin's daily market cap and trading volume which are sourced from the CoinGecko API (CoinGecko, 2022). Data on whether a coin's supply is capped is found on CoinMarketCap (CoinMarketCap, 2021). On the next page in table 1 is an overview of the coins included in this research and the dates for which price data is available.

Table 1
Coins included in this research

This table reports all the coins included in this research. For each coin the table shows the consensus mechanism the coin uses, the dates for which daily price data is available for this research, the launch date of the coin, whether the coin's supply is capped and where the data was sourced from.

Coin	Consensus mechanism	Dates	Launch date	Capped supply	Data source
Aave	PoW (CoinMarketCap, 2022)	06/10/2020 - 06/07/2021	11/2017 (Messari, 2020)	Yes	Kaggle
Bitcoin	PoW (Nakamoto, 2008)	27/12/2013 - 06/07/2021	03/01/2009 (Blockchain.com, 2022)	Yes	Kaggle
Bitcoin Cash	PoW (CoinMarketCap, 2022)	02/08/2017 - 31/03/2022	01/08/207 (Redman, 2017)	Yes	Kraken + CoinGecko
Cardano	PoS (Why Cardano, 2020)	02/10/2017 - 06/07/2021	27/09/2017 (Agapov, 2017)	Yes	Kaggle
Chainlink	PoS (CoinMarketCap, 2022)	21/09/2017 - 06/07/2021	19/09/2017 (CoinFi, 2022)	Yes	Kaggle
Dogecoin	Scrypt PoW (Lodder, 2021)	27/12/2013 - 06/07/2021	6/12/2013 (Blockchair, 2022)	No	Kaggle
EOS	DPoS (Larimer, 2018)	03/07/2017 - 06/07/2021	27/06/2017 (testzcrypto, 2017)	No	Kaggle
Ethereum	PoW (Buterin, Ethereum Whitepaper, 2014)	08/08/2015 - 06/07/2021	30/07/2015 (Etherscan, 2022)	No	Kaggle
Ethereum Classic	PoW (Beck, 2017)	27/07/2016 - 31/03/2022	20/07/2016 (Ethereum Classic, 2022)	Yes	Kraken + CoinGecko
Litecoin	Scrypt PoW (Lee, 2011)	27/12/2013 - 06/07/2021	07/10/2011 (Blockchair, 2022)	Yes	Kaggle

Table 1 (continued)

Coin	Consensus mechanism	Dates	Launch date	Capped supply	Data source
Monero	RandomX (CoinMarketCap, 2022)	22/05/2014 - 06/07/2021	18/04/2014 (Woo, 2018)	No	Kaggle
Polkadot	NPoS (WOOD, 2016)	02/09/2020 - 06/07/2021	26/05/2020 (Polkadot, 2021)	No	Kaggle
Polygon	PoS (Anurag, 2018)	17/05/2021 - 31/03/2022	10/2017 (CoinMarketCap, 2022)	Yes	Kraken + CoinGecko
Shiba Inu	PoW (CoinMarketCap, 2022)	30/11/2021 - 31/03/2022	08/2020 (CoinMarketCap, 2022)	Yes	Kraken + CoinGecko
TRON	DPoS (TRON DAO, 2018)	25/07/2018 - 06/07/2021	07/2017 (TRON DAO, 2018)	No	Kaggle
Uniswap	PoW (CoinMarketCap, 2022)	18/09/2020 - 06/07/2021	16/09/2020 (Uniswap, 2020)	Yes	Kaggle

As mentioned before, volatility is dependent on more than just a coin's consensus mechanism. Not controlling for these influences will cause bias in the results. Controlling for a coin's size, its liquidity and macroeconomic factors influencing volatility is necessary for unbiased results. The following control variables are included in the final regression:

- Market cap
- $Closing\ price * Volume$
- $Volume\ \div Market\ cap$
- Supply cap
- Global Real Economic Activity index (GREA)
- Financial Stress Index (FSI)
- Chinese Economic Policy Uncertainty index (CEPU)
- Covid-19 Panic index
- Time
- Age

Market cap is included to control for a coin's size. It is possible that bigger coins are more likely to use one type of consensus mechanism and are also less volatile. Therefore, to avoid bias, market cap needs to be controlled for. Research finds that for size three variables are effective at predicting returns: market cap, price and maximum price (Liu, Tsyvinski, & Wu, Common Risk Factors in Cryptocurrency, 2022). Only market cap is included, because price and maximum price are already included in the way volatility is calculated and are thus by definition correlated to volatility (see below). $Closing\ price * Volume$, $Volume\ \div Market\ cap$ and whether a coin's supply is capped are the variables used to control for a coin's liquidity. $Closing\ price * Volume$ is the variable Liu et al. (2022) finds successful in predicting future returns. Daily trading volume is also an indicator on a coin's liquidity. Bigger coins will have higher daily trading volumes, therefore volume is taken relative to a coin's market cap. Whether a coin's supply is capped is included, because for some coins only a limited number of coins will be created, which could also affect liquidity (less coins available). GREA, FSI and CEPU are included in the model, because research finds that these macroeconomic factors impact volatility (Walther, Klein, & Bouri, 2019). The Covid-19 Panic Index is also included, because a different study finds that Covid-19 Panic is another factor influencing volatility. Controlling for these macroeconomic factors avoids bias, because some coins could be more heavily influenced by macroeconomic events. These macroeconomic factors are likely somewhat correlated and thus might cause multicollinearity issues, which raises standard errors (Wooldridge, Introduction to Econometrics, 2015). However, research has proven that each variable included has a statistically significant effect on volatilities. Therefore, these variables will be included to avoid bias.

Time is controlled for to avoid spurious regression, where two variables falsely seem statistically correlated because they trend over time. Finally, age (number of days since a coin's launch) is included as the last control variable. PoW was the first consensus mechanism used by coins (Crypto.com, 2022). Thus, it is plausible that older coins are more likely to use PoW. If older coins also are less volatile this could cause bias in the model, therefore a coin's age is controlled for.

Monthly CEPU data is sourced from Economic Policy Uncertainty (Economic Policy Uncertainty, 2022). The index is measured by constructing a scaled frequency count of articles about economic policy uncertainty from the South China Morning Post. Monthly GREA data is received from the Federal Reserve Bank of Dallas (Federal Reserve Bank of Dallas, 2022). The index is expressed in percent deviations from the economic activity trend. Each date is matched to the CEPU and GREA index of the corresponding month. Data on the daily Financial Stress Index is sourced from the Office of Financial Research (Office of Financial Research, 2022). The FSI is constructed using the weighted average of 33 financial market variables, relative to their history. When the index is zero, financial stress is at normal levels. FSI data is only available on trading days, for the missing days the last known value was used. Finally, the daily Covid-19 Panic index is retrieved from the Coronavirus Media Monitor from Ravenpack (Ravenpack, 2022). The panic index can take a value between 0 and 100, where a value expresses the percentage of global news that is about Covid-19. The Covid-19 Panic index contains daily panic indexes starting from 01/01/2020. Before this date Covid-19 did either not exist or panic was very low, therefore these dates will be given an index of 0.

The literature showed different ways of measuring volatility. In this research realized annualized volatility is calculated in the following way:

$$\sigma_{i,t} = \sqrt{T}\sqrt{(\ln\left(\frac{HIGH_{i,t}}{CLOSE_{i,t}}\right) * \ln\left(\frac{HIGH_{i,t}}{OPEN_{i,t}}\right) + \ln\left(\frac{LOW_{i,t}}{CLOSE_{i,t}}\right) * \ln\left(\frac{LOW_{i,t}}{OPEN_{i,t}}\right))}$$

This estimation method is selected, because it gives an unbiased estimation of the realized volatility. Using daily squared log returns from the previous month means results can only be calculated from the second month onwards. Therefore, the method shown above will likely provide the best results. Data on cryptocurrency's opening, highest, lowest and closing prices is available.

To answer the research question a regression analysis will be performed. The literature shows multiple different empirical ways to estimate the influences on cryptocurrency volatility. One research uses a GARCH-MIDAS framework to identify the macroeconomic drivers of cryptocurrency volatility (Walther, Klein, & Bouri, 2019). A study looking into the effects of Covid-19 on cryptocurrency volatility uses a wavelet analyses (Umar & Gubareva, 2020). Cryptocurrency volatility can also be modeled using GARCH models (Chu, Chan, Nadarajah, & Osterrieder, 2017).

These estimation techniques are effective at finding good fitting models, which can then be used to forecast volatility. The goal of this research is not to find a model to forecast cryptocurrency volatility, but to find whether a cryptocurrency's consensus mechanism has an impact on volatility. Therefore, these more complex estimation techniques are not needed. To find the effect of a coin's consensus mechanism on price volatility this research will use a Random Effects estimator. The Fixed Effects, First Differences and Instrumental Variables estimators get rid of the individual specific effect (Wooldridge, Introduction to Econometrics, 2015). They cannot be used in this research, because the coefficient on the consensus mechanisms will not be estimated. Pooled OLS is most efficient when tracking a different coin for each day, which is not the case in this dataset (Wooldridge, Introduction to Econometrics, 2015). For these reasons the Random Effects estimator is the most suitable estimator to estimate the following model:

$$volatility_{i,t} = \beta_0 + \beta_1 npos_i + \beta_2\, dpos_i + \beta_3 pos_i + \beta_4 scryptpow_i + \beta_5 randomxpow_i + \beta_6 marketcap_{i,t} + \beta_7(closingprice_{i,t} * volume_{i,t}) + \beta_8(volume_{i,t} \div marketcap_{i,t}) + \beta_9 supplycap_i + \beta_{10} grea_t + \beta_{11} fsi_t + \beta_{12} cepu_t + \beta_{13} covid19panic_t + \beta_{14} time + \beta_{15} age_{i,t} + u_{i,t}$$

In the model PoW is used as the reference category.

To answer the research question multiple hypotheses are formulated, to test whether each consensus mechanism included in the research has a significant effect on price volatility. The first hypothesis tests whether the cryptocurrency consensus mechanisms jointly have a statistically significantly different price volatility than PoW.

Hypothesis 1:
Jointly the price volatilities of the consensus mechanisms are statistically significantly different than PoW
H0: $\beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = 0$
H1: H0 is not true

If the null hypotheses holds this means that jointly these consensus mechanisms do not have a statistically significantly different price volatility than PoW. The theories suggest that PoS has a more stable equilibrium than PoW (Alsabah and Capponi, 2020; Hinzen et al., 2019; Saleh, 2021). Because 3 of the 5 consensus mechanisms included are consensus mechanisms based on PoS it is expected that the null hypotheses can be rejected.

Next it is tested whether each individual consensus mechanism has a statistically significantly different effect on price volatility than PoW. This is tested with the following hypotheses:

Hypothesis 2:
NPoS has a statistically significant lower average price volatility than PoW
H0: $\beta_1 \geq 0$
H1: $\beta_1 < 0$

Hypothesis 3:
DPoS has a statistically significant lower average price volatility than PoW
H0: $\beta_2 \geq 0$
H1: $\beta_2 < 0$

Hypothesis 4:
PoS has a statistically significant lower average price volatility than PoW
H0: $\beta_3 \geq 0$
H1: $\beta_3 < 0$

Hypothesis 5:
Scrypt PoW does not have a statistically significantly different effect on price volatility than PoW
H0: $\beta_4 = 0$
H1: $\beta_4 \neq 0$

Hypothesis 6:
RandomX does not have a statistically significantly different effect on price volatility than PoW
H0: $\beta_5 = 0$
H1: $\beta_5 \neq 0$

If one of these null hypotheses holds this means that the corresponding consensus mechanism does not have a statistically significantly different effect on price volatility than Proof of Work. If the null hypotheses is rejected this means that the corresponding consensus mechanism does have a statistically significantly different effect.

For β_1, β_2 and β_3 a negative sign is expected. A negative sign indicates that these consensus mechanisms (NPoS, DPoS and PoS), on average have lower volatility than PoW, all else equal. These expectations stem from the theories that suggest that high volatilities might be the equilibrium outcome of the PoW consensus mechanism (Alsabah and Capponi, 2020; Hinzen et al., 2019; Saleh, 2021). Saleh (2021) theorizes that PoS might have a more stable equilibrium. Therefore, a negative sign is expected.

For β_4 and β_5 it is expected that the null hypotheses cannot be rejected. Scrypt PoW and RandomX PoW improve on some aspects of the PoW consensus mechanism, but they do not improve on the mechanisms that makes PoW an unstable consensus mechanism. If transactions increase, so will fees and therefore the number of validators. With more validators online, forks are more likely to happen which causes payment delays and drives people away from the network.

The research question can be answered by either rejecting or not rejecting these null hypotheses.

5. Results

This chapter will go over the results from this research. The first paragraph contains important descriptive statistics, the second paragraph contains the actual regressions.

5.1 Descriptive statistics

In the final database (gathered from Kaggle, Kraken and CoinGecko), there are 23,400 coin-day observations. The database contains information on 16 different cryptocurrencies. Some descriptive statistics of the consensus mechanisms included in the database are summarized below:

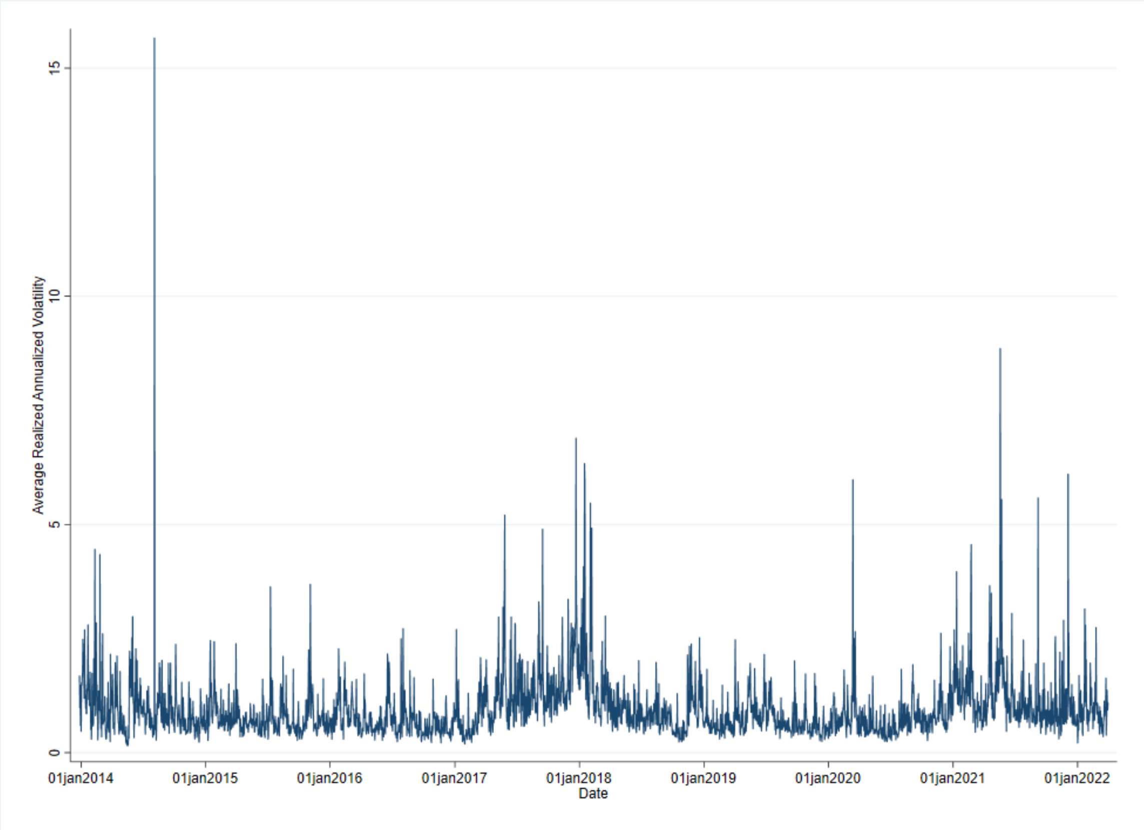
Table 2
Descriptive statistics of the consensus mechanisms

This table reports descriptive statistics for the consensus mechanisms included in this research. It reports the number of coins included per consensus mechanism, the average volatility for coins using that consensus mechanism and the average closing price in USD for coins using that consensus mechanism. The total for average volatility and average closing price denotes the average volatility and closing price for all the coins.

Consensus Mechanism	Number of coins in database	Average volatility	Average closing price (USD)
PoW	7	0.91	2331.32
PoS	3	1.19	3.12
Scrypt	2	0.84	26.54
DPoS	2	0.92	2.68
NPoS	1	1.32	18.64
RandomX	1	1.08	74.13
Total	16	0.96	949.05

These statistics show that NPoS has the highest volatility on average, while Scrypt has the lowest. PoW has the highest average closing price, while DPoS has the lowest. In graph 1 the average realized annualized volatility for all the cryptocurrencies is visible.

Graph 1
Average volatility



This graph reports the average annualized volatility of all coins included in this research.

The huge spike in average volatility happens on 04/08/2014. The spike is caused by Monero which has a realized annualized volatility of 55 on that day. The opening and closing price of Monero on that day were around $2, while the highest price was $37.78, explaining the high volatility. This is not an incorrect value in the dataset, because other services reporting historical price data also show this huge increase in highest price (CoinLore, 2022). Therefore, it is not needed to remove this observation from the dataset. It is not clear what could have caused the big spike of Monero's highest price that day. Table 3 shows summary statistics for the other important variables.

Table 3
Descriptive statistics key variables

This table reports descriptive statistics for key control variables included in the model. A variable's mean, standard deviation, lowest observation and highest observation are reported.

Variable	Mean	Standard Deviation	Min	Max
Daily trading volume	2.89 billion	8.56 billion	7,900	351 billion
Market cap (in USD)	22.4 billion	87.8 billion	1,279,606	1,190 billion
Chinese Economic Policy Uncertainty index	522.3	251.30	66	970
Global Real Economic Activity index	-27.8	48.65	-162	108
Covid-19 Panic index	0.85	1.41	0	9.21
Financial Stress Index	-2.06	2.01	-4.36	10.27
Volatilty	0.96	0.97	0	54.54
Supply cap (1=supply is capped)	0.62	0.49	0	1

The statics show that the average daily trading volume is 2.89 billion and the average market cap is 22.4 billion. The average macroeconomic factors are averages for the dates included in this research. The CEPU average is 522.3, meaning that on average the monthly scaled frequency count of articles on economic policy uncertainty was 522.3. For GREA the average is -27.8, this means that on average monthly Global Real Economic Activity was 27.8% lower than the trend. The Covid-19 Panic index has an average value of 0.85, meaning that on average 0.85% of global news was about Covid-19. FSI has an average value of -2.06, signifying that on average Financial Stress was below normal levels. 62% of the coins included in the database had a capped supply.

5.2 Multiple Regression Analysis

The next step is performing multiple regression analysis to find the relationship between a coin's volatility and its consensus mechanism. As mentioned in the methodology, these regressions will be performed using a Random Effects regression. This regression is estimated with robust standard errors as there is likely heteroskedasticity present in the model. Using robust standard errors significantly changes the standard errors pointing to heteroskedasticity. By using robust standard errors hypotheses tests can still be conducted. No evidence of first order serial correlation is found when testing for this. Control variables are added in groups to show the changes in coefficients and standard errors as more control variables are added. The results are found in table 4.

Table 4
Random Effects regression

This table reports the results of the Random Effects regression of volatility on the consensus mechanisms and control variables. The number of observations is 23,400. First no control variables are added and volatility is regressed on just the consensus mechanisms. Then in each following column one group of control variables is added to the previous model. Robust standard error are reported in parentheses. */**/*** indicate significance at 10%/5%/1% level.

Variable	No control variables	Size	Liquidity	Macroeconomic factors	Age and Time
NPoS	0.192 (0.14)	0.206 (0.15)	0.333*** (0.13)	0.263* (0.15)	-0.043 (0.08)
DPoS	-0.221 (0.15)	-0.197 (0.15)	-0.204 (0.13)	-0.151 (0.12)	-0.197*** (0.04)
PoS	0.114 (0.17)	0.134 (0.17)	0.146 (0.17)	0.230 (0.14)	0.175* (0.09)
Scrypt	-0.291* (0.16)	-0.267 (0.17)	-0.208 (0.18)	-0.248 (0.17)	0.068 (0.05)
RandomX	-0.048 (0.14)	-0.023 (0.14)	0.115 (0.12)	0.081 (0.11)	0.269*** (0.04)
Market cap (in $100 billions)	-	0.066*** (0.02)	0.080 (0.06)	0.051* (0.03)	0.059 (0.04)
$Closing\ price * Volume$ (in $100 trillions)	-	-	-0.005 (0.01)	0.002 (0.01)	0.002 (0.01)
$\frac{Volume}{Market\ cap}$	-	-	0.181** (0.08)	0.425*** (0.14)	0.410*** (0.12)

Table 4 (continued)

Variable	No control variables	Size	Liquidity	Macroeconomic factors	Age and Time
Supply cap	-	-	0.118 (0.13)	0.028 (0.13)	0.007 (0.08)
Global Real Economic Activity	-	-	-	0.002** (0.001)	0.002*** (0.001)
Financial Stress Index	-	-	-	-0.016 (0.01)	-0.023** (0.01)
Chinese Economic Policy Uncertainty	-	-	-	-0.001*** (0.0001)	-0.001*** (0.0001)
Covid-19 Panic	-	-	-	0.001 (0.02)	0.018 (0.03)
Age	-	-	-	-	-0.0002*** (0.00004)
Time	-	-	-	-	0.0002*** (0.0001)
Constant	1.132 (0.14)	1.106 (0.14)	0.951 (0.12)	1.507 (0.13)	-2.109 (1.10)

When no control variables are included Scrypt is found to be statistically significant at 10%. The sign is as expected when looking at table 1 and the average volatilities of each consensus mechanism. The negative sign means that Scrypt has a lower average volatility than PoW.

As a first step a coin's size is controlled for by adding a coin's market cap as a control variable. With size controlled for, none of the consensus mechanisms are statistically significant, market cap itself is however statistically significant at 1%. Market cap seems to have a positive effect on volatility. One would expect lower volatility for bigger coins. This could be caused by macroeconomic factors which are not controlled for yet. Bigger coins could be hit harder by macroeconomic changes and therefore seem more volatile.

Next liquidity will be controlled for by adding the following 3 variables to the model: $Closing\ Price * Volume$, $Volume \div Market\ cap$ and whether a coin's supply is capped. More liquid coins are likely to be less volatile. In this regression NPoS is now statistically significant at 1%. The sign of NPoS is positive, meaning that, on average NPoS has a higher volatility than PoW, all else equal. $Volume \div Market\ cap$ is also found to have a statistically significant positive effect on volatility. It seems that volume has a positive effect on volatility. Research finds that higher trading volume can be positively correlated with volatility (Hrdlicka, 2021). This is because a change in an asset's perceived risk leads to investors looking to rebalance their portfolio. This means that assets with fluctuating risks can have higher trading volumes.

The next step is controlling for macroeconomic factors. This is done by adding the following control variables to the model: the Global Real Economic Activity index (GREA), the Covid-19 Panic index, the Financial Stress Index (FSI) and the Chinese Economic Policy Uncertainty index (CEPU). NPoS is now only statistically significant at 10% with a positive sign. Market cap is marginally statistically significant at 10% and has a positive sign. $Volume \div Market\ cap$ is significant at 1% and has a positive sign. GREA is significant at 5% with a positive sign, meaning that a higher Global Real Economic Activity index score leads to higher cryptocurrency volatilities, all else equal. Finally CEPU is statistically significant at 1%, with a negative sign, this is consistent with what was found in the literature.

Finally, age and time are added as the final control variables. DPoS, RandomX, $Volume \div Market\ cap$, GREA, CEPU, age and time are now all statistically significant at 1%. FSI is statistically significant at 5% and PoS at 10%. A cryptocurrency using DPoS has, on an average day, 20 percentage points lower realized annualized volatility (based on how much a coin's price fluctuated that given day) than coins using PoW, all else equal. The negative sign is in line with hypothesis 3. A cryptocurrency using PoS has, on an average day, 18 percentage points higher realized annual volatility than coins using PoW, all else equal. In hypothesis 4 a negative sign for PoS was hypothesized. Coins using RandomX have, on an average day, 27 percentage points more volatility than coins using PoW, all else equal. In hypothesis 6, an insignificant coefficient was hypothesized. The insignificant coefficient of Scrypt PoW is in line with what was hypothesized in hypothesis 5. Hypothesis 2 hypothesized that NPoS would have a statistically significant negative sign, however the null hypothesis that NPoS has a positive sign cannot be rejected.

If a cryptocurrency's $Volume \div Market\ cap$ increases by 1 a coin's volatility is, on an average day, 41 percentage points higher, all else equal. $Volume \div Market\ cap$ can increase by 1 if, for example daily trading volume increases by $1 * Market\ cap$ while market cap remains equal. If the GREA index increases by 1 a coin's average realized annualized volatility increases by 0.2 percentage points, all else equal. If the FSI increases by 1 a coin's average realized annualized volatility decreases by 2.3 percentage points, all else equal. When the CEPU index increases by 1, a coin's average realized annualized volatility decreases by 0.1 percentage points, all else equal.

When a coin becomes 1 day older, that coin's average realized annualized volatility decreases by 0.02 percentage points, all else equal. As 1 day passes a coin's average realized annualized volatility increases by 0.02 percentage points, all else equal. Thus, it seems that a coin's volatility increases over time, but decreases as a coin becomes older.

To test for the joint significance of the consensus mechanisms (hypothesis 1) an F-test is conducted. At 1% significance the null hypothesis can be rejected, meaning that jointly these consensus mechanisms do have a statistically significantly different price volatility than PoW.

The null hypotheses of hypotheses 2, 4 and 6 cannot be rejected. An explanation for this is that Bitcoin and Ethereum (the 2 biggest cryptocurrencies) are weighing down PoW volatility. This could be because Bitcoin and Ethereum have higher adoption than all other currencies or because they are more famous. Adoption can be measured by the number of wallets holding a coin and fame can be measured by the number of social media mentions a coin gets.

Unfortunately, finding historical data on the number of social media mentions a coin gets is very hard. The same goes for historical data on the number of wallets that hold a cryptocurrency. Because of the limited time available for this research these variables cannot be constructed. Some of these effects are already controlled for by including market cap, because adoption and fame are likely positively correlated with market cap. But not including these variables can still cause a negative bias on the volatility of PoW coins. Adoption and fame are likely negatively correlated with volatility and positively correlated with PoW. To solve this issue another regression has been performed, now without Bitcoin and Ethereum. This should reduce the bias, because the remaining cryptocurrencies are more similar in terms of adoption and fame. This leads to the final regression found in table 5 on the next page.

Table 5
Random Effects regression excluding Bitcoin and Ethereum

This table reports the Random Effects regression of volatility on the consensus mechanisms and control variables, excluding Bitcoin and Ethereum. The number of observations is 18,491. First no control variables are added and volatility is regressed on just the consensus mechanisms. Then in each following column one group of control variables is added to the previous model. Robust standard error are reported in parentheses. */**/*** indicate significance at 10%/5%/1% level.

Variable	No control variables	Size	Liquidity	Macroeconomic factors	Age and Time
NPoS	0.009 (0.10)	-0.249* (0.13)	-0.262 (0.17)	-0.158 (0.14)	-0.284*** (0.10)
DPoS	-0.403*** (0.11)	-0.287** (0.14)	-0.350** (0.17)	-0.248** (0.10)	-0.214*** (0.05)
PoS	-0.071 (0.14)	-0.055** (0.16)	0.014 (0.16)	0.199** (0.11)	0.177 (0.11)
Scrypt PoW	-0.473*** (0.13)	-0.342** (0.16)	-0.348** (0.16)	-0.382*** (0.07)	0.050 (0.14)
RandomX	-0.231** (0.10)	-0.067 (0.14)	-0.098 (0.16)	-0.157** (0.07)	0.223* (0.13)
Market cap (in \$100 billions)	-	2.646*** (0.48)	2.462*** (0.43)	1.290** (0.56)	1.412** (0.56)
$Closing\ price * Volume$ (in \$100 trillions)	-	-	8.048*** (2.70)	2.834 (2.34)	3.026 (2.18)
$\frac{Volume}{Market\ cap}$	-	-	0.178** (0.08)	0.398*** (0.13)	0.428*** (0.14)

Table 5 (continued)

Variable	No control variables	Size	Liquidity	Macroeconomic factors	Age and Time
Supply cap	-	-	-0.095 (0.11)	-0.210*** (0.08)	-0.081 (0.05)
Global Real Economic Activity	-	-	-	0.001* (0.001)	0.002*** (0.001)
Financial Stress Index	-	-	-	-0.027** (0.01)	-0.037*** (0.01)
Chinese Economic Policy Uncertainty	-	-	-	-0.001*** (0.0001)	-0.001*** (0.0002)
Covid-19 Panic	-	-	-	0.005 (0.02)	0.031 (0.04)
Age	-	-	-	-	-0.0002*** (0.0001)
Time	-	-	-	-	0.0001 (0.0001)
Constant	1.314 (0.10)	1.118 (0.14)	1.133 (0.16)	1.702 (0.10)	-0.389 2.40

NPoS and DPoS are now statistically significant at 1% with negative signs. This is in line with what was hypothesized in hypothesis 2 and 3. Coins using NPoS on an average day have 28 percentage points lower realized annualized volatility than coins using PoW, all else equal. The same goes for coins using DPoS which on an average day have 21 percentage points lower realized annualized volatility than coins using PoW, all else equal. RandomX is marginally statistically significant at 10%. Coins using RandomX have on an average day 22 percentage points higher realized annualized volatility than cryptocurrencies using PoW, all else equal. PoS and Scrypt are found to be statistically insignificant.

One possible explanation for the insignificance of PoS could be that PoS does not actually solve the issues PoW faces. As mentioned in the literature review forks are theorized to be resolved quicker in blockchains using PoS (Saleh, 2021). But PoS blockchains can still face the problem that an increase in demand eventually leads to payment delays. Increased demand leads to increased fees. These higher fees will motivate more validators to come online, which increases the probability of forks. These forks will be resolved quicker than for PoW blockchains so demand might keep growing for a while. But as demand keeps growing so will the number of forks and at some point these forks might still cause too many payment delays, which causes users to leave the network. The equilibrium outcome, might still be unstable. DPoS and NPoS blockchains do not face this problem, because validators are chosen by the stakers (Binance Academy, 2021) (Polkadot, 2022). This is in line with a theory regarding the scalability trilemma (Buterin, Why sharding is great: demystifying the technical properties, 2021). The scalability trilemma says that there are three desirable properties a blockchain wants. The properties are a blockchain that is: scalable, decentralized and secure. The theory suggests that cryptocurrencies can only easily achieve two of the three desirable properties. DPoS and NPoS blockchains are less decentralized than PoW and PoS blockchains, because validators are chosen and not everybody can instantly become a validator. Because these blockchains are less decentralized they might be more scalable. In the regression evidence for this is found, because DPoS and NPoS seem to have a more stable equilibrium with lower volatilities than PoW and PoS.

To test for the joint statistical significance of the consensus mechanisms another F-test is performed. At 1% significance the null hypothesis can be rejected, meaning that jointly these consensus mechanisms do have a statistically significantly different price volatility than PoW.

Market cap is now statistically significant at 5% with a positive sign. If a coin’s market cap increases by 100 billion, then on average that coin’s average realized annualized volatility increases by 141 percentage points, all else equal. Messari (2019) finds that a coin’s market cap is generally inversely related to volatility. This is also what makes sense theoretically as bigger coins are likely to be less volatile, because their markets are better established and harder to manipulate. For this research only the top 30 coins by market cap are considered. The coin with the lowest market cap included in the regression still has a market cap of 3.3 billion. It could be that at a certain cutoff point market cap starts to matter less. When Bitcoin and Ethereum are included in the regression market cap is also found to be insignificant. Coins with small market caps will be a lot more volatile, but after a certain point the effect might get a lot smaller. An explanation for the positive sign is that in the final regression Polkadot is one of the coins with the highest market caps, while also showing one of the highest volatilities. Market cap is still controlled for, because theoretically it is logical to assume that market cap influences volatility. This is also confirmed by research done on the subject (Messari, 2019). FSI is still statistically significant with a negative sign, but now at 1%. When the FSI rises by 1, cryptocurrency average realized annualized volatility decreases by 3.7 percentage points, all else equal. If $Volume \div Market\ cap$ increases by 1, cryptocurrency average realized annualized volatility increases by 42.8 percentage points, all else equal. The effects of GREA, CEPU and age remain the same. Time is now no longer statistically significant, meaning a coin's volatility is not trending over time, all else equal.

With these results the null hypotheses of hypotheses 1, 2 and 3 can be rejected at 1% significance. The null hypothesis of hypothesis 6 can be rejected at 10% significance. For hypotheses 1,2 and 3 this was what was hypothesized. Hypotheses 4 and 5 cannot be rejected.

To test for the robustness of the model two robustness checks will be performed. The first robustness check will drop PoW coins from the dataset one by one to see how long results will hold. Coins with the shortest time span will be dropped first. When Shiba Inu is dropped as the first coin the results on the consensus mechanisms remain the same. When Aave is dropped as the second coin results are still very similar. NPoS is now only statistically significant at 5% and RandomX is now no longer statistically significant at 10%. PoS is now also statistically significant at 10% with a positive sign. Uniswap is dropped as the third coin. NPoS is now only statistically significant at 10%. At last Bitcoin Cash was dropped, leaving Ethereum Classic as the last remaining PoW coin. After dropping Bitcoin Cash NPoS is now statistically significant at 1% again. PoS is no longer statistically significant, while Scrypt is statistically significant at 5% and RandomX is statistically significant at 1%.

The signs of DPoS and NPoS do not change when doing this robustness check. DPoS remains statistically significant at 1%, while NPoS was, at its 'worst', statistically significant at 10%. In the last regression Scrypt and RandomX were now both statistically significant at 5% and 10% respectively. Both coefficients had positive signs. During the robustness check none of the consensus mechanism's coefficients changed signs, but the standard errors did fluctuate. For the full results please refer to Appendix Table 1.

For the second robustness check, outliers are removed from the dataset. When volatility is higher than 5 that observation is dropped from the dataset. 5 is chosen as the limit, because in graph 1 it can be seen that the average annualized volatility of all the coins included in the dataset is only very sporadically above 5. This removes 173 observations from the dataset. These new results are very similar to the results shown in table 5. NPoS and DPoS are still statistically significant at 1% with negative signs and PoS and Scrypt are still not statistically significant. For the consensus mechanisms the only difference is that RandomX is now statistically significant at 5% instead of 10%. For the full results please refer to Appendix Table 2.

The model is robust, because there are no major differences that occur when dropping the variables one by one or when dropping outliers. However, adding more cryptocurrencies to the database will likely increase robustness and decrease standard error fluctuations. No more cryptocurrencies were added in this research, because of data availability and time constraints.

6. Discussion and conclusion

This paper aimed to investigate the relationship between a cryptocurrency's consensus mechanism and its price volatilities. Theories suggest that the equilibrium outcome of PoW might be unstable (Alsabah and Capponi, 2020; Hinzen et al., 2019; Saleh, 2021). This study tests this theory by giving an empirical answer to the following research question:

'Does a cryptocurrency's consensus mechanism impact its price volatility?'

The following 6 hypotheses are created to help answering this research question:

Hypothesis 1:
Jointly the price volatilities of the consensus mechanisms are statistically significantly different than PoW
H0: $\beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = 0$
H1: H0 is not true

Hypothesis 2:
NPoS has a statistically significant lower average price volatility than PoW
H0: $\beta_1 \geq 0$
H1: $\beta_1 < 0$

Hypothesis 3:
DPoS has a statistically significant lower average price volatility than PoW
H0: $\beta_2 \geq 0$
H1: $\beta_2 < 0$

Hypothesis 4:
PoS has a statistically significant lower average price volatility than PoW
H0: $\beta_3 \geq 0$
H1: $\beta_3 < 0$

Hypothesis 5:
Scrypt PoW does not have a statistically significantly different effect on price volatility than PoW
H0: $\beta_4 = 0$
H1: $\beta_4 \neq 0$

Hypothesis 6:
RandomX does not have a statistically significantly different effect on price volatility than PoW
H0: $\beta_5 = 0$
H1: $\beta_5 \neq 0$

By performing a Random Effects regression the null hypotheses for hypotheses 1, 2, 3 can be rejected at 1% significance. This means that NPoS and DPoS have statistically significantly different average realized annualized volatilities than PoW. On an average day a coin using NPoS has 28.4 percentage points lower realized annualized volatility than a coin using PoW, all else equal. A coin using DPoS has, on an average day, 21.4 percentage points lower realized annualized volatility than a coin using PoW, all else equal. Jointly the price volatilities of the consensus mechanisms are also statistically significantly different than

PoW. RandomX only has a marginally statistically significantly different average realized annualized volatility than PoW at 10%. On an average day a coin using RandomX has 22.3 percentage points higher realized annualized volatility than a coin using PoW all else equal. One study by Saleh (2021) theorizes that PoS has a lower average price volatility than PoW, but no evidence is found. This could be explained by that PoS blockchains still face the same problems PoW blockchains do.

This is in line with the scalability trilemma proposed by Buterin (2021). The trilemma says that scalability can only easily be achieved by sacrificing either security or decentralization. PoS blockchains do not sacrifice on security or decentralization and thus have trouble achieving scalability. This is the same problem PoW blockchains face, where an increase in demand eventually leads to higher fees and more validators coming online. This increase in the number of validators increases the chances of a fork happening. When a fork happens payment delays occur, which drives users away from the network. This increase and decrease in demand is paired with an increase and decrease in prices. Forks have a positive probability of occurring and happen randomly. The more validators that come online the higher this probability becomes. Because forks happen randomly, there might be long periods where no forks happen. In these periods, demand and prices are higher than in periods where many forks occur. This randomness can cause price swings even in equilibrium. Saleh (2021) theorizes that forks in PoS blockchains will be resolved quicker than forks in PoW blockchains. But as demand keeps rising payment delays might still occur because the number of forks gets too big. Thus leading to an unstable equilibrium even for PoS blockchains.

In NPoS and DPoS blockchains validators are chosen (Binance Academy, 2021) (Polkadot, 2022). This means that these blockchains are less decentralized than a PoS and PoW blockchain, but they are likely more scalable. In the regression NPoS and DPoS blockchains show lower price volatilities than PoW and PoS blockchains. This points towards that NPoS and DPoS blockchains are more scalable, because these blockchains have a more stable equilibrium.

To answer the research question, a cryptocurrency's consensus mechanism does impact its price volatility. When using a 1% significance level evidence for this is found when rejecting the null hypotheses for hypotheses 1, 2 and 3. No evidence is found that PoS has lower average volatility than PoW.

This information helps investors to better manage their risk and portfolio and it helps coin creators to select the right consensus mechanism for their goals. NPoS and DPoS blockchains are not only more stable, but also more environmentally friendly, because they do not require the computational arms race PoW does. Therefore, society also benefits if more coins use these consensus mechanisms instead of PoW.

Future research might try including more coins and consensus mechanisms in the regression. This might give a broader overview of the different consensus mechanisms and their relationship with price volatilities. Including more coins also helps making results more robust, because a bigger sample size is used for each consensus mechanism. Future research might also try including fame and adoption as control variables, so Bitcoin and Ethereum can be included in the regression.

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Appendix

Appendix Table 1
Dropping PoW coins

This table reports the results of the first robustness test, when one by one PoW coins are dropped from the dataset. Each column denotes that coin and the previous coins being dropped from the dataset. Robust standard error are reported in parentheses. */**/*** indicate significance at 10%/5%/1% level.

Variable	Shiba Inu Observations = 18,369	Aave Observations = 18,095	Uniswap Observations = 17,803	Bitcoin Cash Observations = 16,100
NPoS	-0.302*** (0.11)	-0.249** (0.10)	-0.263* (0.14)	-0.531*** (0.12)
DpoS	-0.214*** (0.05)	-0.185*** (0.05)	-0.185*** (0.05)	-0.260*** (0.02)
PoS	0.168 (0.11)	0.210* (0.11)	0.200* (0.12)	0.053 (0.12)
Scrypt PoW	0.088 (0.16)	0.075 (0.18)	0.075 (0.32)	0.335** (0.16)
RandomX PoW	0.254* (0.15)	0.249 (0.17)	0.247 (0.29)	0.450*** (0.16)
Market cap (in $100 billions)	1.430** (0.56)	1.548*** (0.56)	1.569*** (0.57)	1.364** (0.67)
Closing price x Volume (in $100 trillions)	2.859 (2.18)	3.169 (2.08)	3.117 (2.28)	30.821** (15.40)
Volume / Market cap	0.427*** (0.14)	0.444*** (0.14)	0.423*** (0.15)	0.389** (0.17)

Appendix Table 1 (continued)

Variable	Shiba Inu Observations = 18,369	Aave Observations = 18,095	Uniswap Observations = 17,803	Bitcoin Cash Observations = 16,100
Supply cap	-0.069 (0.05)	-0.086 (0.05)	-0.082 (0.08)	0.004 (0.02)
Global Real Economic Activity	0.002*** (0.001)	0.002*** (0.001)	0.002*** (0.001)	0.002*** (0.001)
Financial Stress Index	-0.036*** (0.01)	-0.031*** (0.01)	-0.031*** (0.01)	-0.027** (0.01)
Chinese Economic Policy Uncertainty	-0.001*** (0.0002)	-0.001*** (0.0002)	-0.001*** (0.0002)	-0.001*** (0.0002)
Covid-19 Panic	0.029 (0.04)	0.019 (0.04)	0.021 (0.04)	0.016 (0.04)
Age	-0.0003*** (0.0001)	-0.0002*** (0.0001)	-0.0002* (0.0001)	-0.0005*** (0.00004)
t	0.0001 (0.0001)	0.0001 (0.0001)	0.0001 (0.0002)	0.0003*** (0.0001)
Constant	-0.918 (2.76)	-0.395 (2.76)	-0.471 (4.67)	-5.502 (2.73)

Appendix Table 2
Dropping observations with volatility over 5

This table reports the regression results when all the observations with a realized annualized volatility of over 5 are dropped. Robust standard error are reported in parentheses. */**/*** indicate significance at 10%/5%/1% level.

Variable	Coefficient Observations = 18,318
NPoS	-0.207***
	(0.08)
DPoS	-0.169***
	(0.04)
PoS	0.121
	(0.10)
Scrypt PoW	0.052
	(0.10)
RandomX PoW	0.210**
	(0.10)
Market cap (in $100 billions)	0.952**
	(0.38)
Closing price x Volume (in $100 trillions)	1.885
	(1.69)
Volume / Market cap	0.307***
	(0.10)
Supply cap	-0.039
	(0.04)
Global Real Economic Activity	0.001***
	(0.0005)
Financial Stress Index	-0.030***
	(0.01)
Chinese Economic Policy Uncertainty	-0.001***
	(0.0001)
Covid-19 Panic	0.017
	(0.02)
Age	-0.0002***
	(0.00004)
t	0.0001*
	(0.0001)
Constant	-1.544
	(1.60)