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Are cryptocurrencies homogeneous?

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Abstract

This article investigates if cryptocurrencies returns' are similarly affected by a selection of demand- and supply-side determinants. Homogeneity among cryptocurrencies is tested via a least absolute shrinkage and selection operator (LASSO) model where determinants of Bitcoin returns are applied to a sample of 12 cryptocurrencies. The analysis goes beyond existing research by simultaneously covering different periods and design choices of cryptocurrencies. The results show that cryptocurrencies are heterogeneous, apart from some similarities in the impact of technical determinants and cybercrime. The cryptocurrency market displays evidence of substitution effects, and design choices related explain the impact of the determinants of return.

KEYWORDS

bitcoin, cryptocurrencies, decentralised virtual currencies, homogeneity, LASSO

JEL CLASSIFICATION

E42, G12

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1 | INTRODUCTION

Cryptocurrencies are fiat currencies that differ from traditional currencies in that they do not have a commodity-backed value, no central authority guarantees their value, and the rules governing their supply are determined before their initial launch (European Central Bank [ECB], 2012).[1] This implies that cryptocurrencies are fixed currencies with no room for monetary policy (Gandal & Halaburda, 2014). The demand for a cryptocurrency is therefore mainly driven by its value in future exchanges (Bouri et al., 2017; Kristoufek, 2013).

Similar to a traditional fiat currency, the more users a cryptocurrency has, the easier it is to exchange the cryptocurrency for goods and services (Bouri et al., 2017; Kristoufek, 2013). When a cryptocurrency becomes more popular, its demand increases, which can further increase its popularity through network effects (Gandal & Halaburda, 2014). This suggests a movement towards one or a few strong cryptocurrencies and that newcomers will often try to distinguish themselves to gain an edge on the competition (Gandal & Halaburda, 2014).

These patterns characterise the cryptocurrency market. Bitcoin (BTC), by far the most well-known cryptocurrency, indeed accounts for more than half of the total market capitalisation of all cryptocurrencies.[2] However, there is also considerable diversity across the cryptocurrency market in terms of design choices and even the ultimate purpose of establishing cryptocurrencies (Burnie, 2018). For example, some cryptocurrencies specifically address the technical shortcomings of BTC, for example, by increasing transaction flows or offering a higher level of anonymity (Foley et al., 2019; Østbye, 2018). Despite this diversity, most of the theoretical and empirical research is focused on BTC, and only a limited set of studies distinguishes between different cryptocurrencies (Corbet et al., 2018). This leads to a lack of understanding of the cryptocurrency market, which, in turn, can inhibit the ongoing debate on the social contribution, economic advantages and risks, and potential need for regulation of cryptocurrencies.

The overarching aims of this article are to evaluate whether cryptocurrencies are homogeneous in terms of how various demand- and supply-related determinants influence their returns and to understand the sources of potential heterogeneity. This study thereby contributes to the extensive literature on price discovery across markets and exchanges, as well as the more specific literature on cryptocurrencies' connectedness in terms of prices and volatility (Corbet et al., 2018; Giudici & Abu-Hashish, 2019; Giudici & Polinesi, 2021; Koutmos, 2018; Pagnottoni & Dimpfl, 2019; Pieters & Vivanco, 2017; Yi et al., 2018). The latter suggests a dynamic and growing connectedness between cryptocurrencies. Ciaian et al. (2018) also show that, while cryptocurrency prices are interrelated, they appear to be independent of exogenous factors. This latter point is corroborated by Brière et al. (2015), Corbet et al. (2018) and Dyhrberg (2016), who show that BTC displays hedging capabilities in relation to traditional financial assets. These hedging capabilities are found to be particularly prominent under turbulent financial conditions (Baur et al., 2018; Urquhart & Zhang, 2019). However, while price movements are generally found to be unrelated (an exception is noted by Panagiotidis et al., 2018), volatilities are not (Bouoiyour & Selmi, 2017; Giudici & Polinesi, 2021).

In addition, a growing body of research suggests that the interrelatedness between cryptocurrencies and other assets is dynamic and conditional on the sentiment in financial markets (Corbet et al., 2018; Yi et al., 2018). Dyhrberg (2016) suggests that the isolation of BTC is short-lived,

[1]In this paper, cryptocurrencies are defined following Chu et al. (2017), as digital assets that are designed to work as a medium of exchange using cryptography to secure the transactions and to control the creation of additional units of the currency.

[2]Based on data from Coinmarketcap.com, accessed 21 July 2019.

whereas Bouri et al. (2017) show that BTC has some hedging capacity in bull markets, but not in bear markets. Others reach opposite conclusions and demonstrate that hedging capabilities appear to fade over time (Bouoiyour & Selmi, 2017; Brière et al., 2015; Ciaian et al., 2016). By considering a wide range of financial and macroeconomic drivers and by differentiating between different periods, this article adds to the current literature on cryptocurrency prices.

This article also extends this literature in two important respects. First, in contrast to a large part of the literature, it considers a wide range of cryptocurrencies (for exceptions, see Ciaian et al., 2016; Corbet et al., 2018; Yi et al., 2018). Second, it explicitly considers an additional range of determinants of cryptocurrency prices, which includes the technical supply functions that determine the mining and ultimate number of units in circulation. Research provides mixed results on whether and how such functions affect prices (Bouoiyour & Selmi, 2015; Ciaian et al., 2016; Hayes, 2017; Li & Wang, 2017; Polasik et al., 2015).[3] Another determinant considered in this article is the role of speculation. Cheah and Fry (2015), Cheung et al. (2015), and Corbet et al. (2018) all suggest that BTC is prone to price bubbles. Others show that investor sentiment is significant in explaining BTC prices but that the effect varies depending on the state of the BTC market (Bouoiyour & Selmi, 2015; Kristoufek, 2013; Panagiotidis et al., 2018). Finally, this article also examines the role of cybercrime. It thereby extends the findings of Caporale et al. (2020), who show that cyberattacks in general and those targeting cryptocurrencies in particular have significant negative effects on the ability of cryptocurrencies to maintain stable prices. It also relates to the work of Pieters and Vivanco (2017) and Auer and Claessens (2020), who respectively show that regulatory differences and news about regulatory actions influence cryptocurrency prices.

This article uses a least absolute shrinkage and selection operator (LASSO) model to test a number of determinants of cryptocurrency returns identified in the dominant theoretical framework on cryptocurrencies (and BTC in particular) on a sample of 12 cryptocurrencies. The results are compared over different periods and across a number of design choices that vary across the cryptocurrency market. The results show that, apart from some similarities in the impact of technical determinants and the lack of impact of cybercrime, cryptocurrencies are not homogeneous; the various demand- and supply-related determinants influence and drive the returns of each cryptocurrency in different ways.

These differences and the heterogeneity of the cryptocurrency market have implications beyond academia. Several risks relating to cryptocurrencies have been identified, including consumer protection, being too big to fail or too connected to fail (Minto et al., 2017), a strong link to illegal activities and money laundering (Chilson, 2018; ECB, 2015; Foley et al., 2019), and the potential to break central banks' monopoly on money issuance (Dabrowski & Janikowski, 2018). The ongoing debate on potential regulation requires a better understanding of the diverse cryptocurrency market.[4]

The remainder of the paper is organised as follows: Section 2 discusses theories on the determinants of returns for cryptocurrencies and outlines hypotheses. Section 3 describes the data and methodology. Section 4 presents the findings and analysis. Section 5 concludes the paper.

[3]Interestingly, the effect of technical factors also appears to hinge on whether markets are in bear or bull states (Bouoiyour & Selmi, 2017).

[4]When considering regulation for cryptocurrencies, it is important to distinguish between regulation of the underlying distributed ledger technology and regulation of the cryptocurrencies themselves. Many of the characteristics that raise concerns around BTC, such as anonymity and extensive energy use, are not necessarily representative of the wider distributed ledger technology (Organisation for Economic Co-operation and Development, 2018). Further, they might not be representative of all cryptocurrencies.

2 | THEORETICAL FRAMEWORK

The overarching hypothesis in this article is that cryptocurrencies are heterogeneous with respect to the determinants of returns (H). The overarching hypothesis has been split into several subhypotheses (H_1–H_9) to test the relations between the different determinants of returns suggested by the current literature on cryptocurrencies.

2.1 | Tokens in circulation and technical factors

Central authorities have no influence over cryptocurrencies, since their supply function is either fixed or evolves according to publicly known rules set before the cryptocurrency's launch (Gandal & Halaburda, 2014; Kristoufek, 2013). Since the supply is publicly known and predefined in the long run, the supply of a cryptocurrency becomes exogenous to its own pricing mechanism (Bouri et al., 2017).[5] Unless the supply is fixed or set to increase to a cap, it will continue to increase over time, leading to lower prices.

Ciaian et al. (2016) find that the number of bitcoins has a negative impact on BTC prices. Li and Wang (2017) test determinants of the BTC exchange rate to the US dollar (USD) and find that increases in BTC supply had a significant effect in the early BTC market, but not later.[6] Polasik et al. (2015) find no significant effect of changes in supply on BTC returns. If cryptocurrencies are homogeneous, the choice of rules for token creation should not create any variation across the cryptocurrencies tested; instead, they should all follow the potential negative impact on returns from increased supply.

Technical factors in the protocol design for cryptocurrencies vary and determine how tokens are distributed and transactions validated. The choice of technical factors, such as the technology used and limitation of the quantity produced, can influence the value of a cryptocurrency (Dwyer, 2015), particularly if the technologies differ in their ability to provide efficient transactions. Technical determinants can be proxied by a cryptocurrency's hash rate, a measure of how much computational power a cryptocurrency's network consumes to generate a new block in the blockchain. The higher the hash rate, the more likely a new block will be mined. Cryptocurrencies with higher hash rates decrease the time it takes for transactions to be approved and added to the blockchain. These cryptocurrencies thus become more attractive for trade. Bouoiyour and Selmi (2015) find a significant positive long run impact from increases in the hash rate on BTC prices. Bouoiyour and Selmi (2017) find a significant positive effect on the BTC price index when prices are in bear states, but no significant effect for bull states. Taken together, these arguments lead to the following hypotheses.

H1: Cryptocurrencies' returns are impacted differently by the *number of tokens in circulation.*

H2: Cryptocurrencies' returns are impacted differently by *variations in hash rates.*

[5]This can be contrasted with, for example, gold, where price changes are endogenous, since higher prices could lead to more intensive mining.

[6]The early market is defined as when the Mt. Gox exchange was open, and the late market after the closing of Mt. Gox, in 2014.

2.2 | Monetary velocity

Demand for a cryptocurrency is driven by its value in future exchanges (Bouri et al., 2017; Kristoufek, 2013). The utility of holding a cryptocurrency can be influenced by several factors, such as its perceived usefulness for transactions and confidence in the cryptocurrency's design and in its future increased value.

The monetary velocity of a cryptocurrency describes the rate at which money is exchanged in the cryptocurrency economy, that is, how fast a cryptocurrency passes from one owner to the next. This offers a measure of the perceived usefulness of a cryptocurrency, and thus a higher monetary velocity could contribute to an increase in demand for a cryptocurrency. Monetary velocity might be particularly important, depending on the target market of the token. A business-oriented cryptocurrency that explicitly seeks to provide commercial applications might benefit more from its higher perceived usefulness, as compared to cryptocurrencies targeting content creators online. For cryptocurrencies such as Tron (TRX), a higher monetary velocity might still increase demand, but it is likely not as critical as for cryptocurrencies targeting business applications. Cryptocurrencies that target generic markets can end up on both ends of the spectrum.

The monetary velocity can be proxied by, for example, output volume (Bouoiyour & Selmi, 2015), the number of transactions performed (Polasik et al., 2015), or the number of days destroyed per transaction (Ciaian et al., 2016), calculated as the number of bitcoins in the transaction multiplied by the number of days since those coins were last spent. Bouoiyour and Selmi (2015) find no significant impact of monetary velocity on BTC prices. Bouoiyour and Selmi (2017) discover a general positive effect, but negative effects for bear state quantiles. Polasik et al. (2015) show that monthly changes in the number of BTC transactions have a significant positive impact on BTC returns. Ciaian et al. (2016) find no significant impact of days destroyed on BTC prices. These results lead to the following hypothesis.

H3: Cryptocurrencies' returns are impacted differently by *changes in their monetary velocity.*

2.3 | Network effects and lead behaviour

One particular characteristic of the cryptocurrencies market is a strong presence of positive network effects. Currencies traditionally display large positive network effects, since a currency is more useful when more people adopt it, and the more popular it becomes, the more easily it can attract new users (Gandal & Halaburda, 2014). The presence of network effects often creates multiple equilibria; either many people join the platform because they expect many people to join, or the exact opposite can happen, that is, people do not join because they expect few others to join (Gans & Halaburda, 2015). This tipping effect makes it difficult for smaller networks to stay in business, unless they display distinguishing characteristics. Therefore, the presence of network effects in a market affects competition, since it makes entry more difficult (Waldman & Jensen, 2016). Given the presence of network effects, older cryptocurrencies would be perceived as more useful for future transactions as a consequence of their already established larger market shares. Thus, the increased demand should lead to higher returns. These notions suggest the following hypothesis.

H4: Cryptocurrencies' returns are impacted differently by their *date of implementation.*

Another consequence of network effects could be a move towards one strong currency, in a winner takes all race (Gandal & Halaburda, 2014). Alternatively, if speculation is the main focus of investors, the network effects could give rise to a substitution effect. For example, as BTC becomes more popular and more expensive, users could begin to worry that it might be overvalued and look for an alternative cryptocurrency investment (Gandal & Halaburda, 2014). By including lagged values of returns for some of the major cryptocurrencies, a proxy for these potential effects could be captured. The lead in a winner takes all race should be negatively impacted by increases in the returns of other cryptocurrencies. Cryptocurrencies presented as alternative investments should be positively impacted by increases in the returns of the lead of the winner takes all race. The network effects could help explain the different roles of cryptocurrencies by highlighting their position as, for example, incumbents in the market. Consequently, heterogeneity in cryptocurrencies market capitalisation could lead to different positions, with BTC likely leading a potential winner takes all race, whereas other cryptocurrencies could be more affected by a potential substitution effect.

Lead behaviour mechanisms can also matter. A number of studies have documented a price discovery process between various cryptocurrency exchanges, where the prices on one exchange transmit to another with a lag (Brandvold et al., 2015; Giudici & Abu-Hashish, 2019; Giudici & Polinesi, 2021; Pagnottoni & Dimpfl, 2019; Pieters & Vivanco, 2017). More recent research also suggests that such lead behaviour arises between cryptocurrencies, where the price of more traded or more well-known currencies affect the prices of less traded or less well-known ones. Both Koutmos (2018) and Yi et al. (2018) document interconnectedness between cryptocurrencies in terms of return volatility and that this effect appears to increase over time. Koutmos shows that BTC is a dominant contributor of return and volatility spillover among cryptocurrencies; Yi et al. (2018), however, show that some less-known cryptocurrencies, such as MaidSafeCoin, have even greater transmission than more well-known cryptocurrencies. Corbet et al. (2018) also demonstrate that Litecoin (LTC), Ripple (XRP), and BTC share properties in terms of volatility and price movements. Similar findings for price movements are reported by Ciaian et al. (2018), who also show that BTC is less influenced by macro factors than altcoins. These findings suggest that cryptocurrencies returns are interrelated, but that the relation cannot be expected to be equal among different currencies. This leads to the following hypothesis.

H5: Cryptocurrencies' returns are impacted differently by the lagged values of returns of other cryptocurrencies.

2.4 | Speculation and hedging

Part of what drives demand in the cryptocurrency market is the speculative element, that is, the expected profits of holding a cryptocurrency and selling it later (Baur et al., 2018; Cheah & Fry, 2015). If prices of cryptocurrencies are driven by investors' expectations of future profits, investor sentiment becomes an important demand factor. Bouoiyour and Selmi (2015), Kristoufek (2013) and Panagiotidis et al. (2018) find that the number of Internet searches is significant in explaining BTC prices, but that the effect varies depending on the state of the BTC market. Bouoiyour and Selmi (2017), Ciaian et al. (2016) and Polasik et al. (2015) report similar findings.

An alternative channel is offered by the possibility of using cryptocurrencies for hedging against traditional asset classes (Baur et al., 2018; Dyhrberg, 2016). For example, the ability to hedge global uncertainty could increase demand for a cryptocurrency when the traditional economy experiences a downturn, thereby raising the cryptocurrency's price and increasing its return. Panagiotidis et al. (2018) find a negative effect on BTC returns from increases in both Chinese and British uncertainty indices. Bouri et al. (2017) show that, for short-term frequencies, BTC displays hedging capacities when the market is in a bull state, but that uncertainty has a negative impact in bear regimes. Bouoiyour and Selmi (2017) find a positive effect on the BTC price index from the US volatility index when the market is in normal mode and from the British volatility index when the market is in a bull state.

Traditional assets used for hedging include gold and fiat currencies, but it is also suggested that cryptocurrencies could be used for such purposes (Dyhrberg, 2016). Thus, increases in those variables could signal a move towards more hedging, which, in turn, could also increase demand for cryptocurrencies that are perceived as suitable for hedging. Panagiotidis et al. (2018) discover that gold prices have a positive effect on BTC returns. Bouoiyour and Selmi (2017) report a negative effect of gold prices on the BTC price index when the market is in a bear state, and a negative effect of the Chinese yuan when the market is in a bull state (Bouoiyour & Selmi, 2017). Based on these arguments, the following hypotheses are proposed.

H6: Cryptocurrencies' returns are impacted differently by *levels of speculation.*

H7: Cryptocurrencies' returns are impacted differently by *global and regional uncertainties.*

H8: Cryptocurrencies' returns are impacted differently by the *price developments of assets traditionally used for hedging.*

2.5 | Macroeconomic and financial conditions

The decentralised nature of cryptocurrencies implies that traditional macroeconomic determinants of supply and demand for a currency do not directly influence the pricing mechanism. To offer a comparison, a traditional currency could adjust the exchange rate to accommodate changes in the gross domestic product, unemployment, and financial status in the home country of the central issuer. For the USD, macroeconomic factors in the United States are essential in explaining its price. However, in the case of cryptocurrencies, the lack of a central issuer means that the potential impact of macroeconomic factors and financial indicators works in a more indirect manner.

One example of a potential channel is favourable macroeconomic and financial developments. Such development can lead to the increased use of cryptocurrencies in trade and exchanges, which would strengthen their demand and impact returns positively (Bouri et al., 2017). However, Ciaian et al. (2016) find that global macroeconomic developments, such as the Dow Jones index and oil prices, do not impact BTC prices in the long run. Similarly, Bouoiyour and Selmi (2017) show a short-run positive impact from the Shanghai market index on BTC prices, but no long-run effect. In addition, Panagiotidis et al. (2018) find a positive effect of increases in the Nikkei index and oil prices on BTC returns. While the overall effects of the stock markets appear to be mixed, one could suspect that the effects are stronger for cryptocurrencies targeting individuals, since these users might be more influenced by general movements in the market. Taken together, these findings lend support for the following hypothesis.

H9: Cryptocurrencies' returns are impacted differently by changes in *macroeconomic and financial market conditions.*

2.6 | Cyberattacks

Demand for cryptocurrencies is also likely to be affected by their actual or perceived vulnerability to cyberattacks. Blockchain transactions and markets are not immune to security issues (Benjamin et al., 2019; Li et al., 2020), and cryptocurrencies are no exception. Cryptocurrencies (and BTC in particular) have become favourite targets for cyberattacks in recent years (Caporale et al., 2020). Lazarenko and Avdoshin (2018) review successful cyberattacks on the blockchain industry. Similarly, Ernst and Young (2017) estimates that nearly 10% of all initial coin offerings' proceeds are stolen by hackers. There have also been prominent attacks on the creation platforms and on several cryptocurrency exchanges (Corbet et al., 2019).

Kopp et al. (2017) discuss how cyberattacks can give rise to systemic effects across markets. There is also a growing body of empirical evidence in this area. Caporale et al. (2020) show that cyberattacks in general and those targeting cryptocurrencies in particular have significant negative effects on the ability of cryptocurrencies to maintain stable prices. Moreover, general cyberattacks and attacks targeting cryptocurrencies are mutually reinforcing when it comes to affecting cryptocurrency volatility. These effects are particularly strong for BTC, Ethereum (ETH), and LTC. Although not focusing primarily on cyberattacks, Pieters and Vivanco (2017) demonstrate that prices differ between cryptocurrency markets, depending on regulation or the requirements for market participants.

Taken together, these findings suggest that cryptocurrency prices are influenced by their perceived vulnerability, which, in turn, is influenced by both the frequency of general cyberattacks and, more so, that of attacks targeting cryptocurrencies. However, these effects are likely to differ across cryptocurrency markets, which suggests the following hypothesis.

H10: Cryptocurrencies' returns are impacted differently by *cyberattacks*.

3 | DATA AND METHODOLOGY

3.1 | Sample selection

Cryptocurrencies were included in this article's sample if they had a large userbase relative to other cryptocurrencies, to reduce the influence of random noise on prices (for a discussion, see Burnie, 2018). Userbases are typically measured by market capitalisation or liquidity. The recent top 10 cryptocurrencies, ranked by either market capitalisation or liquidity (measured as total exchange volume), are included in this study, resulting in a final sample of 12 cryptocurrencies. These cryptocurrencies are listed in Table 1, with their dates of implementation and abbreviations.

3.2 | Operationalisations

The data used cover the period 2 October 2013–1 April 2019. The start date is chosen to exclude the early adoption phase of the first cryptocurrencies.[7] The end date for the data also ensures that the more recent developments related to the COVID-19 pandemic are excluded from the

[7]The early adoption phase of cryptocurrencies mainly covers data on BTC prices, few transactions, low prices, and small price fluctuations. Thus, for a comparison of homogeneity among cryptocurrencies, the early adoption phase offers little additional information, and its specific characteristics risk distorting the results.

TABLE 1 Cryptocurrencies in the sample and their abbreviations and dates of implementation

This table reports the sample of 12 cryptocurrencies that are included in this study. The sample is constructed by including recent top 10 cryptocurrencies, ranked by either market capitalisation or liquidity (measured as total exchange volume). For these 12 cryptocurrencies, their dates of implementation and abbreviations are provided.

Cryptocurrency	Abbreviation	Date of implementation
Bitcoin	BTC	2009-01-03
Litecoin	LTC	2011-10-07
Ripple	XRP	2013-01-02
Monero	XMR	2014-04-18
Stellar	XLM	2014-08-05
Ethereum Classic	ETC	2015-07-30
Ethereum	ETH	2015-07-30
Neo	NEO	2016-09-09
EOS	EOS	2017-06-20
Bitcoin cash	BCH	2017-07-23
Tron	TRX	2017-08-28
Cardano	ADA	2017-09-24

analysis. Data that did not have a daily or 5-day frequency were linearly interpolated to a 7-day frequency. All variables were transformed to logarithmic first differences so that they are stationary and their coefficients comparable. After transformation, all the variables are found to be stationary, that is, $I(0)$.[8] For more details on robustness checks see Appendix A.

3.2.1 | Dependent variable: Cryptocurrency returns

Previous research has used returns measured on the basis of a monthly frequency (Polasik et al., 2015), a daily frequency (Balcilar et al., 2017; Panagiotidis et al., 2018), or various frequencies (Bouri et al., 2017). Cryptocurrency returns can also be measured as prices (Ciaian et al., 2016; Kristoufek, 2013), logarithmised prices (Bouoiyour & Selmi, 2015), the exchange rate of the cryptocurrency to the USD (Li & Wang, 2017), or through daily price indices (Bouoiyour & Selmi, 2017). This article uses the daily 7-day pricing data in USD for each cryptocurrency. To ensure the stationarity and comparability of the data, a log transformation is carried out, as well as a first difference calculation of the returns. Durbin–Watson statistics are close to two, indicating that first-order residual autocorrelation is not a problem.

[8]The Durbin–Watson d statistic are close to two for all cryptocurrencies, indicating that first-order residual autocorrelation is not a problem. The augmented Dickey–Fuller test indicates nonstationarity in the time series for several of the variables. After logarithmic transformation, all the results for all the variables fall below 0.05 and are thus stationary.

3.2.2 | Independent variables: Technical and economic determinants

The independent variables can be described as a vector of the form $x_i = (x_{i1}, \ldots, x_{ip})^T$ for each cryptocurrency i, where $i = 1,2, \ldots, N$, at time t. Among the independent variables, some are cryptocurrency specific, that is, they are variables that in one way or another characterise a specific cryptocurrency, such as that cryptocurrency's exchange volume on a certain date. Other variables are not cryptocurrency specific and take on the same values, regardless of the cryptocurrency. Table 2 offers an overview of the variables used to test each hypothesis and their sources.

The following cryptocurrency-specific independent variables are used to operationalise the factors in H1–H5:

- Tokens in circulation are quantified by looking at the current *circulating supply*. Coin Metrics (2018) provides a measure of the number of new coins that are brought into existence each day, calculated as the expected number of tokens per block in the blockchain every 10 min, summed to a daily value of new coins. By summing the number of coins generated at the end of each day, it is possible to create a value for the current supply in circulation. Coin Metrics data are only available for the major currencies, namely, BTC, LTC, ETH, Ethereum Classic (ETC), Monero (XMR) and Bitcoin Cash (BCH).
- Technical factors are proxied by the variable for *average difficulty*.[9] This variable gives a measure in proof-of-work blockchains of how hard it is to solve the hash function to find a new block (Coin Metrics, 2018). The average level of difficulty is used as a proxy for hash power and is available for BTC, LTC, ETH, ETC, XMR and BCH.
- The output volume, the total volume of all transaction outputs per day, proxies for monetary velocity. This is measured as the *exchange volume* in the Coin Metrics data set, which is the USD value of the volume of each cryptocurrency at major exchanges such as GDAX and Bitfinex (Coin Metrics, 2018). It does not include data on over-the-counter exchanges or other trading platforms, a meaningful proportion of all global exchanges, but gives a general notion of output volume.[10]
- The potential first mover advantage resulting from network effects is measured by comparing cryptocurrencies based on the *date of implementation* across three different periods (see Section 3.3.1). This measure allows for a comparison of the cryptocurrencies that were launched in or before the relevant period, thereby identifying common variables in the resulting models for early or later cryptocurrencies.
- Lead behaviour is measured by including *lagged values of returns for the other cryptocurrencies*, using the same calculations for each dependent variable as described in Section 3.2.1 and a

[9]Commonly, this measure is calculated using the hash rate. However, the data availability for this variable is only adequate for the largest cryptocurrencies, such as BTC, and lacking when it comes to other cryptocurrencies. Therefore, a measure comparable to the hash rate has not been possible to find for all cryptocurrencies in the sample.

[10]Two possible measures of monetary velocity are available from the Coin Metrics data set that can be used to test H3, namely, the transaction count and the output volume. The transaction count measures the number of transactions on the public blockchain per day (Coin Metrics, 2018). A problem with this measurement is that blockchains with low transaction fees typically have more and sometimes smaller transactions. Additionally, some networks, such as BTC, can gather several transactions into one, which will then underestimate the true value (Coin Metrics, 2018). This measure is thus difficult to use for comparison across different cryptocurrencies, even if the variable is consistent over time within each cryptocurrency. The use of both the transaction count and output volume variables would likely result in multicollinearity in the model, since the number of transactions is one of the variables that contributes to the calculation of the output volume. Combining this issue with the risks associated with the variable for the transaction count makes the exchange volume the better proxy for monetary velocity. This is the measure therefore used for the analysis.

TABLE 2 Overview of the variables

This table reports all independent variables that are used to test hypotheses H1–H10. Codes that are used in the subsequent tables are provided for all variables. For the variable *Lagged values of log returns of other cryptocurrencies*, CCC indicates the code for each cryptocurrency, as noted in Table 1. Data sources and original frequency are also provided. (Data that did not have a daily or 5-day frequency were linearly interpolated to a 7-day frequency). In terms of data availability, *To the present* means the data is continuously updated up until present day; unless otherwise specified. Tokens in circulation is proxied by *circulating supply* which measures the number of new coins brought into existence each day, calculated as the expected number of tokens per block in the blockchain every 10 min, summed to a daily value of new coins. Technical factors are proxied by the variable for *average difficulty* which is calculated as the hash rate. This variable gives a measure in proof-of-work blockchains of how hard it is to solve the hash function to find a new block. *Exchange volume* proxies for monetary velocity and is the USD value of the volume of each cryptocurrency at major exchanges such as GDAX and Bitfinex. *Time of implementation* is the year when each cryptocurrency was launched. *Lagged values of returns for the other cryptocurrencies* uses daily 7-day pricing data in USD for each cryptocurrency. and lags of 1, 7, 14 and 30 days. *Google searches* for each cryptocurrency proxy levels of speculation and is an index between zero and 100. *Uncertainty measures* include the Chicago Board Options Exchange (CBOE) Standard & Poor's (S&P) 500 Volatility Index (*VIX*), the CBOE S&P 100 *VXO*, the CBOE NASDAQ *VXN* (CBOE, 2019) and measures of political uncertainty for the United States (*USEPU*), Europe (*EEPU*) and China (*CEPU*) and globally (*GEPU*). *Exchange rates* for major currencies and a *gold price* index is used to operationalise hedging capacity. Exchange rates to the USD included the *Chinese yuan*, the *Japanese yen*, the *pound sterling*, and the *euro*. Exchange rates were acquired from the euro reference rates presented by the ECB and recalculated to USD-based values. The World Gold Council (*gold* price index denominated in USD measures developments in gold prices. Macroeconomic conditions include stock market and oil price movements. These include European stock index (*STOXX 600*), the *S&P 500*, the New York Stock Exchange (*NYSE*), the American Stock Exchange (*AMEX*), *NASDAQ*, the *Nikkei 225*, and the Shanghai Composite Index (*SSE*). Changes in *oil price* are measured by the reference price of the OPEC Crude Oil Basket. *Cyberattacks* is an intensity measure is constructed based on the cumulative number of crypto- and cyberattacks, using a 2-week rolling window, which is expected to capture persistence. “To the present” means data is updated regularly to give a data availability up until present day, if nothing else is specified the data used stretches to 2019-06-08. *CCC means the code for each cryptocurrency, described in table XX.

Hypothesis	Variable [original code]	Code	Source	Original frequency	Data availability
H1	Number of tokens in circulation	circulating	Coin Metrics	Daily (7-day)	The data sample stretches back to December 2013, but starts for each cryptocurrency at the time of its introduction
H2	Average difficulty	averagedifficulty	Coin Metrics	Daily (7-day)	The data sample stretches back to December 2013, but starts for each cryptocurrency at the time of its introduction

TABLE 2 (Continued)

Hypothesis	Variable [original code]	Code	Source	Original frequency	Data availability
H3	Exchange volume	exchangevolumeusd	Coin Metrics	Daily (7-day)	The data sample stretches back to December 2013, but starts for each cryptocurrency at the time of its introduction
H4	Year of implementation	introduction	Coin Metrics	n/a	n/a
H5	Lagged values of log returns of other cryptocurrencies (lag = 1)	L. LreturnCCC	Coin Metrics	Daily (7-day)	The data sample stretches back to December 2013, but starts for each cryptocurrency at the time of its introduction
H6	Google searches	google	GoogleTrends	Weekly	Start varies across cryptocurrencies, "To the present"
H7	Global policy uncertainty index [GEPU]	GEPU	policyuncertainty. com	Monthly	1997, "To the present"
	US policy uncertainty index [USEPU]	USEPU	policyuncertainty. com	Monthly	1985, "To the present"
	Europe policy uncertainty index [EEPU]	EEPU	policyuncertainty. com	Monthly	2011, "To the present"
	China policy uncertainty index [CEPU]	CEPU	policyuncertainty. com	Monthly	1995, "To the present"
	CBOE S&P500 Volatility index [VIX]	VIX	WRDS/CBOE	Daily (5-day)	"To the present"
	CBOE S&P100 Volatility index [VXO]	VXO	WRDS/CBOE	Daily (5-day)	"To the present"
	CBOE NASDAQ Volatility index [VXN]	VXN	WRDS/CBOE	Daily (5-day)	"To the present"
H8	Exchange rate for People's Republic of China (Yuan/US$)	exchus	ECB	Daily (5-day)	"To the present"
	Exchange rate for Japan (Yen/US$)	exjpus	ECB	Daily (5-day)	"To the present"
	Exchange rate for United Kingdom Pound (Pound/US$)	exukus	ECB	Daily (5-day)	"To the present"
	Exchange rate for European Monetary Union (Euro/US$)	exeuus	ECB	Daily (5-day)	"To the present"
	Gold price	Gold	Quandl/WGC	Daily (5-day)	1969-12-29, "To the present"

(Continues)

TABLE 2 (Continued)

Hypothesis	Variable [original code]	Code	Source	Original frequency	Data availability
H9	STOXX600 index	STOXX600	YahooFinance	Daily (5-day)	"To the present"
	S&P500 index [GSPC]	SP500	YahooFinance	Daily (5-day)	"To the present"
	NYSE index [NYA]	NYSE	YahooFinance	Daily (5-day)	"To the present"
	AMEX index [XMI]	AMEX	YahooFinance	Daily (5-day)	"To the present"
	NASDAQ index [IXIC]	NASDAQ	YahooFinance	Daily (5-day)	"To the present"
	Nikkei225 index [N225]	NIKKEI	YahooFinance	Daily (5-day)	"To the present"
	Shanghai Composite Index (SSE)	SSE	YahooFinance	Daily (5-day)	"To the present"
	Oil price	Oil	Quandl/OPEC/ORB	Daily (5-day)	2001-03-02, "To the present"
H10	Cyberattacks	Cyberattacks	hackmageddon. com	Daily (5-day)	"To the present"

number of lags. This includes a lag of 1 day to capture short-term interactions on the cryptocurrency market. Lags of 7 and 14 days capture the medium interactions between cryptocurrencies, whereas a lag of 30 days provide more details on the long-term interactions between cryptocurrencies.
- Levels of speculation are proxied by worldwide *Google searches* for the name of the cryptocurrency, available as weekly data from Google Trends (2019). The variable gives an index measure of interest over time, ranging from a value of zero to 100, for interest at its peak, that is, the highest number of Google searches (Google Trends, 2019). Thus, a value of 50 indicates that the search term is half as popular as during its peak. A value of zero indicates that data are missing for the period.[11]

The following noncryptocurrency-specific independent variables are used to operationalise the factors in H6–H10:

- Several measures of *uncertainty* are used, including the Chicago Board Options Exchange (CBOE) Standard & Poor's (S&P) 500 Volatility Index (*VIX*), the CBOE S&P 100 *VXO*, and the CBOE NASDAQ *VXN* (CBOE, 2019). In addition, a measure of political uncertainty for the United States (*USEPU*), Europe (*EEPU*), and China (*CEPU*) and a global measure (*GEPU*) are included. These measures were obtained from Economic Policy Uncertainty (2019), with a monthly index calculated based on three underlying components: a quantification of newspaper coverage related to policy-related economic uncertainty, a measure of the number of federal tax code provisions set to expire in future years, and a measure that uses disagreement among economic forecasters as a proxy for uncertainty.
- Hedging is captured using several measures of classical hedging instruments, such as the *exchange rates* for major currencies and an index price for *gold*. The exchange rates to the USD are included for the *Chinese yuan*, the *Japanese yen*, the *pound sterling*, and the *euro*. The exchange rates were acquired from the euro reference rates presented by the ECB and recalculated to USD-based values for ease of comparison with previous research. The World Gold Council (*gold* price index denominated in USD measures developments in gold prices).
- Macroeconomic conditions are included in the patterns of stock markets and oil price movements. Changes in regional stock markets are quantified by using measures for a 5-day week for the following stock indices: European stock index (*STOXX 600*), the *S&P 500*, the New York Stock Exchange (*NYSE*), the American Stock Exchange (*AMEX*), *NASDAQ*, the *Nikkei 225*, and the Shanghai Composite Index (*SSE*). Changes in *oil price* are measured by the reference price of the OPEC Crude Oil Basket.
- The data for *cyberattacks* were obtained from https://www.hackmageddon.com and include crime, espionage, warfare, and hacktivism cyberattacks. Cyberattacks specifically targeting cryptocurrencies (henceforth cryptoattacks), as well as other cyberattacks (henceforth cyberattacks), are both included in the analysis. The rationale for including the latter is that their extensive media coverage can also affect investors' perceptions of cryptocurrencies, since this type of asset relies heavily on cybersecurity. Each cyberattack in the original data set is identified by binary variables to capture the type of attack, equal to one if the event corresponds

[11]Google searches could be a rough proxy for some cryptocurrencies with more general names, since their search statistics can include a search history that is broader than intended. Further, following Panagiotidis et al. (2018), potential misspellings were not taken into account. For a general measure of changes in investor attention, this could suffice, particularly given the distinct names of several of the cryptocurrencies.

to the attack category, and zero otherwise. From these data, an intensity measure is constructed based on the cumulative number of crypto- and cyberattacks, using a 2-week rolling window, which is expected to capture persistence.

Table 3 presents summary statistics for independent variables that are cryptocurrency specific. Table 4 presents descriptive statistics for independent variables that are not cryptocurrency specific, measured before the transformation of the data.

3.3 | Method

The data were analysed using LASSO regressions, which consider all potential determinants but select only a subset of the variables (Panagiotidis et al., 2018). The LASSO approach for testing the hypotheses exploits the variance–bias trade-off. LASSO reduces the complexity of the model, through shrinking or setting some coefficients to zero, thereby decreasing the variance of the prediction. LASSO allows for the identification of the values of λ that optimise predictive performance by minimising the estimated mean-squared prediction error (Ahrens et al., 2020; Hastie et al., 2001). Accordingly, this article's main model has a max $\lambda = 5$. Alternative specifications—including allowing λ to vary, setting a minimum $\lambda = 2.3$, and performing vector autoregressive (VAR) analyses for each hypothesis—are used for robustness checks (see Appendix A).

By decreasing the variance of the prediction, LASSO allows for potential bias to be introduced into the model. This bias risk making the magnitudes of the estimated effects less reliable, and one should be cautious when interpreting them. However, since the aim of this article is to evaluate homogeneity among cryptocurrencies, the selection, direction of impact, and relative importance of the potential determinants of returns for each cryptocurrency give enough information to evaluate the hypotheses. Essentially, to prove or disprove homogeneity, the most important factor might not be the accuracy of the magnitudes, but, rather, that the selection and relative importance of the potential determinants of the returns are the same for all cryptocurrencies. That is, if the resulting models from a LASSO approach are ranked based on the impact of the coefficients, a similar ranking for all cryptocurrencies should result if they are homogeneous.

3.3.1 | Structural breaks and periods

The first part of the LASSO analysis is conducted using all available data without restrictions on the periods (Table 5). This approach provides a good overview, but it can make the results sensitive to variables with scant available data, such as returns for cryptocurrencies with a relatively recent date of implementation. The shrinking procedure of the LASSO operator should ensure that variables with too few data are excluded if they introduce more variation than what they are able to explain in the model, with their coefficients being shrunken to zero.

The large variation in results from the first part of the analysis suggests structural breaks and the need for further division of the data to extract comparable models. Structural breaks could arise if the market for cryptocurrencies undergoes large changes over time (e.g., due to media attention or acceptance as a medium of exchange or investment). Following Panagiotidis et al. (2018), the structural breaks are calculated using BTC data as a point of reference. The structural breaks are identified through Andrews and Ploberger (1994) tests with p values calculated using Hansen's (1997) approximations. This method results in the identification of three periods (see Figure 1).

TABLE 3 Summary statistics: Cryptocurrency-specific independent variables

This table reports the descriptive statistics for those independent variables that are specific for each cryptocurrency. Data that did not have a daily or 5-day frequency were linearly interpolated to a 7-day frequency. All variables were transformed to logarithmic first differences. For each cryptocurrency, it covers the period from the cryptocurrency's date of implementation to 1 April 2019. For cryptocurrencies implemented before 2 October 2013, this date is the first data point. For this reason, observations vary between the cryptocurrencies.

	Cryptocurrency					
Variable: measurement	**ADA**	**BCH**	**BTC**	**EOS**	**ETC**	**ETH**
Price in USD: mean (SD)	0.17 (0.19)	766.23 (633.12)	2547.11 (3424.60)	5.61 (4.19)	11.21 (9.56)	205.26 (266.37)
Price in USD: min/max	0.018/1.17	77.37/3 909	114.45/19 475.8	0.49/21.64	0.604/43.86	0.43/1 397.48
Return in USD: mean (SD)	0.00009 (0.03)	−0.63 (106.28)	1.98 (238.48)	0.0049 (0.65)	0.004 (1.29)	0.10 (21.31)
Return in USD: min/max	−0.17/0.31	−639.28/1 083.97	−2405/3 536.80	−3.97/4.41	−12.11/8.25	−231.29/154.34
Circulating supply: mean (SD)	n/a	652,878.5 (346 757.1)	3,472,321 (1 682 526)	n/a	1.96e+07/1.12e+07	1.84e+07 (1.01e+07)
Circulating supply: min/max	n/a	0/1,222,800	4775/5,843,019	n/a	39,311.09/3.76e+07	39,311.09/3.35e+07
Average difficulty: mean (SD)	n/a	3.52e+11 (1.98e+11)	1.38e+12 (2.21e+12)	n/a	7.65e+13 (6.08e+13)	1.30e+15 (1.35e+15)
Exchangevolume: mean (SD)	1.26e+08 (2.07e+08)	6.67e+08 (8.96e+08)	1.90e+09 (3.34e+09)	6.97e+08 (6.56e+08)	1.69e+08 (2.10e+08)	1.08e+09 (1.42e+09)
Exchange volume: min/max	1,739,460/1.71e+09	85,013/1.19e+10	0/2.38e+10	4,556,540/4.87e+09	267,367/1.73e+09	102,128/9.21e+09
Date of introduction	2017-09-24	2017-07-23	2009-01-03	2017-06-20	2015-07-30	2015-07-30
Google search intensity: mean (SD)	6.84 (10.09)	3.30 (7.76)	8.62/12.52	72.50 (8.82)	13.61 (20.39)	10.66 (16.97)
Observations of return	547	617	2007	639	981	1333

	Cryptocurrency					
Variable: measurement	**LTC**	**NEO**	**TRX**	**XLM**	**XMR**	**XRP**
Price in USD: mean (SD)	33.90 (54.19)	26.66 (34.62)	0.032 (0.027)	0.075 (0.13)	53.67 (86.89)	0.78 (0.34)
Price in USD: min/max	1.15/359.13	0.08/187.97	0.001/0.22	0.001/0.89	0.22/470.29	0.003/3.36
Return in USD: mean (SD)	0.029 (5.19)	0.10 (3.92)	0.0004 (0.007)	0.00006 (0.015)	0.03 (8.28)	0.0001 (0.043)

(Continues)

TABLE 3 (Continued)

Variable: measurement	Cryptocurrency LTC	NEO	TRX	XLM	XMR	XRP
Return in USD: min/max	−49.99/102.9	−43.24/29.54	−0.05/0.11	−0.16/0.33	−97/94.58	−0.92/0.76
Circulating supply: mean (SD)	2.31e+07 (1.09e+07)	n/a	n/a	n/a	1.16e+07 (4 649 672)	n/a
Circulating supply: min/max	29 550/3.95e+07	n/a	n/a	n/a	15 562.51/1.69e+07	n/a
Average difficulty: mean (SD)	1,880,995 (3,324,578)	n/a	n/a	n/a	2.16e+10 (3.10e+10)	n/a
Exchangevolume: mean (SD)	2.02e+08 (4.32e+08)	1.05e+08 (1.40e+08)	2.41e+08 (3.61e+08)	3.76e+07 (8.81e+07)	2.38e+07 (4.91e+07)	2.28e+08 (6.84e+08)
Exchange volume: min/max	0/6.96e+09	156/1.66e+09	26 475/4.09e+09	491/1.51e+09	7900/5.44e+08	0/9.11e+09
Date of introduction	2011-10-07	2016-09-09	2017-08-28	2014-08-05	2014-04-18	2013-01-02
Google search intensity: mean (SD)	8.82 (12.63)	64.81 (13.35)	30.34 (9.46)	17.75 (7.15)	8.46 (14.04)	5.04 (9.76)
Observations of return	2007	934	565	1700	1776	2007

TABLE 4 Summary statistics: Non–cryptocurrency-specific independent variables

This table reports the descriptive statistics for the variables that do not relate to specific cryptocurrencies. Data that did not have a daily or 5-day frequency were linearly interpolated to a 7-day frequency. Data covers the period from 2 October 2013 to 1 April 2019.

Hypothesis	Variable	Obs	Mean	Standard Deviation	Min	Max
H7	GEPU	2008	153.62	45.96	85.09	260.89
	USEPU	2008	109.69	21.03	71.26	201.03
	EEPU	2008	203.23	60.23	111.80	433.28
	CEPU	2008	212.57	223.37	8.02	1071.73
	VIX	2008	14.94	4.19	9.14	40.74
	VXO	2008	14.35	4.74	6.32	37.66
	VXN	2008	17.55	4.49	10.31	42.95
H8	exeuus	2008	0.85	0.07	0.72	0.96
	exjpus	2008	111.09	6.67	96.86	125.28
	exukus	2008	0.70	0.07	0.58	0.83
	exchus	2008	6.49	0.28	6.04	6.97
	Gold	2008	1244.17	68.08	1049.40	1385.00
H9	STOXX600	2008	360.85	25.01	303.58	414.06
	SP500	2008	2254.87	331.03	1655.45	2930.75
	NYSE	2008	11,236.00	984.60	9029.88	13,637.02
	AMEX	2008	2053.40	295.39	1592.94	2676.69
	NASDAQ	2008	5596.58	1200.10	3677.78	8109.69
	NIKKEI	2008	18,740.75	2678.55	13,853.32	24,270.62
	SSE	2008	2975.65	573.78	1991.25	5166.35
	Oil	2008	63.76	22.63	22.48	110.48
H10	Cyber	2008	27.75	23.92	0.00	102.00

LASSO analysis was conducted for the whole period (Table 5 in Section 4), as well as for each period separately (see Tables 6–8 in Section 4).

3.3.2 | Cryptocurrencies' design choices

Generally, all cryptocurrencies display great variation in what variables are relevant to explaining returns when compared across time. This great variation could suggest that different explanatory variables are important at different stages of implementation for a cryptocurrency. It is also possible that cryptocurrencies with similarities in design go through similar stages of implementation. If that is the case, the importance of a cryptocurrency's design choice could be observed when compared across periods. These design choices build on the work of Burnie (2018) and include the following information (see Appendix B for more details):

TABLE 5 Determinants by cryptocurrencies, all periods

This table reports the results from the main LASSO analysis with cryptocurrencies log transformed first difference returns as the dependent variable. λ is set at max 5 to optimise predictive performance by minimising the estimated mean-squared prediction error. This table presents results using all available data without restrictions on the periods. All variable definitions are given in Table 2. Time fixed effects are reported at the bottom. ***, ** and * indicate statistical significance at the 1%, 5%, and 10% level, respectively. ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

		ADA	BCH	BTC	EOS	ETC	ETH	LTC	NEO	TRX	XLM	XMR	XRP
		Lreturn ADA	**Lreturn BCH**	**Lreturn BTC**	**Lreturn EOS**	**Lreturn ETC**	**Lreturn ETH**	**Lreturn LTC**	**Lreturn NEO**	**Lreturn TRX**	**Lreturn XLM**	**Lreturn XMR**	**Lreturn XRP**
Hypothesis	**Variable**	**I**	**II**	**III**	**IV**	**V**	**VI**	**VII**	**VIII**	**IX**	**X**	**XI**	**XII**
H1	circulating		10.70***			21.11							
H2	averagedifficulty		0.331***	0.0376		0.578***	0.115*	0.349***					
H3	exchangevolumeusd								0.0120	0.00902			
H5	**L.LreturnADA**												−0.149***
	L.7												
	L.14						0.0513**	0.0627*	0.0358	0.0433			0.0694*
	L.30		−0.102**		−0.0528						−0.166***		−0.0511
	L.LreturnBCH												
	L.7												
	L.14												
	L.30	−0.0968			−0.0344								
	L.LreturnBTC				0.168								
	L.7				0.104					0.197			0.352***
	L.14				−0.121					−0.514***			
	L.30				0.306**								

TABLE 5 (Continued)

Hypothesis	Variable	ADA Lreturn ADA I	BCH Lreturn BCH II	BTC Lreturn BTC III	EOS Lreturn EOS IV	ETC Lreturn ETC V	ETH Lreturn ETH VI	LTC Lreturn LTC VII	NEO Lreturn NEO VIII	TRX Lreturn TRX IX	XLM Lreturn XLM X	XMR Lreturn XMR XI	XRP Lreturn XRP XII
	L.LreturnEOS												
	L.7					0.0500	0.0440	0.0692**		0.241***		0.0389	
	L.14	0.0772								0.133*			
	L.30	0.365***	0.193***			0.172***	0.0540*		0.194***	0.0211	0.327***	0.131***	0.345***
	L.LreturnETC									−0.355***			
	L.7	−0.113			−0.0808					−0.308***			−0.162***
	L.14							0.0667	0.0598				
	L.30												
	L.LreturnETH												
	L.7												
	L.14				−0.165								
	L.30												
	L.LreturnLTC				0.142					0.180*			
	L.7				0.113					0.159			
	L.14												
	L.30	−0.142*			−0.168*	−0.108**					−0.166**	−0.177***	−0.171**
	L.LreturnNEO												
	L.7	−0.00612	−0.0949**		−0.159**					−0.367***	−0.114**		−0.164***
	L.14												
	L.30												−0.0984

(Continues)

TABLE 5 (Continued)

Hypothesis	Variable	ADA Lreturn ADA I	BCH Lreturn BCH II	BTC Lreturn BTC III	EOS Lreturn EOS IV	ETC Lreturn ETC V	ETH Lreturn ETH VI	LTC Lreturn LTC VII	NEO Lreturn NEO VIII	TRX Lreturn TRX IX	XLM Lreturn XLM X	XMR Lreturn XMR XI	XRP Lreturn XRP XII
	L.LreturnTRX	0.0796**									0.0285		0.135***
	L.7				0.0586								
	L.14				−0.00678								0.0511
	L.30		0.0842**		0.0473								
	L.LreturnXLM		−0.0307							0.189***			
	L.7	−0.0409								0.114*			
	L.14	0.0845*								0.0320			
	L.30	−0.0796	−0.0306		−0.0994*	−0.0705*			−0.0710*				
	L.LreturnXMR				−0.156*	−0.0717							
	L.7												
	L.14				0.302***						0.175***		
	L.30	−0.139	−0.172**		−0.0734				−0.185***				−0.0897
	L.LreturnXRP		−0.0611		−0.0846	−0.0675	−0.0584*	−0.0829**	−0.0824**			−0.123***	
	L.7												
	L.14									0.111			
	L.30				0.227***								
H6	google	0.131			0.924***		0.194**		1.021*				
H7	GEPU												
	USEPU												
	EEPU									0.817			0.728

TABLE 5 (Continued)

Hypothesis	Variable	ADA Lreturn ADA I	BCH Lreturn BCH II	BTC Lreturn BTC III	EOS Lreturn EOS IV	ETC Lreturn ETC V	ETH Lreturn ETH VI	LTC Lreturn LTC VII	NEO Lreturn NEO VIII	TRX Lreturn TRX IX	XLM Lreturn XLM X	XMR Lreturn XMR XI	XRP Lreturn XRP XII
	CEPU				−0.240*						−0.354***		
	VIX												−0.0707
	VXO												
	VXN	0.410***											
H8	exchus												
	exjpus												
	exukus		1.275										
	exeuus				−0.187					−0.426			
	Gold				0.694					1.079			
H9	STOXX600	0.583											
	SP500												
	NYSE	3.077***											
	AMEX				0.880*								
	NASDAQ												
	NIKKEI												
	SSE				−0.627								
	Oil				−0.355								
H10	Cyber								0.0452*				
Time FE		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2		0.148	0.254	0.001	0.146	0.153	0.040	0.066	0.075	0.168	0.141	0.055	0.217
Observations		547	517	2008	517	609	533	533	533	533	517	609	517

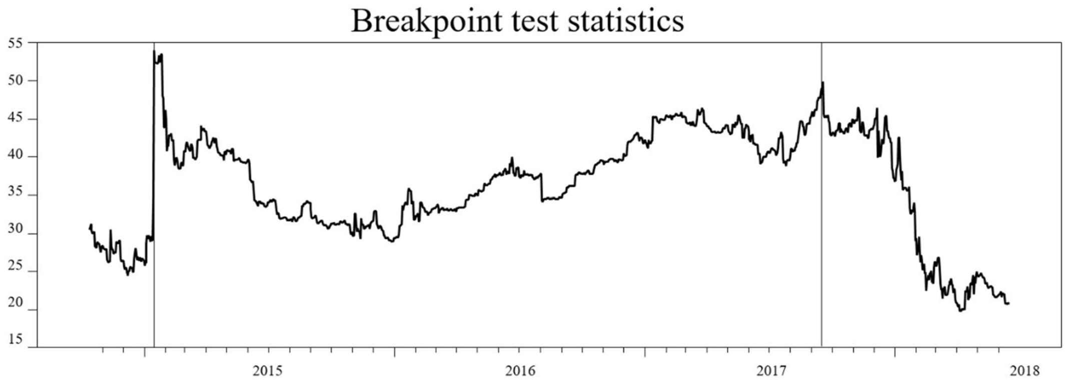

FIGURE 1 Breakpoints and division into periods. The different time periods covered in the regression analyses. The periods were identified through Andrews and Ploberger (1994) tests with *p* values calculated using Hansen's (1997) approximations and BTC data as a point of reference. This method results in the identification of two structural breaks (24 January 2015 and 14 September 2017) and thereby three time periods: (1) *Crash* (2 October 2013 to 24 January 2015). This period omits the first early market of BTC and other cryptocurrencies whose price volatility and existing userbase were relatively low. The analysis thus starts with the BTC boom in early 2013 and the subsequent crash. Cryptocurrencies that had not yet been implemented in this period—namely, Cardano (ADA), BCH, EOS, ETC, ETH, NEO, and TRX—are omitted both from the analysis and as explanatory variables. (2) *Recent* (25 January 2015 to 14 September 2017). This period encompasses the gradual recovery of BTC after the crash, as well as the more recent market and alleged bubble of BTC. Cryptocurrencies that had not yet been implemented in this period are omitted both from the analysis and as explanatory variables (ADA, BCH and TRX). (3) *Current* (16 September 2017–1 April 2019). This period continues beyond the scope of Panagiotidis et al. (2018) and is meant to capture the recent development of cryptocurrencies having become more accepted and increasingly implemented in the traditional economy. It also encompasses a period of higher volatility compared to previous periods.

- How tokens are created
- How tokens are distributed, and transactions validated
- What the token's target market is
- What the token is used for

Any common factors found in the division by categories when evaluating the hypotheses could help explain and further the understanding of what makes some variables relevant in explaining the returns of cryptocurrencies. If variation exists in the impacts of some variables but these impacts appear to be common over categories, then cryptocurrencies sharing these characteristics could display some level of homogeneity that can help explain the impacts.

4 | RESULTS AND ANALYSIS

This section presents and discusses the results of the LASSO regressions based on the themes presented in Section 2: tokens in circulation and technical factors (Section 4.1), monetary velocity (Section 4.2), network and lead effects (Section 4.3), speculation and hedging (Section 4.4), macroeconomic and financial conditions (Section 4.5), and cyberattacks (Section 4.6). For each theme, the results are interpreted using the theoretical framework and are reviewed for the whole period (Table 5) and for the crash, recent and current periods (Tables 6–8). Throughout this section, the results are also considered across the

TABLE 6 Determinants by cryptocurrencies, first period, *crash* (2 October 2013 to 24 January 2015)

This table reports the results from a LASSO analysis with cryptocurrencies log transformed first difference returns as the dependent variable. λ is set at max 5 to optimise predictive performance by minimising the estimated mean-squared prediction error. This table presents results using all available data for the first period, *crash* (2 October 2013 to 24 January 2015), determined by using Andrews–Ploberger tests and BTC data as a point of reference. All variable definitions are given in Table 2. Time fixed effects are reported at the bottom. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively. ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

Hypothesis	Variable	BTC LreturnBTC I	LTC LreturnLTC II	XLM LreturnXLM III	XMR LreturnXMR IV	XRP LreturnXRP V
H1	circulating	−220.4*	98.98			
H2	averagedifficulty		−0.0106			
H3	exchangevolumeusd		0.00536	0.0125		−0.0114
H5	**L.LreturnBTC**		0.241*	−0.740***	0.232	
	L.7		0.249**	0.386*		
	L.14		−0.226			
	L.30		−0.241*			−0.173
	L.LreturnLTC	−0.0103		0.358*		
	L.7					
	L.14	−0.0339				
	L.30	−0.172**		−0.119		−0.0607
	L.LreturnXLM	0.0989***	0.157***			0.0728
	L.7		−0.0204			−0.134**
	L.14		0.0569			
	L.30		−0.0833*			−0.0341

(Continues)

TABLE 6 (Continued)

Hypothesis	Variable	BTC LreturnBTC I	LTC LreturnLTC II	XLM LreturnXLM III	XMR LreturnXMR IV	XRP LreturnXRP V
	L.LreturnXMR		−0.0900			
	L.7	−0.0817*	−0.168**	−0.291**		−0.124*
	L.14		−0.0781	0.0777		
	L.30		0.109	−0.0932		
	L.LreturnXRP	−0.124**	−0.247***	0.0568		
	L.7		−0.0639	−0.144		
	L.14		−0.0190			
	L.30		0.170**	0.133		
H6	google		−0.167			
H7	GEPU		7.348			2.981**
	USEPU		−5.600	2.518*		
	EEPU	0.583	−4.521	−0.274		1.218
	CEPU		−0.398*	−0.0956		−0.115
	VIX		0.579**			
	VXO		−0.206			
	VXN	−0.120	−0.574**	−0.127		
H8	exchus		−2.066	9.580		9.763*
	exjpus	0.464	1.720			
	exukus	2.157**	3.759*	−0.759		

TABLE 6 (Continued)

Hypothesis	Variable	BTC LreturnBTC I	LTC LreturnLTC II	XLM LreturnXLM III	XMR LreturnXMR IV	XRP LreturnXRP V
	exeuus		−0.812			
	Gold	−0.358	−1.039	−1.193		−0.668
H9	STOXX600		0.514	0.255		1.049
	SP500		2.782			
	NYSE		−4.959			
	AMEX		−2.752			−0.675
	NASDAQ	−0.269	3.265			1.958
	NIKKEI		−1.288**	1.903**		
	SSE	−0.344	−0.217	0.828		1.250***
	Oil	−0.939***	−0.970***	−0.611		−0.893**
H10	Cyber	−0.134**	−0.268***			−0.0206
Time FE		Yes	Yes	Yes	Yes	Yes
R^2		0.246	0.503	0.231	0.009	0.336
Observations		171	142	172	248	142

TABLE 7 Determinants by cryptocurrencies, second period, *recent* (25 January 2015 to 14 September 2017)

This table reports the results from a LASSO analysis with cryptocurrencies log transformed first difference returns as the dependent variable. λ is set at max 5 to optimise predictive performance by minimising the estimated mean-squared prediction error. This table presents results using all available data for the second period, *recent* (25 January 2015 to 14 September 2017), determined by using Andrews–Ploberger tests and BTC data as a point of reference. All variable definitions are given in Table 2. Time fixed effects are reported at the bottom. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

		BTC	**EOS**	**ETC**	**ETH**	**LTC**	**NEO**	**XLM**	**XMR**	**XRP**
		Lreturn BTC	**Lreturn EOS**	**Lreturn ETC**	**Lreturn ETH**	**Lreturn LTC**	**Lreturn NEO**	**Lreturn XLM**	**Lreturn XMR**	**Lreturn XRP**
Hypothesis	**Variable**	**I**	**II**	**III**	**IV**	**V**	**VI**	**VII**	**VIII**	**IX**
H1	circulating									
H2	averagedifficulty			0.728***						
H3	exchangevolumeusd							0.0394**		
H5	**L.LreturnBTC**									
	L.7				−0.193					
	L.14				0.204*					
	L.30									
	L.LreturnEOS	−0.00980								0.00291
	L.7									
	L.14									
	L.30	−0.0795**			0.0598**			0.0817*		
	L.LreturnETC	−0.120			−0.239***					
	L.7	−0.154*			−0.0101			−0.209		
	L.14									
	L.30									

TABLE 7 (Continued)

Hypothesis	Variable	BTC Lreturn BTC I	EOS Lreturn EOS II	ETC Lreturn ETC III	ETH Lreturn ETH IV	LTC Lreturn LTC V	NEO Lreturn NEO VI	XLM Lreturn XLM VII	XMR Lreturn XMR VIII	XRP Lreturn XRP IX
	L.LreturnETH	−0.179								
	L.7		−0.307							
	L.14									
	L.30									
	L.LreturnLTC									0.0121
	L.7		−0.0976	−0.0928						−0.336***
	L.14									
	L.30									
	L.LreturnNEO									
	L.7									
	L.14	0.0394	0.363***		0.0710					
	L.30									
	L.LreturnXLM									
	L.7	0.212***	−0.134							
	L.14									
	L.30	0.0487								0.165*
	L.LreturnXMR									
	L.7				−0.0338					
	L.14	−0.127**	−0.268	0.0118	−0.149**			−0.103		
	L.30									

(Continues)

TABLE 7 (Continued)

Hypothesis	Variable	BTC Lreturn BTC I	EOS Lreturn EOS II	ETC Lreturn ETC III	ETH Lreturn ETH IV	LTC Lreturn LTC V	NEO Lreturn NEO VI	XLM Lreturn XLM VII	XMR Lreturn XMR VIII	XRP Lreturn XRP IX
	L.LreturnXRP									
	L.7									
	L.14									
	L.30	0.174	−0.468*							
H6	google		−1.925		0.126			−1.764*		
H7	GEPU									
	USEPU									−4.000
	EEPU									
	CEPU							0.257		
	VIX									
	VXO		−0.281							
	VXN									
H8	exchus	−5.821**	−16.64*	−4.914*	−16.74***	−0.718		−8.407**		−9.862**
	exjpus				1.223					
	exukus									
	exeuus				4.965**					
	Gold									
H9	STOXX600									
	SP500									

TABLE 7 (Continued)

Hypothesis	Variable	BTC Lreturn BTC I	EOS Lreturn EOS II	ETC Lreturn ETC III	ETH Lreturn ETH IV	LTC Lreturn LTC V	NEO Lreturn NEO VI	XLM Lreturn XLM VII	XMR Lreturn XMR VIII	XRP Lreturn XRP IX
	NYSE									
	AMEX									
	NASDAQ				1.577					2.619*
	NIKKEI	4.310***			0.719					
	SSE	−0.192								−0.615
	Oil	0.497								
H10	Cyber									
Time FE		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2		0.721	0.326	0.341	0.758	0.002	0.006	0.461	0.002	0.288
Observations		45	75	417	45	964	370	45	964	74

TABLE 8 Determinants by cryptocurrencies, third period, *current* (16 September 2017 to 1 April 2019)

This table reports the results from a LASSO analysis with cryptocurrencies log transformed first difference returns as the dependent variable. λ is set at max 5 to optimise predictive performance by minimising the estimated mean-squared prediction error. This table presents results using all available data for the third period, *current* (16 September 2017 to 1 April 2019), determined by using Andrews–Ploberger tests and BTC data as a point of reference. All variable definitions are given in Table 2. Time fixed effects are reported at the bottom. ***, ** and * indicate statistical significance at the 1%, 5% and 10% level, respectively. ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

		ADA	BCH	BTC	EOS	ETC	ETH	LTC	NEO	TRX	XLM	XMR	XRP
		Lreturn ADA	Lreturn BCH	Lreturn BTC	Lreturn EOS	Lreturn ETC	Lreturn ETH	Lreturn LTC	Lreturn NEO	Lreturn TRX	Lreturn XLM	Lreturn XMR	Lreturn XRP
Hypothesis	**Variable**	**I**	**II**	**III**	**IV**	**V**	**VI**	**VII**	**VIII**	**IX**	**X**	**XI**	**XII**
H1	circulating		10.70***			36.08*							
H2	averagedifficulty		0.331***	0.274***		0.520***	0.115*	0.349***					
H3	exchangevolumeusd								0.0120	0.00902			
H5	**L.LreturnADA**												−0.149***
	L.7												
	L.14						0.0513**	0.0627*	0.0358	0.0433			0.0694*
	L.30		−0.102**		−0.0528						−0.166***		−0.0511
	L.LreturnBCH												
	L.7												
	L.14												
	L.30	−0.101*			−0.0344								
	L.LreturnBTC				0.168								
	L.7				0.104					0.197			0.352***
	L.14				−0.121					−0.514***			
	L.30				0.306**								

TABLE 8 (Continued)

		ADA	BCH	BTC	EOS	ETC	ETH	LTC	NEO	TRX	XLM	XMR	XRP
		Lreturn ADA	Lreturn BCH	Lreturn BTC	Lreturn EOS	Lreturn ETC	Lreturn ETH	Lreturn LTC	Lreturn NEO	Lreturn TRX	Lreturn XLM	Lreturn XMR	Lreturn XRP
Hypothesis	**Variable**	**I**	**II**	**III**	**IV**	**V**	**VI**	**VII**	**VIII**	**IX**	**X**	**XI**	**XII**
	L.LreturnEOS												
	L.7					0.0641*	0.0440	0.0692**		0.241***		0.0552*	
	L.14	0.210***								0.133*			
	L.30	0.374***	0.193***			0.253***	0.0540*		0.194***	0.0211	0.327***	0.140***	0.345***
	L.LreturnETC									−0.355***			
	L.7	−0.0538			−0.0808					−0.308***			−0.162***
	L.14							0.0667	0.0598				
	L.30												
	L.LreturnETH												
	L.7												
	L.14	−0.339***			−0.165								
	L.30												
	L.LreturnLTC				0.142					0.180*			
	L.7				0.113					0.159			
	L.14												
	L.30	−0.151*			−0.168*	−0.169***					−0.166**	−0.203***	−0.171**
	L.LreturnNEO												
	L.7	−0.0315	−0.0949**		−0.159**					−0.367***	−0.114**		−0.164***
	L.14												
	L.30												−0.0984

(Continues)

TABLE 8 (Continued)

Hypothesis	Variable	ADA Lreturn ADA I	BCH Lreturn BCH II	BTC Lreturn BTC III	EOS Lreturn EOS IV	ETC Lreturn ETC V	ETH Lreturn ETH VI	LTC Lreturn LTC VII	NEO Lreturn NEO VIII	TRX Lreturn TRX IX	XLM Lreturn XLM X	XMR Lreturn XMR XI	XRP Lreturn XRP XII
	L.LreturnTRX	0.149***									0.0285		0.135***
	L.7				0.0586								
	L.14				−0.00678								0.0511
	L.30		0.0842**		0.0473								
	L.LreturnXLM		−0.0307							0.189***			
	L.7	−0.0986*								0.114*			
	L.14	0.132**								0.0320			
	L.30	−0.0783	−0.0306		−0.0994*	−0.0866**			−0.0710*				
	L.LreturnXMR	−0.145**			−0.156*	−0.0719							
	L.7												
	L.14				0.302***						0.175***		
	L.30	−0.117	−0.172**		−0.0734				−0.185***				−0.0897
	L.LreturnXRP		−0.0611		−0.0846	−0.0850*	−0.0584*	−0.0829**	−0.0824**			−0.117***	
	L.7												
	L.14									0.111			
	L.30				0.227***								
H6	google	0.172*			0.924***		0.194**		1.021*				
H7	GEPU												
	USEPU												
	EEPU									0.817			0.728

TABLE 8 (Continued)

Hypothesis	Variable	ADA Lreturn ADA I	BCH Lreturn BCH II	BTC Lreturn BTC III	EOS Lreturn EOS IV	ETC Lreturn ETC V	ETH Lreturn ETH VI	LTC Lreturn LTC VII	NEO Lreturn NEO VIII	TRX Lreturn TRX IX	XLM Lreturn XLM X	XMR Lreturn XMR XI	XRP Lreturn XRP XII
	CEPU	−0.186			−0.240*						−0.354***		
	VIX												−0.0707
	VXO												
	VXN	0.477***											
H8	exchus												
	exjpus												
	exukus		1.275										
	exeuus				−0.187					−0.426			
	Gold				0.694					1.079			
H9	STOXX600	0.406											
	SP500												
	NYSE	3.557***											
	AMEX				0.880								
	NASDAQ												
	NIKKEI												
	SSE				−0.627								
	Oil				−0.355								
H10	Cyber								0.0452*				
Time FE		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2		0.196	0.254	0.018	0.146	0.175	0.040	0.066	0.075	0.168	0.141	0.056	0.217
Observations		534	517	564	517	534	533	533	533	533	517	534	517

cryptocurrencies based on their design choices, to identify common patterns among types of cryptocurrencies (for more details on design choices, see Appendix B).

4.1 | Tokens in circulation and technical factors

Information on tokens in circulation is only available for cryptocurrencies utilising proof of work for distribution and the validation of transactions (BTC, BCH, LTC, ETC, ETH and XMR). When the whole period is considered, the results are only significant for BCH. The effect is positive, and a larger supply contributes to a higher return. When each period is considered, the impact is only positive for BCH and ETC in the third period. By contrast, in the first period, the crash period, the impact is significant and negative for BTC, suggesting that a larger supply leads to lower prices in the first period, ceteris paribus, but that this impact dissipates over time.

These findings support earlier research, where an increased supply leads to lower prices for BTC, thereby decreasing returns (Ciaian et al., 2016), but, similarly to the results of Li and Wang (2017), this negative impact does not persist over time. Li and Wang (2017) find that increased supply shifts from a negative to a positive impact on BTC returns when comparing the early market data to the later BTC market, whereas the current study's model shows instead that the impact dissipates over time. It could be that sufficient demand is established for BTC in the later periods to counterbalance the negative impact of increased supply. If the demand is high enough, then the predictable increases in the supply of BTC might still not be enough to decrease prices. It is also possible that the number of possible trading partners increases as the supply of BTC increases, which, in turn, increases demand and leads to higher prices. By contrast, the positive impact found for BCH and ETC suggests that increases in supply contribute to higher prices, thereby increasing returns in later periods for BCH and ETC.

These results are also found in the alternative specifications, except that the circulating supply is not significant for BTC in the VAR models. This finding could suggest that the impact of the circulating supply on BTC is even smaller than estimated with the LASSO regression models. All three cryptocurrencies with a significant impact from increases in supply share the characteristics of token creation rising up to the cap, utilising a proof-of-work distribution system and having a generic target market. However, the large variation in the significance and direction of impact among the cryptocurrencies makes it possible to accept H1, that cryptocurrencies' returns are impacted differently by the *number of tokens in circulation.*

Hypothesis 2 states that variations in hash rates between cryptocurrencies create differences in the determinants of returns. The proxy used to evaluate hash rates, the variable for *average difficulty*, is only available for some of the cryptocurrencies (BTC, BCH, LTC, ETC, ETH, and XMR). However, among those, there are strong similarities in the effect of average difficulty on returns. The impact of an increase on average difficulty on returns is positive, for both the whole period and the third period, that is, the current period. The exception is XMR, for which this variable is not significant, and BTC, for which the impact is only significant in the third period. These results are also noted in the alternative specifications and in the VAR analysis, although the VAR results highlight that the impact dissipates quickly.

The effect is similar both in direction and over time, which suggests that at least some of the cryptocurrencies are similarly impacted and that improvements in technical determinants such as the hash rate contribute to higher returns. This finding supports the arguments of Dwyer (2015), that the choice of technical determinants and characteristics could contribute to a positive value for a cryptocurrency. The results also correspond to those of Bouoiyour and Selmi (2015). However, due to the lack of data, the effects found might reflect the characteristics of the cryptocurrencies with the information available, such as proof-of-work protocols and a generic target market. Taking the different periods into account, the data on average difficulty offers too little information to determine the common elements across various cryptocurrencies. For example, the information on average difficulty is only available for cryptocurrencies using proof of work and with a generic target market. This could suggest that proof of work and generic target markets are common factors for cryptocurrencies where a higher hash rate leads to greater returns. The one exception, XMR, shows no design features distinct from the other cryptocurrencies that would help explain the results. Given the lack of information, it is not possible to conclude if the results would be similar for the other categories if the data were available.

The similarities in sign and occurrence over time of the effect for the cryptocurrencies with available data suggest H2, that cryptocurrencies' returns are impacted differently by variations in hash rates, should be rejected.

4.2 | Monetary velocity

The impact of increases in monetary velocity is rarely found to be significant in the LASSO models, displaying only a positive impact for Stellar (XLM) in the second period, the recent period (also supported by the alternative specifications). This finding suggests that increases in the total volume of XLM transaction outputs have a positive impact on XLM returns. However, when lambda is restricted to a minimum value, a negative impact is also found on the returns for BCH in the second period. The VAR analysis highlights the short-term impacts for many of the cryptocurrencies, and an immediate positive impact is followed by a negative impact that quickly dissipates (ETC, ETH, LTC, NEO, TRX, XLM, XRP and XMR).

The similarities could suggest some degree of homogeneity among the cryptocurrencies in terms of how they are impacted by changes in monetary velocity or perhaps, instead, in terms of the lack of impact. Both XLM and BCH share the characteristic of mainly being used for transactions. A higher monetary velocity implies a higher rate at which money is exchanged in the economy, which, in turn, adds value and could lead to increases in demand for a cryptocurrency that is particularly used for transactions. The positive impact the exchange volume on the other cryptocurrencies is in line with the findings of Polasik et al. (2015), who conclude that monthly changes in the number of BTC transactions have a significant positive impact on BTC returns. For the cryptocurrencies whose exchange volume is not relevant, the results are similar to those of Ciaian et al. (2016), who find no significant impact on their tested measure (days destroyed).

By contrast, when considering the results from the alternative VAR specification, it is not possible to distinguish any common characteristics among the design choices of the cryptocurrencies; rather, the impact of monetary velocity seems to affect cryptocurrencies in every possible category. This finding, in turn, could suggest that the common factor is something that is not captured by this division into types of design choices, but that similarities could still exist across cryptocurrencies. It is possible that the choice of measurement affects which cryptocurrencies display relevant impacts on returns. Since the variable used for this study, the exchange volume, does not include data on over-the-counter exchanges or trading platforms, the results could be more informative if an overall measure of all transaction outputs were used. The strong focus on exchanges with the variable tested could imply that an effect is observed for cryptocurrencies whose trade on exchanges comprises a large share of the volume, but that cryptocurrencies with alternative trading routes are not captured to the same extent.

This large difference between the number of cryptocurrencies for which the impact of monetary velocity is relevant in explaining returns and the number of cryptocurrencies for which it is not combined with the distinct impacts on BCH and XLM returns makes it possible to accept H3, that cryptocurrencies' returns are impacted differently by changes in their monetary velocity.

4.3 | Network effects and lead behaviour

Comparison over time shows that variations in the date of implementation appear to create differences in cryptocurrency returns, particularly when considering the changes over time in the number of relevant variables or looking at the impact of average difficulty as a competitive advantage. However, it is hard to isolate the effects and to fully distinguish them from the impact of, for example, the proof-of-work protocol as a design choice. Choosing another method that more clearly takes the time aspect into account could offer more detailed results and clearer insights into the impact of network effects and the role of the date of implementation.

In the first period, the crash period (see Table 6), older cryptocurrencies tend to have more variables that are relevant in explaining their returns. These older cryptocurrencies (BTC, LTC and XRP) also have several variables in common that show a strong impact of changes in oil prices or cyberattacks. The more recent cryptocurrencies have fewer variables that are relevant and common in explaining their returns in the crash period, but most of them (BTC, LTC, XRP and XLM) have some overall pairwise similarities in interdependencies with other cryptocurrencies. It is difficult to distinguish any particular common factors related to the date of implementation in the recent period, but overall, the impact of China–United States exchange rates takes on greater relevance for several cryptocurrencies (BTC, XRP, XLM, ETC and ETH). In the third, current period, the variables are slightly more relevant in explaining returns for later cryptocurrencies, particularly regarding interdependencies with other cryptocurrencies. By contrast, the older cryptocurrencies (BTC and LTC) are more impacted by changes in the hash rate, but this is also the case for some of the later cryptocurrencies (ETC, ETH and BCH). The impact is positive, possibly suggesting that cryptocurrencies can use better hash rates to gain an edge on the competition in the more recent market. Further, Google searches offer a mixed picture, more relevant for the recent cryptocurrencies (ETH, NEO and EOS) and only for one of the newest cryptocurrencies (ADA).

The movement from more relevant variables to fewer of them for the older cryptocurrencies could imply that the dominant theoretical framework is appropriate to explain the returns for the older cryptocurrencies during the crash period, but less so in the current period. This would support the view of Corbet et al. (2018), who shows that the results obtained in 2016 differ from those obtained in 2018. Taken together, variations in the date of implementation appear to create differences in the returns of the cryptocurrencies, thus making it possible to accept H4, that cryptocurrencies' returns are impacted differently by their *date of implementation.*

Further, the large variations in relevance over time and whether the impact is positive or negative suggest that the cryptocurrency market is highly integrated, with strong interactions and interdependencies among cryptocurrencies in the short term. However, there is no clear cut winner takes all race across all three periods, and the possible substitution effects change over time.

In detail, the impacts of the lagged values of returns for competing cryptocurrencies move in different directions in different periods for almost all cryptocurrencies. Table 6 shows that, in the first period, the returns of BTC are negatively impacted by the most relevant cryptocurrencies (except for XLM, whose short-term impact is positive), which suggests a leading position in the winner takes all race. Increases in the returns of other cryptocurrencies

(LTC, XMR and XRP) have a negative impact on the returns of BTC, possibly due to a substitution effect with alternative cryptocurrency investments.

However, this result changes in the recent period (Table 7) and the *current* period (Table 8). Here, the impacts on BTC returns from increases in other cryptocurrencies are mixed, with both positive and negative impacts. In the third period, none of the other cryptocurrencies' returns remain relevant. One possible explanation could be if, in the third period, BTC was established enough to avoid the threat of other cryptocurrencies. For all the other cryptocurrencies, the results are mixed in all periods, with both positive and negative impacts. This finding suggests that a strong interaction exists between cryptocurrencies and that this has an impact on returns. However, things might not be as clear-cut as a winner takes all race. Rather, it could be the result of movements on a very liquid market where the substitution effects change depending on the current relative popularity of the cryptocurrencies. The alternative specifications and VAR analysis support these results, though the VAR results highlight that the cryptocurrency market could be even more volatile, with short-term interdependencies among cryptocurrencies (since the impact of a sudden price shock rarely lasts beyond 1 day).

These results confirm the existence of a price discovery process between various cryptocurrency exchanges, where the prices on one exchange transmit to another with a lag (Brandvold et al., 2015; Giudici & Abu-Hashish, 2019; Giudici & Polinesi, 2021; Pagnottoni & Dimpfl, 2019; Pieters & Vivanco, 2017). The results also confirm that the interconnectedness between cryptocurrencies increases over time (Koutmos, 2018; Yi et al., 2018), while highlighting that BTC does not seem to follow the same trend as the other cryptocurrencies in the more recent periods. The impacts of the lagged returns of other cryptocurrencies vary over time across all cryptocurrencies, which makes it possible to accept H5, that is, cryptocurrencies' returns are impacted differently by the *lagged values of the returns of other cryptocurrencies.*

4.4 | Speculation and hedging

The results demonstrate that the impact of investor attention on returns is positive for many cryptocurrencies. Overall, investor attention is relevant in explaining returns, with a positive impact for four cryptocurrencies in the first and third periods (ADA, ETH, NEO and EOS). By contrast, the impact is negative in the second period for XLM. The results are also supported by the alternative specifications and the VAR analysis, although the latter highlights an overall more common positive impact, particularly in the second and third periods (i.e. for BTC, ADA, BCH, EOS, ETH, TRX, NEO, XLM, XRP and XMR). The impact of investor attention generally has a positive impact on the returns of a cryptocurrency, in line with previous studies (Bouoiyour & Selmi, 2015, 2017; Ciaian et al., 2016; Kristoufek, 2013; Li & Wang, 2017; Panagiotidis et al., 2018; Polasik et al., 2015).

When considering the impact of design choices, the LASSO analysis shows that investor attention is particularly important for cryptocurrencies that are business oriented (ADA, EOS and XLM) or that have a less common system for token distribution and the validation of transactions (e.g., proof of stake for ADA and voting for NEO and EOS). Cryptocurrencies that are business oriented could be, overall, more susceptible to investor attention, positive or negative, given that investors' use of cryptocurrencies could directly impact the perception of a company and its investments. Investors could thus be keener to react to sudden changes in speculation. The less common systems for token distribution and the validation of transactions can be of particular interest to speculating investors looking for alternative investment opportunities to the original proof-of-work concept. Overall, the results indicate that changes in investor attention impact cryptocurrencies differently, especially across different periods, and it is thus possible to accept H6, that is, cryptocurrencies' returns are impacted differently by *levels of speculation*.

Regarding the unrestricted results, some effects of regional uncertainty have a positive impact on returns (the VXN on ADA), whereas others have a negative impact (the CEPU on NEO and XLM). The picture remains mixed when considering different periods and alternative specifications, except for the CEPU, whose impact is always negative in the first and third periods. This result could possibly indicate that Chinese investments in cryptocurrencies were substantial at these times. As uncertainty rose in China, investments in cryptocurrencies perhaps became less attractive for these investors, which could have decreased demand, with negative effects on the cryptocurrency returns. The VAR analysis confirms the very mixed impacts of regional uncertainty on all cryptocurrencies, also displaying some short-term positive impacts to sudden shocks to the CEPU.

The impacts of different measures of uncertainty vary between positive and negative, not displaying any clear patterns over time for any cryptocurrency. Further, there is no uncertainty index that has an either all positive or all negative impact on returns for the cryptocurrencies for which it is relevant, although shocks to the CEPU seem to have a mostly negative impact on the returns of the cryptocurrencies where it is significant. Taken together, these findings suggest large differences among cryptocurrencies in how their returns are impacted by global and regional uncertainty. It is thus possible to accept H7, that cryptocurrencies' returns are impacted differently by *global and regional uncertainties*.

The impact of exchange rates on the returns of cryptocurrencies is mostly relevant in the first and second periods. In the first period (Table 7), the impact is positive for changes in the exchange rate of the USD to the Chinese yuan (XRP) and to the British pound (BTC and LTC). In the second period (Table 8), the impact is instead negative for changes in the exchange rate of the USD to the Chinese yuan (BTC, EOS, ETC, ETH, XLM and XRP) and positive for changes to the exchange rate of the USD to the euro (ETH). Gold prices do not have a significant impact on cryptocurrency returns in any period. The alternative specifications confirm these results, although the VAR analysis also indicates a minor short-term positive impact of shocks to gold prices for XMR's returns. The results are similar to the negative effect of the Chinese yuan determined by Bouoiyour and Selmi (2017), who find that the impact on the BTC price index is negative when the market is in a bull state. In the current study's models, there is no separation between the bull and bear states of the cryptocurrency markets, but some overlap is likely in the timing. The state of the market could help explain this study's findings and further illustrate that the findings of Bouoiyour and Selmi (2017) might be of relevance beyond the BTC market.

Overall, the impact of exchange rates and the gold price index were more relevant in the earlier periods. The large differences in impact on the returns of different cryptocurrencies and the potential uncertainties the cryptocurrencies are used to hedge make it possible to accept H8, that cryptocurrencies' returns are impacted differently by the *price development of assets traditionally used for hedging*.

4.5 | Macroeconomic and financial conditions

The large variation and differences in effects across cryptocurrencies suggest that variations in macrofinancial development create differences in the determinants of the returns of cryptocurrencies, both over time and for each cryptocurrency. When the whole period is considered, one notable result is that half the cryptocurrencies' returns are unaffected by changes in macroeconomic and financial developments. For the remaining half (ADA, EOS, NEO, ETC, LTC and BTC), the results tend to display mostly positive effects on returns. Both US and Japanese stock indices (NYSE/AMEX and the Nikkei) tend to lead to significant increases in the returns of cryptocurrencies. These results are also seen in the alternative specifications. One exception is the negative impact of the Shanghai Stock Exchange Index on BTC. The positive effects from increases in the AMEX Index on both EOS and NEO could result from both cryptocurrencies being used for applications. If many of the companies working with these applications are based in the United States, positive developments in the AMEX Index can signal improved conditions for those companies, which, in turn, can increase demand for their products and the cryptocurrencies themselves. BTC, however, is negatively impacted by increases in the SSE Index. If BTC is extensively used as an alternative investment to traditional Chinese stock, investors will not seek out alternative investments to the same extent if the Chinese market improves. This can decrease demand for the cryptocurrency and reduce returns.

There is also considerable variation in terms of how stock and oil indices impact cryptocurrencies over time. In the first period, the crash period, increases in oil prices significantly reduced returns for BTC, LTC and XRP. This result supports earlier research that demonstrates spillover effects between the oil and cryptocurrency markets (Okorie & Lin, 2020) but shows that the effect is opposite that Panagiotidis et al. (2018) find. Regarding stock indices, the Nikkei index influences the returns of XLM and LTC, albeit in different directions. In the second and third periods, the impacts are confined to result from stock indices and seem less common compared those in earlier periods. These tendencies of a more prominent role of oil prices in the first period and of stock markets in the more recent periods are supported by the alternative specifications. These results could suggest that early investors might have used cryptocurrencies as a complementary investment to their traditional stocks, with a movement towards less interaction between the markets and a more active userbase noted later. It is possible that the cryptocurrency market established itself as a market on its own and that spillover effects across markets have become less frequent compared to earlier periods.

Overall, these results show that the returns of many cryptocurrencies are unaffected by changes in macroeconomic and financial conditions, whereas others are influenced in different directions and by different magnitudes. This large variation makes it possible to accept H9, that cryptocurrencies' returns are impacted differently by *changes in macroeconomic and financial market conditions*. It thereby appears that the decentralised nature of some cryptocurrencies implies that their pricing is not influenced by traditional macroeconomic determinants of supply and demand, either directly or indirectly.

4.6 | Cyberattacks

The results suggest that cyberattacks have little effect on most cryptocurrencies' returns, especially in later periods. The coefficients are positive, small, and nonsignificant in the main model. The alternative specifications rarely show any significance for the variable, apart from significant positive effects on NEO's returns. In the VAR analysis in all periods, the confidence interval never peaks above or below zero, implying no significant response of cryptocurrencies to the shocks of cyberattacks. However, considering developments over time, some tentative patterns emerge. In the first period, the crash period, cyberattacks have a significant negative impact on the returns of BTC and LTC. For the latter, this result is also supported by the VAR analysis, where LTC is temporarily negatively impacted by the sudden shock of cyberattacks, although the impact dissipates after a few (approximately four) days. For the recent and current periods, no significant impacts on returns are found (apart from a small positive effect on XMR).

These results do not corroborate earlier research (Caporale et al., 2020) that demonstrates negative effects on cryptocurrency price stability from cyberattacks. Despite increasing attacks on the blockchain industry (Lazarenko & Avdoshin, 2018), creation platforms, and exchanges (Corbet et al., 2019), the effects of cyberattacks over time appear to be waning. This finding could suggest that the effects of cyberattacks have decreased over time, as the cryptocurrency market has matured and is increasingly perceived as being relatively robust to cybercrime. Given the relatively few cryptocurrencies for which cyberattacks are significant it is hard to draw conclusions on the impact of design choices.

BTC, LTC and XMR share several characteristics, namely, a supply rise up to the cap, using a proof-of-work concept for distributing transactions, and a generic target market, whereas NEO has a fixed supply and uses a voting system. Common to all of these is the generic target audience, and perhaps these investors are more susceptible to the effects of cyberattacks. For example, if the generic target audience has less detailed knowledge of the functionality and inherent risks of their cryptocurrency investments, they might be more prone to react when cyberattacks occur, regardless of the type and target of the attack. The significant negative results in the crash period are thus similar to those of Caporale et al. (2020), who document that BTC, LTC and ETC experience heightened volatility after cyberattacks.

Taken together, the results suggest that the returns on cryptocurrencies are relatively untouched by cyberattacks and cybercrime. Since this absence of effects is common to most cryptocurrencies, particularly for latter periods, H_{10}, that is, cryptocurrencies' returns are impacted differently by *cyberattacks,* is thus rejected.

5 | DISCUSSION AND CONCLUSION

This article analyses the homogeneity of cryptocurrencies by testing the determinants of returns that have been identified for BTC in recent research on a sample of 12 cryptocurrencies. It thereby offers insights into whether particular determinants and their impact on cryptocurrencies' returns differ between cryptocurrencies. The findings show that cryptocurrencies are heterogeneous with respect to the determinants of returns. More specifically, variations in the number of tokens in circulation, monetary velocity, the date of implementation, the level of speculation, uncertainty, and macroeconomic and financial conditions all create differences in the determinants of the returns of cryptocurrencies. Overall, the results suggest that the overarching hypothesis should be accepted, that cryptocurrencies are heterogeneous with respect to the determinants of returns. However, some exceptions exist: the choice of technical determinants and hash rates have similar impacts on most cryptocurrencies, whereas, by contrast, all cryptocurrencies seem to be rather unaffected by cyberattacks and cybercrime.

The results also show that different periods and design choices matter. Cryptocurrencies with a supply that rises up to the cap appear to be more sensitive to the circulating supply, particularly in later periods. In the earlier periods, cryptocurrencies with a supply that rises up to the cap were more sensitive to the returns of other cryptocurrencies, whereas cryptocurrencies with a supply that rises indefinitely were not impacted. In the more recent period, this image is reversed, and only cryptocurrencies with either a fixed supply or a supply that rises indefinitely were impacted by other cryptocurrencies' returns. Cryptocurrencies that are business oriented appear to be more sensitive to investor attention and speculation, and cryptocurrencies that are used for applications appear to be slightly more sensitive to stock market development and traditional hedging measures.

Generally, the results illustrate that BTC displays several distinguishing traits, thus making it unlikely to be seen as a representative cryptocurrency. For example, the effect on BTC returns stands out compared to the other cryptocurrencies in terms of variables measuring tokens in circulation and monetary velocity. Regarding the relation to other cryptocurrencies, BTC appears to have taken the lead in a winner takes all race in the earlier periods, but this lead is later replaced by substitution effects and shifting interactions between all cryptocurrencies, suggesting strong integration in the cryptocurrency market. Since cryptocurrencies are heterogeneous, the strong BTC focus could make the existing models and current theoretical framework less relevant in explaining how the cryptocurrency market works. This, in turn, carries the risk of misinterpretation and misdirected regulation if heterogeneity among cryptocurrencies is not considered.

The generalisability of the results is subject to certain limitations. For instance, some of the cryptocurrency-specific determinants of the returns evaluated only have data available for cryptocurrencies using a proof-of-work protocol. Further, the lack of cryptocurrencies in some categories of design choices makes comparison difficult. Another consideration relates to the method and alternative specifications applied in this article; while they offer comparative results across cryptocurrencies, future research could benefit from looking at specific cryptocurrencies more in detail. A nonlinear analysis allowing for differences across each cryptocurrency's quantiles of the conditional distribution of the dependent variable would likely yield more information. This could deepen the understanding of a subsample of cryptocurrencies with specific characteristics, such as proof-of-work-protocols.

Moreover, cryptocurrencies are by nature global, but their investors are often individuals with a more local perspective. In-depth analysis of behavioural economics could help clarify how the cryptocurrency market works and decrease the risks associated with endogeneity in the current models, particularly if it can offer a deeper understanding of user activity, the role of speculation and investor motivation, the perceived substitutability between cryptocurrencies, and so on. The aim of such research should be to gain a deeper understanding of individuals' interest in and perceived usefulness of a cryptocurrency. Further, the potential connection to illegal activity, investor protection, and systemic risk are matters that should be at the forefront of the regulatory debate on cryptocurrencies, and future studies on these topics is therefore recommended.

REFERENCES

Ahrens, A., Hansen, C. B., & Schaffer, M. E. (2020). Lassopack: Model selection and prediction with regularized regression in stata. *The Stata Journal: Promoting communications on statistics and Stata*, *20*(1), 176–235.

Andrews, D. W. K., & Ploberger, W. (1994). Optimal tests when a nuisance parameter is present only under the alternative. *Econometrica*, *62*(6), 1383–1414.

Auer, R., & Claessens, S. (2020). Cryptocurrency market reactions to regulatory news. In K. Thomas (Ed.), *The Routledge handbook of FinTech* (pp. 455–468). Routledge Handbooks Online.

Balcilar, M., Bouri, E., Gupta, R., & Roubaud, D. (2017). Can volume predict bitcoin returns and volatility? A quantiles-based approach. *Economic Modelling*, *64*, 74–81.

Baur, D. G., Dimpfl, T., & Kuck, K. (2018). Bitcoin, gold and the US dollar—A replication and extension. *Finance Research Letters*, *25*, 103–110.

Benjamin, V., Valacich, J. S., & Chen, H. (2019). DICE-E: A framework for conducting Darknet identification, collection, evaluation with ethics. *MIS Quarterly*, *43*(1), 1–22.

Bouoiyour, J., & Selmi, R. (2015). What does bitcoin look like? *Annals of Economics and Finance*, *16*(2), 449–492.

Bouoiyour, J., & Selmi, R. (2017). The Bitcoin price formation: Beyond the fundamental sources. arXiv preprint arXiv:1707.01284.

Bouri, E., Gupta, R., Tiwari, A. K., & Roubaud, D. (2017). Does bitcoin hedge global uncertainty? Evidence from wavelet-based quantile-in-quantile regressions. *Finance Research Letters*, *23*, 87–95.

Brandvold, M., Molnár, P., Vagstad, K., & Andreas Valstad, O. C. (2015). Price discovery on bitcoin exchanges. *Journal of International Financial Markets, Institutions and Money*, *36*, 18–35.

Brière, M., Oosterlinck, K., & Szafarz, A. (2015). Virtual currency, tangible return: Portfolio diversification with bitcoin. *Journal of Asset Management*, *16*(6), 365–373.

Burnie, A. (2018). Exploring the Interconnectedness of Cryptocurrencies using Correlation Networks. In *Proceedings of the Cryptocurrency Research Conference 2018, Anglia Ruskin University Lord Ashcroft International Business School Centre for Financial Research, Cambridge, UK, 24 May 2018.*

Caporale, G. M., Kang, W. Y., Spagnolo, F., & Spagnolo, N. (2020). Non-linearities, cyber attacks and cryptocurrencies. *Finance Research Letters*, *32*, 101297.

Cheah, E. T., & Fry, J. (2015). Speculative bubbles in bitcoin markets? An empirical investigation into the fundamental value of bitcoin. *Economics Letters*, *130*, 32–36.

Cheung, A. W., Roca, E., & Su, J. J. (2015). Crypto-currency bubbles: An application of the Phillips–Shi–Yu (2013) methodology on Mt. Gox bitcoin prices. *Applied Economics*, *47*(23), 2348–2358.

Chicago Board Options Exchange. (2019). *White paper CBOE volatility index*. Retrieved February 1, 2019, from http://www.cboe.com/micro/vix/vixwhite.pdf

Chilson, N. (2018). *It's time for a FTC Blockchain Working Group*. Federal Trade Commission. Retrieved February 1, 2019, from https://www.ftc.gov/news-events/blogs/techftc/2018/03/its-time-ftc-blockchain-working-group

Chu, J., Chan, S., Nadarajah, S., & Osterrieder, J. (2017). GARCH modelling of cryptocurrencies. *Journal of Risk and Financial Management*, *10*(4), 17.

Ciaian, P., Rajcaniova, M., & Kancs, A. (2018). Virtual relationships: Short-and long-run evidence from BitCoin and altcoin markets. *Journal of International Financial Markets, Institutions and Money*, *52*, 173–195.

Ciaian, P., Rajcaniova, M., & Kancs, A. (2016). The economics of bitcoin price formation. *Applied Economics*, *48*(19), 1799–1815.

Coin Metrics (2018). *On data and certainty* [Blog post]. Retrieved January 2, 2019, from https://CoinMetrics.io/on-data-and-certainty/

Corbet, S., Lucey, B., Urquhart, A., & Yarovaya, L. (2019). Cryptocurrencies as a financial asset: A systematic analysis. *International Review of Financial Analysis*, *62*, 182–199.

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.

Dabrowski, M., & Janikowski, L. (2018). Virtual currencies and central banks monetary policy: Challenges ahead. *Monetary Dialogue. Policy Department for Economic, Scientific and Quality of Life Policies*. European Parliament.

Dwyer, G. P. (2015). The economics of bitcoin and similar private digital currencies. *Journal of Financial Stability*, *17*, 81–91.

Dyhrberg, A. H. (2016). Bitcoin, gold and the dollar—A GARCH volatility analysis. *Finance Research Letters*, *16*, 85–92.

Economic Policy Uncertainty (2019). *Methodology*. Retrieved March 1, 2019, from https://www.policyuncertainty.com/methodology.html

Ernst & Young. (2017). *EY research: initial coin offerings (ICOs)*, December 2017. Retrieved January 22, 2022, from https://assets.ey.com/content/dam/ey-sites/ey-com/en_gl/topics/banking-and-capital-markets/ey-research-initial-coin-offerings-icos.pdf

European Central Bank. (2012). *Virtual currency schemes*. Frankfurt am Main. Retrieved January 2, 2019, from https://www.ecb.europa.eu/pub/pdf/other/virtualcurrencyschemes201210en.pdf

European Central Bank. (2015). *Virtual currency schemes—A further analysis*. Frankfurt am Main. Retrieved January 2, 2019, from https://www.ecb.europa.eu/pub/pdf/other/virtualcurrencyschemesen.pdf

Foley, S., Karlsen, J. R., & Putniņš, T. J. (2019). Sex, drugs, and bitcoin: How much illegal activity is financed through cryptocurrencies? *The Review of Financial Studies*, *32*(5), 1798–1853.

Gandal, N., & Halaburda, H. (2014). *Competition in the cryptocurrency market*. Bank of Canada WP. Retrieved January 1, 2018, from https://www.bankofcanada.ca/wp-content/uploads/2014/08/wp2014-33.pdf

Gans, J. S., & Halaburda, H. (2015). Some economics of private digital currency. In A. Goldfarb, S. Greenstein, & C. Tucker (Eds.), *Economic analysis of the digital economy* (pp. 257–276). Chicago: University of Chicago Press.

Giudici, P., & Abu-Hashish, I. (2019). What determines bitcoin exchange prices? A network VAR approach. *Finance Research Letters*, *28*, 309–318.

Giudici, P., & Polinesi, G. (2021). Crypto price discovery through correlation networks. *Annals of Operations Research*, *299*(1), 443–457.

Google Trends. (2019) *Interest over time*. Retrieved May 8, 2019, from https://trends.Google.com/trends/explore

Hansen, B. E. (1997). Approximate asymptotic *p*-values for structural change tests. *Journal of Business & Economic Statistics*, *15*(1), 60–67.

Hastie, T., Tibshirani, R., & Friedman, J. (2001). *The elements of statistical learning: Data mining, inference, and prediction*. Springer.

Hayes, A. S. (2017). Cryptocurrency value formation: An empirical study leading to a cost of production model for valuing bitcoin. *Telematics and Informatics*, *34*(7), 1308–1321.

Kopp, E., Kaffenberger, L., & Wilson, C. (2017). *Cyber risk, market failures, and financial stability* (International Monetary Fund working paper no. 17/185).

Koutmos, D. (2018). Return and volatility spillovers among cryptocurrencies. *Economics Letters*, *173*, 122–127.

Kristoufek, L. (2013). Bitcoin meets google trends and wikipedia: Quantifying the relationship between phenomena of the Internet era. *Scientific Reports*, *3*, 3415.

Lazarenko, A., & Avdoshin, S. (2018). Financial risks of the blockchain industry: A survey of cyberattacks. *Proceedings of the Future Technologies Conference* (pp. 368–384). Springer.

Li, X., Jiang, P., Chen, T., Luo, X., & Wen, Q. (2020). A survey on the security of blockchain systems. *Future Generation Computer Systems*, *107*, 841–853.

Li, X., & Wang, C. A. (2017). The technology and economic determinants of cryptocurrency exchange rates: The case of bitcoin. *Decision Support Systems*, *95*, 49–60.

Minto, A., Voelkerling, M., & Wulff, M. (2017). Separating apples from oranges: Identifying threats to financial stability originating from fintech. *Capital Markets Law Journal*, *12*(4), 428–465.

Okorie, D. I., & Lin, B. (2020). Crude oil price and cryptocurrencies: Evidence of volatility connectedness and hedging strategy. *Energy Economics*, *87*, 104703.

Østbye, P. (2018). *Will regulation change cryptocurrency protocols?* Available at SSRN 3159479.

Organisation for Economic Co-operation and Development. (2018). *Blockchain technology and competition policy*. OECD.

Pagnottoni, P., & Dimpfl, T. (2019). Price discovery on bitcoin markets. *Digital Finance*, *1*(1), 139–161.

Panagiotidis, T., Stengos, T., & Vravosinos, O. (2018). On the determinants of bitcoin returns: A LASSO approach. *Finance Research Letters*, *27*, 235–240.

Pieters, G., & Vivanco, S. (2017). Financial regulations and price inconsistencies across bitcoin markets. *Information Economics and Policy*, *39*, 1–14.

Polasik, M., Piotrowska, A. I., Wisniewski, T. P., Kotkowski, R., & Lightfoot, G. (2015). Price fluctuations and the use of bitcoin: An empirical inquiry. *International Journal of Electronic Commerce*, *20*(1), 9–49.

Urquhart, A., & Zhang, H. (2019). Is bitcoin a hedge or safe haven for currencies? An intraday analysis. *International Review of Financial Analysis*, *63*, 49–57.

Waldman, D., & Jensen, E. (2016). *Industrial organization: Theory and practice*. Pearson.

Yi, S., Xu, Z., & Wang, G. -J. (2018). Volatility connectedness in the cryptocurrency market: Is bitcoin a dominant cryptocurrency? *International Review of Financial Analysis*, *60*, 98–114.

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APPENDIX A: ROBUSTNESS CHECKS

Alternative specifications were used for robustness checks, including allowing λ to vary (i.e., with no limitations imposed on the λ parameter) and setting a minimum restriction on λ (that it be at least equal to 2.3). These results were largely similar to the findings in Tables 5–8. Detailed results are available upon request.

Another test for robustness compared the results obtained through the LASSO methodology to an alternative model specification, performing a VAR analysis for each hypothesis. Using Akaike's information criterion, the optimal number of lags for the VAR analysis was determined to be one. The VAR models were computed to test each hypothesis, cryptocurrency, and period, including an assessment of the effects of orthogonalised shocks (Cholesky decomposition) to the system through graphing impulse response functions. The results of these robustness checks largely confirm the findings from the LASSO analysis, that the determinants of returns are not homogeneous among cryptocurrencies. In addition, the VAR analysis highlights that the impact of shocks in the cryptocurrency markets could have an even stronger short-term effect; the effects on cryptocurrency returns rarely last beyond 2 days for any hypothesis. Detailed results from the VAR analysis are available upon request.

APPENDIX B: DIFFERENCES IN DESIGN CHOICES AMONG CRYPTOCURRENCIES

The choice of design when implementing a cryptocurrency is written into the initial coding and reflects a variety of potential uses, such as providing a new type of money (e.g., Bitcoin Cash), providing opportunities for a decentralised storage network (e.g., Filecoin), or generally providing a tool for application development (e.g., EOS and Qtum; see Burnie, 2018). Burnie (2018, pp. 9–10) provides a comprehensive overview of some of the differences in design choices found among cryptocurrencies, summarised in Table B1.

TABLE B1 Design choices among some of the most traded cryptocurrencies

This table reports the key design choices among some of the most traded cryptocurrencies. The choice of design when implementing a cryptocurrency is written into the initial coding and reflects a variety of potential uses, such as providing a new type of money (e.g., Bitcoin Cash), providing opportunities for a decentralised storage network (e.g., Filecoin), or generally providing a tool for application development (e.g., EOS and Qtum; see Burnie, 2018). Burnie (2018) provides a comprehensive overview of some of the differences in design choices found among cryptocurrencies, summarised in Table B1 (Reprinted from Burnie, 2018, pp. 9–10).

Token supply		
How tokens are created		
Fixed supply	**Rises up to the cap**	**Rises indefinitely**
Neo	Bitcoin	Ethereum
Tron	Litecoin	Stellar
Cardano	Ethereum Classic	EOS
Qtum	Monero	**Varies to maintain the peg**
Ripple	Bitcoin Cash	Tether

How tokens are distributed and transactions validated		
Proof of work	**Voting**	
Bitcoin	Neo	
Litecoin	EOS	
Ethereum	Stellar	
Ethereum Classic		
Monero		
Bitcoin Cash		
Run on top of proof-of-work systems		
Tron (on top of Ethereum)		
Tether (on top of Bitcoin)		
Validators selected	**Proof of stake**	
Ripple	Cardano	
	Qtum	
Token demand		
The target market for the token		
Generic	**Business oriented**	
Bitcoin	Cardano	
Litecoin	Ripple	
Ethereum	EOS	
Ethereum Classic	Stellar	
Monero	Qtum	
Neo	**Content creators on the Internet**	
Bitcoin Cash	Tron	
Tether		
What the token is being used for		
Transaction	**Hybrid**	**Applications**
Litecoin	BitcoinEthereum Cardano	Neo
Monero		Tron
Bitcoin Cash		Qtum
Ripple		EOS
Stellar		Ethereum Classic