# MARKET INTEGRATION BETWEEN CRYPTOCURRENCY AND TECHNOLOGY INDICES

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I hereby declare that I have read and understood the regulations governing the submission of Master of Commerce dissertations, including those relating to length and plagiarism, as contained in the rules of the University, and that this dissertation conforms to those regulations.

**SUPERVISOR: Mr Carlos De Jesus**

**December 2023**

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## ABSTRACT

This study investigates the relationship between cryptocurrency and semiconductor/technology indices for the period 2018(Q2) to 2023(Q2). The relationship was explored through use of correlation, Johansen cointegration, and Granger pairwise causality testing. The findings are key for determining the diversification benefits of cryptocurrencies and further examining the direction of causal relationships. The correlation results indicated weak to moderate correlation between cryptocurrencies and equity indices. The findings indicated that cryptocurrencies are cointegrated among each other and a bilateral causal relationship is present. Cointegration was found between cryptocurrencies and the Philadelphia Stock Exchange Semiconductor index, NASDAQ, S&P500, and Dow Jones. The NASDAQ, S&P500 and Dow Jones were found to cause crypto prices movements, but the reverse was true – for the latter two – when Binance was removed from the index. These findings suggest a lack of diversification benefits of cryptocurrencies compared to the semiconductor/technology sector. Investors should be careful when including cryptocurrencies into their portfolios as to not overexpose themselves to risk pervasive in both markets.

### Keywords:

Correlation, Johansen Cointegration, Granger pairwise causality, Cryptocurrency, Philadelphia Stock Exchange Semiconductor index, NASDAQ, S&P500, Dow Jones

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## ACRONYMS AND ABBREVIATIONS

| | |
|---|---|
| ADF | Augmented Dicky-Fuller |
| AIC | Akaike Information Criterion |
| API | Application Programming Interface |
| ASIC | Application-Specific Integrated Circuits |
| BTC | Bitcoin |
| CAPM | Capital Asset Pricing Model |
| CPU | Central Processing Unit |
| DJIA | Dow Jones industrial average |
| EMH | Efficient Market Hypothesis |
| FPE | Final Prediction Error |
| FPGA | Field Programmable Gate Arrays |
| GPU | Graphics Processing Unit |
| HQC | Hannan-Quinn information criterion |
| MC | Mined Crypto |
| MPT | Modern Portfolio Theory |
| MSCI | Morgan Stanley Capital International |
| NASDAQ | National Association of Securities Dealers Automated Quotations |
| NMC | Non-Mined Crypto |
| PoS | Proof-of-Stake |
| PoW | Proof-of-Work |
| PP | Philips-Perron |
| S&P500 | Standards and Poor 500 |
| SIC | Schwarz Information Criterion |
| US/USD | United States / United States Dollar |

**Specific to data and results section**

| | |
|---|---|
| CHMC | Capped Hashrate-weighted Mined-Crypto |
| CMC | Capped Mined-Crypto |
| HMC | Hashrate-weighted Mined-Crypto |
| MCI | Mined-Crypto Index |
| NMCB | Non-Mined Crypto Excluding Binance |
| NMCI | Non-Mined Crypto Index |
| PHLX | Philadelphia Stock Exchange Semiconductor |
| SI | Created Semiconductor Index |

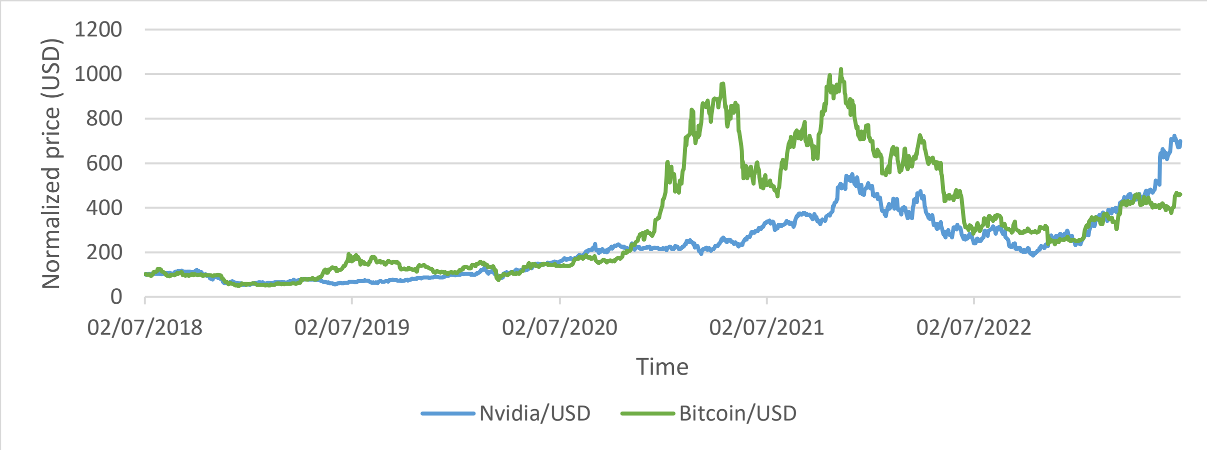
# SECTION 1 INTRODUCTION

The forces behind prices in our markets have always been of particular interest to investors and with good reason. Understanding the prices of stocks, cryptos and commodities allows investors to predict movements and profit from their estimates. As the future is unknown, investors need to manage the risk of errors in their estimates. Diversification is a valuable tool for managing risk. Diversification of portfolios hinges on the lack of integration between markets and stocks to limit risk and exposure (Markowitz, 1952). Pricing assets based on risk gave rise to the Capital Asset Pricing Model (Sharpe, 1964) and the Arbitrage Pricing Theory (Ross, 1976). Thus, elimination of unsystematic risk is crucial to investors wishing to achieve long-term, risk-limiting growth.

The crypto market exploded in popularity in early 2017 (Dastgir et al., 2019) with Bitcoin as the headline 'coin'. This market exhibited extreme volatility and left many investors feeling risk-averse for not wanting to participate in such uncertainty. Bitcoin in under 10 years saw gains of over 80 000%, eclipsing the 127% growth of securities like the S&P500. In addition, the market capitalisation for Bitcoin alone rivals major United States of America (US) companies in its share of investors. Bitcoin, with a market cap of over 500 million USD at the end of 2023(Q1), would be considered the fastest growing company in the US if it were considered equity.

Diversification is the process of eliminating market risk factors by spreading portfolios over differing markets and asset types. The purpose is to minimise risk while maximising returns as per modern portfolio theory (Markowitz, 1952). The diversification benefits of crypto are said to exist against equity markets and further to out-hedge gold by acting as a safe haven asset (Bouri et al., 2020; Zeng & Ahmed, 2022). This study holds that it is critical to eliminate lack of diversification between crypto equity indices that could exist in portfolios. For example, if a hedge fund or retirement fund manager in the US creates a portfolio focused on massive technology stock giants like Apple or Microsoft with further inclusion of index funds such as the S&P500, the portfolio will be heavily affected by changes and news in the technology market (such as the recent artificial intelligence (AI) boom). The fund manager could seek to diversify the portfolio through commodities, real estate and crypto. However, if the crypto market is related to the tech stock market and further to semiconductor manufacturers such as Nvidia (**Figure 1**) the fund manager will have failed to lower his exposure and risk in this portfolio.

**Figure 1. A comparison of Bitcoin/USD to Nvidia share price over five years**




The interest in profiting from the crypto market has brought about more creative ways to gain exposure, which can be seen in various crypto centric investment bundles available. These investment strategies hinge on investing into US companies related to the crypto industry in order to share in the positive movements during bullish cycles. Hence, this strategy relies on the presence of market integration between US semiconductor stock and crypto. The existence of these kinds of fund puts into question the diversification benefits of crypto and highlights the relevance of this study to investors.

The approach followed in this study is initially to introduce cryptocurrency and then to differentiate between Mined Crypto (MC) from Non-Mined Crypto (NMC). The underlying difference being that MC relies on the physical hardware used by miners. This hardware forms the basis of the relationship between MC and semiconductor manufacturers. Contrastingly, NMC forms a relationship with tech-related indices due to its reliance on serving a technology function, being the value of blockchain. This distinction between cryptocurrency types allows us to examine relationships separately depending on the cryptocurrency characteristics.

The literature surrounding crypto falls into two groups. Firstly, cryptocurrency as a tool for diversification against traditional assets including stock/indices (Bouri et al., 2017, 2020; Chan et al., 2019; Ciaian et al., 2016; Lee et al., 2018; Qarni & Gulzar, 2021; Zeng & Ahmed, 2022) and secondly, literature arguing for integration between markets such as US technology markets and semiconductor industries (Didisheim & Somoza, 2022; Ergenoğlu & Şenol, 2022; Nguyen, 2022; Rathi, 2022; Şahin, 2022; Wang et al., 2020; Zhang et al., 2018). Crypto has matured since its first introduction as an investment option, this is demonstrated by its introduction into US retirement funds (Browning, 2022). This evolution motivates the need for further research to expand, refresh and solidify conclusions.

This study challenges the viability of crypto as a tool for diversification as it pertains to tech-related indices and semiconductor manufacturers and suppliers. The research approach is through integration econometrics, namely, correlation, cointegration and causality. This leads to the following research questions:

1 Does integration exist between mined crypto and non-mined crypto, and what is the direction?
2 Does integration exist between mined crypto and the semiconductor industry, and what is the direction?
3 Does integration exist between non-mined crypto and the technology industry, and what is the direction?

The outcomes of the study found that MC and NMC are cointegrated and share bidirectional causal relationships at differing lag lengths. Further, semiconductor related stocks, such as Nvidia, AMD, TSMC and Philadelphia Stock Exchange Semiconductor index (PHLX), also share a cointegrating relationship with MC but no statistically significant causality was found. NMC does not provide diversification benefits against the NASDAQ, S&P500 and Dow Jones due to cointegration and causal relationships. The direction of this relationship is mainly that the equity indices are said to Granger-cause the NMC, but bilateral causality was also found with the S&P500 and Dow Jones. The presence of these cointegrating and causal relationships are crucial to investor decisions when building diversified portfolios. Cryptos do not provide diversification benefits in relation to the technology-dominated US Indices and semiconductor manufacturers and suppliers.

The next section provides a deeper understanding of the background and literature relating to cryptocurrency. This is followed by an explanation of the process behind the data collection and index creation and a description of the methodology for testing. The results of testing and conclusions on the research questions are then presented.

# SECTION 2 LITERATURE REVIEW

This literature review outlines the core theory around integration and basic functioning of crypto and blockchain technology, followed by a presentation of the links among cryptocurrencies, semiconductor manufacturer stocks and technology stocks. This is followed by the existing research on crypto and markets.

## 2.1 FINANCE THEORIES

Market integration finds itself rooted in three finance theories that are the focus of this study. Modern Portfolio Theory (MPT) popularised by Markowitz (1952), links the creation of portfolios to diversification and the benefits thereof. The Capital Asset Pricing Model (CAPM), introduced by Sharpe (1964), is widely used for gauging integration. Further, the Efficient Market Hypotheses (EMH) by Fama (1965) is highly relevant for information prevalence in markets.

MPT’s guiding principles are to reduce exposure to risk and maximise returns for investors. This theory provides for the construction of a portfolio with a diversified approach to reduce risk (Markowitz, 1952). It then follows that when building a portfolio, if the investor is unaware of certain assets or markets that are integrated, the risk would be incorrectly diversified.

CAPM is a model created to determine the relationship between the returns and risks of securities (Sharpe, 1964). This theory is a basis for pricing risky assets and describes two types of risk, namely, systematic and unsystematic risk. Systematic risk relates to overarching factors in markets that affect price, while unsystematic risk is company specific. The link to integration stems from the process of diversification through exposure to unsystematic risk. The creation of a portfolio using many different companies and industries reduces exposure to unsystematic risk. However, when markets become more integrated, this creates overexposure to the same unsystematic risk affecting either market, thus limiting the effects of the diversification.

EMH states that prices incorporate all information and expectations and as a result, the current prices reflect intrinsic value (Fama, 1965). EMH is closely related to market integration due to the reliance on information prevalence in the markets. When market integration occurs, markets also become more efficient and opportunities for arbitrage are lost. Although EMH is theoretical and subject to much debate in literature, it still represents core theory that can be used as a framework.

## 2.2 BACKGROUND OF CRYPTOCURRENCY

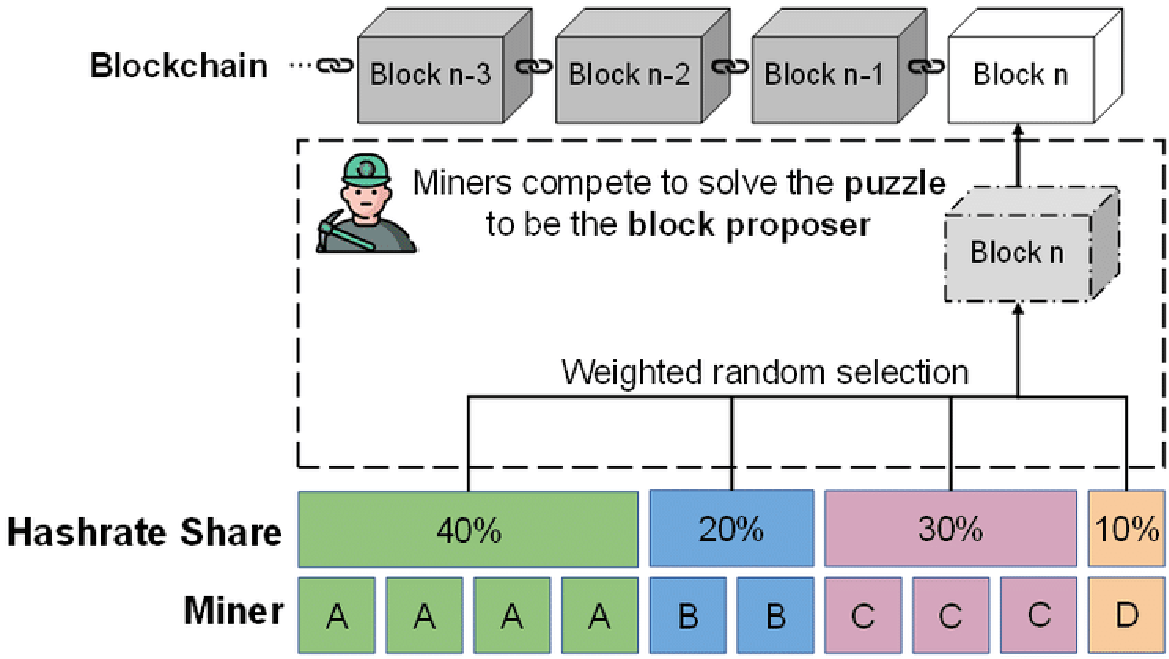
Cryptocurrency is a form of digital currency that was created to allow direct cash transactions without third-party intermediaries. The terms used to refer to cryptocurrencies include cryptos, coins and tokens. This study will use crypto as a collective and consistent term beyond this point. The supposed creator of Bitcoin (the first crypto), Satoshi Nakamoto, published a white paper on Bitcoin's technology in 2008 before starting to trade in early 2009. Satoshi Nakamoto has long been speculated to be a pseudonym for a group of creators, hence assumed anonymity (Pinkerton & Davis, 2023). Bitcoin relies on a decentralised system called the blockchain, which verifies, encrypts, and stores transaction data. This contrasts with traditional fiat currencies that governments and banks centralise to allow for the flow of currency (Yano et al., 2020). The decentralised nature of crypto introduces a problem of securing its value as a currency as it is not bound to any physical measure.

The innovation behind blockchain has created valuable technology apart from its use in crypto. Blockchain works by validating transactions that are then grouped together to form a block. Once a block has been formed, it is added onto a chain of prior blocks and stored in a decentralised manner (over a wide network of computers). Blockchain is a cheap, secure, traceable, and fast method of storage that does not require reliance on third parties. The data overheads and transaction costs are greatly reduced. The business applications for blockchain have expanded to supply chain information and accounting related storage. From an individual's perspective, identification such as drivers' licences or medical records can be stored. There is immense value in this innovative technology.

Two types of cryptos are available, Mined Crypto (MC) and Non-Mined Crypto (NMC). The mining of crypto refers not to physical mining but rather to the solving of complex calculations in exchange for a reward in the form of crypto. MC uses blockchain technology which functions using digital ledgers. These ledgers store and hold all transactions that occur between participants trading in that crypto. The ledgers are compiled and verified by crypto miners that perform complex calculations. A consensus method (known as Proof-of-Work) is computed with processing hardware – the Central

Processing Unit (CPU) or Graphics Processing Unit (GPU) of a computer or specialised mining machine. As a reward for their processing, miners are given small amounts of crypto for the use of their CPU/GPU and the electricity consumed to complete the Proof-of-Work (PoW) (Satoshi, 2008). Since Bitcoin's initial launch, the reward system has proved to be very risky due to random allocation of rewards to whomever solves the problem first. However, as mining has evolved, miners have begun linking together forming mining pools to reduce random allocation and share proportionally in the rewards earned as shown in **Figure 2** below. This collective mining approach reduces the risk of random allocation.

**Figure 2. Proof-of-work consensus mechanism**

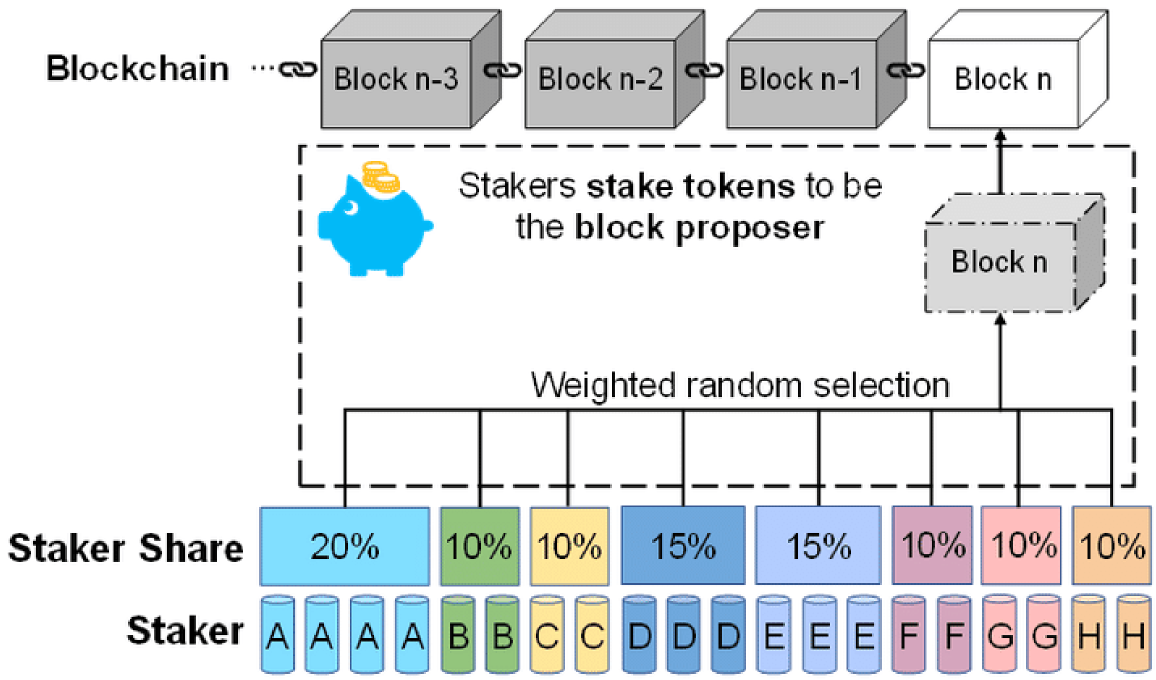



**Note to Figure 2**

From "Confronting the Carbon-footprint Challenge of Blockchain," by Shi, X., Xiao, H., Liu, W., Chen, X., Lackner, K. S., Buterin, V., & Stocker, T. F. (2021) *Environmental science & technology*, 57(3), 1403-1410. (https://doi.org/10.1021/acs.est.2c05165). CC-BY-NC https://creativecommons.org/licenses/by/4.0/

NMC, similar to its counterpart, also uses digital ledgers that need to be verified by validators. However, Proof-of-Stakes (PoS) (**Figure 3** below*)* are used to process transactions. PoS functions using a consensus method in which no complex calculations are performed but ownership in the crypto is staked for the randomised chance to validate blocks and earn rewards (Buterin, 2016). Different cryptos (such as Cardano or Binance Coin) have implemented differing versions of PoS but a common trait is that the more crypto that is staked, the higher your chance to validate the block, albeit the selection is still randomised. Some PoS mechanisms increase the chance depending on the age of the staked crypto (encouraging holding the crypto for lengthy periods). Unlike MC, the requirements to be a validator are not processing power but mere storage capacity. The rewards are in the form of transaction fees that users share in once they have validated the transaction having staked their own crypto. Unlike mined-crypto, the rewards received are not related to the value of the crypto being validated. There are other consensus methods besides PoS that result in an NMC classification; these include Delegated Proof-of-Stake, Proof-of-Activity, Proof-of-Location, Proof-of-Importance. However, these methods are mainly used for individual cryptos that are not within the scope of this study.

**Figure 3. Proof-of-stake consensus mechanism**

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## 2.3 LINK BETWEEN NON-MINED CRYPTO AND TECH-RELATED STOCKS

Crypto was introduced to provide functionality for users using blockchain technology. Some crypto facilitates digital payments while others allow for cloud storage of important information. The value of crypto is rooted in the technological value that blockchain provides. To make a comparison, companies such as Google, Apple, and Meta also provide a technology-focused function, albeit in the form of a company. These large tech companies largely comprise the intangible value of assets like patents, customer data and software (Cate Elsten & Hill, 2017). Thus, it follows that their share price is linked to this value and to technology.

This exposure to technology creates an inherent link between tech-related stocks and cryptos and allows them to be affected by similar market information such as the AI boom in mid-2023. Investigation of this shared exposure is the first objective of this study. Building on this theoretical link, from a behavioural side, research has shown that crypto-orientated retail investors drive integration due to cross-asset trading that creates similar volumes in share and crypto markets (Didisheim & Somoza, 2022). This study used the S&P500 for its analysis, indicating the correlation began in March 2020 due to uniform trading flows of customers in crypto and equity markets simultaneously.

Prior literature on stock influence over crypto is contradictory. Bouoiyour et al. (2015) found that the Shanghai Stock Exchangeis positively correlated with Bitcoin in the short run, with insignificant results in the long-run from 2010–2014. Ciaian et al. (2016) found similar results using the Dow Jones, indicating short-run correlation from 2009–2015. Wang et al. (2020), using a Vector Autoregression Model (VAR), found that from 2010 to 2018, the S&P500, NASDAQ and Dow Jones significantly impacted Bitcoin but the reverse was not true. Further, Nguyen (2022) found similar results for the S&P500 and Bitcoin using a VAR model over the period 2016–2020.

To contrast this, Baur et al. (2018) measured Bitcoin's correlation with the S&P500 during normal periods and periods of financial turmoil but found no positive or negative correlation from 2010–2015. Lee et al. (2018) found no correlation between a constructed portfolio of crypto assets and the S&P500 from 2014–2017. Chan et al. (2019) found that Bitcoin is proven to be a hedge against the S&P500 using monthly data points. Umar et al. (2021) examined crypto as a diversifier for the technology-sector investing and found causality between crypto and the US technology sector. However, they concluded that crypto is an effective diversifier for the global technology market due to systematic risk being shared among global technology markets.

To test the relation fairly between NMC and tech-related stocks, the NASDAQ-100 technology sector is used for comparison, which has been used by other researchers

(Ergenoğlu & Şenol, 2022; Şahin, 2022). Unlike the S&P500, the NASDAQ incorporates a larger portion of tech-related companies. In addition, the S&P500 and the Dow Jones Industrial Average are also used as they are proxies for the US market, being used throughout the literature (Baur et al., 2018; Lee et al., 2018). Although these indices are not purely non-financial stock, such as the NASDAQ, they do include tech giants that drive the US economy. A market cap-weighted portfolio of these NMCs is used for testing. The most popular NMCs are Ripple (XRP), Cardano (ADA), Binance (BNB), Solana (SOL), Polkadot (DOT) and Tronix (TRX). Creating the index will serve as a proxy for the NMC market which will be compared to stock indices. NMC and tech-related stocks will form two of the variables used in testing.

## 2.4 LINK BETWEEN MINED CRYPTOS AND SEMICONDUCTOR MANUFACTURER STOCKS

Due to the Proof-of-Work (PoW) method of MC, the profitability of mining is linked to the value of the cryptos mined because of the compensation in the form of crypto. Thus, when Bitcoin reached its first peak in 2017, the interest in mining surged creating a cause-and-effect relationship between crypto price and mining. Fantazzini & Kolodin (2020) researched this cause and effect, which indicated a unidirectional causality of bitcoin price to the hashrate (the sum of computational power mining a network). Further, Kristoufek (2020) used weekly data to reach the same conclusion. Lastly, Marthinsen states that mining and the cost thereof has no effect on Bitcoin's price, again indicating unidirectional relationship (2022). These conclusions are significant as they imply that the increasing price of cryptos drives the need for hardware to support the hashrate on the blockchain.

The process of mining crypto can be achieved using various types of hardware. CPU or GPU mining were initially common methods for mining crypto. However, as mining increased in popularity, the competitiveness of the industry increased. In 2011 and 2012 two more hardware options appeared: Field Programmable Gate Arrays (FPGAs) and Application-Specific Integrated Circuits (ASICs). The general consensus is that ASIC mining is the most efficient and powerful way to mine but it is limited to specific cryptos such that an ASIC miner used for Bitcoin cannot be used for Ethereum classic (Taylor, 2017) because ASICs are built for specific hashing algorithms in mind. FPGAs solve this limitation as they can be reprogrammed to different hashing algorithms, however FPGAs have still largely been overrun by the introduction of ASIC mining. **Table 23** in Appendix A contains more on each crypto's hashing algorithms. Both ASIC and FPGA are largely industrial products and although prices are becoming consumer friendly, these low-end models are less profitable with poor resale value. GPUs and CPUs, although not as powerful, are still price-friendly and hold value better than ASICs and FPGAs for average consumers. GPUs and CPUs are still competitive because certain cryptos are ASIC resistant, thus encouraging the prior two methods. All methods of mining, however, rely on semiconductor manufacturers and suppliers to produce the required hardware.

As found in literature, crypto prices are said to Granger-cause the hashrate (Fantazzini & Kolodin, 2020), The increased hashrate is as a result of more hardware mining a crypto network. Thus, the crypto prices are creating demand for hardware which is increasing sales for semiconductor manufacturers. The increase in sales is due to an increasing market size and higher sales prices which can be charged due to demand levels. This increase in sales is leading to larger return figures for companies and finally increased valuations in the market. This creates the link for market integration; the MC price is linked to mining hardware demand which in turn is linked to the share price of semiconductor companies. This forms a theoretical demand-pull; the increased crypto prices lead to increased hardware prices. The reverse is that as hardware becomes more efficient and cheaper this would drive the hashrate leading to increased crypto prices. However, literature does not support the hashrate driving the pricing of cryptos (Fantazzini & Kolodin, 2020; Kristoufek, 2020).

The second objective of this study is to establish whether integration exists between the semiconductor industry and the MCs. Cryptos that would be affected by their ability to be mined are chosen to test against the semiconductor industry. A range of popular cryptos using various primary methods of mining were selected: Bitcoin (BTC), Ethereum (ETH), Dodgecoin (DOGE), Ravencoin (RVN), Monero (XMR) and Ethereum classic (ETC). These MCs can be tested together by using their market capitalisations and hashrates to weight an index for crypto assets. The hashrate-weighted index is used as a method of factoring in the hardware supporting the crypto's blockchains. Using this index will serve as a proxy for MC which can be used for comparison to the Philadelphia Stock Exchange Semiconductor index and a created semiconductor index.

## 2.5 PRIOR LITERATURE ON CRYPTOCURRENCY

Kristoufek's (2015) research has been a pivotal starting point for most literature around crypto using wavelet coherence analysis to conclude on many hypotheses. In 2015, the following was found:

1. Crypto responds to monetary economics and quantity theory of money;
2. The price of Bitcoin motivates mining but this effect decreases in the long-run;
3. Investor interest drives crypto pricing;
4. Bitcoin does not appear to be a safe haven asset.

These conclusions have created a diverse pool of interest and conflicting research around the pricing and drivers of crypto resulting in many studies investigating the changes in the crypto market and how these factors have evolved.

The academic literature on crypto is still relatively new but is gaining popularity because of heightened interest in the workings of the crypto market. Studies have been concluded exploring the static and dynamic independence between crypto and more traditional assets (Lee et al., 2018). Traditional assets like gold, oil, equity indices, private equity, REITs, and forex markets are found to have low correlation to crypto and thus provide effective diversification for investors looking to decrease market-related risk and use of crypto as a safe haven asset (Lee et al., 2018; Qarni & Gulzar, 2021; Zeng & Ahmed, 2022; Zeng et al., 2020).

When looking at macroeconomic factors, research suggests that crypto is unaffected in the long-run by macro-financial movements (Al-Khazali et al., 2018; Ciaian et al., 2016). Further, the lack of centralisation of control over crypto and its prices leads it to be independent of macroeconomic factors such as inflation (Baur et al., 2018). This is further amplified due to the halving of cryptos such as Bitcoin which reduce supply to hamper inflation of crypto prices. These studies present a disintegration between the value of crypto to real-world events in financial markets. Contrary to this, a newer study performed on the Japanese, Korean and Hong Kong Stock exchanges concluded that equity market spillovers affected Bitcoin's returns, but Bitcoin spillovers did not affect equity returns, showing directionality of causality from equity to crypto (Zeng & Ahmed, 2022). Spillovers are positive or negative economic events which affect a market.

These spillovers from equity markets may indicate a shift in that crypto is increasingly being exposed to market-related factors. Further, a study by Giudici and Polinesi (2021) indicates that Bitcoin's price is unaffected by classic assets, but the volatility of its price is negatively affected by these classic assets, again showing exposure to market conditions.

Studies investigating the volume of Bitcoin transactions found that the price of Bitcoin was positively correlated to the number of transactions processed (Ciaian et al., 2016; Kristoufek, 2015). There are limitations; correlation was proven but causality was not because of the difficulty in isolating trends in a noisy crypto market.

Ergenoğlu & Şenol (2022) conducted research using the NASDAQ and CCi30 Crypto index and found bidirectional Granger causality. The CCi30 is an index of the top 30 cryptos, both MC and NMC. Further, Şahin (2022) used the NASDAQ against Bitcoin and Ethereum and found correlation and causality from 2012 to 2021. Lastly, Rathi (2022) used the Morgan Stanley Capital International (MSCI) worldwide semiconductor index which contains the top 64 stocks in the global industry. Rathi's study resulted in finding of bilateral Granger causality relationship for Bitcoin returns to the MSCI indices returns. This study deems the PHLX index more suitable due to including a smaller range of companies and thus reducing the inclusion of companies unrelated to crypto. Further Rathi only made use of Bitcoin to represent the crypto market and this study will add on 11 additional cryptos.

### 2.5.1 The change in crypto over time

The emergence of crypto as an investment opportunity rather than a currency (Baur et al., 2018) has given rise to market assets that are difficult to predict (Qureshi et al., 2020). Over time cryptos have gained popularity and investor interest, which has and ultimately led to market maturity. Investors show signs of removing their equity interests in favour of crypto in Eastern Europe as they increasingly treat cryptos like high-return equity (Çikrikçi & Özyeşil, 2019). Crypto markets have stabilised to the point that 401K in the US has started offering this as a retirement investment (Browning, 2022).

The evolution could impact the drivers and volatility of crypto as larger long-term investments could stabilise the market as large institutional investors have in other markets (Fong et al., 2022). This shows the continued evolution of crypto from initially being used for illegal activities and hobbyists to a large investor market for short-term gains and possibly a safe haven asset for long-term investment. The study by Didisheim et al. (2022) supports this evolution of crypto through retail investors' participation in equity and crypto markets with similar mindsets. This evolution could lead to the sharing of unsystematic risk due to similar investor behaviour across markets.

It has been suggested that tech stocks and cryptos share an investor base because of the interests of investors. As shown by Yelowitz (2015), the investors in crypto tend to be individuals interested in the computer science space. Companies like Nvidia and AMD are giants in the computer hardware space and thus a mutually inclusive group of investors is formed linked by their interest and knowledge base. The aligning of these investors' interests has given rise to new Exchange-Traded Funds (ETF), such as Amplify Transformational Data Sharing or Siren Nasdaq NexGen Economy ETF, which further confirms the overlap in interests. A decision by the US Securities and Exchange Commission during January 2024 was made to approve Bitcoin spot ETFs which will increase the ease of investing into the crypto market. These spot ETFs allow investors to bypass setting up crypto wallets on alternative exchanges which is considered an administrative barrier to investing. Contrary to this, it is still clear that cryptos possess different risk characteristics than equity, so the size of the shared investor base and the herding effect is questionable (Bouoiyour & Selmi, 2015; Lee et al., 2018; Qureshi et al., 2020).

### 2.5.2 Mining

Research into the causality between crypto prices and mining has proven that an increase in Bitcoin's price causes increases in hashrate (Fantazzini & Kokorin, 2020; Kristoffer, 2020; Marthinsen & Gordon, 2022). This relationship leads to equilibrium in the mining market. These studies explore how the costs of mining increase with the price of crypto. This follows arbitrage theory that when the mining becomes more profitable, an influx of new miners will offset the increased profitability by taking up market share. This effect is, however, not long lasting and the increase in interest tapers off as the hashrate pool increases, which is suggested to be linked to the expensive mining hardware required. The consensus is that the crypto price drives the cost of mining but not the reverse. This contributes to the link between MC and semiconductor stock. The cost of mining increases because of the increase in computational power added onto the blockchain; the increase in power is the result of more GPUs mining concurrently.

### 2.5.3 News and regulations

Crypto is a speculative market, which plays a part in its volatility. This speculation means the asset is highly susceptible to swings in price following news and other outside information. For example, when Tesla's CEO, Elon Musk, changed his Twitter biography to "#bitcoin," the price surged by 20% (Shead, 2021). A study based on news around crypto was successfully able to predict the movement in crypto prices using a model developed to interpret news and market sentiment (Lamon et al., 2017). A similar study has built on this using machine learning to extract a graph of investor sentiment from news articles on Bitcoins price with a 59% accuracy (Yao et al., 2019). The above studies in theory prove weak causality of the relationship between media news and price movement. The news is only one variable correlated with crypto assets.

China has been active in its aim to limit crypto transactions and mining. The initial regulatory lockdowns on crypto were due to the capital flight of currency leaving the Chinese economy. To reduce this, regulations have been introduced to limit Initial Coin Offerings (ICOs) and more recently to ban the transactions and mining of crypto (Shin, 2022; Sun, 2018). The market has been plagued by these announcements since 2017, which have caused noticeable drops in crypto prices. A study by Chen and Liu (2022) shows that with every law introduced, the prices and liquidity of the cryptos have suffered while volatility has increased. China has been a large market participating in cryptos and this regulatory disruption has noticeably driven investors and thus the price of cryptos.

### 2.5.4 Market efficiency

To understand crypto prices, it is necessary to understand whether these markets are efficient. In other words, it is necessary to determine if the price reacts quickly to all information available, as proposed in the EFM (Fama, 1965). A study performed by Urquhart (2016) found that in the sample period, August 2010 to July 2016, Bitcoin was inefficient in the earlier period but was becoming increasingly more efficient towards the later period. The increase in efficiency links to the shift in drivers mentioned and the fact that the crypto market is becoming more established with an influx of investors. Following this, Bariviera (2017), Nadarajah & Chu (2017) and Sensoy (2019) confirm the efficiency in their studies on Bitcoin price, showing it has become more efficient since its inception, particularly from 2016 onwards. Another study has indicated weak efficiency, as shown by Zhang W et al. (2018) while Al-Yahyaee et al. (2018) concluded that Bitcoin is the least efficient when compared to stock, gold, and currency. Kang et al. (2022) found that cryptos created before 2017 are more efficient than those created after. The efficiency strength of the crypto market cannot be concluded definitively but the literature suggests that as the market has matured, an increase in efficiency has been achieved in the mature cryptos.

### 2.5.5 Between Cryptos

Similar to commodity prices, crypto assets like Bitcoin are subject to a fixed supply. Due to the fixed supply, this has also been the argument for why crypto is seen as an asset rather than a currency. Gronwald (2019) researched this relationship with supply, concluding that all movements in Bitcoin are demand shocks; as there is no uncertainty of supply in Bitcoin, all movement is assumed to be demand related. When looking at the whole crypto market, Ethereum, the second biggest coin, is not supply limited. The logical conclusion is that if all bitcoin movements are demand-linked but Ethereum is not demand-linked, they would not share any correlation. However, Bitcoin and Ethereum do share in correlation, as shown by Nakagawa & Sakemoto (2022) who concluded that Bitcoin and Ethereum are correlated in periods of uncertainty. Supporting this, research was conducted on the 12 leading cryptos, stating that these currencies have been increasingly integrated since 2017 with shared trading volumes creating the link (Bouri et al., 2021).

The sharing of trading volumes is formed from similar investor behaviour in the market, which can drive all crypto in bull or bear markets. This could be linked to the herd behaviour seen in markets (Cipriani & Guarino, 2009). Furthering on the interdependence of different cryptos, pairs such as Ripple and Ethereum are proved to be correlated when using low-frequency data. (Qureshi et al., 2020). Keilbar & Zhang (2021) presented comprehensive cointegration testing following the approach by Onatski and Wang (2018), using 10 cryptos and finding a long-run equilibrium among all. Sovbetov (2018) also found cointegration from 2010 to 2018, whereas Leung and Nguyen (2019) found cointegration among four MCs: Bitcoin, Ethereum, Bitcoin Cash and Litecoin.

## 2.6 CONCLUSION

The literature available around cryptos, integration and diversification properties allows us to find opportunities for research. The isolation of MC and NMC is crucial for analysis in this study and the addition of the link to semiconductor manufacturers and technology stocks adds to the discussions around market integration to equity. The use of the PHLX and the created index will make it possible to bridge a gap in the literature and further discuss demand-pull inflation. The link to this equity will add to the existing understanding of the pricing of crypto and how it operates as diversification. The implication of this research is important for fund managers and investors exploring diversification with crypto. Further, this research will help confirm or deny prior studies as crypto reaches a more mature stage since its introduction.

**Table 1. Summary of integration literature on crypto assets**

| *Independent variable* | **Relationship to crypto** | **Research** |
|---|---|---|
| *Commodities* | Weak | (Baur et al., 2018) |
| *Inflation rates* | None | (Baur et al., 2018). |
| *Gold* | Weak | (Baur et al., 2018; Lee et al., 2018; Zeng et al., 2020). |
| *Oil* | Weak | (Lee et al., 2018; Zeng et al., 2020). |
| *Stocks/Equity* | Weak | (Baur et al., 2018; Lee et al., 2018). |
| | Positive | (Bouoiyour & Selmi, 2015; Ciaian et al., 2016; Didisheim et al., 2022; Wang et al., 2020; Zeng & Ahmed, 2022) |
| *Dow Jones* | Positive | (Zhang et al., 2018) |
| | Weak | (Ciaian et al., 2016) |
| *S&P500* | Positive | (Didisheim & Somoza, 2022; Nguyen, 2022; Wang et al., 2020) |
| | Weak | (Baur et al., 2018; Lee et al., 2018; Sovbetov, 2018) |
| | Negative | (Chan et al., 2019) |
| *NASDAQ/Dow Jones* | Positive | (Ergenoğlu & Şenol, 2022; Şahin, 2022; Zhang et al., 2018) |
| *US technology sector* | Positive | (Umar et al., 2021) |
| *MSCI Semiconductor index* | Positive | (Rathi, 2022) |
| *REITs* | Weak | (Lee et al., 2018; Zeng & Ahmed, 2022). |
| *Chinese stock market* | Positive | (Zeng & Ahmed, 2022) |
| *Bonds* | Weak | (Baur et al., 2018) |
| *Stock trading volumes* | Negative | (Çikrikçi & Özyeşil, 2018) |
| *Forex ($, €, ¥, £, Canadian $, Australian $)* | Weak | (Qarni & Gulzar, 2021) |
| *Ripple and Ethereum* | Positive | (Qureshi et al., 2020). |
| *Bitcoin and Ethereum* | Positive | (Nakagawa & Sakemoto, 2022) |
| *Volume of transactions* | Positive | (Ciaian et al., 2016; Kristoufek, 2015). |
| *Hashrate* | Positive | (Kristoufek, 2015) (Fantazzini & Kokorin, 2020; Kristoffer, 2020; Marthinsen & Gordon, 2022). |
| *Investor Interest* | Positive | (Dastgir et al., 2019; Kristoufek, 2013, 2015; Lamon et al., 2017) |
| *Between cryptos* | Positive | (Bouri et al., 2021; Giudici & Polinesi, 2021; Keilbar & Zhang, 2021; Leung & Nguyen, 2019; Qureshi et al., 2020; Sovbetov, 2018) |
| *Regulations* | Positive | (Chen & Liu, 2022) |
| *Mining costs* | Positive | (Marthinsen & Gordon, 2022) |

# SECTION 3 DATA

## 3.1 CRYPTO DATA

Data for MC and NMC was obtained from Coinwarz and CoinMarketCap. The data for cryptos was daily spot prices at the close of the New York Stock Exchange (NYSE) market each day. The time series for the data spanned 1 July 2018 to 30 June 2023. This data was then used to create indices for NMC and MC respectively. Coinwarz and CoinMarketCap are used as reliable sources, as demonstrated by other academics in the research area (Antipova, 2021; Kwon et al., 2019; Podhorsky, 2021; Zhao, 2022).

## 3.2 CRYPTO INDICES CREATION

NMC market capitalisations have been used to create a market capitalisation-weighted (market cap-weighted) index which creates high comparability to stock indices such as the S&P500 and the NASDAQ. The indices were rebalanced as new cryptos were added. The rebalancing dates align with the equity indices used, being the end of March, June, September, and December. The market capitalisation data for crypto was also obtained from CoinMarketCap on the last day of each quarter. The selection of NMC and MC can be seen in **Table 2** below.

**Table 2. Summary of crypto used in indices**

| Non-mined cryptos – first block date | Mined cryptos – first block date |
|---|---|
| 1 Ripple (XRP) – 2012 | 1 Bitcoin (BTC) – 2009 |
| 2 Cardano (ADA) – 2017 | 2 Ethereum (ETH) – 2015 |
| 3 Binance (BNB) – 2017 | 3 Dodgecoin (DOGE) – 2013 |
| 4 Solana (SOL) – 2020 | 4 Ravencoin (RVN) – 2018 |
| 5 Polkadot (DOT) – 2020 | 5 Monero (XMR) – 2014 |
| 6 Tronix (TRX) – 2017 | 6 Ethereum classic (ETC) – 2015 |

MCs were used to create a market capitalisation-weighted and hashrate-weighted index (rebalanced quarterly). As the purpose of the MC is to examine the relationship between the MC and the semiconductor stock, the hashrate is an additional but suitable weighting method for each coin's effect on the stock due to the hashrate representing hardware power contributing to mining. As a market capitalisation-weighted index would yield largely Bitcoin returns, the use of this hashrate weighting yields a computational power perspective, which therefore avoids arbitrary allocation due to Bitcoin's market capitalisation dominance. Bitcoin's hashrate still proves to be a dominating factor in this weighting method and as a result, a capping similar to the Capped SWIX Top 40 index was added. This index caps the largest impact of shares to 10%. The methodology of this capped index is that for 40 shares, a fair cap is 10% for each share so no share's market capitalisation may exceed 10% of the total index value. If we use this relationship applied to the indices being created, it is possible to conclude that for an index of six cryptos, a fair cap per crypto would be 66.66%. This amount uses the indirect relationship between the number of assets and the size of the cap and is calculated as follows:

40 assets x 0.15 = 6 assets, thus 10%/0.15 = 66.66% or

40 assets / 6 cryptos = 6.66, thus 10% x 6.66 = 66.66%.

This alternative capping calculation had to be used as traditional capping methods could not apply to an index of six assets and so had to be modified. This capping method is a limitation of the study.

As a result, four versions of the MC indices exist, being the market capitalisation-weighted index without capping to 66.66%, the MC market capitalisation index with a cap of 66.66% and similarly for the hashrate-weighted indices. The hashrate data was obtained from Coinwarz using its Application Programming Interface (API). The use of an API was necessary because of the lack of more easily accessible data relating to the hashrates. The API enables access to data held on the Coinwarz server; it uses "get" functions to pull data from the servers. Specifically, the data relating to hashrates was pulled from the API using Python as a method to process requests for data. The API documentation and key with the requests processed can be found on the Coinwarz website. The hashrate data was requested from the server which then had to be imported into MS Excel to be cleaned into quarterly hashrate data used for weighting.

A problem encountered within the indices was that Binance proved to be an outlier for the NMC index. Binance experienced over 1 800% growth in 2021 and this inflated the NMC index price and returns. As a result, a separate index was created by winsorizing Binance (Hastings et al., 1947). This second index was created for robustness.

## 3.3 STOCK MARKET DATA

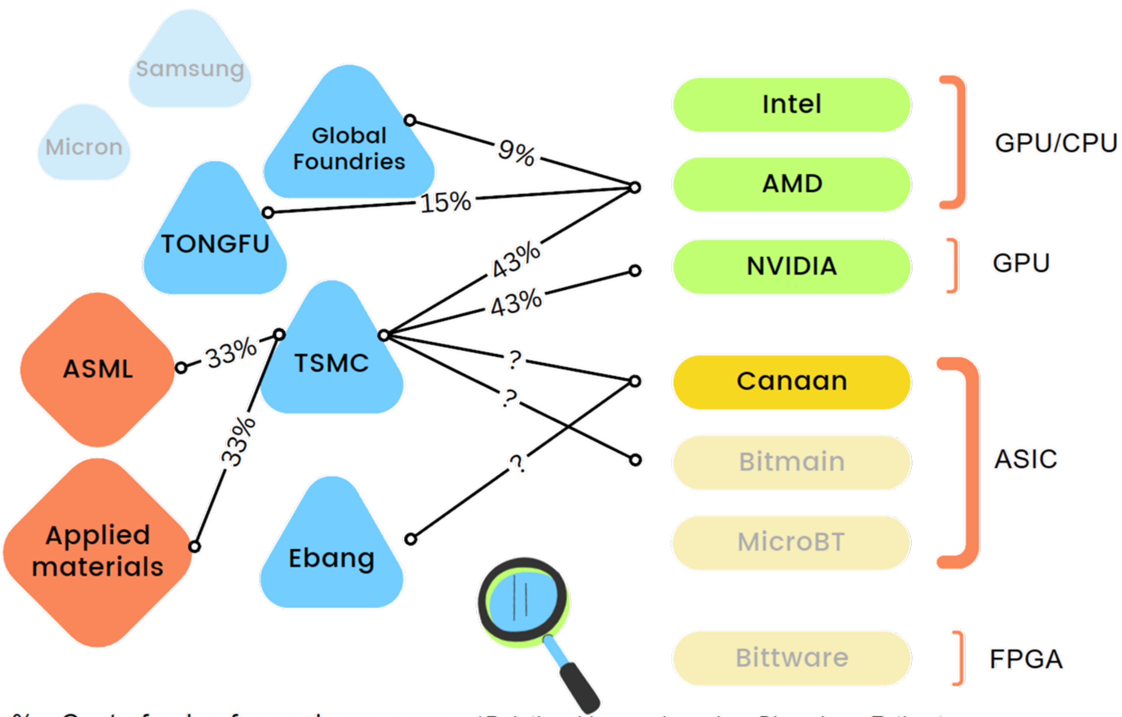
Share and index price data was obtained from Eikon, using the shares/index closing price. The time series for the data spanned 1 July 2018 to 30 June 2023. The shares were used to create a free-float market capitalisation equity index representing major role players within the semiconductor industry.

**Table 3. Summary of indices and stocks**

| Index | Semiconductor manufacturer/supplier – role |
|---|---|
| 1 Philadelphia Stock Exchange Semiconductor (PHLX)<br>2 NASDAQ-100 Technology sector<br>3 Standards and Poor 500 (S&P500)<br>4 Dow Jones Industrial Average (DJIA) | 1 Canaan Inc. (ASIC production).<br>2 Nvidia Corporation (GPU production).<br>3 Advanced Micro Devices (AMD) Inc. (CPU/GPU production).<br>4 Intel Corporation (CPU/GPU production).<br>5 Taiwan Semiconductor Manufacturing Company (TSMC) Ltd (Supplier).<br>6 TongFu Microelectronics Co Ltd (Supplier).<br>7 Ebang International Holdings Inc (Supplier).<br>8 Global foundries Inc. (Supplier).<br>9 ASML Holding NV (Supplier).<br>10 Applied materials Inc. (Supplier). |

Due to the various ways of mining, a host of semiconductor manufacturing and supplying companies were selected that all have direct or indirect links to mining hardware production. To test the relationship, this study used the Philadelphia Stock Exchange Semiconductor Index (PHLX) as a proxy for the semiconductor industry. Further, to eliminate companies not involved directly in mining hardware production, an index was created using a supply chain analysis (see **Figure 4** below). This index includes many of the same companies within the PHLX but narrows it down by whether the companies are involved - directly or indirectly - in the crypto market. Many companies are in the production and supply of crypto mining hardware but due to the private status of some major companies, such as Bitmain Technologies Ltd and MicroBT, these were excluded from testing. Further as supplier relationship became immaterial, suppliers were excluded from testing. This was the case for Samsung as although it is involved in memory production and so forth, this contributes an irrelevant portion of value creation to the overall company. All supply-chain analysis was performed using Bloomberg estimates.

**Figure 4. Supply-chain analysis of semiconductor industry**




% - Cost of sales for each company **Relationships are based on Bloomberg Estimates.*

## 3.4 DESCRIPTIVE STATISTICS

Through data collection, the final variables created can be summarised as follows:

- Non-Mined Crypto Indices (NMC Indices)
  - Non-Mined Crypto Index (NMCI)
  - Non-Mined Crypto (Excluding Binance) (NMCB)
- Mined Crypto Indices (MC Indices)
  - Mined-Crypto Index (MCI)
  - Capped Mined-Crypto (CMC)
  - Hashrate-weighted Mined-Crypto (HMC)
  - Capped Hashrate-weighted Mined-Crypto (CHMC)
- Equity Indices
  - Philadelphia Stock Exchange Semiconductor (PHLX)
  - Created Semiconductor Index (SI)
  - NASDAQ-100 (NASDAQ)
  - Standards and Poor 500 (S&P500)
  - Dow Jones Industrial Average (DJIA

**Table 25, Table 26** and **Table 27** in Appendix B summarise the properties of each variable obtained from the data, being the index price, return and logged return. The final cleaned data resulted in a sample size of 1 257 index prices and 1 256 return and logged return values that were used for testing. All return data exhibits leptokurtic levels of kurtosis, with crypto showing the most; this contributes to the perceived volatility of cryptos.

### 3.5 ISSUES

Ethereum is one of the most well-known cryptos after Bitcoin but as of September 2022, the MC has become an NMC, resulting in a limitation to its inclusion in the indices for MC. The MC indices had to be rebalanced on 15 September 2022 to remove Ethereum and it was introduced into the NMC index as of 30 September 2022.

The use of stock indices such as the S&P500 exposes the risk of larger companies dominating price movement. To combat this, the NASDAQ is used, which is a modified market capitalisation-weighted index and further, the Dow Jones, which is price weighted. This combination of US market indices allows for elimination of biases because of the weighting method. Further, due to Bitcoin's dominance, two capped versions of each MC index were created to limit Bitcoins effect to 66.66%.

To match the price data obtained for crypto to equity, the dates where equity prices do not exist were removed (the weekend and public holiday data). The result was crypto prices for each day the markets were open, thus matching the share/index data.

Certain cryptos had to be introduced into the indices at later dates because of their more recent introductions and trading dates. The indices were rebalanced quarterly to introduce any cryptos not included from the start. This issue does not majorly affect the testing as the behaviour of crypto is changing and maturing, as discussed in the literature, and thus is still highly relevant to include. Additionally, the constituents of all indices change over time.

# SECTION 4 METHOD

To test integration, the study considered three econometric approaches to form the results: correlation, Johansen cointegration, and Granger pairwise causality testing. To perform these tests, lag length was also considered using various information criteria and unit root tests for stationarity.

The price data to be used was tested in differenced form and logged differenced to create return data. The use of logged returns is prevalent in econometrics, as discussed by Campbell et al. (1998). Logged returns are beneficial due to their linearity and continuous compounding nature, which enhances comparability between assets (Hudson, 2010). Hudson continues by discussing the undesirable properties of logged returns, being that the mean of the simple return differs from the mean of the logged return depending on the variance within returns. Furthermore, logged returns do not give a direct measure of the increasing or decreasing wealth of the investor over time. Thus, to improve robustness, the testing within this study uses both normal returns and logged returns.

## 4.1 CORRELATION

Correlation focuses on the symmetry and asymmetry of variables over time. The relationship obtained is in the form of a coefficient of correlation, which is a percentage that explains how often the movement in $x$ relates to the movement in $y$ (Sharma, 2005). Correlation testing makes it possible to further examine relationships between variables. The data used in this testing is the returns and logged returns (stationary data) on the time series data. First, the indices of NMC and MC were tested against each other. The indices of NMC were then tested against the share index. Similarly, the indices of MC were tested against the PHLX and the SI. A similar order follows for the Johansen cointegration and Granger causality testing.

The measure of correlation or negative correlation is, however, not the most suitable indicator for connectivity. Correlation does not imply causality as it does not imply cause and effect relationships (Johansen, 2007). The use of correlation is highly affected by delays in the market, which may lead to incorrect conclusions as shown by Papana (2021). This gives rise to the need for optimal lag testing to eliminate delays in further econometrics.

## 4.2 COINTEGRATION

Causality is a more informative measure of connectivity among variables and so is used in this study to draw further conclusions (Granger, 1988). This being said, in order to test causality, it is necessary to first consider cointegration testing. Cointegration testing allows meaningful long-run relationships to be determined and thus long-run equilibrium between variables. The use of two non-stationary variables in combination with this model could produce stationary data. This entails that variables share an underlying stationary trend to reach said equilibrium (Gujarati, 2021).

The Johansen cointegration test is a Vector Autoregressive Model (VAR) that incorporates an Error Correction Model (ECM). This test is said to be superior to Engle-Granger testing because a dependent variable does not have to be chosen which can derail results (Johansen, 1991). When successful, this test implies causality as causality is needed for equilibrium (Granger, 1988). To perform the tests, the price data (non-stationary data) was used to determine if a relationship exists between variables.

The use of the following hypotheses is presented as:

*H0: The data is not cointegrated.*

*H1: The data is cointegrated.*

The test is represented by the following:

Transitory Vector Error Correction Model (VECM):

$$\Delta x_t = \mu + \Phi D_t + \pi \prod x_{t-1} - \sum_{j=1}^{p-1} T_j \, \Delta x_{t-j} + \varepsilon_t, t = 1, \ldots, T \tag{1}$$

Where,

$$T_i = (\prod x_{i+1} + \cdots + \prod p), i = 1, \ldots, p-1$$

*Formula 1,* (Johansen, 1991)

## 4.3 CAUSALITY

Granger causality testing was then performed to determine the direction of the relationship between variables (Granger, 1988). To perform this testing, similar to correlation testing, the returns and logged returns were used as data.

The use of the following hypothesises is presented as:

*H0: $x$ does not Granger-cause $y$.*

*H1: $x$ does Granger-cause $y$.*

The test is represented by the following:

Granger Causality Model:

$$\mathbb{P}[Y(t+1)\epsilon \mathrm{A}|L(t)] \neq \mathbb{P}[Y(t+1)\epsilon \mathrm{A}|L_{-x}(t)] \quad (2)$$

- $\mathbb{P}$ = *Probability*
- $A$ = *is an arbitrary non-empty set*
- $L(t)$= *Information available as of t*
- $L_{-x}(t)$= *Information available as of t for – $x$*

*The results are that X is said to Granger-cause Y.*

*Formula 2,* (Granger, 1988)

## 4.4 LAGS

As discussed by Fama in his EMH, the efficiency of the market relies on the time it takes the market to absorb all information (1965). This implies a timing delay between efficient and non-efficient markets. As there is doubt within the literature discussed on whether crypto is an efficient or an inefficient market, this creates the need for lags within the data to fairly test relationships. Lags consisting of the levels 1 - 30 have been incorporated in response to the daily data used.

To perform lag testing, the following criteria were used: Schwarz Information Criterion (SIC) and Hannan-Quinn Criterion (HQC) were used to determine the optimal lag length between 1 - 30. As shown by Asghar and Liew (2007; 2004), for large data sets, SIC and HQC proves to be the most accurate determinant of lag length, however, when structural breaks are present, this conclusion does not hold (Zivot & Andrews, 2002).

To increase robustness, two additional lag criteria were used, Akaike Information Criterion (AIC) and the Final Prediction Error (FPE).

The selected criterion can be summarised as follows:

*(b) Schwarz Information Criterion,* *SIC* = $ln(\sigma^{\wedge 2}_{p}) + [p\, ln(T)]/T$ (3)

*(c) Hannan-Quinn Criterion,* *HQC* = $ln(\sigma^{\wedge 2}_{p}) + 2T^{-1}p\, ln\, [ln(T)]$ (4)

The additional criterion can be summarised as follows:

*(d) The Final Prediction Error,* *FPE* = $\sigma^{\wedge 2}_{p} + (T-p)^{-1}(T+p)$ (5)

*(a) Akaike Information Criterion,* *AIC*= $-2T[ln(\sigma^{\wedge 2}_{p})] + 2P$ (6)

*Where* $\sigma^{\wedge 2}_{p} = (T-p-1)^{-1} \sum_{t=p}^{T} \varepsilon_t^2$, $\varepsilon_t$ *is the models residuals and T is the sample size.*

*Formulae 3,4,5,6,* (Akaike, 1973; Akaike, 1998; Hannan & Quinn, 1979; Schwarz, 1978)

## 4.5 UNIT ROOT TESTS

To test correlation and causality, the data needs to be stationary (Ouma & Muriu, 2014). Stationary data has stable variances and co-variances over time. In essence, this data can be modelled and predicted. For cointegration testing, the data should be non-stationary and thus have fluctuating variances and co-variances are needed (Johansen, 2007). The returns and logged returns were tested for stationarity (correlation, causality testing) while the price data was tested for non-stationarity (cointegration testing).

To determine if data is stationary or non-stationary, the Augmented Dickey-Fuller (ADF) test is performed on the data. As shown by literature, the ADF test is well established (Sharma & Seth, 2012). To supplement this test, the Philips-Perron (PP) test was used as robustness test. The use of the following hypothesises is presented as:

*H0: The data is non-stationary*

*H1: The data is stationary.*

If the data contains a unit root, then the alternative hypothesis will be rejected and if it does not contain a unit root, the null hypothesis will be rejected (Alexander, 2008).

## 4.6 LIMITATIONS

The following were found to be limitations to this study, but they also serve as areas for further research:

- No structural breaks were considered within the data, as seen within Zivot and Andrews' (2002) method of determining lag lengths.
- The created semiconductor index (SI) was limited to companies listed on an exchange and have a material role within the supply chain of crypto mining hardware. The choice of companies although based on materiality of relationships, is a subjective decision. Further, these relationships change very fast and new deals and supplier relationships are formed continuously, thus it is only correct as of June 2023.
- The capping was a limitation to this study. The Capped SWIX Top 40 methodology of capping was selected and adapted to the index within this study. This capping is subjective to limit the effects of Bitcoin as a dominating asset within the index.

# SECTION 5 RESULTS

The results of the study are presented below in the following order: the unit root tests, correlation testing, lag length results, cointegration testing and lastly, causality testing. All data used was based on daily market capitalisations using the United States Dollar (USD) as a consistent currency.

## 5.1 UNIT ROOT TESTS FOR RETURNS AND LOGGED RETURNS

The requirements for correlation and causality testing are that the data should be stationary. Conversely, the requirements for cointegration testing are that the data should be non-stationary. The results for the ADF and PP test are summarised in **Table 4, Table 5,** and **Table 6** below.

**Table 4. Unit root test for ADF and PP on the price data for all variables**

| Price data | | Augmented Dickey-Fuller | | Phillips-Perron | |
|---|---|---|---|---|---|
| | | T-stat | P-value | T-stat | P-value |
| Non-mined | NMCI | -2.4544 | 0.3511 | -2.6520 | 0.2572 |
| | NMCB | -1.9237 | 0.6414 | -1.8323 | 0.6885 |
| Mined | MCI | -1.7345 | 0.7355 | -1.7345 | 0.7355 |
| | CMC | -1.3775 | 0.8672 | -1.3884 | 0.8642 |
| | HMC | -1.3915 | 0.8633 | -1.3915 | 0.8633 |
| | CHMC | -1.3723 | 0.8686 | -1.3723 | 0.8686 |
| Semiconductor | SI | -1.8866 | 0.6609 | -1.8123 | 0.6984 |
| | PHLX | -1.7313 | 0.7369 | -1.7338 | 0.7358 |
| Equity | NASDAQ | -1.4068 | 0.8589 | -1.4480 | 0.8464 |
| | S&P500 | -2.1248 | 0.5309 | -2.0474 | 0.5741 |
| | DJIA | -2.7800 | 0.2050 | -2.6740 | 0.2477 |

**Notes to Table 4**

The p-value is the probability of drawing the related t-statistic (T-stat) obtained from t-test.

The critical values were respectively: 1% level -3.9657, 5% level -3.4135, 10% level -3.1288 (MacKinnon (1996) one sided p values).

* - denotes rejection of the null hypothesis at the 1% significance level.

The ADF test uses the Schwartz Information Criterion.

## Table 5. Unit root test for ADF and PP on the return data for all variables

| Return data | | Augmented Dickey-Fuller | | Phillips-Perron | |
|---|---|---|---|---|---|
| | | T-stat | P-value | T-stat | P-value |
| Non-mined | NMCI | -34.5723 | 0.0000* | -34.6024 | 0.0000* |
| | NMCB | -33.0001 | 0.0000* | -32.9833 | 0.0000* |
| Mined | MCI | -34.4070 | 0.0000* | -34.4137 | 0.0000* |
| | CMC | -34.2401 | 0.0000* | -34.3257 | 0.0000* |
| | HMC | -34.3628 | 0.0000* | -34.3756 | 0.0000* |
| | CHMC | -34.3629 | 0.0000* | -34.3739 | 0.0000* |
| Semiconductor | SI | -38.9383 | 0.0000* | -38.9200 | 0.0000* |
| | PHLX | -41.8094 | 0.0000* | -41.7793 | 0.0000* |
| Equity | NASDAQ | -10.8770 | 0.0000* | -41.2746 | 0.0000* |
| | S&P500 | -10.3780 | 0.0000* | -41.2402 | 0.0000* |
| | DJIA | -10.6030 | 0.0000* | -41.2439 | 0.0000* |

**Notes to Table 5**

The p-value is the probability of drawing the related t-statistic (T-stat) obtained from t-test.

The critical values were respectively: 1% level -3.9657, 5% level -3.4135, 10% level -3.1288 (MacKinnon (1996) one sided p values).

* - denotes rejection of the null hypothesis at the 1% significance level.

The ADF test uses the Schwartz Information Criterion.

## Table 6. Unit root test for ADF and PP on the logged return data for all variables

| Log return data | | Augmented Dickey-Fuller | | Phillips-Perron | |
|---|---|---|---|---|---|
| | | T-stat | P-value | T-stat | P-value |
| Non-mined | NMCI | -34.3083 | 0.0000* | -34.3227 | 0.0000* |
| | NMCB | -33.8549 | 0.0000* | -33.8463 | 0.0000* |
| Mined | MCI | -34.4416 | 0.0000* | -34.4467 | 0.0000* |
| | CMC | -34.2602 | 0.0000* | -34.3392 | 0.0000* |
| | HMC | -34.3759 | 0.0000* | -34.3862 | 0.0000* |
| | CHMC | -34.3490 | 0.0000* | -34.3628 | 0.0000* |
| Semiconductor | SI | -38.9317 | 0.0000* | -38.9454 | 0.0000* |
| | PHLX | -41.8193 | 0.0000* | -41.8554 | 0.0000* |
| Equity | NASDAQ | -10.9607 | 0.0000* | -41.3544 | 0.0000* |
| | S&P500 | -10.4819 | 0.0000* | -41.3841 | 0.0000* |
| | DJIA | -10.7111 | 0.0000* | -41.3918 | 0.0000* |

**Notes to Table 6**

The p-value is the probability of drawing the related t-statistic (T-stat) obtained from t-test.

The critical values were respectively: 1% level -3.9657, 5% level -3.4135, 10% level -3.1288 (MacKinnon (1996) one sided p values).

* - denotes rejection of the null hypothesis at the 1% significance level.

The ADF test uses the Schwartz Information Criterion.

The results for the stationarity tests performed within **Table 4, Table 5** and **Table 6** above indicate that all index data is stationary after being differenced and non-stationary when not differenced. The null hypothesis for each test is that the data contains a unit root and is thus non-stationary, and the alternative is that the data is stationary. Thus, as per the probability values and t-statistics obtained, the price data is non-stationary as the null hypothesis is not rejected. The return and logged return data is stationary as the null hypothesis is rejected and the alternative is accepted. This aligns with prior literature on stationarity testing for crypto and indices like the S&P500 (Bouri et al., 2021; Hagemann, 2018; Kılıç & Uğur, 2018; Sharma & Bhardwaj, 2022). Thus, it is possible to proceed with Johansen cointegration testing for long term relationships.

## 5.2 CORRELATION RESULTS FOR RETURNS AND LOGGED RETURNS

The results for the non-lagged correlation testing performed on the stationary data, being returns and logged returns, are presented in **Table 7** and **Table 8** below. The context of the relationships being examined can also be seen in **Figure 5** below.

**Figure 5. Time series comparison of price data**

**Table 7. Correlation results for returns for cryptos, semiconductor industry and technology industry**

| | NMCI | NMCB | MCI | CMC | HMC | CHMC | SI | PHLX | NASDAQ | S&P500 | *DJIA* |
|---|---|---|---|---|---|---|---|---|---|---|---|
| NMCI | | | | | | | | | | | |
| NMCB | 0.29 | | | | | | | | | | |
| MCI | 0.46 | 0.24 | | | | | | | | | |
| CMC | 0.46 | 0.29 | 0.92 | | | | | | | | |
| HMC | 0.46 | 0.29 | 0.94 | 0.98 | | | | | | | |
| CHMC | 0.47 | 0.30 | 0.94 | 0.98 | 1.00 | | | | | | |
| SI | 0.13 | 0.08 | 0.31 | 0.31 | 0.31 | 0.31 | | | | | |
| PHLX | 0.13 | 0.08 | 0.31 | 0.31 | 0.31 | 0.31 | 0.91 | | | | |
| NASDAQ | 0.13 | 0.08 | 0.32 | 0.32 | 0.32 | 0.32 | 0.83 | 0.89 | | | |
| S&P500 | 0.13 | 0.10 | 0.30 | 0.30 | 0.30 | 0.30 | 0.76 | 0.84 | 0.93 | | |
| DJIA | 0.11 | 0.09 | 0.26 | 0.27 | 0.26 | 0.26 | 0.66 | 0.76 | 0.83 | 0.96 | |

**Note to Table 7**

Correlation coefficients across the variables. The sample period is 1 July 2018 to 30 June 2023.

**Table 8. Correlation matrix of results for logged returns for cryptos, semiconductor industry and technology industry**

| | NMCI | NMCB | MCI | CMC | HMC | CHMC | SI | PHLX | NASDAQ | S&P500 | *DJIA* |
|---|---|---|---|---|---|---|---|---|---|---|---|
| NMCI | | | | | | | | | | | |
| NMCB | 0.49 | | | | | | | | | | |
| MCI | 0.54 | 0.46 | | | | | | | | | |
| CMC | 0.53 | 0.50 | 0.94 | | | | | | | | |
| HMC | 0.54 | 0.50 | 0.96 | 0.98 | | | | | | | |
| CHMC | 0.54 | 0.50 | 0.96 | 0.98 | 1.00 | | | | | | |
| SI | 0.17 | 0.18 | 0.32 | 0.32 | 0.31 | 0.31 | | | | | |
| PHLX | 0.16 | 0.17 | 0.31 | 0.31 | 0.31 | 0.31 | 0.91 | | | | |
| NASDAQ | 0.17 | 0.18 | 0.33 | 0.33 | 0.33 | 0.33 | 0.83 | 0.89 | | | |
| S&P500 | 0.17 | 0.19 | 0.31 | 0.31 | 0.31 | 0.31 | 0.76 | 0.85 | 0.93 | | |
| DJIA | 0.14 | 0.17 | 0.28 | 0.28 | 0.27 | 0.28 | 0.66 | 0.76 | 0.83 | 0.96 | |

**Note to Table 8**

Correlation coefficients across the variables. The sample period is 1 July 2018 to 30 June 2023.

As seen in **Table 7** and **Table 8** above, the MC and NMC are correlated in the range 0.24-0.54 with the logged returns yielding slightly higher correlations. This is in line with literature from Bouri (2021), who examined 12 leading cryptos from 2015 to 2019, five of which are shared with this study and found similar ranges of correlation. Similar comparisons by Bouri found Bitcoin and Monero to have a correlation of 0.5041, which is within the range found. Further, Bitcoin and Ripple were found to be 0.3101, again within the ranges found. Other literature has also concluded on positive relationships between cryptos (Giudici & Polinesi, 2021; Qureshi et al., 2020).

When comparing cryptos with indices, very weak correlation is seen (0.08-0-18) for NMC to the indices, with slightly stronger correlations (0.26-0.33) for MC to the indices. This differing correlation strength drives the argument for separation between NMC and MC when testing to isolate relationships. This positive weak correlation between cryptos and indices is in line with literature (Bouoiyour & Selmi, 2015; Ciaian et al., 2016; Nguyen, 2022; Wang et al., 2020).

Baur et al. (2018) is where the correlation results contrast with literature, where no correlation was found between Bitcoin and the S&P500, but the time period used was 2010–2015 and further, Lee et al. (2018) found no correlation using 2014–2017. The results also contrast with those of Chan et al. (2019) as they found Bitcoin to be a hedge against the S&P500, although for an earlier time period, and they used monthly data compared to this study’s use of daily data.

It can also be noted that the results for returns, and logged returns, are slightly different although these differences are largely immaterial as they relate to the results of the correlation testing. These differences arise from the strengths and weaknesses of each, as discussed in Section 4 which describes the method. An investigation of the differences due to logging is outside the scope of this study.

A further observation is that the SI and the PHLX are highly correlated which confirms the choice of companies included in the semiconductor index to represent the companies involved in production and supply of hardware used for mining. Moreover, an interesting observation can be seen with the correlations between the SI and PHLX (0.91), NASDAQ (0.83), S&P500 (0.76), and DJIA (0.66). The further removed from semiconductors and technology the indices become, the further the decline in correlation, thus confirming the importance of having a created index for comparison to cryptos to isolate relationships as a result of semiconductors and technology. Additional observations are made with further testing below. The correlation testing does not preclude progressing in testing, it does, however, give an indication of relationships that may exist.

## 5.3 LAG LENGTH TESTING

As expected from the literature, most non-stationary economic data contains lags lengths of only one or two, which was common in the results obtained (Gujarati, 2021). The lag results obtained (see **Table 9** below) may be used going forward in the cointegration and causality test to find the model with the greatest relationships. Lag lengths beyond one or two are not uncommon, as shown in literature; between cryptos, lag lengths are usually one but against equities like the NASDAQ, they have been found to be as long as 18 to 20 (Şahin, 2022).

**Table 9. Matrix of lag length testing results**

| | NMCI | NMCB | MCI | CMC | HMC | CHMC |
|---|---|---|---|---|---|---|
| MCI | 1, 7, 30 | 1, 29 | | | | |
| CMC | 1, 7, 30 | 1, 29 | | | | |
| HMC | 1, 7, 30 | 1, 29 | | | | |
| CHMC | 1, 7, 30 | 1, 30 | | | | |
| SI | | | 1, 8 | 1, 8 | 1, 8 | 1, 8 |
| PHLX | | | 1, 2, 8 | 1, 2, 8 | 1, 2, 8 | 1, 2, 8 |
| NASDAQ | 1, 2, 16 | 1, 2, 23 | | | | |
| S&P500 | 1, 2, 16 | 1, 2, 23 | | | | |
| DJIA | 1, 2, 28 | 1, 2, 23 | | | | |

**Notes to Table 9**

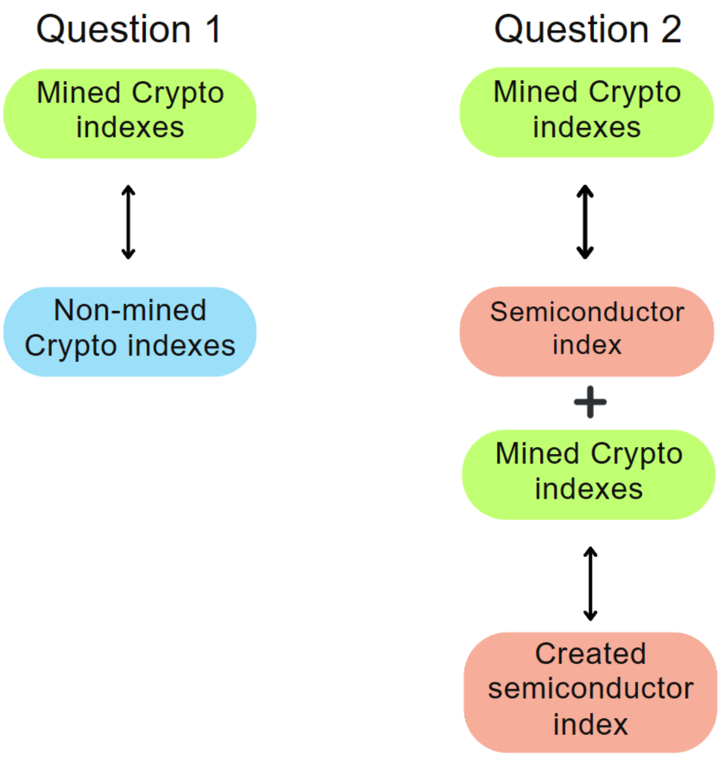
The values presented represent the optimal lag length in days obtained from each of the four information criterion namely SIC and HQC and the robustness tests of AIC and FPE. Multiple values were presented for criterion which had conflicting results.

The lag length tests were performed on non-differenced price data testing intervals up to 30 due to the daily data used.

## 5.4 COINTEGRATION AND CAUSALITY TESTING

The results for the testing have been summarised below per research question, as shown in **Figure 6** below. Each question was tested first for cointegration and then for causality if cointegration was present. The cointegration tests were performed on the non-differenced (non-stationary price data) and the causality on the differenced data (stationary data), being the returns and logged returns.

**Figure 6. Summary of research questions**




When interpreting the cointegration tests, the first point that must be noted is that the trace statistic is deemed the more accurate test of cointegration in bivariate testing. Thus, where the trace statistic and max-eigen statistic differ, the trace statistic is relied on (Serletis & King, 1997). To simplify the process of analysis, the trace and max-eigen statistics were looked at in relation to the critical values. If the aforementioned statistics are higher than the critical value, we then reject the null hypothesis. This is further confirmed by the probability values (p-value) given, if these values are less than 0.05 (5% significance level), the null hypothesis stated can be rejected. It is possible to then conclude the following:

- No cointegration exists if the null hypothesis '*none*' is not rejected; simply no relationship exists.
- One cointegrating equation exists if only the null hypothesis '*none*' is rejected.
- Two cointegrating equations exist if both hypotheses '*none*' and '*at most 1*' are rejected.

It is important to note that the p-values are used to help draw conclusions, but the p-value represents statistical significance, and it is not clear cut when drawing conclusions. The value merely quantifies evidence against the null hypothesis. Thus, there is a limitation on all conclusions drawn from statistical tests. (Fisher, 1956). However, the p-values allow a picture to be formed and similarities and patterns to be seen in a logical way. Significance levels were considered to be 1% and 5% for drawing statistically significant conclusions although 10% is not ignored to avoid arbitrary significance level cutoffs.

### 5.4.1 Research question 1. Does integration exist between mined crypto and non-mined crypto, and what is the direction?

The results are presented for the NMCI followed by the NMCB, both compared to the mined crypto indices. The trace and max-eigen cointegration testing is shown which is followed by analysis of the results and ultimately the causality testing for variables with cointegrating equations present.

**Table 10. Johansen cointegration test results relating to the long-run relationship between non-mined crypto index and mined crypto indices**

| **NMCI** | | **Null Hypothesis: No. of cointegrating equations = none** | | | **Null Hypothesis: No. of cointegrating equations = At most 1** | | |
|---|---|---|---|---|---|---|---|
| Var | lag interval | T-statistic | P-value | rejection of H0 | T-statistic | P-value | rejection of H0 |
| MCI | 1 - 1 | 43.0333 | 0.0000 | * | 14.6611 | 0.0001 | * |
| | 1 - 7 | 41.1356 | 0.0000 | * | 9.5150 | 0.0020 | * |
| | 1 - 30 | 27.2688 | 0.0022 | * | 6.1739 | 0.0130 | * |
| CMC | 1 - 1 | 43.1899 | 0.0000 | * | 10.0232 | 0.0015 | * |
| | 1 - 7 | 40.8169 | 0.0000 | * | 7.5287 | 0.0061 | * |
| | 1 - 30 | 20.8991 | 0.0219 | * | 4.0986 | 0.0429 | ** |
| HMC | 1 - 1 | 45.1211 | 0.0000 | * | 11.7986 | 0.0006 | * |
| | 1 - 7 | 41.2753 | 0.0000 | * | 7.2884 | 0.0069 | * |
| | 1 - 30 | 23.5056 | 0.0088 | * | 4.5354 | 0.0332 | ** |
| CHMC | 1 - 1 | 44.2250 | 0.0000 | * | 11.3131 | 0.0008 | * |
| | 1 - 7 | 40.7732 | 0.0000 | * | 7.0198 | 0.0081 | * |
| | 1 - 30 | 23.2531 | 0.0096 | * | 4.4793 | 0.0343 | ** |

| NMCI | | Null Hypothesis: No. of cointegrating equations = none | | | Null Hypothesis: No. of cointegrating equations = At most 1 | | |
|---|---|---|---|---|---|---|---|
| Var | lag interval | Max-Eigen statistic | P-value | rejection of H0 | Max-Eigen statistic | P-value | rejection of H0 |
| MCI | 1 - 1 | 28.3722 | 0.0008 | * | 14.6611 | 0.0001 | * |
| | 1 - 7 | 31.6207 | 0.0002 | * | 9.5150 | 0.0020 | * |
| | 1 - 30 | 21.0949 | 0.0127 | ** | 6.1739 | 0.0130 | ** |
| CMC | 1 - 1 | 33.1668 | 0.0001 | * | 10.0232 | 0.0015 | * |
| | 1 - 7 | 33.2882 | 0.0001 | * | 7.5287 | 0.0061 | * |
| | 1 - 30 | 16.8004 | 0.0561 | *** | 4.0986 | 0.0429 | ** |
| HMC | 1 - 1 | 33.3225 | 0.0001 | * | 11.7986 | 0.0006 | * |
| | 1 - 7 | 33.9868 | 0.0001 | * | 7.2884 | 0.0069 | * |
| | 1 - 30 | 18.9703 | 0.0269 | ** | 4.5354 | 0.0332 | ** |
| CHMC | 1 - 1 | 32.9119 | 0.0001 | * | 11.3131 | 0.0008 | * |
| | 1 - 7 | 33.7534 | 0.0001 | * | 7.0198 | 0.0081 | * |
| | 1 - 30 | 18.7738 | 0.0288 | ** | 4.4793 | 0.0343 | ** |

**Notes to Table 10**

The 5% critical values that results in a rejection of the null hypothesis of no cointegrating equations and at most one cointegrating equations through comparison of the trace statistic are 18.3977 and 3.8415 respectively.

The 5% critical values that results in a rejection of the null hypothesis of no cointegrating equations and at most one cointegrating equations through comparison of the Max-Eigen statistic are 17.1477 and 3.8415 respectively.

*Please see the list of abbreviations for the names in the table.*

MacKinnon, Haug, and Michelis (1999) p-values.

* - denotes rejection of the null hypothesis at the 1% significance level.

** - denotes rejection of the null hypothesis at the 5% significance level.

*** - denotes rejection of the null hypothesis at the 10% significance level.

**Table 11. Johansen cointegration test results relating to the long-run relationship between non-mined crypto index excluding Binance and mined crypto indices**

| NMCB | | Null Hypothesis: No. of cointegrating equations = none | | | Null Hypothesis: No. of cointegrating equations = At most 1 | | |
|---|---|---|---|---|---|---|---|
| Var | lag interval | T-statistic | P-value | rejection of H0 | T-statistic | P-value | rejection of H0 |
| MCI | 1 - 1 | 16.4432 | 0.0919 | *** | 6.2004 | 0.0128 | ** |
| | 1 - 29 | 20.7640 | 0.0229 | ** | 6.0290 | 0.0141 | ** |
| CMC | 1 - 1 | 14.6848 | 0.1533 | | 4.4263 | 0.0354 | ** |
| | 1 - 29 | 17.8453 | 0.0596 | *** | 4.2468 | 0.0393 | ** |
| HMC | 1 - 1 | 15.7893 | 0.1117 | | 4.5806 | 0.0323 | ** |
| | 1 - 29 | 20.7979 | 0.0227 | ** | 4.4279 | 0.0353 | ** |
| CHMC | 1 - 1 | 15.6983 | 0.1147 | | 4.4552 | 0.0348 | ** |
| | 1 - 29 | 20.9035 | 0.0219 | ** | 4.3149 | 0.0378 | ** |

| NMCB | | Null Hypothesis: No. of cointegrating equations = none | | | Null Hypothesis: No. of cointegrating equations = At most 1 | | |
|---|---|---|---|---|---|---|---|
| Var | lag interval | Max-Eigen statistic | P-value | rejection of H0 | Max-Eigen statistic | P-value | rejection of H0 |
| MCI | 1 - 1 | 10.2428 | 0.3752 | | 6.2004 | 0.0128 | ** |
| | 1 - 29 | 14.7350 | 0.1086 | | 6.0290 | 0.0141 | ** |
| CMC | 1 - 1 | 10.2585 | 0.3739 | | 4.4263 | 0.0354 | ** |
| | 1 - 29 | 13.5985 | 0.1528 | | 4.2468 | 0.0393 | ** |
| HMC | 1 - 1 | 11.2087 | 0.2956 | | 4.5806 | 0.0323 | ** |
| | 1 - 29 | 16.3700 | 0.0646 | *** | 4.4279 | 0.0353 | ** |
| CHMC | 1 - 1 | 11.2431 | 0.2930 | | 4.4552 | 0.0348 | ** |
| | 1 - 29 | 16.5886 | 0.0601 | *** | 4.3149 | 0.0378 | ** |

**Notes to Table 11**

The 5% critical values that results in a rejection of the null hypothesis of no cointegrating equations and at most one cointegrating equations through comparison of the trace statistic are 18.3977 and 3.8415 respectively.

The 5% critical values that results in a rejection of the null hypothesis of no cointegrating equations and at most one cointegrating equations through comparison of the Max-Eigen statistic are 17.1477 and 3.8415 respectively.

*Please see the list of abbreviations for the names in the table.*

MacKinnon, Haug, and Michelis (1999) p-values.

* - denotes rejection of the null hypothesis at the 1% significance level.

** - denotes rejection of the null hypothesis at the 5% significance level.

*** - denotes rejection of the null hypothesis at the 10% significance level.

As shown in **Table 10** and **Table 11** above, there are many instances of cointegration between MC and NMC. For the results compared with the NMCI, two cointegrating equations can be found at multiple lag intervals for the trace and Max-Eigen statistic. The results are significant at a mix of 1% and 5% levels, with shorter lag intervals being more significant on average. The results here show long-run relationships between cryptos despite differences in their consensus mechanisms. This aligns with Bouri (2021), who concluded on market integration using a dynamic equicorrelation model. Bouri argued that share trading volumes by investors created this integration. Keilbar and Zhang (2021) also drew positive conclusions on cointegration between cryptos. Further research using wavelet analysis revealed relationships between Ripple and Ethereum, both of which feature within the NMC indices and MC indices respectively (Qureshi et al., 2020).

Comparing this to the results for NMCB in **Table 11** above, there are fewer significant relationships as only at a 5% level is cointegration found, and this is found at longer lag intervals of 1–29. Again, two cointegrating equations are present. Using two separate indices allows the effects of Binance to be seen. The NMCB index consists of only Ripple, Cardano, Solana, Polkadot and Tronix, and this weakening of cointegration and the differing lag intervals give an indication of the abnormal behaviour of these cryptos compared to Binance.

Building on the results, **Table 12** and **Table 13** below are concerned with causality. There is strong evidence for NMCI driving MCs at a 1% significance level at multiple lag lengths between the returns and logged returns. Simultaneously, there is evidence at a 5% significance level for a bilateral relationship at a lag length of 7. The results for a lag length of 30 cannot be concluded on definitively as the returns differ from the logged returns. Thus, results at a lag length of 1 indicate NMCI Granger-causes MCs and a lag length of 7 indicates a bilateral relationship. This differs from conclusions drawn by Ciaian et al. (2018) as they determined that Bitcoin was not driving other cryptos, but this study indicates a bilateral relationship as the MC indices are largely made up of Bitcoin. The results in **Table 13** below indicate no causal relationship exists, which contrasts with **Table 12** below. A point of further research could be to investigate why the bilateral relationship disappears when Binance is removed as this indicates that Binance does not share the same causal relationship to MC as other NMCs share.

**Table 12. Causality test results between non-mined crypto and mined crypto indices**

| **Returns** | | **Null hypothesis** | | **Null hypothesis** | |
|---|---|---|---|---|---|
| NMCI | lag length: | NMCI does not Granger-cause variable | | Variable does not Granger-cause NMCI | |
| Var | | F-statistic | P-value | F-statistic | P-value |
| MCI | 1 | 10.1296 | 0.0015* | 0.2482 | 0.6184 |
| | 7 | 3.2590 | 0.0020* | 1.9825 | 0.0544*** |
| | 30 | 1.1790 | 0.2335 | 1.0390 | 0.4092 |
| CMC | 1 | 7.9204 | 0.0050* | 0.4349 | 0.5097 |
| | 7 | 3.5404 | 0.0009* | 2.3578 | 0.0215** |
| | 30 | 1.2382 | 0.1772 | 1.0815 | 0.3499 |
| HMC | 1 | 9.9590 | 0.0016* | 0.4744 | 0.4911 |
| | 7 | 3.5188 | 0.0010* | 2.3158 | 0.0239** |
| | 30 | 1.2573 | 0.1614 | 1.1126 | 0.3097 |
| CHMC | 1 | 9.9739 | 0.0016* | 0.3978 | 0.5284 |
| | 7 | 3.5395 | 0.0009* | 2.2551 | 0.0279** |
| | 30 | 1.2841 | 0.1410 | 1.0538 | 0.3881 |
| **Logged returns** | | **Null hypothesis** | | **Null hypothesis** | |
| NMCI | lag length: | NMCI does not Granger-cause variable | | Variable does not Granger-cause NMCI | |
| Var | | F-statistic | P-value | F-statistic | P-value |
| MCI | 1 | 9.8089 | 0.0018* | 0.0339 | 0.8541 |
| | 7 | 3.5348 | 0.0009* | 1.6284 | 0.1233 |
| | 30 | 1.3467 | 0.1014 | 0.8695 | 0.6697 |
| CMC | 1 | 8.4635 | 0.0037* | 0.1247 | 0.7240 |
| | 7 | 4.1310 | 0.0002* | 2.0998 | 0.0409** |
| | 30 | 1.5153 | 0.0377** | 0.9004 | 0.6220 |
| HMC | 1 | 10.1757 | 0.0015* | 0.1325 | 0.7159 |
| | 7 | 4.0079 | 0.0002* | 1.9827 | 0.0543*** |
| | 30 | 1.5171 | 0.0372** | 0.9417 | 0.5573 |
| CHMC | 1 | 9.9744 | 0.0016* | 0.1506 | 0.6980 |
| | 7 | 4.0231 | 0.0002* | 1.9653 | 0.0567*** |
| | 30 | 1.4491 | 0.0565*** | 0.9767 | 0.5027 |

**Notes to Table 12**

The Granger causality test is conducted within the framework of f-test. If the p-value of f-test is significant (i.e., α=<0.05) at the 5% significance level, the null hypothesis is rejected within this study. The 1% and 10% significance levels are also looked at.

Granger-causality is tested between the variables for the periods outlined in the optimal lag length results (see **Table 9**)

* - denotes rejection of the null hypothesis at the 1% significance level.

** - denotes rejection of the null hypothesis at the 5% significance level.

*** - denotes rejection of the null hypothesis at the 10% significance level.

**Table 13. Causality test results between non-mined excluding Binance crypto and mined crypto indices**

| Returns | | Null hypothesis | | Null hypothesis | |
|---|---|---|---|---|---|
| NMCB | lag length: | NMCB does not Granger-cause variable | | Variable does not Granger-cause NMCB | |
| Var | | F-statistic | P-value | F-statistic | P-value |
| MCI | 1 | 1.6559 | 0.1984 | 0.0815 | 0.7754 |
| | 2 | 0.8195 | 0.4409 | 1.7200 | 0.1795 |
| | 29 | 0.4885 | 0.9901 | 0.4315 | 0.9965 |
| CMC | 1 | 0.0070 | 0.9331 | 1.8227 | 0.1773 |
| | 2 | 1.8258 | 0.1615 | 0.8789 | 0.4155 |
| | 29 | 0.5213 | 0.9834 | 0.5312 | 0.9809 |
| HMC | 1 | 2.1011 | 0.1475 | 0.0837 | 0.7723 |
| | 2 | 1.0632 | 0.3457 | 1.8835 | 0.1525 |
| | 29 | 0.4597 | 0.9940 | 0.4519 | 0.9948 |
| CHMC | 1 | 0.0257 | 0.8726 | 2.0600 | 0.1515 |
| | 2 | 1.7673 | 0.1712 | 1.0349 | 0.3556 |
| | 30 | 0.4361 | 0.9967 | 0.4464 | 0.9959 |
| **Logged returns** | | **Null hypothesis** | | **Null hypothesis** | |
| NMCB | lag length: | NMCB does not Granger-cause variable | | Variable does not Granger-cause NMCB | |
| Var | | F-statistic | P-value | F-statistic | P-value |
| MCI | 1 | 1.0918 | 0.2963 | 0.0851 | 0.7705 |
| | 2 | 0.5413 | 0.5821 | 0.4083 | 0.6649 |
| | 29 | 0.3143 | 0.9998 | 0.3799 | 0.9989 |
| CMC | 1 | 0.3357 | 0.5624 | 1.3184 | 0.2511 |
| | 2 | 0.6093 | 0.5439 | 0.6340 | 0.5306 |
| | 29 | 0.4854 | 0.9905 | 0.3320 | 0.9997 |
| HMC | 1 | 1.4022 | 0.2366 | 0.1121 | 0.7379 |
| | 2 | 0.7052 | 0.4942 | 0.4872 | 0.6145 |
| | 29 | 0.3193 | 0.9998 | 0.4103 | 0.9978 |
| CHMC | 1 | 0.0787 | 0.7791 | 1.4271 | 0.2325 |
| | 2 | 0.4914 | 0.6119 | 0.7225 | 0.4858 |
| | 30 | 0.4089 | 0.9982 | 0.3137 | 0.9999 |

**Notes to Table 13**

The Granger causality test is conducted within the framework of f-test. If the p-value of f-test is significant (i.e., α=<0.05) at the 5% significance level, the null hypothesis is rejected within this study. The 1% and 10% significance levels are also looked at.

Granger-causality is tested between the variables for the periods outlined in the optimal lag length results (see **Table 9**).

* - denotes rejection of the null hypothesis at the 1% significance level.

** - denotes rejection of the null hypothesis at the 5% significance level.

*** - denotes rejection of the null hypothesis at the 10% significance level.

### 5.4.2 Research question 2. Does integration exist between mined crypto and the semiconductor industry, and what is the direction?

The results are presented below for the Philadelphia Stock Exchange Semiconductor index (PHLX). Similar to the above, the order is the cointegration testing, followed by analysis of the results and ultimately the causality testing.

**Table 14. Johansen cointegration test results relating to the long-run relationship between the Philadelphia semiconductor index and mined crypto indices**

| **PHLX** | | **Null Hypothesis: No. of cointegrating equations = none** | | | **Null Hypothesis: No. of cointegrating equations = At most 1** | | |
|---|---|---|---|---|---|---|---|
| Var | lag interval | T-statistic | P-value | rejection of H0 | T-statistic | P-value | rejection of H0 |
| MCI | 1 - 1 | 16.5236 | 0.0897 | *** | 2.3220 | 0.1276 | |
| | 1 - 2 | 16.8368 | 0.0815 | *** | 2.3365 | 0.1264 | |
| | 1 - 8 | 18.2715 | 0.0521 | *** | 2.1647 | 0.1412 | |
| CMC | 1 - 1 | 18.4893 | 0.0485 | ** | 2.0929 | 0.1480 | |
| | 1 - 2 | 18.8379 | 0.0434 | ** | 1.5624 | 0.2113 | |
| | 1 - 8 | 18.5109 | 0.0482 | ** | 1.6190 | 0.2032 | |
| HMC | 1 - 1 | 18.8266 | 0.0436 | ** | 1.9385 | 0.1638 | |
| | 1 - 2 | 18.5766 | 0.0472 | ** | 1.6027 | 0.2055 | |
| | 1 - 8 | 18.6027 | 0.0468 | ** | 1.6694 | 0.1963 | |
| CHMC | 1 - 1 | 18.9157 | 0.0423 | ** | 1.9177 | 0.1661 | |
| | 1 - 2 | 18.8342 | 0.0435 | ** | 1.5790 | 0.2089 | |
| | 1 - 8 | 18.7004 | 0.0454 | ** | 1.6471 | 0.1994 | |

| PHLX | | Null Hypothesis: No. of cointegrating equations = none | | | Null Hypothesis: No. of cointegrating equations = At most 1 | | |
|---|---|---|---|---|---|---|---|
| Var | lag interval | Max-Eigen statistic | P-value | rejection of H0 | Max-Eigen statistic | P-value | rejection of H0 |
| | 1 - 1 | 14.2016 | 0.1277 | | 2.3220 | 0.1276 | |
| MCI | 1 - 2 | 14.5003 | 0.1167 | | 2.3365 | 0.1264 | |
| | 1 - 8 | 16.1068 | 0.0704 | *** | 2.1647 | 0.1412 | |
| | 1 - 1 | 16.3964 | 0.0641 | *** | 2.0929 | 0.1480 | |
| CMC | 1 - 2 | 17.2755 | 0.0479 | ** | 1.5624 | 0.2113 | |
| | 1 - 8 | 16.8920 | 0.0544 | *** | 1.6190 | 0.2032 | |
| | 1 - 1 | 16.8881 | 0.0545 | *** | 1.9385 | 0.1638 | |
| HMC | 1 - 2 | 16.9739 | 0.0530 | *** | 1.6027 | 0.2055 | |
| | 1 - 8 | 16.9333 | 0.0537 | *** | 1.6694 | 0.1963 | |
| | 1 - 1 | 16.9980 | 0.0525 | *** | 1.9177 | 0.1661 | |
| CHMC | 1 - 2 | 17.2552 | 0.0482 | ** | 1.5790 | 0.2089 | |
| | 1 - 8 | 17.0534 | 0.0516 | *** | 1.6471 | 0.1994 | |

**Notes to Table 14**

The 5% critical values that results in a rejection of the null hypothesis of no cointegrating equations and at most one cointegrating equations through comparison of the trace statistic are 18.3977 and 3.8415 respectively.

The 5% critical values that results in a rejection of the null hypothesis of no cointegrating equations and at most one cointegrating equations through comparison of the Max-Eigen statistic are 17.1477 and 3.8415 respectively.

*Please see the list of abbreviations for the names in the table.*

MacKinnon, Haug, and Michelis (1999) p-values.

* - denotes rejection of the null hypothesis at the 1% significance level.

** - denotes rejection of the null hypothesis at the 5% significance level.

*** - denotes rejection of the null hypothesis at the 10% significance level.

As can be seen by the result in **Table 14** above, the trace statistic indicates a single cointegrating equation for CMC, HMC and CHMC for lag intervals 1–1, 1–2 and 1–8 with the PHLX. Thus, a long-run relationship exists between these variables at a 5% significance level. The MCI was found to be significant at a 10% level which is insufficient to conclude on. As mentioned above, the trace statistic is given preference over the Max-Eigen statistic. The positive weak levels of correlation for MCs and the PHLX seen in earlier testing is confirmed to be a relationship and thus does not appear to be spurious.

Using the cointegration results causality testing can proceed, with the results shown below in **Table 15**, to determine directionality of relationships. Causality is found using returns and logged returns at a 10% significance level for the PHLX Granger-causing

CMC, HMC, CHMC. This is found at a lag length of 1. The 10% significance level is not strong enough to conclude on, although it is in line with the literature which found causality at 10% significance between the US technology sector and a crypto index that served as a proxy for the crypto market (Umar et al., 2021) . Furthermore Rathi (2022) found a bilateral relationship using Bitcoin and the MSCI semiconductor index. Rathi indicated a significance level of 1% for the semiconductor index causing Bitcoin, and a weak causality relationship for the reverse. This study does not agree with a bilateral relationship, as stated by Rathi, instead only that the semiconductor index drives MC.

These findings support a lower level of diversification when investing in the MC and semiconductor industry is.  This study builds on the conclusions of previous literature but uses a wider range of cryptos and a different set of semiconductors indices.

The MCI sits in an interesting position; this index is mainly made up of Bitcoin (70–85%), which differs from the HMC (99%) and the CMC and CHMC (66.66%). This index sits between these indices for share of Bitcoin but does not result in the same conclusions for causality. The MCI indicates weak cointegration but falls short of weak causality.

**Table 15. Causality test results between Philadelphia Semiconductor Index and mined crypto indices**

| Returns | | Null hypothesis | | Null hypothesis | |
|---|---|---|---|---|---|
| PHLX | lag length: | PHLX does not Granger-cause variable | | Variable does not Granger-cause PHLX | |
| Var | | F-statistic | P-value | F-statistic | P-value |
| MCI | 1 | 1.2436 | 0.2650 | 0.0129 | 0.9095 |
| | 2 | 0.5532 | 0.5752 | 0.7540 | 0.4707 |
| | 8 | 1.1360 | 0.3359 | 0.4861 | 0.8667 |
| CMC | 1 | 2.7696 | 0.0963*** | 0.0669 | 0.7960 |
| | 2 | 1.1794 | 0.3078 | 1.5796 | 0.2065 |
| | 8 | 1.1176 | 0.3482 | 0.8272 | 0.5786 |
| HMC | 1 | 2.7967 | 0.0947*** | 0.0144 | 0.9044 |
| | 2 | 1.2587 | 0.2844 | 1.2006 | 0.3014 |
| | 8 | 1.0731 | 0.3794 | 0.7761 | 0.6239 |
| CHMC | 1 | 3.4664 | 0.0629*** | 0.0062 | 0.9373 |
| | 2 | 1.5742 | 0.2076 | 0.8774 | 0.4161 |
| | 8 | 1.1991 | 0.2959 | 0.6949 | 0.6964 |

| **Logged returns** | | **Null hypothesis** | | **Null hypothesis** | |
|---|---|---|---|---|---|
| PHLX | lag length: | PHLX does not Granger-cause variable | | Variable does not Granger-cause PHLX | |
| Var | | F-statistic | P-value | F-statistic | P-value |
| MCI | 1 | 1.2533 | 0.2631 | 0.0644 | 0.7997 |
| | 2 | 0.5667 | 0.5676 | 0.3923 | 0.6756 |
| | 8 | 1.2586 | 0.2614 | 0.3982 | 0.9219 |
| CMC | 1 | 3.3863 | 0.0660*** | 0.0259 | 0.8721 |
| | 2 | 1.4696 | 0.2304 | 1.0584 | 0.3473 |
| | 8 | 1.2373 | 0.2734 | 0.6995 | 0.6923 |
| HMC | 1 | 3.4174 | 0.0648*** | 0.0011 | 0.9739 |
| | 2 | 1.5579 | 0.2110 | 0.7474 | 0.4738 |
| | 8 | 1.1912 | 0.3007 | 0.6505 | 0.7354 |
| CHMC | 1 | 2.8292 | 0.0928*** | 0.0581 | 0.8096 |
| | 2 | 1.2544 | 0.2856 | 1.0105 | 0.3643 |
| | 8 | 1.0606 | 0.3884 | 0.7155 | 0.6781 |

**Notes to Table 15**

The Granger causality test is conducted within the framework of f-test. If the p-value of f-test is significant (i.e., α=<0.05) at the 5% significance level, the null hypothesis is rejected within this study. The 1% and 10% significance levels are also looked at.

Granger-causality is tested between the variables for the periods outlined in the optimal lag length results (see **Table 9**).

* - denotes rejection of the null hypothesis at the 1% significance level.

** - denotes rejection of the null hypothesis at the 5% significance level.

*** - denotes rejection of the null hypothesis at the 10% significance level.

The results are presented below for the created semiconductor index (SI). Similar to the above, the order is the cointegration testing, followed by analysis of the results and ultimately the causality testing.

**Table 16. Johansen cointegration test results relating to the long-run relationship between created semiconductor index and mined crypto indices**

| SI | | Null Hypothesis: No. of cointegrating equations = none | | | Null Hypothesis: No. of cointegrating equations = At most 1 | | |
|---|---|---|---|---|---|---|---|
| Var | lag interval | T-statistic | P-value | rejection of H0 | T-statistic | P-value | rejection of H0 |
| MCI | 1 - 1 | 16.1679 | 0.0998 | *** | 2.4122 | 0.1204 | |
| | 1 - 8 | 19.7122 | 0.0326 | ** | 2.6609 | 0.1028 | |
| CMC | 1 - 1 | 13.2819 | 0.2241 | | 1.7280 | 0.1887 | |
| | 1 - 8 | 15.8225 | 0.1106 | | 2.2082 | 0.1373 | |
| HMC | 1 - 1 | 13.3333 | 0.2211 | | 1.7361 | 0.1876 | |
| | 1 - 8 | 16.1423 | 0.1006 | | 2.2517 | 0.1335 | |
| CHMC | 1 - 1 | 13.2937 | 0.2234 | | 1.7197 | 0.1897 | |
| | 1 - 8 | 16.0683 | 0.1028 | | 2.2401 | 0.1345 | |

| SI | | Null Hypothesis: No. of cointegrating equations = none | | | Null Hypothesis: No. of cointegrating equations = At most 1 | | |
|---|---|---|---|---|---|---|---|
| Var | lag interval | Max-Eigen statistic | P-value | rejection of H0 | Max-Eigen statistic | P-value | rejection of H0 |
| MCI | 1 - 1 | 13.7557 | 0.1459 | | 2.4122 | 0.1204 | |
| | 1 - 8 | 17.0513 | 0.0516 | *** | 2.6609 | 0.1028 | |
| CMC | 1 - 1 | 11.5539 | 0.2703 | | 1.7280 | 0.1887 | |
| | 1 - 8 | 13.6143 | 0.1521 | | 2.2082 | 0.1373 | |
| HMC | 1 - 1 | 11.5972 | 0.2673 | | 1.7361 | 0.1876 | |
| | 1 - 8 | 13.8906 | 0.1402 | | 2.2517 | 0.1335 | |
| CHMC | 1 - 1 | 11.5741 | 0.2689 | | 1.7197 | 0.1897 | |
| | 1 - 8 | 13.8281 | 0.1428 | | 2.2401 | 0.1345 | |

**Notes to Table 16**

The 5% critical values that results in a rejection of the null hypothesis of no cointegrating equations and at most one cointegrating equations through comparison of the trace statistic are 18.3977 and 3.8415 respectively.

The 5% critical values that results in a rejection of the null hypothesis of no cointegrating equations and at most one cointegrating equations through comparison of the Max-Eigen statistic are 17.1477 and 3.8415 respectively.

*Please see the list of abbreviations for the names in the table.*

MacKinnon, Haug, and Michelis (1999) p-values.

* - denotes rejection of the null hypothesis at the 1% significance level.

** - denotes rejection of the null hypothesis at the 5% significance level.

*** - denotes rejection of the null hypothesis at the 10% significance level.

The results presented in **Table 16** above and **Table 17** below for testing the created semiconductor index show less relationship than when using the PHLX. A cointegrating equation at a 5% and 10% significance level is still found for MCI and SI using the trace statistic and a lag interval of 1–1 and 1–8. No significance was found for CMC, HMC and CHMC using the same interval. Thus, the results for the MCI and SI support the cointegration discussed for the PHLX index above. However, when examining the causality, no causal relationship is found which is in contrast with the results of the PHLX which found a 10% significance level causal relationship.

The difference in results obtained from the PHLX and the SI are indicative that the SI composition of companies chosen to represent the hardware producers involved does not adequately represent the semiconductor industry, even with the very high levels of correlation they share. This could be due to dominance of the index by companies like Nvidia which produce GPUs that are capable of mining but are not the preferred method of mining in more recent years, which in turn harms the demand-push inflation link between producers and crypto prices. The reason behind the discrepancy in the relationship is not explored in this study.

**Table 17. Causality test results between created semiconductor index and MC indices**

| **Returns** | | **Null hypothesis** | | **Null hypothesis** | |
|---|---|---|---|---|---|
| **SI** | **lag length:** | **SI does not Granger-cause variable** | | **Variable does not Granger-cause SI** | |
| Var | | F-statistic | P-value | F-statistic | P-value |
| MCI | 1 | 0.7954 | 0.3726 | 0.0523 | 0.8191 |
| | 8 | 0.5907 | 0.7862 | 0.6329 | 0.7506 |
| **Logged returns** | | **Null hypothesis** | | **Null hypothesis** | |
| **SI** | **lag length:** | **SI does not Granger-cause variable** | | **Variable does not Granger-cause SI** | |
| Var | | F-statistic | P-value | F-statistic | P-value |
| MCI | 1 | 0.8296 | 0.3626 | 0.0069 | 0.9338 |
| | 8 | 0.6781 | 0.7112 | 0.5495 | 0.8194 |

**Notes to Table 17**

The Granger causality test is conducted within the framework of f-test. If the p-value of f-test is significant (i.e., α=<0.05) at the 5% significance level, the null hypothesis is rejected within this study. The 1% and 10% significance levels are also looked at.

Granger-causality is tested between the variables for the periods outlined in the optimal lag length results (see **Table 9**).

* - denotes rejection of the null hypothesis at the 1% significance level.

** - denotes rejection of the null hypothesis at the 5% significance level.

*** - denotes rejection of the null hypothesis at the 10% significance level.

### 5.4.3 Research question 3. Does integration exist between non-mined crypto and the technology industry, and what is the direction?

The results are presented below for the NASDAQ and non-mined indices. Cointegration testing is followed by analysis of the results and lastly, the causality testing.

**Table 18. Johansen cointegration test results relating to the long-run relationship between NASDAQ and non-mined crypto indices**

| NASDAQ | | Null Hypothesis: No. of cointegrating equations = none | | | Null Hypothesis: No. of cointegrating equations = At most 1 | | |
|---|---|---|---|---|---|---|---|
| Var | lag interval | T-statistic | P-value | rejection of H0 | T-statistic | P-value | rejection of H0 |
| NMCI | 1 - 1 | 13.7861 | 0.1961 | | 3.1628 | 0.0753 | |
| | 1 - 2 | 12.9313 | 0.2454 | | 2.8698 | 0.0903 | |
| | 1 - 16 | 13.0588 | 0.2375 | | 2.3570 | 0.1247 | |
| NMCB | 1 - 1 | 10.9913 | 0.3899 | | 2.5041 | 0.1135 | |
| | 1 - 2 | 10.4198 | 0.4409 | | 2.3937 | 0.1218 | |
| | 1 - 23 | 25.8552 | 0.0038 | * | 2.2985 | 0.1295 | |

| NASDAQ | | Null Hypothesis: No. of cointegrating equations = none | | | Null Hypothesis: No. of cointegrating equations = At most 1 | | |
|---|---|---|---|---|---|---|---|
| Var | lag interval | Max-Eigen statistic | P-value | rejection of H0 | Max-Eigen statistic | P-value | rejection of H0 |
| NMCI | 1 - 1 | 10.6233 | 0.3423 | | 3.1628 | 0.0753 | |
| | 1 - 2 | 10.0615 | 0.3916 | | 2.8698 | 0.0903 | |
| | 1 - 16 | 10.7019 | 0.3357 | | 2.3570 | 0.1247 | |
| NMCB | 1 - 1 | 8.4872 | 0.5498 | | 2.5041 | 0.1135 | |
| | 1 - 2 | 8.0261 | 0.6000 | | 2.3937 | 0.1218 | |
| | 1 - 23 | 23.5566 | 0.0051 | * | 2.2985 | 0.1295 | |

**Notes to Table 18**

The 5% critical values that results in a rejection of the null hypothesis of no cointegrating equations and at most one cointegrating equations through comparison of the trace statistic are 18.3977 and 3.8415 respectively.

The 5% critical values that results in a rejection of the null hypothesis of no cointegrating equations and at most one cointegrating equations through comparison of the Max-Eigen statistic are 17.1477 and 3.8415 respectively.

*Please see the list of abbreviations for the names in the table.*

MacKinnon, Haug, and Michelis (1999) p-values.

* - denotes rejection of the null hypothesis at the 1% significance level.

** - denotes rejection of the null hypothesis at the 5% significance level.

*** - denotes rejection of the null hypothesis at the 10% significance level.

The results seen in **Table 18** above indicate a single cointegrating equation between the NASDAQ and NMCB index at a lag interval of 1–23. The lag interval of 1–23 was produced by the robustness tests of FPE and AIC. The NMCB was added into the methodology to winsorize the effects of Binance on the index and further, the information criteria of FPE and AIC were introduced as an additional element of robustness. This cointegration relationship would not be found without the robustness measures in the methodology. Building on the long-run relationship found, the test for causality in **Table 19** below indicates a causal relationship using returns and logged returns such that the NASDAQ Granger-causes the NMCB Index at a lag length of 2. This is in line with the directionality found in research question 2, that the equity indices drive crypto.

Comparing this to current literature, Şahin (2022) concluded a causal relationship between the NASDAQ and Bitcoin and Ethereum. He went further to mention that the correlation and causation had become stronger in more recent years.

This study expands the relationship beyond Bitcoin and Ethereum to include other cryptos such as Ripple, Cardano, Solana, Polkadot and Tronix. No causal relationship was found but long-run cointegration. Further research found a bilateral relationship between the NASDAQ and the CCi30 index, a market capitalisation-weighted index of the top 30 cryptos (Ergenoğlu & Şenol, 2022). This study does not find a bilateral relationship but indicates a statistically significant causal relationship from NASDAQ to NMCs, exclusive of Binance.

**Table 19. Causality test results between NASDAQ and non-mined crypto indices**

| **Returns** | | **Null hypothesis** | | **Null hypothesis** | |
|---|---|---|---|---|---|
| NASDAQ | lag length: | NASDAQ does not Granger-cause variable | | Variable does not Granger-cause NASDAQ | |
| Var | | F-statistic | P-value | F-statistic | P-value |
| NMCB | 1 | 0.5048 | 0.4775 | 0.2869 | 0.5923 |
| | 2 | 3.2482 | 0.0392** | 0.9882 | 0.3726 |
| | 23 | 1.1059 | 0.3438 | 0.7163 | 0.7793 |

| **Logged returns** | | **Null hypothesis** | | **Null hypothesis** | |
|---|---|---|---|---|---|
| NASDAQ | lag length: | NASDAQ does not Granger-cause variable | | Variable does not Granger-cause NASDAQ | |
| Var | | F-statistic | P-value | F-statistic | P-value |
| NMCB | 1 | 0.1480 | 0.7005 | 2.2022 | 0.1381 |
| | 2 | 3.1894 | 0.0489** | 1.2479 | 0.2875 |
| | 23 | 0.9556 | 0.5221 | 0.8461 | 0.6735 |

**Notes to Table 19**

The Granger causality test is conducted within the framework of f-test. If the p-value of f-test is significant (i.e., α=<0.05) at the 5% significance level, the null hypothesis is rejected within this study. The 1% and 10% significance levels are also looked at.

Granger-causality is tested between the variables for the periods outlined in the optimal lag length results (see **Table 9**).

* - denotes rejection of the null hypothesis at the 1% significance level.

** - denotes rejection of the null hypothesis at the 5% significance level.

*** - denotes rejection of the null hypothesis at the 10% significance level.

The results are presented below for the S&P500 and non-mined indices. Cointegration testing is followed by analysis of the results and lastly, the causality testing.

**Table 20. Johansen cointegration test results relating to the long-run relationship between S&P500 and non-mined crypto indices**

| **S&P500** | | **Null Hypothesis: No. of cointegrating equations = none** | | | **Null Hypothesis: No. of cointegrating equations = At most 1** | | |
|---|---|---|---|---|---|---|---|
| Var | lag interval | T-statistic | P-value | rejection of H0 | T-statistic | P-value | rejection of H0 |
| NMCI | 1 - 1 | 16.2070 | 0.0986 | | 3.5292 | 0.0603 | |
| | 1 - 2 | 16.8575 | 0.0810 | | 3.7495 | 0.0528 | |
| | 1 - 16 | 19.2638 | 0.0378 | ** | 3.7087 | 0.0541 | |
| NMCB | 1 - 1 | 12.5780 | 0.2683 | | 2.7140 | 0.0995 | |
| | 1 - 2 | 13.3732 | 0.2188 | | 2.6454 | 0.1039 | |
| | 1 - 23 | 29.2375 | 0.0010 | * | 3.6356 | 0.0565 | |

| **S&P500** | | **Null Hypothesis: No. of cointegrating equations = none** | | | **Null Hypothesis: No. of cointegrating equations = At most 1** | | |
|---|---|---|---|---|---|---|---|
| Var | lag interval | Max-Eigen statistic | P-value | rejection of H0 | Max-Eigen statistic | P-value | rejection of H0 |
| NMCI | 1 - 1 | 12.6778 | 0.1992 | | 3.5292 | 0.0603 | |
| | 1 - 2 | 13.107 | 0.1762 | | 3.7495 | 0.0528 | |
| | 1 - 16 | 15.5551 | 0.0840 | *** | 3.7087 | 0.0541 | |
| NMCB | 1 - 1 | 9.8640 | 0.4099 | | 2.7140 | 0.0995 | |
| | 1 - 2 | 10.7279 | 0.3336 | | 2.6454 | 0.1039 | |
| | 1 - 23 | 25.6019 | 0.0023 | * | 3.6356 | 0.0565 | |

**Notes to Table 20**

The 5% critical values that results in a rejection of the null hypothesis of no cointegrating equations and at most one cointegrating equations through comparison of the trace statistic are 18.3977 and 3.8415 respectively.

The 5% critical values that results in a rejection of the null hypothesis of no cointegrating equations and at most one cointegrating equations through comparison of the Max-Eigen statistic are 17.1477 and 3.8415 respectively.

*Please see the list of abbreviations for the names in the table.*

MacKinnon, Haug, and Michelis (1999) p-values.

* - denotes rejection of the null hypothesis at the 1% significance level.

** - denotes rejection of the null hypothesis at the 5% significance level.

*** - denotes rejection of the null hypothesis at the 10% significance level.

As shown in **Table 20** above, long-run equilibrium is found between NMCI and NMCB indices and the S&P500 at a 1% and 5% significance level using trace statistics and a 1% and 10% level using Max-Eigen statistics. A one cointegrating equation is therefore present, similar to the conclusions drawn for the NASDAQ but now inclusive of both NMC indices. Thus, the effects of Binance disrupt the presence of a relationship with the NASDAQ but not the S&P500.

Looking further at the results of the causality testing in **Table 21** below, an interesting result can be seen in that the S&P500 Granger-causes the NMCI at lag length of 2 at a 1% and 5% significance level, using returns and logged returns respectively. Contrasting this, it can also be found that the NMCB index Granger-causes the S&P500 at lag length of 1 at a 5% significance level. Simply, NMC was found to have a bilateral relationship with the S&P500 at a 1% and a 5% significance level.

The directionality – that the S&P500 Granger-causes the NMCI – aligns with literature by Wang et al. (2020) who concluded that the S&P500, NASDAQ and Dow Jones significantly impacted Bitcoin, but the reverse was not true. This was testing using a VAR model. Nguyen (2022) also used a VAR model to reach the conclusion that the S&P500 influences Bitcoin for the period 2016 to 2020. Didisheim (2022) argued for high levels of correlation between cryptos and concluded that the relationship present between the S&P500 and crypto was due to cross-asset trading during the Covid-19 period. Thus, the result contrasts with the literature in that a bidirectional relationship exists.

**Table 21. Causality test results between S&P500 and non-mined crypto indices**

| Returns | | Null hypothesis | | Null hypothesis | |
|---|---|---|---|---|---|
| S&P500 | lag length: | S&P500 does not Granger-cause variable | | Variable does not Granger-cause S&P500 | |
| Var | | F-statistic | P-value | F-statistic | P-value |
| NMCI | 1 | 0.5099 | 0.4753 | 0.6452 | 0.4220 |
| | 2 | 4.6609 | 0.0096* | 0.8294 | 0.4366 |
| | 16 | 0.9296 | 0.5763 | 0.7705 | 0.8084 |
| NMCB | 1 | 0.0042 | 0.9486 | 4.3621 | 0.0370** |
| | 2 | 0.9957 | 0.3698 | 1.9223 | 0.1467 |
| | 23 | 0.6258 | 0.9137 | 0.7374 | 0.8098 |
| **Logged returns** | | **Null hypothesis** | | **Null hypothesis** | |
| S&P500 | lag length: | S&P500 does not Granger-cause variable | | Variable does not Granger-cause S&P500 | |
| Var | | F-statistic | P-value | F-statistic | P-value |
| NMCI | 1 | 0.5269 | 0.4681 | 0.1047 | 0.7463 |
| | 2 | 2.9980 | 0.0482** | 0.3345 | 0.7158 |
| | 16 | 0.7493 | 0.7440 | 0.6721 | 0.8236 |
| NMCB | 1 | 0.0751 | 0.7841 | 3.8941 | 0.0487** |
| | 2 | 0.5062 | 0.6029 | 1.8598 | 0.1562 |
| | 23 | 0.7501 | 0.7953 | 0.7635 | 0.7795 |

**Notes to Table 21**

The Granger causality test is conducted within the framework of f-test. If the p-value of f-test is significant (i.e., α=<0.05) at the 5% significance level, the null hypothesis is rejected within this study. The 1% and 10% significance levels are also looked at.

Granger-causality is tested between the variables for the periods outlined in the optimal lag length results (see **Table 9**).

* - denotes rejection of the null hypothesis at the 1% significance level.

** - denotes rejection of the null hypothesis at the 5% significance level.

*** - denotes rejection of the null hypothesis at the 10% significance level.

The results are presented below for the Dow Jones and non-mined indices. Cointegration testing is followed by analysis of the results and lastly, the causality testing.

**Table 22. Johansen cointegration test results relating to the long-run relationship between DJIA and non-mined crypto indices**

| DJIA | | Null Hypothesis: No. of cointegrating equations = none | | | Null Hypothesis: No. of cointegrating equations = At most 1 | | |
|---|---|---|---|---|---|---|---|
| Var | lag interval | T-statistic | P-value | rejection of H0 | T-statistic | P-value | rejection of H0 |
| NMCI | 1 - 1 | 19.9019 | 0.0306 | ** | 4.3500 | 0.0370 | ** |
| | 1 - 2 | 24.0052 | 0.0074 | * | 5.4227 | 0.0199 | ** |
| | 1 - 28 | 24.2206 | 0.0068 | * | 4.7789 | 0.0288 | ** |
| NMCB | 1 - 1 | 15.4099 | 0.1248 | | 3.2182 | 0.0728 | |
| | 1 - 2 | 15.3914 | 0.1254 | | 3.2059 | 0.0734 | |
| | 1 - 23 | 27.9820 | 0.0017 | * | 5.7101 | 0.0169 | ** |

| DJIA | | Null Hypothesis: No. of cointegrating equations = none | | | Null Hypothesis: No. of cointegrating equations = At most 1 | | |
|---|---|---|---|---|---|---|---|
| Var | lag interval | Max-Eigen statistic | P-value | rejection of H0 | Max-Eigen statistic | P-value | rejection of H0 |
| NMCI | 1 - 1 | 15.5519 | 0.0841 | *** | 4.3500 | 0.0370 | ** |
| | 1 - 2 | 18.5825 | 0.0308 | ** | 5.4227 | 0.0199 | ** |
| | 1 - 28 | 19.4417 | 0.0228 | ** | 4.7789 | 0.0288 | ** |
| NMCB | 1 - 1 | 12.1917 | 0.2279 | | 3.2182 | 0.0728 | |
| | 1 - 2 | 12.1855 | 0.2283 | | 3.2059 | 0.0734 | |
| | 1 - 23 | 22.2719 | 0.0082 | * | 5.7101 | 0.0169 | ** |

**Notes to Table 22**

The 5% critical values that results in a rejection of the null hypothesis of no cointegrating equations and at most one cointegrating equations through comparison of the trace statistic are 18.3977 and 3.8415 respectively.

The 5% critical values that results in a rejection of the null hypothesis of no cointegrating equations and at most one cointegrating equations through comparison of the Max-Eigen statistic are 17.1477 and 3.8415 respectively.

*Please see the list of abbreviations for the names in the table.*

MacKinnon, Haug, and Michelis (1999) p-values.

* - denotes rejection of the null hypothesis at the 1% significance level.

** - denotes rejection of the null hypothesis at the 5% significance level.

*** - denotes rejection of the null hypothesis at the 10% significance level.

As shown in **Table 22** above, evidence was found of cointegration at 1% and 5% levels for all lag intervals for NMCI and only for interval 1–23 for the NMCB using trace statistics. Both null hypotheses are rejected leading to the presence of two cointegrating equations that establish long-term equilibrium.

**Table 23** below displays causality results which indicate that the DJIA Granger-causes the NMCI at lag length of 2 at a 1% and 5% significance level. This is in line with literature from Wang et al. (2020) who indicated using a VAR that the Dow Jones impacts Bitcoin but not the reverse. Zhang et al. (2018) also found power-law cross-correlation but did not test further. The results contrast with the literature at a lag length of 1, the 5% significance of the NMCB index Granger causing the DJIA. This result indicates a bilateral relationship. Further, the presence of a relationship contrasts Ciaian et al. (2016) who concluded on no relationship.

**Table 23. Causality test results between DJIA and non-mined crypto indices**

| **Returns** | | **Null hypothesis** | | **Null hypothesis** | |
|---|---|---|---|---|---|
| DJIA | lag length: | DJIA does not Granger-cause variable | | Variable does not Granger-cause DJIA | |
| Var | | F-statistic | P-value | F-statistic | P-value |
| NMCI | 1 | 0.4735 | 0.4915 | 1.2708 | 0.2598 |
| | 2 | 4.9366 | 0.0073* | 0.6700 | 0.5119 |
| | 28 | 1.4179 | 0.1585 | 0.8135 | 0.6266 |
| NMCB | 1 | 0.0000 | 0.9963 | 4.9117 | 0.0269** |
| | 2 | 0.9968 | 0.3694 | 2.0750 | 0.1260 |
| | 23 | 0.4355 | 0.9405 | 0.8229 | 0.6171 |
| **Logged returns** | | **Null hypothesis** | | **Null hypothesis** | |
| DJIA | lag length: | DJIA does not Granger-cause variable | | Variable does not Granger-cause DJIA | |
| Var | | F-statistic | P-value | F-statistic | P-value |
| NMCI | 1 | 0.4902 | 0.4840 | 0.2753 | 0.5999 |
| | 2 | 0.9239 | 0.0410** | 0.5459 | 0.8853 |
| | 28 | 0.6605 | 0.9113 | 0.6437 | 0.9240 |
| NMCB | 1 | 0.0323 | 0.8573 | 4.1353 | 0.0422** |
| | 2 | 0.6050 | 0.5462 | 1.6015 | 0.1873 |
| | 23 | 0.6597 | 0.5769 | 0.7964 | 0.7389 |

**Notes to Table 23**

The Granger causality test is conducted within the framework of f-test. If the p-value of f-test is significant (i.e., α=<0.05) at the 5% significance level, the null hypothesis is rejected within this study. The 1% and 10% significance levels are also looked at.

Granger-causality is tested between the variables for the periods outlined in the optimal lag length results (see **Table 9**).

* - denotes rejection of the null hypothesis at the 1% significance level.

** - denotes rejection of the null hypothesis at the 5% significance level.

*** - denotes rejection of the null hypothesis at the 10% significance level.

# SECTION 6 CONCLUSION

This study sought to examine the relationship between crypto and equity index returns and ultimately where crypto stands from a diversification perspective. Further, this study differentiates between mined cryptos and non-mined cryptos when testing against semiconductor and technology related indices. This is answered through correlation, Johansen cointegration, and Granger pairwise causality testing of indices. The Indices used include the Philadelphia Stock Exchange Semiconductor index, NASDAQ 100, S&P500 and Dow Jones. Additionally, indices were created to represent mined crypto, non-mined crypto, and a condensed semiconductor industry.

The study set out to answer the following research questions.

1. ***Does integration exist between mined cryptos and non-mined cryptocurrencies, and what is the direction?***

The results found moderate (0.24–0.54) correlation between MCs and NMCs, which is in line with literature (Bouri et al., 2021; Giudici & Polinesi, 2021; Qureshi et al., 2020). The cointegration results then indicated two cointegrating equations with significance at 1% for shorter lags and 5% for longer lags. Cointegration results were as expected within the literature (Bouri et al., 2021; Keilbar & Zhang, 2021; Qureshi et al., 2020). The index exclusive of Binance showed less evidence of cointegration, indicating differing behaviour of certain NMCs. The causality testing revealed a bilateral relationship of the NMCs inclusive of Biance to the MCs that was statistically significant at 1% and 5%; however, once Binance was removed no causal relationship was found.

2. ***Does integration exist between mined cryptos and the semiconductor industry, and what is the direction?***

The results found weak (0.26–0.33) correlation levels were found between MCs and the Philadelphia Semiconductor Index and the created semiconductor index. Literature found similar evidence to the US technology sector and the semiconductor industry (Rathi, 2022; Umar et al., 2021). This study further found cointegration at multiple lag intervals for a single equation, mostly at the 5% significant level for the Philadelphia index. No statistically significant causal relationship could be found although the 10% significance level found is in line with literature which also found 10% using the US technology sector and a crypto index (Umar et al., 2021). This unidirectional relationship goes against the literature that discusses bilateral causality (Rathi, 2022). Using the created index, which is a condensed version of the Philadelphia index, cointegration was found but no causal relationship.

3. ***Does integration exist between non-mined cryptos and the technology industry, and what is the direction?***

The results found weak (0.08-0.18) correlation was found between the NMCs and the NASDAQ, S&P500 and Dow Jones. Although the literature did not examine strictly NMCs, it did find relationships between cryptos and the above indices (Bouoiyour & Selmi, 2015; Ciaian et al., 2016; Nguyen, 2022; Wang et al., 2020). Cointegration results lead to the conclusion on one cointegrating equation between the NASDAQ and S&P500 and NMC, and two cointegrating equations to the Dow jones. This study then builds on Şahin (2022) who indicated causality for two cryptos; this study suggests a further five within this causal relationship driven by the NASDAQ. The S&P500 was found to Granger-cause NMCs but the reverse was true when Biance was removed. Literature leans in the direction of the S&P500 having the driving power but it only considered Bitcoin in its analysis (Didisheim & Somoza, 2022; Nguyen, 2022; Wang et al., 2020). This study also found a bidirectional causal relationship to the Dow Jones which challenges Wang et al. (2020) who indicated that the Dow Jones impacts NMC but not the reverse.

The findings above present evidence that cryptos do not provide diversification benefits against traditional indices such as NASDAQ, S&P500 and Dow Jones, because of both cointegrating relationships and causal ones. The same is true for the Philadelphia Stock Exchange Semiconductor index and semiconductor related stock such as Nvidia, AMD and TSMC. The crypto market is highly cointegrated with itself and has increasingly become integrated with financial markets, as seen in this study and within the development of crypto's literature.

This study is relevant to investors' diversification decisions to avoid duplicating risk exposure within integrated markets. An investor could be seeking to invest into the crypto market but already have exposure through existing investments in equity instruments or indices such as the S&P500. However, by investing into the US technology or semiconductor indices investors could utilise the cointegration present as an opportunity in order to gain exposure to movements in the crypto market. This method could prove a safer alternative than direct investments in crypto. This method could benefit investors through exposure to the crypto market's movements whilst mitigating the associated risk and volatility.

## 6.1 AREAS FOR FURTHER RESEARCH

The field of research on crypto is ready for further studies as a result of the evolving landscape. As noted within the testing of this study, where MCs were examined against the Philadelphia Stock Exchange Semiconductor index (PHLX) and the created semiconductor index, this could easily be expanded to compare the MCs with the NASDAQ, S&P500 and Dow Jones. As seen in the correlation testing, the NASDAQ yielded the highest correlation to MC – even more than the PHLX – and thus the lags, the cointegration and the causality relationship could be explored in more detail.

Many cointegrating equations were found within variables and the qualitative reasons behind these relationships could be examined in further studies. Although rationales such as the demand-pull inflation of semiconductor sales are alluded to, the reasoning will have to be tested in further research for true conclusions. A further observation was the differing results when Binance was removed from the index. Binance's unique properties leave an area for further exploration.

Due to the many causal relationships found within this study, the next step would be to use VAR to forecast using the lagged causal relationships. The relationships between cryptos and the various indices can be tested against forecasted models in the long-run. Another point of expansion would be the strength of relationships between variables. This study did not investigate the cointegration coefficients, but these could be examined to determine strength to give more depth to the interpretation of the findings.

Lastly, this study did not consider structural breaks in the data and further studies looking at crypto could incorporate tests such as the ones by Zivot & Andrews (2002). This limitation to this study could be expanded on to allow the results to be further validated.

# SECTION 7 REFERENCE LIST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# SECTION 8 APPENDICES

## Appendix A

**Table 24. Summary of cryptos**

| Non-mined crypto | Mined crypto |
|---|---|
| **Ripple (XRP)**<br>Year launched – 2012<br>Federated consensus algorithm<br>Max Supply – 100,000,000,000 | **Bitcoin (BTC)**<br>Year launched – 2009<br>Preferred mining method – ASIC<br>Algorithm – SHA-256<br>Max Supply – 21,000,000 |
| **Cardano (ADA)**<br>Year launched – 2017<br>Proof-of-stake<br>Max Supply – 45,000,000,000 | **Ethereum (ETH)**<br>Year launched – 2015<br>Preferred mining method – GPU (prior to merge)<br>Algorithm – DaggerHash/ Ethash<br>Max Supply – Uncapped |
| **Binance (BNB)**<br>Year launched – 2017<br>Proof-of-stake<br>Max Supply – 200,000,000 | **Dodgecoin (DOGE)**<br>Year launched – 2013<br>Preferred mining method – ASIC<br>Algorithm – Scrypt<br>Max Supply – Uncapped |
| **Solana (SOL)**<br>Year launched – 2020<br>Proof-of-stake<br>Max Supply – Uncapped | **Ravencoin (RVN)**<br>Year launched – 2018<br>Preferred mining method – GPU<br>Algorithm – x16r<br>Max Supply – Uncapped |
| **Polkadot (DOT)**<br>Year launched – 2020<br>Nominated Proof of Stake<br>Max Supply – Uncapped | **Monero (XMR)**<br>Year launched – 2014<br>Preferred mining method – CPU<br>Algorithm – RandomX<br>Max Supply – Uncapped |
| **Tronix (TRX)**<br>Year launched – 2017<br>Delegated Proof-of-Stake<br>Max Supply – Uncapped | **Ethereum classic (ETC)**<br>Year launched – 2015<br>Preferred mining method – GPU/ASIC<br>Algorithm – Ethash<br>Max supply – 210,700,000 |

**Notes to Table 23**

The above crypto data was obtained from Blockchain.com, CoinGecko.com and NiceHash.com

## Appendix B

### Table 25. Descriptive statistics for return data

| *Returns* | NMCI | NMCB | MCI | CMC | HMC | CHMC | SI | PHLX | NASDAQ | S&P500 | DJIA |
|---|---|---|---|---|---|---|---|---|---|---|---|
| *Mean* | 0.01 | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| *Standard Error* | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| *Median* | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| *Standard Deviation* | 0.09 | 0.13 | 0.05 | 0.04 | 0.04 | 0.04 | 0.03 | 0.02 | 0.02 | 0.01 | 0.01 |
| *Kurtosis* | 212.49 | 582.79 | 19.83 | 4.87 | 5.00 | 4.98 | 3.99 | 3.96 | 5.59 | 12.42 | 18.36 |
| *Skewness* | 10.34 | 20.96 | 1.44 | 0.04 | 0.06 | 0.05 | 0.16 | -0.17 | -0.33 | -0.53 | -0.57 |
| *Minimum* | -0.34 | -0.32 | -0.27 | -0.27 | -0.27 | -0.27 | -0.14 | -0.16 | -0.12 | -0.12 | -0.13 |
| *Maximum* | 1.94 | 3.77 | 0.54 | 0.25 | 0.25 | 0.25 | 0.17 | 0.11 | 0.10 | 0.09 | 0.11 |
| *Count* | 1256.00 | 1256.00 | 1256.00 | 1256.00 | 1256.00 | 1256.00 | 1256.00 | 1256.00 | 1256.00 | 1256.00 | 1256.00 |

### Table 26. Descriptive statistics for logged return data

| *Logged returns* | NMCI | NMCB | MCI | CMC | HMC | CHMC | SI | PHLX | NASDAQ | S&P500 | DJIA |
|---|---|---|---|---|---|---|---|---|---|---|---|
| *Mean* | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| *Standard Error* | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| *Median* | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| *Standard Deviation* | 0.07 | 0.08 | 0.04 | 0.04 | 0.04 | 0.04 | 0.03 | 0.02 | 0.02 | 0.01 | 0.01 |
| *Kurtosis* | 53.04 | 139.46 | 11.94 | 5.75 | 5.87 | 5.87 | 3.78 | 4.55 | 6.08 | 13.44 | 19.70 |
| *Skewness* | 3.50 | 7.45 | 0.40 | -0.42 | -0.41 | -0.42 | -0.06 | -0.38 | -0.53 | -0.83 | -0.99 |
| *Minimum* | -0.41 | -0.38 | -0.32 | -0.32 | -0.32 | -0.32 | -0.15 | -0.17 | -0.13 | -0.13 | -0.14 |
| *Maximum* | 1.08 | 1.56 | 0.43 | 0.22 | 0.22 | 0.22 | 0.16 | 0.11 | 0.10 | 0.09 | 0.11 |
| *Count* | 1256.00 | 1256.00 | 1256.00 | 1256.00 | 1256.00 | 1256.00 | 1256.00 | 1256.00 | 1256.00 | 1256.00 | 1256.00 |

**Table 27. Descriptive statistics for price data**

| *Price* | NMCI | NMCB | MCI | CMC | HMC | CHMC | SI | PHLX | NASDAQ | S&P500 | DJIA |
|---|---|---|---|---|---|---|---|---|---|---|---|
| *Mean* | 18365.75 | 2304.92 | 307.27 | 337.83 | 21963.13 | 330.70 | 242.18 | 2392.39 | 11032.84 | 3586.14 | 29900.86 |
| *Standard Error* | 558.80 | 104.01 | 5.97 | 7.32 | 470.28 | 7.13 | 3.33 | 23.02 | 82.60 | 18.26 | 111.70 |
| *Median* | 1928.42 | 381.31 | 245.52 | 255.43 | 16929.96 | 251.28 | 239.46 | 2489.16 | 11546.76 | 3674.84 | 29999.26 |
| *Standard Deviation* | 19811.76 | 3687.49 | 211.57 | 259.45 | 16673.41 | 252.96 | 118.20 | 816.28 | 2928.46 | 647.49 | 3960.40 |
| *Kurtosis* | -1.36 | 6.31 | -0.73 | -0.45 | -0.46 | -0.46 | -1.09 | -1.37 | -1.31 | -1.36 | -1.26 |
| *Skewness* | 0.47 | 2.50 | 0.67 | 0.85 | 0.84 | 0.85 | 0.29 | 0.02 | 0.00 | 0.02 | -0.11 |
| *Minimum* | 52.13 | 29.08 | 47.51 | 47.68 | 3156.89 | 47.17 | 79.96 | 1069.39 | 5899.35 | 2237.40 | 18591.93 |
| *Maximum* | 67330.53 | 19631.28 | 856.76 | 1054.83 | 67734.04 | 1029.54 | 550.53 | 4039.51 | 16573.34 | 4796.56 | 36799.65 |
| *Count* | 1257.00 | 1257.00 | 1257.00 | 1257.00 | 1257.00 | 1257.00 | 1257.00 | 1257.00 | 1257.00 | 1257.00 | 1257.00 |