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Comparing the Traditional S&P 500 Market with the Carbon Credit Market: Analyzing the Impact of Blockchain on Market Efficiency, Liquidity, and Risk Dynamics

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Abstract

In recent times, blockchain has emerged as an innovative solution and a supposed game-changer in many different domains such as Healthcare, Logistics, Business and more importantly, Finance. There is a common perception being held around blockchain technology, that it is a driving force and can streamline the processes involved in both traditional and emerging financial markets. It is seen as a solution that can fix all the inefficiencies and obstacles that exist within the financial market framework. This study approaches the matter by gauging whether adoption of blockchain brings improvement to financial markets our not. The analysis will revolve particularly around the following mix of traditional and emerging financial markets, that includes theblockchain-based companies listed in the S&P 500, non-blockchain companies listed in the S&P 500 and blockchain-based carbon trading.

This study determines the efficiency of a given financial market based of off Price Discovery, Volatility, Transparency, Liquidity. Risk Dynamics and Price Delays. The researchers of this study also separately determine the mediating effects of Risk Dynamics and Liquidity on the Market Efficiency. Descriptive statistics, correlation analysis, regression and mediation analysis are used to achieve the purpose of this analysis.

At the end, the study finds that the blockchain-based technology does improve the market efficiency of a market; however, to achieve the improvement, the market structure must be maintained.

Keywords: Market Efficiency, Price Discovery, Transparency, Volatility, Liquidity, Risk Dynamics, S&P 500, Carbon Markets, Blockchain.

Chapter 1: Introduction

In recent times, blockchain has been gaining a lot of traction, especially in the domain of financial markets. This is mainly due to the decentralized nature of blockchain and how it is seen as the solution of common problems found in today's financial markets, such as, problems with transparency, liquidity and market inefficiency.

Adopting blockchain technology in the financial markets can significantly impact the efficiency of the financial market (Babu & Das, 2023). Blockchain can assist in lowering transaction costs, promote transparency during each transaction, promote greater security and optimize the efficiency of the financial markets' systems. According to a study conducted by Zhang (2024), blockchain has been proven to improve the efficiency of transactions and lower its costs. Similarly, in another study by Goean et al. (2024), using blockchain technology can improve the liquidity, this was especially observed in environmental markets like the carbon credits market.

When talking about adoption of blockchain in both traditional equity markets and emerging markets like the carbon credits market, liquidity is also seen as a centre of concern. As blockchain technology becomes more well-known and grows as a potential solution towards financial inefficiencies, it is worth gauging whether blockchain actually increases liquidity or creates obstacles for it. There are a handful of literature that suggest that blockchain adoption can help increase the liquidity in a market via simplifying processes and reducing the time it takes to perform a transaction (Baklaga, 2024). Furthermore, studies also suggest that announcing the integration of blockchain into financial markets can have positive impacts on the market's outlook (Xu, 2021).

After looking at the impact and influence that Liquidity and Transparency has on the Market Efficiency, another factor look into is the Risk Dynamics. The risk structures in traditional equity markets are well structured and maintained, meanwhile for the emerging carbon credits market, the risk structure is not well-defined (Field & Inci, 2023). This is mainly due to the fact that traditional equity markets are more established and mature, where as the carbon market is an emerging one which has yet to create a standard around risks. With that in mind, integrating blockchain into such financial markets can introduce new types of risks. On the flip side, there is also literature that indicate that blockchain adoption can reduce risk due to its decentralized nature and its ability to enhance transparency, which as a result can slash the risk involved (Rathore, 2019).However, further literature also point out the regulatory related uncertainty when adopting a new technology like blockchain, which can be detrimental and can increase the risk (Zhang, 2024). Hence it is important to assess how risk changes when adopting blockchain technology in financial markets.

Despite increase in blockchain adoption in the financial markets, there is little to no empirical evidence that suggests that such technological adoption results in improving the market efficiency, improvement of liquidity or reduction of volatility. Moreover, these variables may differ from framework to framework. This creates uncertainty around the blockchain adoption in the financial market and its results.

The aim of this study is to assess whether adopting the blockchain technology in a financial market result in improvement in market efficiency or not. Additionally, the study aims to see the effects of the adoption on whether it increases liquidity, decreases risk dynamics or not. The target markets in our case to determine these assessments would be the S&P 500 Companies, both blockchain-based and non-blockchain based, and the emerging blockchain-based carbon credits market. There is existing literature that calls for empirical data-driven research around the advancement in technology and its impact on the financial market performance (Hughes et al., 2019). Such literature will be used to achieve the gap between the theoretical perception and the practical adoption around both traditional and emerging financial markets.

Lastly, the main objective of this study is to raise awareness and contribute towards the discussion around adoption of technological advancements in the field of financial markets. Moreover, the studies aim to provide insights into the effects of adopting the blockchain technology. Such information would prove valuable for financial market stakeholders, investors and policymakers. Spreading awareness and providing clear insights would enable the concerned stakeholders to carry out informed decisions around the adoption of such new advancements.

Chapter 2: Literature Review

2.1 Introduction to Blockchain and Financial Markets

Blockchain has transformed from a segment of digital innovations to an infrastructure that has implications towards environmental market systems and financial assets. Early foundational studies suggest that the blockchain technology possesses both, technical and non-technical characteristics, such as transparency, decentralized nature, and tamper resistance (Hughes et al., 2019). Although there is significant enthusiasm and publicity around the blockchain technology, existing literature and empirical evidence show that implementing such a technology result in many complex patterns and obstacles, such as regulations, sentiments and technological constraints.

Recent studies have emphasized the potential that the Blockchain can have on both the traditional stock markets as well as the contemporary carbon markets. Babu and Das (2023) assert that using Blockchain into the stock market can restructure the whole platform, particularly in terms of removing the middleman or intermediaries, which would in turn reduce the cost per transaction and improve the efficiency of the market. On the other hand, in the carbon market space, Tsai (2025) demonstrates that by integrating Blockchain into the carbon markets can help with real-time decision making and assist in identifying suspicious activities, this in turn also improves the market efficiency.

2.2 Blockchain Integration and Regulations

It has also been observed that the blockchain has been coupled with other technologies such as Artificial Intelligence, can further improve the efficiency as well as assist the integration with complying with regulations. Paramesha et al. (2024) argue that by combining the integration of blockchain along with artificial intelligence (AI) provide better regulatory compliances by presenting a transparent audit trail powered by AI-driven automation and anomaly detection. This combination can enable institutions to efficiently fulfil compliance related tasks as well reduce the risk of regulatory violation, which is a common concern observed in the blockchain implementation space.

A major challenge that is faced when trying to integrate blockchain into Carbon Market is the lack of collaboration and standardization. Vinod et al. (2025) raised that the lack of standardization can result in risks for the blockchain implementation, particularly in terms of interoperability issues and declining the trust issues of the market participants. If a carbon credit was obtained by a company due to their operations in Country A, and if they wanted their carbon offset emissions to take place in another country, this cross-border operability won’t be possible without any standardizations. This calls for a mechanism to verify the carbon trading, which is most definitely possible with the integration of blockchain, but will also require standardization and regulation.

In blockchain-powered financial markets, such as the crypto exchanges, liquidity is significantly sustained by algo-traders and large investors, who continuously place buy and sell orders. This mechanism is crucial in ensuring the smooth functioning of decentralized markets. Bianchi et al. (2022) highlights that, in the absence of centralized intermediaries, such participants provide consistent trading volume. A similar situation is faced by emerging blockchain markets like the Carbon Market, where such liquidity challenges can emerge, and may require reliance on algo-traders or automated liquidity strategies to sustain the trading activity. It is also worth pointing out that ensuring a high trading volume can make it easier to buy/sell without large price changes, which basically increases the liquidity of the market.

From a marketing and transparency point of view, blockchain also builds trust between firms and their stakeholders. Rathore (2019) demonstrates how blockchain reduces fraud, improves authenticity of digital data, and enhances traceability. As a result, this promotes blockchain’s adoption in cross-disciplinary reach beyond industries like finance and operations.

2.3 Benefits of Blockchain Adoption

Carbon Tokenomics Model (CTM) is another blockchain technology-based method to create accountability in the carbon markets. Goean et al. (2024), introduced the use of AI and Smart Contracts in order to create, store and trade carbon credits to enhance the inefficiencies in the existing carbon markets. These existing inefficiencies include creating transparent processes for all stake-holders in the carbon markets, reducing validation period of transactions and reducing transaction costs. Moreover, in order to enhance the efiiciency of carbon markets, the CTM can assist in achieving operational efficiencies by selecting validators to validate transactions depending upon the reputation score; resultantly achieving the needed trust in the system. Depending upon the potential of CTM's operational efficiencies, the study could create transparency in carbon markets which would help in creating trust with regulatory authorities by reducing the risks of regulatory related issues.

Balaga (2024) also highlighted that the combination of blockchain with AI could provide carbon markets with additional tools to help with pricing mechanism and provide transparency to transactions. The study considered a unique pricing model that optimally utilized AI powered predictive models in sync with the blockchain based trading platforms; which significantly reduced the pricing errors to 66 % as compared to the traditional pricing models. More accurate price quotes provided to different stake-holders will result in greater reliance on data driven decision making. In addition to the technical advantages of utilizing blockchain technologies, the Study also highlighted the need for additional research in decentralized carbon trading systems using intelligent automation to help address the policy implications related to use of blockchain technology in environmental markets.

Most of the available literature highlights the various benefits of adopting the blockchain technology at the organizational level. Hughes et al., (2019), emphasized that the use of blockchain technology within organizations can result in various advantages including elimination of middlemen, enhancement of data integrity and transparency. He also noted that the potential benefits of utilizing blockchain technology are immense, however the number of organizations that have adopted blockchain technology is extremely low. This is mainly due to the challenges being faced by the organizations in its implementation including regulatory hurdles and cultural barriers. Aswin Aloraet et al., emphasized that through the adoption of the blockchain technology in financial sector, the study can achieve reduction in cost of capital by enhancing transparency and reducing information asymmetry.

In summary these studies suggest the while there are various benefits of adopting blockchain technology, the effective implementation of blockchain technology at the organizational level is significantly hindered by practical limitations and industry specific requirements. Further studies also highlight that the use of blockchain technologies can change the internal behavior of the market. Tlili (2025), provides evidence-based insights towards the concept of tokenized carbon credits, demonstrating that the blockchain based carbon assets exhibit identifiable liquidity mechanisms, continuous flow of buy and sell orders and efficiency characteristics compatible to those of the traditional financial instrument. This re-enforces the fact that blockchain technology has both direct and indirect behavior impacts, which further enhances liquidity and efficiency.

2.4 Perception of Blockchain Adoption

One additional important aspect to take into account is how the general public perceives blockchain technology. Research and literature have been conducted regarding other aspects, which examined how financial markets reacted to announcements about blockchain. A study demonstrates that investors react to blockchain news even if they cannot find anything that has changed in terms of reality. Jain and Jain (2019), for example, found that when a company adds the term "blockchain" to its name, it generates abnormal returns, clearly indicating that the initial reaction to the announcement was based on public awareness of the news and not based on the actual value of the company. In addition, event-based studies also contribute to the understanding of these analyses, Xu (2021), for example, identifies large positive returns in Chinese listed companies shortly after announcements of blockchain applications were made. Furthermore, Rogalski (2023) examines this phenomenon in greater detail and confirms that blockchain announcements lead to short-term positive returns; however, the size of those returns depend on several factors including maturity of project, degree of consortium participation, and ESG related use cases. Additionally, he states that blockchain announcements may also impact systematic risk (beta) of individual firms and therefore indicate that market implications exist in excess of the short-term price shock.

Earlier studies also suggest that technological adoption of blockchain is not the sole factor behind the perception of the investors, rather it is also determined on the basis of factors such as the visibility. Puthineedi et al. (2025), showed in their event study that firm-level disclosures around blockchain adoption is not the sole factor behind the prices of stocks, rather it is also dependent on the market movement of other cryptocurrencies like the Bitcoin (BTC). Furthermore, Shilov and Zubarev (2025), also showed that the involvement of investors through the bitcoin exchange traded funds, has shown a new insight that there is a pattern between blockchain technology and the price movements of such tokens. However, this still does not always give the investor a direct link between blockchain adoption as an enabling technology and the price movement of the assets.

Moving backward from the announcement effects, research related to blockchain technology is also starting to evaluate how blockchain technology affects financial markets as a whole. Ghaemi Asl et al. (2021), for example, demonstrate strong positive correlation between cryptocurrency price returns and technology firms using the blockchain technology, indicating that investor sentiment regarding blockchain also applies to various markets related to the blockchain technology. The study done by Kalamen et al. (2024) extends this by showing a high correlation between Bitcoin prices and the S&P 500, indicating growing integration between blockchain-based assets and traditional equity markets.

2.5 Criticism of Blockchain Adoption

Research on blockchain technology and its applications in finance, has created a new area of risk that companies may face.Field and Inci (2023), found that if a company owns cryptocurrency, it will affect the firm's volatility, beta, and risk-adjusted returns. Their research also indicated potential volatility spillovers between markets because of the connection of blockchain-based financial instruments with the stock markets.

In addition to volatility from the use of blockchain technology, several studies indicate a relationship with internal market structure-related outcomes. Similarly, Zhang (2024) concluded that blockchain technology would create more efficient markets by improving liquidity and reducing trading costs through the increased transparency and automation of smart contracts in the market. These three areas represent the three types of market efficiencies that blockchain technology could influence: spreads, volatility, and price discovery.

The idea of implementing blockchain into carbon markets is also gaining a lot of traction, but also has been receiving criticism for it. Mzoughi et al. (2023) highlights that the main criticism that blockchain receives is due to the energy-intensive nature it has, which calls for policymakers to support such innovations while also making sure that it mitigates harm. In the case of implementing blockchain within the carbon market, which aims to control and reduce carbon emission, would face a lot of backlashes if the technology itself consumes a lot of energy and causes ecological damage. Similarly, Zhang et al. (2024) also acknowledged that implementing blockchain into carbon markets come with such challenges, they use the example of Shanghai Environment and Energy Exchange as the case study for the examination. They also acknowledged that there could be additional constraints such as elevated costs, delays in transaction and the increase in complexity especially for new participants. To counteract these challenges, they proposed energy-efficient such as using mechanisms like Proof of Stake, using Layer 2 solutions such as zkSync Era and the possible use of “super node”. One thing to point out here is that by using “super node” it may raise question mark around the decentralized nature of the blockchain technology. However, such a mechanism will assist in regulatory compliance, as it adds the element of oversight. Moreover, the literature also suggests a unified global carbon emission framework, to assist in cross-border cooperation and reduce any manipulation in such a case.

A significant portion of the literature in the environmental assets space looks into blockchain adoption in carbon markets. Zhao et al. (2022) and Yang et al. (2025) both highlight the benefits of adopting blockchain technology for environmental reporting, monitoring, tracking and verification, emphasizing its role in fraud reduction and establishing a sustainable eco-system. However, such technological adoption is not straightforward and also comes with challenges. Chen and Lloyd (2025) analyze blockchain adoption in China’s carbon markets and found that technical limitations are not the main concern. Rather it is the political, legal, regulatory, organizational, and data governance related obstacles that create hesitation among the stakeholders. Moreover, in the case of tokenized carbon markets, blockchain adoption is far-more rapid and market-driven (Tlili, 2025), this suggests that voluntary markets adopt blockchain faster than the regulated markets, which face governance challenges. Hence, such regulations can cause friction and slow down the adoption of blockchain technology in such financial frameworks.

2.6 Hypothesis Development

Existing research typically associates blockchain technology with increased transparency, better access to information, and reduced issues associated with transactions. A number of studies further indicate that these features can impact how well markets function (through price discovery, liquidity and risk) however, they are also highly inconsistent as many studies have compared traditional equity markets to newer blockchain-based markets such as tokenized carbon credits. This study will therefore propose a series of hypotheses to test both the direct and indirect effects of a number of market-related variables on market efficiency.

Transparency is one of the primary benefits of blockchain technology. As blockchain provides permanent and more transparent records than other technologies, it is anticipated that transparency will assist in closing the information gap between the parties of the market and assist in adjusting prices faster. Therefore, the following hypothesis was developed:

Hypothesis 1: Transparency positively impacts market efficiency.

Price discovery is another major feature; it is an indication of how quickly new information becomes incorporated into prices. The literature indicates that blockchain systems may facilitate price discovery by providing greater access to information and reducing the role of intermediaries in facilitating information exchange. Hence, the following was proposed:

Hypothesis 2: Price discovery positively impacts market efficiency.

Moving forward, the next variable is the volatility, which indicates the amount of price movement. It is often measured through the uncertainty in the market. As the existing literature show mixed conclusions around volatility, the study would not be making an assumption around its sign (negative or positive), and keep it open. Therefore, the following hypothesis was derived:

Hypothesis 3: Volatility significantly impacts market efficiency.

Aside from the variables directly affecting the market efficiency, now the mediating variables will be introduced. As the first mediator of this study, liquidity, is often associated with price adjustments. Keeping it as the mediator, the study derives the following hypotheses:

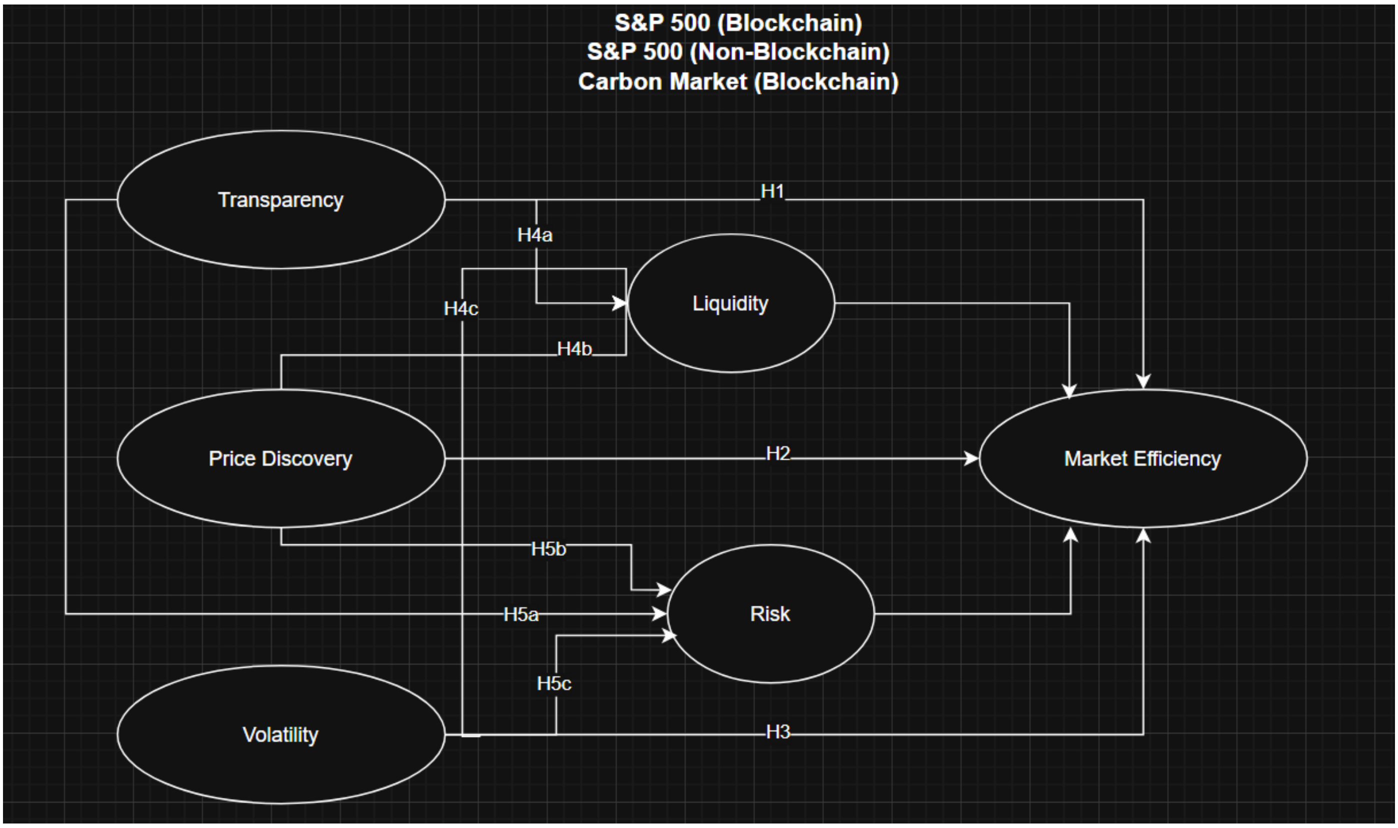
Hypothesis 4a: Liquidity mediates the relationship between transparency and market efficiency.
Hypothesis 4b: Liquidity mediates the relationship between price discovery and market efficiency.
Hypothesis 4c: Liquidity mediates the relationship between volatility and market efficiency.

Another mechanism through which blockchain-related factors may influence market efficiency is risk dynamics. Change in transparency, price discovery, and volatility may alter investors' perceptions and the exposure to systematic risk, which in return can affect how efficiently prices adjust. Existing studies indicate that blockchain-related assets and announcements can influence firm-level risk and volatility spillovers across markets.

Consequently, risk dynamics are introduced as an additional mediating variable as the following hypotheses:

Hypothesis 5a: Risk dynamics mediate the relationship between transparency and market efficiency.
Hypothesis 5b: Risk dynamics mediate the relationship between price discovery and market efficiency.
Hypothesis 5c: Risk dynamics mediate the relationship between volatility and market efficiency.

Together, these hypotheses form the basis for the empirical analysis conducted in this study. Since the study also aims to keep a comparative nature, the hypotheses will be tested across the three different market frameworks the study had established, S&P 500 blockchain firms, S&P 500 non-blockchain firms, and the blockchain-based carbon market. These frameworks allow for a comparative assessment of whether blockchain adoption interacts with market structure to influence market efficiency through multiple channels or not.



Chapter 3: Research Methodology

3.1 Research Design

The current research will use an explanatory (comparative) quantitative approach for this study to investigate if the blockchain technology affects the market efficiency under varying market conditions. This research also aims at establishing the relationship among key variables that affect market efficiency, including price discovery, transparency, volatility, liquidity, and risk dynamic, and how they can influence the market efficiency.

Quantitative methods are best suited to this study because secondary data is used in the form of numbers; the study relies on statistical inference and hypothesis testing; an explanatory model was chosen to establish the relationship among the variables using regression models and mediation analysis; a comparative design was developed to identify the difference between the three selected market frameworks: S&P 500 blockchain firms, S&P 500 non-blockchain firms, and the blockchain-based carbon market.

Additionally, instead of treating the blockchain adoption as a continuous explanatory variable, it is being treated as a structural classification mechanism. This method permits the study to determine how similar variables behave differently with respect to the mechanism under various market environments, thus providing consistent application of the same definition of the variables and analytical methodologies across all market conditions.

3.2 Research Framework and Conceptual Model

he conceptual framework of this study is basically built around market microstructure and market efficiency theory. Market efficiency is treated as the main outcome variable, and it is influenced by three key factors, which are price discovery, transparency, and volatility. Along with this, two mediating variables, liquidity and risk dynamics, are included to basically see how these factors pass through and affect market efficiency.

Blockchain technology is viewed as an underlying factor, but is not considered to be a factor that would alter the model itself. Therefore, to evaluate whether blockchain impacts the relationship among these variables, the markets are divided into two groups - blockchain and non-blockchain - and evaluated separately. The partial mediation structure of the model allows for both direct and indirect effects of each factor on market efficiency through both liquidity and risk dynamics.

Overall, this framework provides an opportunity to examine and compare traditional equity markets with new environmental markets while ensuring the generalizability of the findings beyond a single type of market.

3.3 Hypotheses Development

Based on the literature and theoretical base of the market efficiency, this study develops hypotheses to examine the direct effects of transparency, price discovery, and volatility on market efficiency, as well as the mediating roles of liquidity and risk dynamics, like mentioned earlier.The study will be revisiting each of the hypotheses again to link it to the measurables and variables that it has set.

3.3.1 Transparency and Market Efficiency

Transparency reduces information asymmetry and improves information availability among market participants. Blockchain technology is often associated with enhanced transparency due to unmodifiable ledgers and traceable transactions. As mentioned earlier, the study proposes:

H1: Transparency has a positive effect on market efficiency.

3.3.2 Price Discovery and Market Efficiency

Price discovery reflects the speed and accuracy with which information is incorporated into asset prices. Efficient price discovery is a key characteristic of efficient markets, whether or not blockchain adoption takes place or not. Therefore this proposes:

H2: Price discovery has a positive effect on market efficiency.

3.3.3 Volatility and Market Efficiency

Volatility represents market uncertainty and instability. High volatility can slow price adjustment and impair market efficiency. Since the prior studies show mixed theoretical expectations around the volatility factor, a non-directional hypothesis is proposed:

H3: Volatility has a significant effect on market efficiency.

3.3.4 Liquidity as a Mediating Variable

Moving towards the mediating variables, liquidity enhances trading and enables faster price adjustment. Blockchain is often expected to improve liquidity by lowering transaction frictions, as suggested in the literature.However, liquidity may also depend on broader market structure. Therefore,the following mediation hypotheses are proposed:

H4a: Liquidity mediates the relationship between transparency and market efficiency. H4b: Liquidity mediates the relationship between price discovery and market efficiency. H4c: Liquidity mediates the relationship between volatility and market efficiency.

3.3.5 Risk Dynamics as a Mediating Variable

Risk dynamics is mainly linked to the market-wide uncertainty. In the study, the variables have mainly kept this conceptually different from the Volatility variable as discussed earlier. Therefore, through prior literature,change in transparency, price discovery, and volatility may influence market efficiency indirectly through risk transmission. Thus, this proposes the following:

H5a: Risk dynamics mediate the relationship between transparency and market efficiency. H5b: Risk dynamics mediate the relationship between price discovery and market efficiency. H5c: Risk dynamics mediate the relationship between volatility and market efficiency.

3.4 Variables and Operational Definitions

3.4.1 Independent Variables

The following are the IVs and their respective measurables.

a. Price Discovery:
Price discovery is measured using three measurables:

1. High–Low price spread
2. Return Autocorrelation
3. Adjustment Speed

For the High-Low price spread, for all the three frameworks, the study used the following equation:

$$\text{High–Low Spread} = (H+L)/((H-L)/2)$$

For the Return Autocorrelation, the study had to initially find the returns on daily basis, which could be found with the following equation:

$$\text{Return on Day T} = \log(\text{Price of Day T} / \text{Price of Dat T-1})$$

Once the daily returns are calculated, the study used the autocorrelation equation with a lag of 1.

$$\text{Return on Time T} = \alpha + \rho(\text{Return on Time T}) - 1 + \varepsilon$$

Where, α is the intercept term and is constant, ρ (rho) first order return autocorrelation coefficient, and lastly the ε is the error term at Time T.

From the autocorrelation equation, the study extracts the ρ (rho), and that becomes the value for our return autocorrelation. Running the equation and extraction the ρ (rho) value is done through the statsmodel library of python, particularly the "autocorr()" function.

Lastly, for Adjustment Speed, the study used the following equation:

$$\text{Adjustment Speed} = 1 - \text{Price Delay}$$

Regarding how to find the value of Price Delay, will be discussed later in the market efficiency variable.

Upon their successful calculation, all the measurables were normalized through z-score to give a single value to the variable.

b. Transparency:
Transparency is measured using:

1. Number of holders
2. Number of on-chain transfers (carbon market)
3. Market openness
4. Information availability indicators

In the case of carbon market, the study had used the Number of Holders and Number of on-chain transfers as our measurables, which are different from the ones the study set for the equity markets. This was primarily since both the markets have different mechanism, and the measurables were expected to be slightly different, but indicating the same variable. Meanwhile, for the equity markets (S&P 500 Blockchain and S&P 500 Non-blockchain), the study used the Market Openess and Information Availability.

The Number of Holders and Daily Transfers were given and available from the data sources, there was no need for applying equations or calculations to derive their values.

Meanwhile, in the case of Market Openess, the study had used the following equation:

Market Openness = Free Float Shares / Total Shares Outstanding

Lastly, for Information Availability,the Number of Analysts of each firm within the equity market for the current year (2025) was calculated. This was also given by the data source and did not require any additional calculations.

Upon their successful calculation of the respective measurable, the values were normalized through z-score standardization to give a single value to the variable.

c. Volatility:

Volatility is simply measured as the standard deviation of daily returns. The daily returns for all the three frameworks were calculated till 1 year, on the same day (3rd December 2025).

No normalization was required in this case, as there was only one suitable measurable for the variable.

3.4.2 Mediating Variables

The following are the Mediating Variabels and their respective measurables were:

a. Liquidity

Liquidity is measured using:

1. Dollar Trading Volume
2. Amihud'sIlliquidity Ratio

Both the measurables remained consistent for all the frameworks. For the Dollar Trading Volume, the carbon market did not require any additional calculations since the volume extracted from its data is already in the form of Dollar Volume. However, in the case of the equity markets (S&P 500 Blockchain and S&P 500 Non-blockchain), the study had to calculate for each firm using the Volume and Closing Price into the following equation:

Dollar Volume = Price x Volume

After achieving the Dollar Volume for every firm and token within the framework markets, it can be then proceeded to calculate the Amihud's Illiquidity Ratio:

Illiquidity = Average Returns / Average Dollar Volume

Lastly, using both the measurables, each firm got a standardized z-score value for Liquidity.

b. Risk Dynamics

Risk is captured using:

1. Systematic risk (beta)
2. Value-at-Risk (VaR)

Similarly for Risk Dynamics, the measurables remained consistent across all the three market frameworks.

For Beta (Systematic Risk), which measures how sensitive an asset's returns are compared to the market returns, the study used a benchmark to compute the risk. In the case of the equity market, S&P Blockchain and S&P Non-blockchain, the benchmark was kept as the S&P 500 Index. Meanwhile, for the Carbon Market blockchain, the benchmark was set to Bitcoin (BTC). Using the historical data of the benchmark, along side its respective historical data of the firm or token, would enable the calculation of Systematic Risk.

Initially, the Asset Return and Market Return (Benchmark) are calculated using:

Asset Return = log(Firm or Token Price of Today / Firm or Token Price of Yesterday)

Market Return = log(Benchmark Price of Today / Benchmark Price of Yesterday)

Once the required values are achieved, they are put into the Market Model Regression (also known as the CAPM-style regression), which will assist in extracting the value of Beta. The regression to be used is:

$$\text{Asset Return} = \alpha + \beta(\text{Market Return}) + \varepsilon$$

Where, α is the intercept and remains constant, ε is the error term, and β (Beta) is the Systematic Risk.

For VaR, the following equation was used on a firm/token level:

VaR = (Mean of Returns of the Asset) – (Z-Score of Alpha at 95%)(Std. Dev of Returns)

An important detail to note here is that in our equation of the study have kept alpha at 95% confidence (0.95) for calculation of VaR. This was particularly because 95% is commonly used as confidence level when calculating VaR.

Once both VaR and Beta are obtained, the z-score standardization is calculated for each value to obtain a firm-level singular value for Risk Dynamics.

3.4.3 Dependent Variable

The research only has one DV, which in this case would be:

Market Efficiency
Market efficiency is measured using price delay, derived from regression-based models comparing lagged market returns. Higher price delay indicates lower market efficiency.

In order to calculate Price Delay, the initial step is to calculate the Asset (firm / token) return, and the Market (Benchmark) return, similar to how it was done in the Risk Dynamics variable. Just like it was mentioned earlier, the benchmark for the carbon market was set to the historical data of the Bitcoin, while the benchmark for the equity markets (S&P Blockchain and S&P Non-blockchain) were set to the historical data of the S&P 500 Index.

With that in mind, the following equations were again used to calculate the returns:

Asset Return = log(Firm or Token Price of Today / Firm or Token Price of Yesterday)

Market Return = log(Benchmark Price of Today / Benchmark Price of Yesterday)

Once the required values are obtained, the time-series OLS regression is used, specifically the market model with lagged market returns. The regression was also run separately for each firm/token. The OLS function was used in Python’s statsmodel library in order to extract the value of R-Square (restricted) and R-Square (full). After the R-Square values are extracted, they are placed in the following equation:

Price Delay = 1 – ((R-Square (restricted))/(R-Square (full)))

Once the price delay value is obtained, there will no need for running standardization of values as Market Efficiency is only using one measurable.

3.5 Population and Sampling Strategy

The study focuses on three populations:

1. S&P 500 blockchain-adopting firms (30 firms)
2. S&P 500 non-blockchain firms (30 firms)
3. Blockchain-based carbon market tokens (4 major carbon-based tokens)

A purposive sampling approach is used based on data availability and relevance to blockchain adoption.

The 30 firms for blockchain-adopting firms of S&P 500 were selected by picking the companies within the S&P 500 Index that had publicly announced ventures or adoption of blockchain within their firm. Meanwhile, the Non-blockchain S&P 500 firms were selected if no public announcement or news existed regarding the firm adopting or investing into a blockchain venture. Market cap was another factor in picking the 30 firms from each category.

Moreover, the 4 tokens were picked that are based of carbon credit trading and if public data around it was available. The 4 tokens were also picked on the basis of being blockchain-native carbon credits and its market activity.

The companies and tokens used as sample for the research have been listed in the **Appendix**.

3.6 Data Collection Procedures

The study is based entirely on secondary data. Daily price, return, volume, and token-level data are collected from publicly available financial and blockchain sources. All data are standardized to daily data and cleaned to cater for missing values, unnecessary information and outliers. For instance, when extracting data from Yahoo Finance, it also mentions dividends in its data, which was not in our concern so it had to be cleaned. Throughout the process, the initial data was collected in the form of a excel or csv file.

3.7 Data Sources

The data was gathered from the following sources:

- Yahoo Finance
- Investing.com

- Public blockchain explorers
- CoinMarketCap
- CoinGecko
- Kaggle

3.8 Data Processing and Preparation

During our data pre-processing and preparation, the following methods were used:

1. Cleaning missing observations
2. Calculating daily returns
3. Standardizing measures
4. Computing volatility, liquidity, risk, and price delay
5. Z-score normalization where required
6. Taking Averages

After the normalization of all the variable values, and before taking the averages, the data was as follows:

S&P 500 Blockchain Firms:

Firm	**Price Discovery**	**Market Efficiency**	**Transparency**	**Volatility**	**Liquidity**	**Risk Dynamics**
MSFT	0.1545	-0.0007	0.6184	0.0155	0.7006	-0.5492
IBM	-0.0379	-0.0100	-0.2446	0.0191	0.0814	-0.7125
AMZN	0.4033	-0.0024	1.0979	0.0219	-0.0153	0.2518
GOOG	0.1318	-0.0076	1.1320	0.0202	-0.0300	-0.0330
META	0.2054	0.0193	1.1775	0.0242	1.6740	0.5242
NVDA	0.3074	0.0227	0.5365	0.0316	-0.1623	1.4453
INTC	-0.4156	-0.0225	0.6153	0.0395	-2.9171	2.2695
V	1.1325	0.0069	0.1546	0.0145	0.2871	-0.8534
MA	-0.2573	0.0088	0.4551	0.0144	1.0912	-0.7552
PYPL	0.5872	-0.0134	0.6512	0.0245	-0.3615	0.3491
JPM	-0.8194	0.0030	-0.6180	0.0161	0.1154	-0.4605
BAC	-1.1516	0.0664	-0.2461	0.0172	-0.5066	-0.3484
GS	-0.8867	0.0034	-0.2755	0.0199	1.7127	0.2470
MS	-0.5066	-0.0026	-1.5142	0.0198	-0.1575	0.2725
WMT	-0.5477	0.1515	-1.5038	0.0160	-0.2206	-0.9066
SBUX	-0.4894	0.0110	0.3013	0.0216	-0.2658	-0.0312
TSLA	-0.9703	0.0114	-0.7945	0.0408	0.3335	2.7639
ORCL	-0.8743	0.0161	-1.3011	0.0371	-0.0475	1.1119

CSCO	1.1691	-0.0009	-0.0817	0.0148	-0.3126	-0.6474
ACN	0.8451	0.1327	-0.2495	0.0186	0.1678	-0.4796
CRM	-0.0356	0.0075	0.7979	0.0205	0.1067	-0.0490
ADBE	0.7598	0.0314	0.3511	0.0198	0.4137	-0.4352
QCOM	1.1018	0.0091	-0.0278	0.0244	-0.1257	0.5154
AXP	-0.1100	0.0000	-0.9939	0.0201	0.2008	0.2918
VZ	0.1215	0.6647	-0.1628	0.0136	-0.4966	-1.5121
T	0.1249	0.5174	-0.1179	0.0141	-1.0136	-1.5139
NKE	0.7895	0.1233	0.3088	0.0254	-0.3882	0.0786
DIS	-0.0180	0.0539	-0.0355	0.0188	-0.2045	-0.3309
HD	0.5660	-0.0068	0.3720	0.0149	0.3953	-0.7399
BA	-1.2796	0.0474	-0.4028	0.0236	-0.0550	0.2369

S&P 500 Non-blockchain Firms:

Firm	Price Discovery	Market Efficiency	Transparency	Volatility	Liquidity	Risk Dynamics
KO	0.5392	0.8698	-0.6813	0.0112	-0.0421	-0.8531
PEP	0.3964	0.4865	0.1327	0.0143	0.0201	-0.5705
MCD	0.4601	0.1630	1.1343	0.0118	0.2061	-0.5997
PG	0.3500	0.5608	0.0642	0.0118	0.0357	-0.8261
CL	0.4061	0.9289	-0.6381	0.0133	-0.0274	-0.7581
KMB	-0.7567	0.8296	-0.4050	0.0159	0.0081	-0.7944
JNJ	0.7882	0.7624	0.4821	0.0124	0.0430	-0.8237
MRK	-0.6592	0.1416	-0.1587	0.0192	-0.0365	0.0298
PFE	-0.3897	0.1245	0.3716	0.0166	-0.3891	-0.0618
ABBV	-0.5225	0.2113	0.6227	0.0166	0.0742	0.0760
BMY	-0.6937	0.3367	0.4390	0.0187	-0.1153	-0.0474
LLY	-0.9823	0.1307	0.7488	0.0260	1.6642	0.7411
COST	-0.2938	0.0596	1.1230	0.0138	2.3052	-0.3932
TGT	1.0114	0.0947	1.1224	0.0217	-0.0226	0.7195
LOW	0.2129	0.0214	0.7491	0.0153	0.1178	0.1192
GIS	0.2988	0.8328	-0.1257	0.0145	-0.0827	-0.6796
CVS	-1.3648	0.4932	0.5772	0.0204	-0.0749	0.0695
XOM	-0.1342	0.0874	0.4613	0.0149	-0.0074	-0.2307
CVX	-0.4618	0.0660	-0.2350	0.0157	0.0258	-0.1552
NEE	-0.4234	0.2612	0.0066	0.0179	-0.0527	0.0604
DUK	-0.0482	0.9965	-0.0145	0.0108	0.0024	-1.0416
SO	0.0734	0.8078	0.0066	0.0111	-0.0206	-0.9689
AAL	0.8296	0.0876	-0.0251	0.0340	-2.8222	2.3173
DAL	0.4147	0.0285	0.1879	0.0315	-0.1573	2.3450
UAL	0.3913	0.0433	0.0309	0.0354	-0.0632	2.7728
DHI	-0.0312	0.1042	-1.3243	0.0239	0.0135	0.8081
PLD	0.4308	0.0010	-1.3591	0.0183	-0.0090	0.2960
KDP	-0.3666	-0.0700	-1.0570	0.0171	-0.2345	-0.5187
MDLZ	0.2156	0.6793	0.2919	0.0141	-0.0594	-0.6114

KHC	0.3096	0.1794	-2.5285	0.0153	-0.2992	-0.4208

Carbon Market Blockchain Tokens:

Token	Price Discovery	Market Efficiency	Transparency	Volatility	Liquidity	Risk Dynamics
BCT	-0.1956	0.7817	-0.8506	0.0533	0.5571	-1.0747
KLIMA	-0.5046	0.9848	0.6590	0.0584	0.8533	-0.1897
MCO2	-0.1209	0.9948	-0.4382	0.0986	0.2651	1.4829
NCT	0.8211	0.9560	0.6297	0.0749	-1.6755	-0.2185

The aforementioned data for all three markets will be averaged before proceeding to Data Analysis.

3.9 Data Analysis Techniques

The following techniques for data analysis took place after the pre-processing of the data (which was done in Python/Excel)**:**

1. Descriptive statistics (Mean, Min-Max, Std. Dev)
2. Correlation analysis (Pearson's)
3. Ordinary Least Squares (OLS) regression
4. Mediation analysis (Stepwise Regression Approach)
5. Cross-market comparative analysis (Conceptual)

3.10 Ethical Considerations

The study uses publicly available secondary data. No human subjects are involved, and ethical risks remaininsignificant.

3.11 Methodological Limitations

Limitations include sample size constraints for the carbon market, proxy measurement limitations, and the relatively short time horizon. Moreover, the availability of free data was another limitation we had. Since, we could get free data of prices for about an year, and any historical data beyond that required a premium. Hence, this became a constraint for us in obtaining historical data. For most of the cases in this research, it is to be observed that the time-period in the data was mostly kept at 1-year old. Despite these limitations, the methodology was implemented for the study.

Chapter 4: Data Analysis

4.1 Introduction

This chapter presents the empirical (data-based) analysis and results of the study. The main objective of this chapter is to examine whether or not blockchain adoption influences market efficiency through various market variables. The study will basically look into the effects of Price Discovery, Transparency and Volatility on Market Efficiency. Moreover, the Liquidity and the Risk Dynamics' mediating effect will also be observed.

The empirical (data-based) analysis is conducted across three distinct frameworks:

1. S&P 500 Blockchain-Adopting Firms
2. S&P 500 Non-Blockchain Adopting Firms
3. Blockchain-Based Carbon Credit Market

The above three mentioned market frameworks will be the representatives in our comparative analyses that will take place between traditional equity markets and the emerging blockchain environmental market. This chapter will start the analysis with the descriptive statistics, then the correlation analysis, the direct relation regression, then the mediating relation analysis and at the end the chapter will have a comparative analyses around the aforementioned markets.

4.2 Descriptive Statistics

The purpose of the descriptive statistics is to provide an overview of the data and the most basic characteristics of the variables contained within the data set. The variables considered in this research are Market Efficiency, Price Discovery, Transparency, Volatility, Liquidity, and Risk Dynamics.

Each of the market frameworks was analyzed using the descriptive statistics as individual markets before they would be compared with one another.

4.2.1 S&P 500 Blockchain Firms

The descriptive statistics for the S&P 500 firms that use blockchain show a lot of variability across each of the major statistics. The variability of the firms within the sample suggests that none of the firms behave similarly as investors in the marketplace. For example, the average measure of market efficiency (i.e., price delay) indicates that there was moderate spread around the mean, which suggests that some firms can rapidly adjust prices in response to new information, while other firms may take longer to make such adjustments.

In terms of price discovery, the firms also demonstrate considerable variation in this respect; since price values range from positive to negative, firms clearly vary in how well they are able to incorporate new information into their stock prices. The firms' level of transparency, on average, is standardized at zero, however, it also exhibits considerable variation. Therefore, while some firms provide greater amounts of information than others regarding their firms, all firms ultimately provide some amount of information regarding their firms.

Moving towards the volatility variable, it is observed that almost all the firms within the S&P 500 Blockchain market are experiencing the same pattern in returns. This is mainly due to how little variability is amongst the firms for the volatility value. In other words, the data pattern amongst the firms are mostly consistent, which some firms have small inconsistencies compared to others.

Finally, liquidity exhibits considerable variability, which implies that the firms in the sample do not exhibit uniformly high levels of trading activity. Similarly, the firms exhibit considerable variability in terms of risk dynamics, which reflects the degree to which firms are exposed to both general market risk and firm specific risk. Ultimately, the descriptive statistics indicate that the firms that utilize blockchain technology in the S&P 500 sample are relatively diverse in terms of market efficiency and in terms of the various market characteristics associated with each firm, and therefore do not form a single, homogeneous group.

	Mean	Std. Deviation	Min	Max
Price Discovery	-6 x 10^-16	0.6945	-1.2795	1.1690
Market Efficiency	0.0613	0.1515	-0.0225	0.6646
Transparency	3.18 x 10^-16	0.7282	-1.5142	1.1774
Volatility	0.0214	0.0072	0.0135	0.0407
Liquidity	-1.7 x 10^-16	0.8028	-2.917	1.7127
Risk Dynamics	1.81 x 10^-16	0.9552	-1.513	2.763

4.2.2 S&P 500 Non-Blockchain Firms

The descriptive statistics of non-blockchain S&P 500 firms are highly variable in comparison to all other key variables. The non-blockchain firms exhibit distinct behavior within the market place, therefore, it is evident that there are significant variations in the market behavior of each type of firm.

In regards to the market efficiency, as determined by price delay, the average of the non-blockchain firms was significantly larger than that of the blockchain firms and exhibited an even wider range of values. Therefore, the data implies that, on average, the non-blockchain firms' prices take longer to reflect changes in information and that the time frame it takes to reflect changes in information differs greatly between firms.

Similarly, the price discovery mechanism exhibited a high degree of variability as well; although the average of the price discovery was near zero (most likely due to the standardization), the distribution of the data indicates that the non-blockchain firms have varying degrees of effectiveness at having their stock prices accurately reflect changes in information.

Transparency also varied significantly, therefore, it appears that some non-blockchain firms report their financial activities in a manner that provides investors with sufficient information and transparency whereas other firms may utilize more traditional methods of reporting that do not include as much detail.

The volatility of the non-blockchain firms exhibited moderate levels of volatility overall, however, the level of volatility did vary significantly between firms. There are several possible reasons why there were such differences in volatility levels including, the size of the firms, the types of industries that the firms operated in, and the perception of investors towards these firms.

Liquidity exhibited a high degree of variability as well, therefore, it appears that the trading activity of the various non-blockchain firms was not distributed equally, and as a result, some firms had very liquid markets while others experienced relatively low levels of liquidity.

Risk dynamics also exhibited a high degree of variability as well; therefore, it appeared that the non-blockchain firms exhibited varying degrees of risk to both market wide and firm specific risks.

As a whole, the descriptive statistics indicate that non-blockchain firms operating in the S&P 500 exhibit a high degree of variability in terms of market efficiency and related factors, when compared to the blockchain adopting firms, this implies that the traditional firms experience higher levels of information friction and less efficient price discovery mechanisms.

	Mean	Std. Deviation	Min	Max
Price Discovery	-7.7 x 10^-16	0.5707	-1.364	1.011
Market Efficiency	0.344	0.3384	-0.0704	0.9964
Transparency	7.4 x 10^-17	0.8054	-2.528	1.1343
Volatility	0.0177	0.0065	0.0107	0.0353

Liquidity	5.55 x 10^-18	0.7537	-2.8221	2.3052
Risk Dynamics	2.44 x 10^-16	0.9811	-1.0416	2.7727

4.2.3 Blockchain Carbon Credit Market

This Carbon Credit Market's Blockchain-based Market behaves considerably different from other types of Equity Markets, primarily because the Descriptive Statistics indicate there is considerable variability in each of the primary variables. Not surprisingly, the Carbon Credit Market is at the beginning stages of development and maturity. Therefore, the data shows that Carbon Tokens behave similarly or differ from one another mostly due to the varying characteristics of the tokens, trading activity, and the amount of participation from investors.

As for Market Efficiency (measured by price delay), the results display a relatively high mean (average) for price delay but low spread. It appears that the blockchain carbon credit market is responding at a significantly slower pace to new information compared to equity markets but that there is still a reasonable consistency in the rates of price delays for all the tokens examined. There is considerable variability in terms of Price Discovery, which suggests that some tokens are adapting to new information quicker than others; however, there is much less variability in terms of spreads than would normally be seen in equity markets.Transparency Data represents values around a mean of zero due to how the transparency metric has been established, but there is a great deal of variation among the different Tokens represented in the Transparency Data, which suggests that differences in the amount of information available to investors in order to make investment decisions regarding their carbon tokens could be an important consideration.The Volatility of the carbon credit market is substantially greater than the Volatility of the S&P 500 sample data, and it is expected that much of this difference will be a result of the high degree of speculation that exists in the carbon token market, as well as the fact that the carbon credit market is still in its development stage. The data on Liquidity also show considerable variability in liquidity among the different carbon tokens, and thus while there appears to be active trading in some carbon tokens, many carbon tokens have low volumes of trading (and/ or limited depth).

Lastly, the data on Risk Dynamics represent significant variability among the different carbon tokens studied and, therefore, they seem to provide a measure of both the general level of risk and uncertainty present in the market, as well as the risks associated with each individual token. As a result, the findings of this study should be viewed with caution because of the relatively small sample size, and the fact that the Carbon Credit Market is in its infancy, but the descriptive statistics provided by this study give a preliminary indication of how the Carbon Credit Market is currently operating through the use of blockchain technology.

	Mean	Std. Deviation	Min	Max
Price Discovery	-1.4 x 10^-16	0.572	-0.5046	0.8210
Market	0.9293	0.0997	0.7817	0.9948

Efficiency				
Transparency	2.78 x 10^-17	0.7629	-0.8505	0.6590
Volatility	0.0713	0.0203	0.0533	0.0985
Liquidity	1.67 x 10^-16	1.1425	-1.6755	0.8533
Risk Dynamics	6.94 x 10^-18	1.0704	-1.074	1.4828

4.3 Correlation Analysis

Before conducting the regression analyses, a correlation analysis was performed to show whether the variables in the study relate to one another or not. A Pearson Correlation Coefficient will be calculated for each of the three markets being studied (S&P 500 Blockchain Firms, S&P 500 Non-Blockchain Firms and Blockchain-based Carbon Markets). The results from this correlation analysis will enable to understand the behaviour of the various variables within each of the individual markets and assist in determining whether multiple correlations exist among variable pairs or not. After that the results may show significant correlations among the variable pairs. These pairs will create the regression models to account for the multicollinearity (highly correlated variables).

4.3.1 Correlation Results for S&P Blockchain Firms

	Price Discovery	Market Efficiency	Transparency	Volatility	Liquidity	Risk Dynamics
Price Discovery	1	0.04725	0.4513	-0.2732	0.0113	-0.2921
Market Efficiency	0.04725	1	-0.1352	-0.3038	-0.23659	-0.47265
Transparency	0.4513	-0.1352	1	-0.03568	0.053121	-0.0009
Volatility	-0.2732	-0.3039	-0.03568	1	-0.30088	0.943667
Liquidity	0.0113	-0.23659	0.053121	-0.30088	1	-0.1839
Risk Dynamics	-0.2921	-0.47265	-0.0009	0.943667	-0.1839	1

The correlation matrix of S&P 500 Blockchain Firms highlights a few key connections between the metrics used in this research. A weak positive connection exists between Price Discovery and Market Efficiency; thus, the direct relationship between the two is relatively small. In addition, a moderate negative connection exists between volatility/risk dynamics and Market Efficiency.Therefore, high volatility/risk levels correspond with both longer time frames to price adjustments (price delay) and lower levels of market efficiency across Blockchain Firms.

A weak negative relationship exists between Transparency and Market Efficiency; therefore, higher levels of transparency are associated with faster price adjustments (lower price delay), though this relationship is not large in magnitude. Likewise, a moderate negative relationship exists between Market Efficiency and Liquidity; hence, more liquid Blockchain Firms have prices that adjust more quickly. Nevertheless, the magnitude of this relationship is moderate; thereby indicating that while liquidity may be an influence on changes in market efficiency, it does not provide complete insight into these changes.

Looking at the independent variables, volatility and risk dynamics show a very strong positive relationship with each other. This means that firms with higher volatility usually also have higher risk exposure, which suggests some overlap between these two measures. The remaining relationships between the explanatory variables range from low to moderate, and no extreme relationships are observed that would cause serious issues for the regression analysis. To avoid any multicollinearity problems, the regression models are estimated separately for each explanatory variable in the later analysis.

4.3.2 Correlation Results for S&P Non-Blockchain Firms

	Price Discovery	Market Efficiency	Transparency	Volatility	Liquidity	Risk Dynamics
Price Discovery	1	0.091502	-0.10289	0.026782	-0.34876	0.141572
Market Efficiency	0.091502	1	-0.05021	-0.53311	-0.0195	-0.59992
Transparency	-0.10289	-0.05021	1	0.013894	0.285962	0.073467
Volatility	0.026782	-0.53311	0.013894	1	-0.31422	0.970551
Liquidity	-0.34876	-0.0195	0.285962	-0.31422	1	-0.30399
Risk Dynamics	0.141572	-0.59992	0.073467	0.970551	-0.30399	1

The correlation results for the S&P 500 non-blockchain firms show a few clear relationships between the variables. Market efficiency has only a weak positive relationship with price discovery and a weak negative relationship with transparency. This means that, at this level, changes in price discovery and transparency are only loosely linked with changes in price delay. This suggests that the way information moves in non-blockchain firms may not be very strong or consistent.

Market efficiency shows a strong negative relationship with volatility and risk dynamics. These results show that as volatility and risk increase so does price delay and therefore market efficiency decreases. The strength of these relationships is much greater than those found for price discovery and transparency, indicating that risk-related factors have a larger impact on price discovery inefficiency in non-blockchain firms. The results do not indicate a strong inverse relationship between liquidity and market efficiency (i.e., high liquidity firms were not more efficient), and therefore it appears that liquidity did not play a significant role in facilitating price adjustment for these firms.

The results for the independent variables show that volatility and risk are strongly positively correlated with each other, showing that these two are highly related. Additionally, liquidity had an inverse, or moderately negative correlation with both volatility and risk.Firms with low liquidity levels typically experience both increased volatility and risk. Transparency showed a moderate positive correlation with liquidity, which suggests that firms with more transparent information may also be experiencing higher levels of trading activity.

Overall, the correlation results suggest that non-blockchain firms are more affected by volatility and risk when it comes to market efficiency, while price discovery and transparency play a much smaller role. This points to higher information frictions and a stronger impact of risk related factors in non-blockchain firms compared to firms that have adopted blockchain.

4.3.3 Correlation Results for Blockchain Carbon Market

	Price Discovery	Market Efficiency	Transparency	Volatility	Liquidity	Risk Dynamics
Price Discovery	1	0.086755	0.308416	0.276766	-0.99318	-0.02874
Market Efficiency	0.086755	1	0.657664	0.626125	-0.18195	0.747192
Transparency	0.308416	0.657664	1	-0.06215	-0.41406	0.0007
Volatility	0.276766	0.626125	-0.06215	1	-0.28367	0.938391
Liquidity	-0.99318	-0.18195	-0.41406	-0.28367	1	-0.00038
Risk Dynamics	-0.02874	0.747192	0.0007	0.938391	-0.00038	1

The relations found in the aboveanalysis on the blockchain based carbon market were also consistent among all of the variables researched. Market efficiency was positively related to both transparency, meanwhile volatility was significantly more positively related to risk dynamics. Therefore, for carbon tokens that had a higher level of transparency, were more volatile and presented more risk. Essentially what this means is that the amount of information an investor has regarding a specific asset does not necessarily equal to shorter price delay.Reason being the carbon token market is still somewhat immature and therefore more speculative.

A very strong negative relationship exists between liquidity and price discovery and a very weak negative relationship exists between liquidity and market efficiency. Hence, more liquid carbon tokens generally will have better price discovery and somewhat less price delay. Transparency had a moderate positive relationship with market efficiency and a moderate negative relationship with liquidity, suggesting that more transparent tokens are not always more active. There was a significant positive correlation between volatility and risk dynamics.Resultantly, there appears to be movement in the same direction relative to each other, within the carbon market.

Moreover, the data provided in the prior sections indicates that the primary influence on market efficiency in the blockchain-based carbon market is the value of volatility and risk associated with the market, rather than liquidity or price discovery.

Since the number of observations is limited and the market is still developing, these results should be seen as indicative and not final conclusions.

4.4 Direct Effects Regression Analysis (H1–H3)

This section presents the results of Ordinary Least Squares (OLS) regression analyses used to test hypotheses H1 to H3. Separate regressions are estimated for each independent variable to avoid multicollinearity concerns.

4.4.1 Transparency and Market Efficiency (H1)

Name	Beta (Coefficient)	p-value	R-Square	Hypothesis Support
S&P Blockchain	-0.02812	0.476248	0.01828	Not Supported
S&P Non-Blockchain	-0.0211	0.792181	0.00252	Not Supported
Carbon Market (Blockchain)	0.086	0.342336	0.432522	Not Supported

Regression analysis reveals that there are no significant effects from transparency on market efficiency in any of the analyzed markets. A negative relationship was found between transparency and market efficiency for blockchain firms listed on the S&P 500, however, it did not pass a statistical test. As such, although theoretically greater levels of transparency could reduce price delay; the evidence was not sufficient to support this theoretical position. Furthermore, the model accounted for an extremely small amount of the variance in market efficiency, indicating that transparency plays a negligible role as well for blockchain firms.

Similar results were observed for the non-blockchain firms listed on the S&P 500, where transparency showed a negative relationship with market efficiency; however, it also did not pass a statistical test. Additionally, the explanatory power of the model was nearly zero; thus, transparency had virtually no influence in explaining market efficiency for traditional companies. Transparency demonstrated a positive relationship with market efficiency for the blockchain based carbon market; however, the result was both statistically insignificant and contrary to theoretical expectations. Although the model had a much larger explanatory power than the previous two models, the fact that the direction was opposite of expected and not statistically significant means that the result cannot be relied upon.

Therefore, the results provide no empirical evidence to support the hypothesis that transparency increases market efficiency in any of the three examined markets.

4.4.2 Price Discovery and Market Efficiency (H2)

Name	Beta (Coefficient)	p-value	R-Square	Hypothesis Support
S&P Blockchain	0.0103	0.0375	0.00223	Not Supported
S&P Non-Blockchain	0.0542	0.6306	0.00837	Not Supported
Carbon Market (Blockchain)	0.0151	0.9132	0.00757	Not Supported

The regression results show that price discovery does not have a clear or consistent effect on market efficiency across the different markets. For the S&P 500 blockchain firms, price discovery shows a positive and statistically significant relationship with market efficiency. However, this result goes against what theory suggests, since better price discovery is usually expected to reduce price delay and improve efficiency. In addition, the model explains almost none of the variation in market efficiency, which means price discovery does not explain much in this case.

For the S&P 500 non-blockchain firms, price discovery also shows a positive relationship with market efficiency, but this result is not statistically significant. The explanatory power of the model is again very low, suggesting that price discovery does not meaningfully explain changes in market efficiency for traditional firms. A similar pattern is seen in the blockchain-based carbon market, where price discovery has a positive but insignificant relationship with market efficiency and very low explanatory power.

Overall, even though price discovery appears statistically significant in one case, the direction of the relationship is inconsistent with theory across all three markets. As a result, the findings do not support the idea that price discovery leads to higher market efficiency.

4.4.3 Volatility and Market Efficiency (H3)

Name	Beta (Coefficient)	p-value	R-Square	Hypothesis Support

S&P Blockchain	-6.3141	0.1025	0.0923	Not Supported
S&P Non-Blockchain	-27.6903	0.0024	0.2842	Supported
Carbon Market (Blockchain)	3.06364	0.3739	0.3920	Not Supported

Results from the regressions indicate that volatility has different effects on market efficiency for each market type. For blockchain firms listed on the S&P 500, there is a negative relationship between volatility and market efficiency; however, it is not statistically significant. Therefore, the findings suggest that volatility could be related to changes in price delays (even though the relationship was statistically insignificant), indicating that volatility is too weak to support the hypothesis. Also, the model explains very little of the variation in market efficiency for blockchain firms listed on the S&P 500, suggesting that volatility alone can explain very little of the variation in market efficiency.

On the other hand, for blockchain firms not listed on the S&P 500, volatility had a statistically significant and negative effect on market efficiency. In essence, volatility appears to play an important role in reducing market efficiency in traditional equity markets. Volatility also had a positive relationship with market efficiency for the blockchain-based carbon market; however, the results were again not statistically significant. Although the model explained a larger portion of the variation than did the model for blockchain equity firms, the results suggested that volatility was not a meaningful factor in determining market efficiency for the blockchain-based carbon market.

Overall, the results provide support for the hypothesis only for the non-blockchain firms listed on the S&P 500, while there is little to no evidence of a relationship between volatility and market efficiency for either the blockchain-based equity firms or the blockchain-based carbon market.

4.5 Mediation Analysis: Liquidity (H4a–H4c)

This section examines whether liquidity mediates the relationship between the independent variables and market efficiency.

4.5.1 Transparency → Liquidity → Market Efficiency (H4a)

For S&P Blockchain:

Path	Beta	p-value	New Beta (Step B Transparency)	Significance
Transparency to Liquidity	0.0585	0.7804	-	Not Significant
Liquidity to	-0.0434	0.2261	-0.0255	Not Significant

Market Efficiency				

The mediation analysis indicates that neither the effect of transparency on liquidity nor the effect of liquidity on market efficiency is statistically significant; therefore, no mediating effect of liquidity is observed.

For S&P Non-Blockchain:

Path	Beta	p-value	New Beta (Step B Transparency)	Significance
Transparency to Liquidity	0.267	0.125	-	Not Significant
Liquidity to Market Efficiency	-0.0025	0.9779	-0.0204	Not Significant

For S&P 500 non-blockchain firms, neither the effect of transparency on liquidity nor the effect of liquidity on market efficiency is statistically significant, indicating that liquidity does not mediate the relationship between transparency and market efficiency.

For Carbon Market Blockchain:

Path	Beta	p-value	New Beta (Step B Transparency)	Significance
Transparency to Liquidity	-0.6200	0.5859	-	Not Significant
Liquidity to Market Efficiency	0.0095	0.9159	0.0919	Not Significant

With the above mediation analysis, it can be seen that the p-value of the Transparency to Liquidity exceed 0.1, this automatically makes the path not significant. Similarly, the studyshows that the Liquidity to Market Efficiency also has a p-value higher than 0.1, making it not significant as well. Since both the paths are not significant, it means that liquidity does not mediate a relationship between transparency and market efficiency.

4.5.2 Price Discovery → Liquidity → Market Efficiency (H4b)

For S&P Blockchain:

Path	Beta	p-value	New Beta (Step B Price Discovery)	Significance

Price Discovery to Liquidity	0.0130	0.952	-	Not Significant
Liquidity to Market Efficiency	-0.0447	0.2150	0.0108	Not Significant

For the above mentioned mediation analysis, the p-value for the Price Discovery to Liquidity is going above 0.1, this makes it not significant. The same case is for the Liquidity to Market Efficiency, which goes beyond 0.1 for the p-value, making it not significant as well. As both the paths are not significant, this study concludes that for this framework Liquidity doesn't mediate a relation between Price Discovery and Liquidity.

For S&P Non-Blockchain:

Path	Beta	p-value	New Beta (Step B Price Discovery)	Significance
Price Discovery to Liquidity	-0.4605	0.05	-	Significant
Liquidity to Market Efficiency	0.0063	0.945	0.0571	Not Significant

For this market framework of S&P non-blockchain, the p-value is below 0.1, this makes the path from Price Discovery to Liquidity as statistically significant. However, the studyindicates that the value for Liquidity to Market Efficiency's p-value exceeds 0.1, so it makes that path not significant. Since both the paths are not significant, this means that Liquidity is not a mediator for the relationship between Price Discovery and Market Efficiency.

For Carbon Market Blockchain:

Path	Beta	p-value	New Beta (Step B Price Discovery)	Significance
Price Discovery to Liquidity	-1.9836	0.0068	-	Significant
Liquidity to Market Efficiency	-0.6149	0.3830	-1.204	Not Significant

In the above results, Price Discovery to Liquidity is below 0.1, this makes the path significant again. However, in this case the Liquidity to Market Efficiency's p-value exceeds 0.1, hence making it not significant. Again, in this case as well, the study shows that the Liquidity does not mediate between Price Discovery and Market Efficiency, as both the paths were not significant.

4.5.3 Volatility → Liquidity → Market Efficiency (H4c)

For S&P Blockchain:

Path	Beta	p-value	New Beta (Step B Volatility)	Significance
Volatility to Liquidity	-33.1337	0.106	-	Not Significant
Liquidity to Market Efficiency	-0.068	0.054	-8.5690	Significant

In the above results, Volatility was close to 0.1, but still higher, hence making its path not significant. Moreover, this time the Liquidity to Market Efficiency has a p-value below 0.1, making it significant. Since both the paths did not pass as Significant, Liquidity does not mediate between Volatility and Market Efficiency in this case.

For S&P Non-Blockchain:

Path	Beta	p-value	New Beta (Step B Volatility)	Significance
Volatility to Liquidity	-36.3434	0.0908	-	Significant
Liquidity to Market Efficiency	-0.0931	0.2241	-31.07	Not Significant

In the results for S&P Non-blockchain, Volatility to Liquidity's path has p-value below 0.1, making this path significant. On the other hand, the p-value of Liquidity to Market Efficiency exceeds 0.1, this makes it not significant. As a result, the Liquidity also does not mediate in this case, as both paths were not significant.

For Carbon Market Blockchain:

Path	Beta	p-value	New Beta (Step B Volatility)	Significance
Volatility to Liquidity	-15.8945	0.7163	-	Not Significant
Liquidity to Market Efficiency	-0.0004	0.9963	3.057	Not Significant

In the market framework of carbon markets, the p-value of both the paths are above 0.1, this means that both paths become not significant. As a result, Liquidity also does not mediate in this case.

4.6 Mediation Analysis: Risk Dynamics (H5a–H5c)

4.6.1 Transparency → Risk → Market Efficiency (H5a)

For S&P Blockchain:

Path	Beta	p-value	New Beta (Step B Transparency)	Significance
Transparency to Risk	-0.0018	0.9962	-	Not Significant
Risk to Market Efficiency	-0.0750	0.008	-0.0282	Significant

With the above mediation results, the study can conclude that Risk does not mediate between Transparency and Market Efficiency. Particularly, due to the path of Transparency to Risk being not significant.

For S&P Non-Blockchain:

Path	Beta	p-value	New Beta (Step B Transparency)	Significance
Transparency to Risk	0.0894	0.6996	-	Not Signfiicant
Risk to Market Efficiency	-0.2068	0.0006	-0.0026	Significant

In this case the 2nd path is significant, but the first is not significant, due to the first path having a p-value above 0.1. As a result, it can be concluded that Risk also does not mediate between Transparency and Market Efficiency in this case.

For Carbon Market Blockchain:

Path	Beta	p-value	New Beta (Step B Transparency)	Significance
Transparency to Risk	0.00009	0.9993	-	Not Significant
Risk to Market	0.0696	0.0842	0.0859	Significant

Efficiency				

In the above results, the p-value of the 2nd path is below 0.1, while the first path has a p-value above 0.1, making the latter not significant. As a result, Risk does not mediate between Transparency and Market Efficiency in this market framework as well.

4.6.2 Price Discovery → Risk → Market Efficiency (H5b)

For S&P Blockchain:

Path	Beta	p-value	New Beta (Step B Price Discovery)	Significance
Price Discovery to Risk	-0.4018	0.1172	-	Not Significant
Risk to Market Efficiency	-0.0795	0.0083	-0.0216	Significant

For this market framework, the first path was close to 0.1, but above it, making it not significant. Meanwhile, the second path has a p-value of below 0.1, making it significant. Since both the paths are not significant, this means that Risk is not a mediator for Price Discovery and Market Efficiency in this case.

For S&P Non-Blockchain:

Path	Beta	p-value	New Beta (Step B Price Discovery)	Significance
Price Discovery to Risk	0.2433	0.4555	-	Not Signficant
Risk to Market Efficiency	-0.2157	0.0003	0.106	Significant

In the above results, the first path is not significant, due to it having a p-value above 0.1, while the second path has a p-value below 0.1. However, since both paths have not passed as significant, Risk is not considered to mediate between Price Discovery and Market Efficiency.

<u>For Carbon Market Blockchain:</u>

Path	Beta	p-value	New Beta (Step B Price Discovery)	Significance
Price Discovery to Risk	-0.05378	0.9712	-	Not Significant
Risk to Market Efficiency	0.0699	0.4573	0.0188	Not Significant

For the carbon market blockchain framework, both the paths are not significant, due to both paths having a p-value above 0.1. This results in Risk not being the mediator in the above case.

4.6.3 Volatility → Risk → Market Efficiency (H5c)

<u>For S&P Blockchain:</u>

Path	Beta	p-value	New Beta (Step B Volatility)	Significance
Volatility to Risk	123.65	5.61 × 10^-15	-	Significant
Risk to Market Efficiency	-0.269	0.0007	26.96	Significant

The mediation analysis done above shows that the path of Volatility to Risk is below 0.1, making it significant. Moreover, the second path also has a p-value of below 0.1, making that significant as well. Since both the paths are significant, this means that Risk strongly mediates between Volatility and Market Efficiency, in the case of S&P Blockchain.

<u>For S&P Non-Blockchain:</u>

Path	Beta	p-value	New Beta (Step B Volatility)	Significance
Volatility to Risk	146.1211	7.55x10^-19	-	Significant
Risk to Market Efficiency	-0.4905	0.02936	43.9866	Significant

The result in above case shows that the path of Volatility to Risk has a p-value below 0.1, making it significant. Further, the path from Risk to Market Efficiency also has a p-value below 0.1, also making it significant. Therefore, risk also strongly mediates between Volatility and Market Efficiency.

<u>For Carbon Market:</u>

Path	Beta	p-value	New Beta (Step B Volatility)	Significance
Volatility to Risk	49.262	0.0616	-	Significant
Risk to Market Efficiency	0.124	0.5963	-3.074	Not Signifiicant

In the above case, it is observed that the path of volatility to risk in this case has a p-value below 0.1, making it significant. Meanwhile, the path of Risk to Market Efficiency has a p-value of above 0.1, making it not significant. As a result, Risk does not mediate between Volatility and Market Efficiency.

4.7 Comparative Analysis Across Frameworks

The comparative analysis across the different market frameworks is taken directly from the descriptive statistics, correlation results, regression outputs, and mediation analysis that were already presented earlier in the study. Since these results were already available, no additional data collection or estimations were required at this stage. By bringing these results together, the study compares how market efficiency and its main influencing factors behave across the S&P 500 blockchain firms, S&P 500 non-blockchain firms, and the blockchain based carbon market.

In general, the results show that the relationships between transparency, price discovery, volatility, liquidity, and market efficiency are not the same across different market structures. Within the S&P 500 firms, those that have adopted blockchain tend to show lower average price delay and more stable links between market efficiency and information related variables when compared to non-blockchain firms. On the flip side, it appears as though the non-blockchain companies have a higher degree of dependency upon volatility and risk dynamics, suggesting that the traditional equity markets are subject to a greater degree of risk-related inefficiencies compared to the blockchain-based carbon market.

The blockchain-based carbon market has an entirely different behaviour. While some of the relationships in the carbon market moved similarly to those in the equity markets, the main driver of market efficiency in the carbon market was volatility and risk dynamics as opposed to transparency or liquidity alone. This demonstrates that although blockchain-based mechanisms can potentially enhance traceability and provide more information for investors, the blockchain's overall impact on market efficiency is heavily influenced by the maturity level of the market, the volume of trades and the behaviour of investors. Therefore, the overall comparison of the two markets' analyses indicate that there are no uniform results from adopting blockchain across all markets; blockchain adoption will interact with the inherent features of each individual market and influence efficiency differently.

4.8 Summary of Findings

An empirical and data-based analysis of market efficiency and its determinants is provided in this chapter for the S&P 500 blockchain companies, the S&P 500 non-blockchain companies and the blockchain based carbon market. For the first objective around measure of different variables, the statistical analysis of the descriptive statistics of the data shows there are many differences in market behaviour between the three types of markets analyzed; therefore, blockchain technology does not have the same effects in all markets. The results of the analysis using regression and correlation methods also confirm that transparency and price discovery do not lead to the same improvements in market efficiency consistently across the markets investigated; whereas, volatility and risk behaviour were shown to be significantly more influential (especially in the traditional stock markets).

In addition, the mediation analysis shows that liquidity is not a significant mediator of the relationships between transparency, price discovery and volatility, and market efficiency in any of the markets investigated. Instead, the mediation analysis indicates that risk behaviour partially mediates the relationship between volatility and market efficiency, indicating that volatility impacts market efficiency primarily through increased risk exposure, rather than through improved informational flows directly. Keeping the second objective in light, the study's findings suggest that, although blockchain technology can positively impact the informational aspects of some markets, the primary drivers of market efficiency remain largely determined by market structures, market maturity and factors associated with risk.

Lastly, for the third objective of the research, the analyses indicates that there is differences in relationship across the different market frameworks and how the blockchain adoption impacts it.

The next chapter will provide a discussion of how the findings of this study relate to prior research and how they contribute to a broader understanding of the theoretical and practical implications of blockchain technology.

Chapter 5: Discussion

5.1 Overview of the Study's Key Findings

In this chapter, the empirical and data based results that were found in the previous chapter related to Data Analysis will be discussed. Here in this chapter will also discuss them in light of the literature that was reviewed. The purpose of this discussion is to give an explanation behind why the hypotheses were not supported and what factors did influence the market efficiency of the market frameworks. In this discussion the study will also have a look at the results that each market produced and have a comparative discussion around them.

5.2 Discussion of Direct Effects (H1–H3)

The first hypothesis proposed that transparency has a positive effect on market efficiency. However, the empirical results across all three frameworks does not provide a strong support for this hypothesis. Although blockchain-adopting firms and blockchain-based carbon markets are expected to benefit from higher transparency due to immutable records and traceable transactions, the regression results indicate that transparency does not significantly reduce price delay.

Another possible reasoning behind this finding could be that transparency alone may not be sufficient to improve market efficiency if market participants are unable or unwilling to act on available information. In mature equity markets, such as the S&P 500, information is already widely available through traditional disclosure channels. As a result, incremental improvements in transparency introduced by blockchain adoption may have limited impact on how quickly prices adjust. In other words, since the index that was used to pick our firms already has information disclosure practices in place, filtering out the blockchain firms does not result in enhancement of transparency. On the other hand,in the carbon market, higher transparency seems to coexist with limited liquidity and trading, this can delay efficient price formula despite the availability of information.

The second hypothesis suggested that improved price discovery would enhance market efficiency. Similar to the transparency variable, the empirical evidence in this case also does not show support to the relationship across the examined markets. While price discovery mechanisms are theoretically linked to efficient markets, the statistical results of this study show weak and statistically insignificant effects on market efficiency, in both blockchain and non-blockchain settings.

This outcome somewhat also suggests that price discovery processes may already be relatively efficient in developed equity markets, leaving little room for further improvement through blockchain adoption. A possible exaplanation towards this could be thatin the blockchain carbon market, price discovery may be affected by low trading volume, varying investor expectations, and regulatory uncertainty. These factors can as a result weaken the link between price discovery measures and overall market efficiency, even when blockchain infrastructure is present.

The third hypothesis examined the effect of volatility on market efficiency, and it proposed that. The results indicate that volatility plays a more prominent role in influencing the market efficiency variable, as compared to transparency and price discovery variables. In particular, the volatility variable shows a significant negative relationship with market efficiency in non-blockchain S&P 500 firms.Whereas, its effects are weaker or insignificant in blockchain-adopting firms and the carbon market.

These findings align with the view that high volatility reflects uncertainty and unstable trading conditions, which can slow down the integration of information into prices. In the traditional equity markets, volatility appears to be a significantfactor contributing towards inefficiency. In blockchain-related markets, volatility may already be higher, especially in the carbon market, which could be the reason as to why its direct impact on market efficiency is less observed.

5.3 Discussion of Liquidity as a Mediating Variable (H4)

The Hypotheses H4a, H4b and H4c, examined whether liquidity mediates the relationship between transparency, price discovery, volatility, and market efficiency, and with what intensity. The mediation analysis done in the study consistently showed that liquidity does not serve as a significant mediating factor across any of the three examined market frameworks.

These results suggest that even though blockchain adoption is often expected to improve liquidity by reducing transaction costs and increasing participation, such factors may not be strong enough to influence market efficiency indirectly. This was consistently shown in our empirical analysis. In the equity markets (S&P Blockchain and S&P Non-blockchain), liquidity is influenced by a wide range of multiple factors such as size of the firm, the ownership, and the market conditions, which can overshadow the effects of blockchain adoption. In the carbon market, liquidity remains uneven across the tokens examined in our carbon markets, and in this case increased transparency does not necessarily translate into higher trading activity.

Such results and the absence of liquidity mediation highlights that improved trading volume alone does not guarantee faster price adjustment. Market efficiency appears to depend more on how risk and uncertainty are managed rather than on liquidity conditions alone.

5.4 Discussion of Risk Dynamics as a Mediating Variable (H5)

The mediation analysis for hypotheses H5a, H5b and H5c, provides more varying insights. While risk dynamics did not mediate the relationships involving transparency and price discovery, it partially mediated the relationship between volatility and market efficiency across all three frameworks.

The findings indicate that volatility impacts market efficiency mainly through its effect on risk exposure. As volatility increases, the level of perceived risk in the market also rises, which slows down the process of information incorporation and price adjustment. This relationship is particularly evident in markets where uncertainty is high or where investors tend to be risk averse, such as the blockchain-based carbon market. It is also important to mention that although volatility and risk are closely linked and often rely on similar measurables, they were treated as conceptually separate variables for the purpose of this study.

The partial mediation observed in the results further supports the argument that blockchain-related markets are more sensitive to risk transmission rather than purely information-based improvements. Therefore, even in the presence of higher transparency and improved price discovery mechanisms, elevated levels of risk can limit their effectiveness and result in persistent market inefficiencies.

5.5 Cross-Market Comparison and Structural Differences

There was visible differences found in the comparative analyses of the study against the three market frameworks. Keep in mind, that the comparative analyses was kept on a conceptual level and did not involve any additional calculations or derivations. It was observed that the S&P 500 Blockchain firms showed better market efficiency and slower Price Delay, compared to the Non-blockchain counterpart. Risk and Volatility remained the driving factors of efficiency, rather than the Price Discovery, Liquidity and Transparency in the case of the S&P Blockchain firms..

On the other hand, the non-blockchain firms of S&P showed a lot of inconsistencies and variation in its Risk Dynamics and Volatility variable. This can point to the fact that traditional non-blockchain firms are more vulnerable to inefficiencies. Moreover, the blockchain based carbon market showed a completely different pattern, as it showed consistent but low values for the volatility and risk variables. This means that the market is currently in its early stages and is transitioning towards being a more mature financial framework. It can also point towards speculative trading behaviour and inefficiencies in the regulations.

The findings of the study suggests that blockchain adoption doesn't necessarily replace the market structure, rather it simply interacts with it.

5.6 Practical and Policy Implications

The findings made by the studies provides several implications. For the firms, in the order to increase the market efficiency to the maximum, the risk management practices need to be employed alongside the blockchain adoption. Next, for the investors, the study suggests that adopting blockchain will always carry significant amount of risk, regardless of providing higher transparency or not. Lastly, for the regulators, they should not rely on the technological advancements rather the focus should mainly be on clarifying the regulations around blockchain adoption and reducing the instability/uncertainty in the market.

In line with the first research objective, it can be seen that increasing the transparency doesn't result in increase in market efficiency, especially when volatility remains high. In conclusion, firms or policy-makers aiming to adopt the blockchain technology should make sure to complement it with other technologies that assist in controlling the volatility.

In order to maximize the market efficiency in the carbon credits market, through blockchain adoption, the policymakers will need to work on enhancing the regulatory compliance, standardization and removing unnecessary obstacles towards adoption of blockchain.

For the second objective, it is observed that there is a critical mediating role of risk dynamics and liquidity when it comes to market efficiency. This means that firms that wish to adopt blockchain should invest in risk management and liquidity management strategies.

According to our empirical results, the blockchain may not have outright benefits or differences as suggested on a theoretical level. This may be interpreted with caution as there could be several reasons towards this. Primarily due to the study using recent and limited data of the years (2024-2025).

Lastly, for the final objective, the results show that the impact of blockchain varies throughout the different market frameworks. This means that the policy-makers will need to keep the impact in mind and customize their policies according to the type of the market.

5.7 Summary of the Discussion

In summary, this chapter has shown that blockchain adoption does not improve market efficiency across different markets, as promised in prior literature. According to the results,transparency and price discovery play limited roles in the examined market framework, while volatility and risk dynamics emerged as the key significant drivers of inefficiency. Liquidity did not act as a significant mediating mechanism, whereas risk partially mediated the impact of volatility on market efficiency. These findings showthat market structure and maturity of the market frameworks are important in determining the effectiveness of blockchain related solutions.

Chapter 6: Conclusion

6.1 Summary of the Study

This study examined the impact of blockchain adoption on market efficiency across three different market frameworks: S&P 500 blockchain firms, S&P 500 non-blockchain firms, and the blockchain-based carbon market. In the study, the Market Efficiency was measured using the Price Delay as the measurable, meanwhile the others such as Liquidity, Transparency, Price Discovery, Risk Dynamics and Volatility were kept as the independent or mediators in the framework.The study also looked into the mediating roles of the two factors and to assess how they affect each variable with the Market Efficiency.

For our analyses, the study used descriptive statistics, correlation analysis, regression models, and mediation analysis. As a result, the study provided a comparative and extensive assessment of how blockchain adoption interacts with marketstructure and maturity of the frameworks.

6.2 Key Findings

The empirical results of the study indicate that by adopting blockchain, it does not automatically translate to increase in market efficiency. Although the theory suggests that blockchain directly improves the transparency and the flow of information in a market, the study suggests otherwise. It suggests that when looked at the data, both the Price Discovery and the Transparency do not consistently affect the Market Efficiency across the three different markets. In short, the flow of information alone is not the deciding factor of price adjustments.

Moving towards Volatility and Risk, they both proved to have a significant role in influencing the Market Efficiency. In the traditional S&P 500 Markets (Blockchain and Non-blockchain), the higher the volatility and risk got, the lower the market efficiency became. This trend was especially noticeable in the non-blockchain firms. In both the blockchain based markets (S&P Blockchain and Carbon Market), the volatility was a more dominant factor than risk dynamics in determining the value of market efficiency. Coming towards the mediation effects, Risk Dynamics partially mediated the relationship between Volatility and Market Efficiency. Meanwhile the other independent variables did not mediate significant with Risk Dynamics. Meanwhile for liquidity, it did not properly mediate thoroughout the variables affecting the Market Efficiency.

While comparing the different market frameworks and applying comparative analyses, it was observed that the blockchain adoption does not replace, rather it interacts with the existing markets. In traditional equity market, blockchain provided greater returns and benefits. Meanwhile, in the more innovative markets like the carbon credits market, market efficiency was observed to be low, primarily due to factors like not being a mature market, regulatory uncertainty and skewed liquidity.

6.3 Implications

This study challenges the results and points made by the prior literature around blockchain adoption improving the market efficiency of the financial markets. The study, through its empirical evidence, also suggests that in the blockchain-based carbon market, risk plays a significant role in the result of the market efficiency. However, this is not the case for the other two market frameworks.

The results also suggest that in order to leverage and enhance market efficiency, one must couple blockchain with additional risk management strategies. This study also provides a disclaimer or suggestion to the investors that they need to be more cautious when evaluating the adoption of blockchain, as statistical data tell a different story. The study also implies that the study should not solely rely on the technological advancements to hope for efficient markets. Rather, the policy makers should also gauge into clarifying the regulatory terms and stabilizing the market, instead of assuming that the transparency provided by the blockchain would automatically improve the efficiency. The study also recommends that stakeholder take an empirical or data-driven approach towards assessing blockchain adoption, rather than solely relying on theoretical information.

6.4 Limitations and Future Research

The study faces certain limitations such as the limited time period of the data obtained, a small sample size (especially for the carbon market), the use of different measurables within a single variable, and the access to data for different types of measurables. Future research seeking to carry out their studies in this domain should analyze with data that has longer time period, larger sample size, additional types of markets and having different types of analyses and measurables available for Market Efficiency and Transparency. Moreover, further different types of data analyses techniques should also be tested. Further studies can also examine how blockchain adoption can be made effective through development in its regulatory oversight.

6.5 Concluding Remarks

To conclude this study, it was found that the adopting blockchain does not directly enhance or impact the market efficiency across the three market frameworks that were set. In theory, blockchain is supposed to improve the transparency and market efficiency; however, in practice, volatility and risk dynamics are the deciding factor for market efficiency. Meanwhile, blockchain's adoption supports the enhancement in transparency. The findings emphasize and suggest that the blockchain in financial and environmental markets are dependent on important factors such the maturity of the market and the overall structure. In other words, the empirical results contradict with the theoretical interpretations and expectations.

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Appendix

This appendix provides the companies that were used as our data for the research.

I. <u>S&P 500 Blockchain Companies:</u>

1. IBM (IBM)
2. Microsoft (MSFT)
3. Amazon (AMZN)
4. Alphabet / Google (GOOG)
5. Meta Platforms / Facebook (META)

6. NVIDIA (NVDA)
7. Intel (INTC)
8. Visa (V)
9. Mastercard (MA)
10. PayPal (PYPL)
11. JPMorgan Chase (JPM)
12. Bank of America (BAC)
13. Goldman Sachs (GS)
14. Morgan Stanley (MS)
15. Walmart (WMT)
16. Starbucks (SBUX)
17. Tesla (TSLA)
18. Oracle (ORCL)
19. Cisco Systems (CSCO)
20. Accenture (ACN)
21. Salesforce (CRM)
22. Adobe (ADBE)
23. Qualcomm (QCOM)
24. American Express (AXP)
25. Verizon Communications (VZ)
26. AT&T (T)
27. Nike (NKE)
28. Disney (DIS)
29. Home Depot (HD)
30. Boeing (BA)

II. <u>S&P 500 Non-blockchain Companies:</u>

1. The Coca-Cola Company (KO)
2. PepsiCo (PEP)

3. McDonald’s (MCD)
4. Procter & Gamble (PG)
5. Colgate-Palmolive (CL)
6. Kimberly-Clark (KMB)
7. Johnson & Johnson (JNJ)
8. Merck & Co. (MRK)
9. Pfizer (PFE)
10. AbbVie (ABBV)
11. Bristol-Myers Squibb (BMY)
12. Eli Lilly & Co. (LLY)
13. Costco Wholesale (COST)
14. Target (TGT)
15. Lowe’s Companies (LOW)
16. General Mills (GIS)
17. CVS Health (CVS)
18. Exxon Mobil (XOM)
19. Chevron (CVX)
20. NextEra Energy (NEE)
21. Duke Energy (DUK)
22. Southern Company (SO)
23. American Airlines Group (AAL)
24. Delta Air Lines (DAL)
25. United Airlines Holdings (UAL)
26. D.R. Horton (DHI)
27. ProLogis (PLD)
28. Keurig Dr Pepper (KDP)
29. Mondelez International (MDLZ)
30. Kraft Heinz (KHC)

III. Carbon Credits Blockchain Tokens:

1. BCT (Base Carbon Tonne)
2. NCT (Nature Carbon Tonne)
3. MCO2 (Moss Carbon Credit)
4. KLIMA (KlimaDAO Token)