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Does a Market Reaction Occur as a Result of Companies Accepting Cryptocurrency as Payment?

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ABSTRACT

This paper examines whether a market reaction occurs due to publicly traded companies announcing their acceptance of cryptocurrency as a form of payment. The rationale behind this research is that there has been observable dramatic investor sentiment on the use and existence of cryptocurrency both as a currency and an investment vehicle. We theorize that due to investors' strong opinions on cryptocurrency, there may be a market reaction to a company's announcement of its acceptance. To test this, we perform an event study on a sample of thirty firms in addition to multiple levels of analysis on the performance and characteristics of the firms. We find that firms announcing their acceptance of cryptocurrency tend to be small, fall into the information technology or consumer discretionary sectors, and underperform the market index. We also find no abnormal returns on or directly after the event dates, indicating no market reaction due to the event. We believe further research and testing can be done to determine why these firms are significantly underperforming the index and if there is any correlation to their associations with cryptocurrency.

TABLE OF CONTENTS

LIST OF TABLES

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Chapter 1

Introduction

The first cryptocurrency was launched in 2009 by a person or a group operating under the pseudonym of Satoshi Nakamoto (Pinkerton 2023). This cryptocurrency, known as Bitcoin, later paved the way for many other cryptocurrencies. Cryptocurrency is a purely digital currency, an alternative form of payment created using encryption algorithms. This use of encryption technologies allows cryptocurrencies to function both as a currency and as a virtual accounting system for the transactions concerning each currency. Since its initial introduction, it has been widely debated how to classify cryptocurrencies. They are too volatile to define as a currency technically, and many people treat them like investments.

Regardless of classification choice, it is undeniable that cryptocurrency has found a place in our financial markets, and many researchers are investigating how to best use and trade cryptocurrencies. In this paper, we take a different approach and instead analyze whether or not a firm's announcement of the acceptance of cryptocurrency as a form of payment for its particular goods or services affects its stock price or returns. The justification is that financial market participants tend to be quite opinionated on cryptocurrency, and many professionals argue against holding cryptocurrency as a type of investment asset class. This study explores whether these skepticisms translate to the companies they invest in.

To test this hypothesis, we collect a sample of 30 publicly traded firms that publicly announced their acceptance of cryptocurrency as payment. We then classify the firms by market capitalization and announcement date and divide each classification into two groups, creating four subsamples overall. Most firms fell into the small market capitalization and later period subsamples. We then performed an extensive event study methodology to check for abnormal returns in the five days preceding and following the announcement date. We found that there were no statistically significant abnormal returns following the announcement. However, there were negative abnormal returns found in the main sample and the subsamples containing the majority of each classification on the day preceding the announcement. We also go further and test the performance of the samples with multiple risk-adjusted models for both the short and long term. We found that the samples generally underperformed their benchmark in both the short and long run on a risk-adjusted and raw return basis.

The organization of the rest of the paper is as follows: Chapter 2 reviews the previous literature on cryptocurrency in connection with the stock market. Chapter 3 presents our hypothesis and methodology and explains the methodology for collecting the data sample. Chapter 4 details our empirical results, and Chapter 5 discusses our results and conclusions.

Chapter 2

Literature Review

Little to no research exists on the effects of a company accepting cryptocurrency as a form of payment for their product or services. However, significant research exists on whether cryptocurrency markets move in correlation or relation to the stock and commodity markets. This research is crucial in exploring the investment and diversification qualities cryptocurrency can have for asset managers. Kumaran (2022) uses the vector error correction model to explore the relationship dynamics between five major cryptocurrencies (i.e., Bitcoin, Litecoin, Ethereum, Ripple, and Neo) and the Middle Eastern Stock Market indices. Kumaran's model finds that the cryptocurrencies were co-integrated, meaning that over the evaluated time frame, the cryptocurrencies' movements were correlated to one another. Conversely, the cryptocurrencies were not co-integrated with any stock market indices, indicating no co-movement between middle eastern stock market indices and cryptocurrency markets. Kumaran concludes from the latter finding that cryptocurrency can be an option for portfolio diversification.

The middle eastern stock markets are not the only international markets that have been shown not to move in correlation with their related cryptocurrency markets. Nyakurukwa and Seetharam (2022) evaluate stock and cryptocurrency market integration in Africa under an information-theoretic framework. Under this framework, a significant flow of information indicates integration between markets. The study finds a weak flow of information between Bitcoin (the most prominent cryptocurrency in Africa) and African stock exchanges, indicating that African stock exchanges are weakly integrated with Bitcoin. Kumah and Odei-Mensah (2021) find the opposite regarding integrating African stock exchanges and cryptocurrency markets. Using wavelet-based methods and frequency domain spillover index, Kumah and Odei-Mensah find that the “medium-term” African stock markets are highly integrated with cryptocurrency markets. The conflict between these studies implies that the timeframe may affect the co-integration of African stock exchanges and cryptocurrency markets. A study conducted in Vietnam by Ha et al. (2022) have findings similar to those of Kumah and Odei-Mensah in that Vietnam’s stock market is significantly impacted by movements in their cryptocurrency market, specifically Bitcoin and Ethereum due to their large market capitalization in Vietnam. The findings of Ha et al. in Vietnam are parallel to that of China and Taiwan, as determined by Chi-Ming Ho (2020) in a comparative study utilizing the capital assets pricing model and foreign exchange exposure theory to investigate how stocks are affected by cryptocurrency. It was found that both China and Taiwan stocks were impacted by cryptocurrency but with a higher effect in China than in Taiwan.

The above findings show that the integration and correlation of cryptocurrency markets and stock exchanges vary from region to region. As a result, it can be inferred that the diversification benefit of cryptocurrency in an equity portfolio will vary from region to region. A review performed by Chupradit et al. (2021) confirms this inference in its findings that cryptocurrencies have varying connectedness to stock market volatility and economic policy across the globe. So therefore, the ability of cryptocurrencies to mitigate portfolio risk varies between economies. In a more extensive study of cryptocurrency and stock markets, Shanaev and Ghimire (2022) use a generalized seasonality test with sequential dummy variable regressions to test for any seasonal patterns across 76 national stock markets and 772 cryptocurrency markets. This seasonality test was used to detect the existence of trading cycles and the length of those cycles and as a test of the weak-form efficient market hypothesis. The test operated under a null hypothesis of no seasonality.

Despite the conceptual and computational simplicity of the test, the results are quite insightful. The result of the most relevance to the cryptocurrency market is that cryptocurrency markets were shown to be more susceptible to seasonal anomalies and yet displayed unconventional seasonal patterns at the same time. This finding indicates that cryptocurrency markets are less efficient than stock markets and are uncorrelated with stock markets regarding seasonal patterns. Dong et al. (2022) find contrasting results to those of Shanaev and Ghimire regarding correlations between cryptocurrency and stock market anomalies. Through a custom model, Dong et al. found that many widely recognized anomalies in the stock market could also be observed in the cryptocurrency market. Because these findings are generalized to market anomalies, many market anomalies other than seasonal ones may be found in cryptocurrency and stock markets. As a result, the two studies do not necessarily conflict in their findings. Cryptocurrency and stock markets can be compared in more ways than anomalies and integration. Using a dynamic modeling approach, Borgards (2021) explores the momentum effect of twenty cryptocurrencies compared to the U.S. stock market. The dynamic modeling approach allows for a test of momentum periods following the formation period for interday and intraday price levels. The findings show that cryptocurrencies have significantly longer and larger momentum periods than the U.S. stock market. This difference is attributed to cryptocurrencies having a higher degree of noise traders than the U.S. stock market.

So far, previous research comparing cryptocurrency and stock markets worldwide shows various similarities and differences that depend on what is being compared and where it is being compared. Most of the research points to cryptocurrency markets having different properties and being uncorrelated to the relevant stock markets. Dheeriya and Malladi (2021) confirm this argument from a global perspective through a time series analysis of the returns of the two cryptocurrencies, Bitcoin and Ripple, and the global gold and stock markets. Their findings show that the global stock and gold markets do not affect these cryptocurrencies' returns. There is, however, an effect on Bitcoin prices due to Ripple returns. This finding indicates there is integration between cryptocurrencies. Hossain and Ismail (2021) utilize various econometrics models to further evaluate potential correlations between cryptocurrencies. Specifically, they focus on how other cryptocurrencies, such as Ethereum, Litecoin, Zcash, Monero, and Dash, influence Bitcoin. The Findings of Hossain and Ismail confirm the findings of Dheeriya and Malladi, showing significant correlations between other cryptocurrencies and Bitcoin, including Ripple.

Thus far, it can be observed that cryptocurrency markets are correlated and affected by other markets and cryptocurrencies to varying degrees worldwide. However, these are not the only areas researched regarding the effect of cryptocurrencies. Researchers have examined social sentiment, macro-financial factors, and exchange rates more specifically. Kim, Lee, and Assar (2022) investigate how social sentiment about cryptocurrencies observed on various platforms in South Korea affects cryptocurrency market behavior through a hidden Markov model. This model reveals the extent to which the chosen cryptocurrency markets may shift due to posts on social media and stock market sites about said markets and the patterns of these markets under both bull and bear market conditions. Three key conclusions could be drawn from the results of the model. The first is that social sentiment affects cryptocurrency markets, but more so during bull markets than bear markets. That said, positive social sentiment has a greater observable impact during bear markets, while negative social media sentiment has a greater observable impact on bull markets. This finding implies that cryptocurrency investors are reactive to the sentiment that indicates the opposite outlook of the current market standing. Jayaraman and Koranteng (2019) express similar findings while investigating whether specifically *celebrity* social media sentiment has an effect/can be a predictor of cryptocurrency market behavior and returns. A more specific look was taken using Twitter messages containing sentiment regarding cryptocurrency and stocks. A daily times series of these posts were regressed against the daily returns of the S&P 500, DJIA, Bitcoin, and Ethereum. It was found that these sentiments are a significant predictor of returns and behavior in both the equity indices and cryptocurrencies previously listed. However, the sentiments were a stronger predictor of the cryptocurrencies than the equity indices. Additionally, positive sentiments were a stronger predictor of equity and cryptocurrencies than negative sentiments.

Moving away from social factors, researchers have examined various economic factors focusing on interest and exchange rates. Havidz, Karman, and Mambea (2021) conduct a comprehensive study of eighteen countries and 2,826 total observations regarding foreign exchange rates, stock market indices, interest rates, and gold. Applying a fixed-effect model and generalized method of movement yielded a few significant results. Firstly, Bitcoin trading is amplified by the U.S. Dollar, meaning an increase in U.S. interest rates will decrease investors' intention to invest in Bitcoin as a speculative asset. Vivien and Martin (2022) approach this issue differently by looking at specific events and their effects on cryptocurrency exchange rates. A going concern in cryptocurrency markets is cyber-attacks because cryptocurrency is completely digital. Through an event study, Vivien and Martin determine that cyber-attacks did not significantly impact the exchange rates of Bitcoin and Ethereum. That said, there were effects due to regulatory action. However, any effects were found to be short-lived.

It can be seen that cryptocurrency is used globally, and many social, economic, and financial factors impact investor behavior. So, investors do buy it, and their choices to buy and sell are affected by various elements. Still, the question of what type and why investors choose cryptocurrency as an investment vehicle has yet to be answered. Bonaparte (2022) examines who owns cryptocurrency and how the average cryptocurrency owner views cryptocurrency as an investment asset. The research finds that college degree holders and investors who directly own stocks (meaning not through a fund or other indirect investment vehicle) are the most common groups to own cryptocurrency. In other words, educated and financially literate households are most likely to invest in cryptocurrencies. The research also indicates that the investment time horizon significantly impacts the propensity to hold cryptocurrency. Specifically, households with long time horizons were more likely to own cryptocurrency. In summary, educated, financially literate investors with long time horizons are those most likely to invest in and buy cryptocurrency. This result indicates that these investors do not view cryptocurrency as a speculative asset class but as a pseudo-productive/long-term asset class.

Despite the above research indicating that the investors who most commonly invest in cryptocurrency view it as a long-term pseudo-productive asset, significant research shows cryptocurrency to be useful to investors in other ways and the best way to do so. Cryptocurrency has been proven to not act or react the same as traditional investments like equity. He et al. (2022) find that their HAR-SPCA model through external information is statistically effective at predicting and forecasting Bitcoin. Liu et al. (2022) use a three-factor model of the cryptocurrency market, size, and momentum to predict expected cryptocurrency returns effectively. This model uses ten characteristics of cryptocurrency drawn as stock market counterparts to formulate long and short techniques that result in statistically significant sizable returns in the cryptocurrency market. Bruzgė and Šapkauskienė (2022) take a risk mitigation approach to maximizing cryptocurrency returns. Through the exploration of arbitrage data Bruzgė and Šapkauskienė find that using the correct exchanges can mitigate the risk of investing in Bitcoin. Network analysis showed that Bitstamp and Kraken lead in market-forming trends. As a result, they are the best for buying Bitcoin.

Conversely, Cexio, Bitmarketlt, and Coindeal are the best for selling. This research shows that knowing which exchanges are best for selling and buying allows cryptocurrency investors to take advantage of any arbitrage opportunities and mitigate their risks while buying and selling Bitcoin. Basios et al. (2021) approach the issue from yet another perspective through the lens of machine learning. Due to the volatility of popular cryptocurrencies, predicting the short to mid-term is difficult. Using machine learning, Basios et al. can predict live exchange mid-price movements of Bitcoin to U.S. dollars with 78% accuracy. Borgards and Czudaj (2021) move away from the technical side of investing towards a behavioral approach by investigating overreaction strategies. Their research analyzes features of market overreaction and their ability to enhance prediction for twelve cryptocurrencies and the S&P 500. It was observed that an overreaction strategy could enhance prediction in both the stock and equity markets. Still, the results were significantly stronger in the cryptocurrency market, with positive overreactions rather than negative ones.

The above literature details the various ways that have been researched to maximize returns and mitigate risk while traditionally investing in cryptocurrency. That being said, cryptocurrency has been shown to have other uses like hedging and diversification. Jiang et al. (2021) explore the effectiveness of cryptocurrency as a haven and diversifier, as well as its hedging ability. Using a novel quantile coherency approach and daily cryptocurrency data, it was determined that the examined cryptocurrency showed a positive dependence on stock indices, indicating that it could not act as a haven or be effective in hedging for said stock indices. It does suggest, however, that cryptocurrency could be an effective diversifier. Specifically, Ethereum stands out as the most effective short-term diversifier. Similar research by Bayracı and Demiralay (2021) yielded similar results regarding using cryptocurrency as a diversifier in equity portfolios. It was determined that due to low time-varying correlations between cryptocurrencies and stock markets, cryptocurrency was an effective diversifier up until late 2017, when diversification benefits vastly diminished. Bandhu Majumder (2022) investigated both cryptocurrency's hedging and safe haven ability in India and find partially conflicting results. Through the analysis of both the Indian stock market and the broader market indices, it was found that cryptocurrency did display significant hedging abilities against the stock market but was not shown to be a safe haven asset.

Similar to the research discussed above, a significant portion of the literature on cryptocurrency and the stock market discusses the potential uses cryptocurrency could have served during the COVID-19 Pandemic, specifically its safe haven and hedging ability. Agata Kliber (2022) investigates what could have been the best assets to use as a safe haven for investors in the American market during and since the COVID-19 pandemic. Kliber studies quantile coherency between the S&P 500 and all traditional and new asset classes, including U.S. bonds, gold, silver, stable coins, and popular cryptocurrencies (Bitcoin and Ether). The study of quantile coherency between the S&P 500 and each asset class aims to find the respective conditional correlation over a research period of March 2020 to May 2022. During this period, it was found that all of the studied asset classes had safe haven properties, which varied over time. Additionally, dynamic correlation analysis found that only centralized stablecoins, a type of cryptocurrency considered stable based on a stable commodity or currency, could have been effectively used as a safe haven against the American stock market during the COVID-19 pandemic. This result does not say the other asset classes could not have been used as a safe haven. However, using Kliber's methodology, stable coins would be the only studied cryptocurrencies proven effective.

Kliber conducts another study with Barbara Będowska-Sójka (2021), primarily in the Chinese stock market and only studying gold, Bitcoin, and Ether. The study also explores the asset class abilities in American and European markets. However, the chosen time frame was specifically based on turbulence in the Chinese stock market. They explain that a safe haven is a financial asset that allows an investor to protect his portfolio during times of market turmoil, like such created by the pandemic. Their study covers the five years between pre-existing Chinese stock market turbulences in 2015-2016 up to the end of the pandemic, ending in 2020. The results varied in strength across both the asset classes and the markets. Ether is a weak but possible safe have against the DAX and S&P 500, while Bitcoin is the same against the FTSE 250, STOXX 600, and S&P 500. Gold is the only asset class the study found to be a strong safe haven during the above-noted turbulences, specifically in the Chinese market. However, Będowska-Sójka and Kliber do note that all of the safe haven abilities observed in any of the asset classes cease right after the end of the turbulence caused by the COVID-19 pandemic.

In a more extensive analysis of cryptocurrency's ability to act as a safe haven asset during the pandemic, Jeribi et al. (2021) investigate the safe haven properties of five different cryptocurrencies (Bitcoin, Ethereum, Dash, Monero, and Ripple) in addition to gold against the BRICS (Brazil, Russia, India, China, and South Africa) stock markets during the pandemic. They utilize nonlinear autoregressive distributed lag (NARDL) methodology to compare the pre-pandemic period of 2016-2019 to the pandemic period of 2020. The results varied across the currencies, markets, and periods. They find Hash and Ripple a safe haven for all five of the BRICS markets in the pre-pandemic period. Alternatively, during the pandemic, all five cryptocurrencies were found to be effective safe havens in Brazil, China, and Russia. Lastly, gold was only found to be an effective safe haven in Brazil and Russia during the pandemic. Barbu et al. (2022) conduct a similar study except with the added dimension of cryptocurrencies having properties of a diversifier in addition to a safe haven. To do this, they employ a threshold regression conditioned to test the ability of Bitcoin and Ether to exhibit short-term safe haven or diversifier features in both stock and bond markets. It was found that both Ether and Bitcoin can fulfill a diversifier role in the stock market indices and a safe haven role in the bond market during the pandemic. It was also discovered that during increasing reported COVID-19 cases/deaths, the statistical relationship between the studied cryptocurrencies and markets weakened.

Taking a different approach to the uses of cryptocurrency during the pandemic, Maitra et al. (2022) explore how cryptocurrency can serve as a hedging tool for the major equity markets during the pandemic. This study employs copula models with five-minute price data to assess both the hedging effectiveness and the risk spillover from Bitcoin and Ethereum to eight international stock markets during pre-pandemic and pandemic periods. The results indicate that the pandemic increased risk spillover from Bitcoin and Ethereum to stock market returns. Additionally, they find the potential for hedging gains during the pandemic. However, the cost of hedging increased while the return on normal investment in cryptocurrencies decreased. The findings confirm that the studied cryptocurrencies would not have provided incremental gains from hedging stock market risk during the pandemic. Yousaf and Ali (2021) find confounding results regarding spillover between cryptocurrencies and stock markets during pre-pandemic and pandemic time frames. Yousaf and Ali take a somewhat different approach and evaluate the return and volatility spillover between major cryptocurrencies (Litecoin, Bitcoin, and Ethereum) and the S&P 500 through a VAR-BEKK-AGARCH model on hourly instead of 5-minute data. They also seek to quantify these currencies' optimal portfolio weights and hedge ratios with the market during the specified periods. It was found that there was no significant return or volatility spillover during the pre-pandemic period. However, there was a unidirectional volatility spillover between the S&P 500 and Litecoin during the pandemic but no notable spillover with the other currencies. In terms of portfolio weight, they found that during the pandemic, the hedge weight of the S&P 500 to each of the currencies was higher, implying higher hedging costs during that time than in the pre-pandemic period. Despite these findings, Yousaf and Ali recommend that based on the optimal portfolio weights found in their research, investors should have decreased their investment in the S&P 500 relative to the studied cryptocurrencies for optimal hedging.

Moving away from the various potential uses of cryptocurrencies during the COVID-19 pandemic, the remaining literature explores how the pandemic may have affected cryptocurrency price dependencies, portfolio allocations, market behavior, and investor sentiment. Of these topics, Aysan et al. (2021) examine the inter-relationship of nine (Bitcoin, Ethereum, Ripple, Litecoin, Eos, BitcoinCash, Binance, Stellar, and Tron) of the top cryptocurrencies during pre-pandemic and pandemic timeframes based on daily closing price data from 2017-2020. They find strong evidence of a long-run relationship between Bitcoin and Altcoins during both studied timeframes. Additionally, it was found that these same currencies' relationship and pricing were resilient to the pandemic. These findings support the previously discussed research that correlates to cryptocurrencies' potential for hedging, safe haven, and diversification abilities. Alternatively to the impact of the pandemic on cryptocurrency behavior and relationships discussed above, Altınbaş (2022) discusses the change in investor asset class preference during the pandemic through a cross-sectional study performed in Turkey. It was found that Turkish investors generally increased their risk propensity during the pandemic and increased their investment in cryptocurrencies and stocks. Ngo and Nguyen take a different approach to the change in investor behavior and evaluate whether or not the change in public sentiment due to the pandemic created the “V-shaped” behavior observed in the global financial markets at that time. Through the use of a text-mining technique on a large dataset of tweets, they found that fearful public sentiment as a result of discourse regarding COVID-19 and financial topics and then a subsequent reversal of that fear towards the end of the pandemic contributed significantly to the V-shaped behavior of stock and cryptocurrency markets.

The last piece of literature, and possibly the most relevant to our research, is exploring the impact of blockchain or cryptocurrency-related name changes on firm performance by Akyildirim et al. (2020) in a study published in *the Journal of Corporate Finance*. Although this does not directly match our research, it does venture into the realm of strong profitability/returns potentially being impacted by the association with cryptocurrency due to investor sentiment. To explore this, the study utilizes a sample of 82 companies that changed their names from December 2015 through June 2019. They then divided the sample into two groups containing name changes with cryptocurrency or blockchain components and without cryptocurrency or blockchain components to effectively compare the results of the two subsamples in their analysis. The study resulted in four major findings. Firstly, they found that crypto-related name changes directly harmed a company’s profitability in the short term, in addition to being correlated to a decrease in the company’s financial leverage in the quarter following the announcement. Secondly, they found evidence of significant “crypto-exuberant” pricing premiums that persisted up to six months after the announcement. Thirdly, they found a sharp increase in companies’ share price performance volatility with blockchain or cryptocurrency-related named changes. Lastly, they found that the companies partaking in name changes involving blockchain or cryptocurrency components were thereafter subject to changing market perception and associated with higher-risk cryptocurrency markets. However, no corporate structural changes correlated with these name changes or results.

Based on these four major findings, Akyildirim et al. conclude that these name changes have generated information asymmetry in the market and masked the transparency of the true operations of the companies involved to investors.

Chapter 3

Hypothesis and Methodology

Our null hypothesis is that the announcement of cryptocurrency acceptance will not affect a firm's stock price. Our alternative hypothesis is that the announcement of the acceptance of cryptocurrency will have a negative effect on a firm's stock price. To test this, we analyze the abnormal returns of eleven trading days surrounding the announcement date of each of the companies in the data sample with an event study. These eleven days represent the five trading days before the announcement date, the announcement date, and the five trading days after the announcement date. We also test the long-term effect after the announcement using several risk-adjusted measures. The Sharpe ratio (Sharpe 1966), Treynor ratio (Treynor 1965), and Jensen's Alpha (Jensen 1968) are used to analyze the samples' returns adjusted for risk. We also use the 3-factor (Fama and French 1993) and 5-factor (Fama and French 2015) Fama-French models to measure risk-adjusted returns in the long term with various factors. Lastly, we calculate and analyze the market capitalization, return on assets, and book-to-market ratios of all the samples to gain further insight into the normal characteristics and distribution of the firms in each sample.

Data Sample

Our data sample was collected by manually searching the Nexis Uni database for news announcements containing "acceptance of cryptocurrency." After the preliminary collection of companies with this announcement, the sample was further narrowed down to publicly traded and domestic companies so that an event study could be done all at once. The dataset was further narrowed to companies with available data from the CRSP dataset at the announcement date. We eliminated companies with no return data from CRSP and companies only listed on foreign stock exchanges. The market capitalizations and year of announcement further defined the subsamples. We then were able to create four subsamples by dividing each of these into two categories. The sample was divided into small and large market capitalization and announcements before and after COVID-19. These divisions created subsamples labeled Small Market Capitalization Companies (referred to as Small Company Subsample), Large Market Capitalization Companies (referred to as Large Company Subsample), Years 2014-2019 (referred to as Period 1 Subsample), and Years 2020-2022 (referred to as Period 2 Subsample).

We also broke down our data samples by GICS sectors. All the samples fell into one of five sectors: Consumer Discretionary, Health Care, Financials, Information Technology, and Communication Services. With the majority of the companies falling in either Information Technology or Consumer Discretionary. These findings also hold when classifying the four previously discussed subsamples by sector. We believe it makes sense that most firms in the data sample would fall into Information Technology because technology firms tend to work closer with cryptocurrency and be quicker to take on technological advancements since they are technology firms themselves. The consumer discretionary sector also makes sense because these firms often seek ways to increase convenience for their clientele due to their business being discretionary and not essential. Adding cryptocurrency as a form of payment can be rationally seen as a way to do this.

Chapter 4

Empirical Results

First, we evaluate the sample by looking at its distribution in the subsamples and each of the samples' distribution across the GICS sectors. Table 1 displays both of these distributions. From this, we can see that of the 30 firms sampled, a larger proportion of the firms (17) fell into the small companies subsample, while 16 fell into the period 2 subsample. Each sample shows that most companies are categorized as the Consumer Discretionary Sector or the Information Technology Sector, with the rest mostly falling into the Communication Services sector. Health Care and Financial are the only other sectors the firms are categorized as. However, no more than one firm falls into these categories in any sample. These results are not to be unexpected. With cryptocurrency being a form of technology, it is unsurprising that the information technology sector would be leading in the type of firm to accept cryptocurrency as a form of payment. The consumer discretionary sector consists of firms selling products that are not necessary to the consumers. It would make sense for firms in this sector to make purchase options as current and inclusive for their customers as possible. It also makes sense that more firms fall in period 2 and the small company subsamples. Smaller companies cater to a small customer base and can tailor their decisions to that customer base.

Additionally, a small company would have significantly fewer steps and complications in introducing a cryptocurrency to its financial statements. Period 2 covers announcements made in the years 2020-2022. Cryptocurrency did not grow in popularity until the few years preceding this period, so it would make sense for companies to start experimenting with it as a form of payment in the years following its sudden growth in popularity.

To gain more insight into the firms of each sample, we also investigate the mean, standard deviation, and distribution of the market capitalization, return on assets, and book-to-market ratios. Our results showing this data can be seen in Table 2. The sample had an average market capitalization of $108,642.81, a return on assets of -4.97%, and a book-to-market ratio of 0.34. This finding indicates that firms that announce the acceptance of cryptocurrency as a form of payment tend to be on the smaller side, have a net loss concerning total assets, and have a significantly higher market value than book value, which could imply that, on average, the firms are overvalued. We calculated the relevant market capitalization for each of the firms on the event date by multiplying the number of shares outstanding by the price per share on the event date, the Return on Assets of each of the firms by dividing the net income of the firms by the average total assets, and the Book to Market Ratio by dividing the book value of the equity of the firm by the market value of equity, or the market capitalization of the firm.

We also observed that the small company subsample has a significantly lower return on assets and market capitalization, both of which are to be expected due to the normal characteristics of smaller companies. Also, the period 2 subsample, which encompasses announcements between 2020 and 2022, has an average market capitalization of $140,498, higher than that of the whole sample. This result may be because, after COVID-19, larger companies like Tesla followed in the footsteps of smaller firms and announced the acceptance of cryptocurrency as a form of payment. Just one large firm like Tesla can skew the average to the higher side due to the sensitive nature of extreme values of averages. Additionally, the large company subsample is the only subsample with a positive return on assets; this would make sense as it contains larger and more successful companies like Tesla.

To explore the short-term effects of the announcement, we compare the abnormal returns of the whole sample in addition to each subsample to the market on the announcement date. The announcement day used in the event study is the date the articles announcing each company's acceptance of cryptocurrency as a form of payment were published. We calculated the abnormal returns by subtracting the expected return from the actual realized return on that date. The expected return was calculated using the Fama-French 4-Factor Model (Carhart 1997), also known as the Fama-French Plus Momentum Model, as shown in Equation 1.

Equation 1: $R_{pt} - R_{ft} = a_i + b(R_{mt} - R_{ft}) + s\ SMB_t + hHML_t + m\ UMD_t + e_t$

Where:

R_{pt} = the simple return on the Whole sample

R_{ft} = the return on one-month T-bills

R_{mt} = the return on the market index

SMB_t = the return on small firms less the return on large firms

HML_t = the return on high book-to-market firms less the return on low book-to-market firms

UMD_t = the return on the two prior high-return firms less the returns on the two prior low-return firms

In Panel A of Table 3, we show the abnormal returns on the event date in addition to each of the five days prior and five days following the event date, creating an eleven-day event window. The five days on either side of the event date account for the potential of news leakage or other events causing a delayed or early market reaction. For the whole sample, the only statistically significant abnormal returns were found on the day preceding the event date, indicated by the table as -1, which was an abnormal return of -1.11 at a 10% significance level. This finding indicates that the sample underperformed the day before the event date by -1.11%. No significant abnormal returns could be observed in the large company data sample. However, in the small company data sample, the sample underperformed by 1.69% at a 5% significance on the day preceding the event date. No abnormal returns were observed in period one, except for day three after the event date, an abnormal return of -1.1% at the ten percent significance level can be observed. Like the whole sample and small company subsample, period 2 also shows an abnormal return on the day before the event date, showing the sample to underperform by 1.38% at the five percent significance level.

Additionally, period two also has statistically significant abnormal returns on the fourth date following the event date of -0.61, indicating that this subsample underperformed by 0.61% at the 10% significance level on the fourth day after the event date. The trend of the day before the event date consistently showing an abnormal return across 3 of the 5 subsamples may indicate that the news was seen in places earlier than where we gathered our event data. If our database was a day late, the market could react to the first news announcement observed, which would explain the negative abnormal return and imply a negative market reaction to companies announcing the acceptance of cryptocurrency as a form of payment.

In Panel B of Table 3, we calculate the cumulative abnormal returns surrounding the event date in windows of five days before, two days prior (-5, -2), one day before the event date (-1, 0), one day following to five days following (+1, + 5) and the event window discussed above, five days before five days following (-5, +5). None of these event windows showed any statistically significant cumulative abnormal returns.

In Table 4, we compare the raw monthly returns (not risk-adjusted) and the risk-adjusted returns of the whole sample and subsamples against the market index, which is the S&P 500. To calculate a t-test statistic for the returns, we use a paired difference test with n-1 degrees of freedom. The equation for the t-test statistic is shown below as Equation 2. This paired difference test allows us to test the statistical significance of the raw returns of the sample against the benchmark.

Equation 2: $t \equiv \frac{\bar{d}}{s_d}\sqrt{n}$

Where:

$\bar{d}$ = the mean difference between the market and sample return each day

s_d = the standard deviation of the daily difference between the returns of the market and the sample

n = equals the number of days corresponding to the annual holding period.

To calculate the returns adjusted for risk, we used two common measures of calculating risk-adjusted returns: the Sharpe (1966) ratio and the Treynor (1965) ratio.

First, we calculated the Sharpe ratio for each of the samples. Equation 3, shown below, displays the Sharpe ratio, which calculates the excess return per unit of risk, with standard deviation as the risk measurement.

Equation 3: $Sharpe\ Index = \frac{d}{s_d}$

Where:

d = mean daily difference between the sample and the T-bill return, calculated over respective holding periods

s_d= the sample standard deviation of the daily return differences

Second, we calculated the Treynor ratio for each of the samples. Equation 4 shows the Treynor ratio, which measures excess return per unit of risk, where risk is measured with the beta, which represents systematic risk.

$$\text{Equation 4: } Treynor\ Index = \frac{d}{\beta}\sqrt{n}$$

Where:

d = mean daily difference between the return on the samples and the T-bill return, calculated over respective holding periods

β = portfolio beta

n = number of days in the respective holding periods

It is useful to use both ratios in our analysis due to their different methods of measuring risk. The Sharpe ratio is helpful in cases where a portfolio or sample is less diversified because it uses the sample's standard deviation to consider non-systematic risk. Conversely, the Treynor ratio uses beta, a systematic risk measurement, to adjust more accurately for well-diversified portfolios or samples. Table 1 lists the firms that fall into each market sector for each sample. It can be seen that over 20 of the 30 firms used in the sample fall into just two sectors, indicating that this sample is not very diversified from a sector viewpoint. As a result, the Sharpe ratio may be slightly more insightful to us.

The results of Table 4 show that when comparing the monthly raw return of our samples to the index, all of the samples are significantly underperforming the index. However, it is important to note that the Period 1 subsample result is not considered statistically significant. Nonetheless, the whole sample, small company subsample, and period 2 subsample are all statistically significant at the 5% level, while the large company subsample is significant at the 10% level. Although these results are not risk-adjusted, they provide insight into the overall raw performance of our sample of firms, and this performance appears to translate to all the subsamples.

When assessing the Sharpe and Treynor ratios we calculated, it can be observed that for every sample, both ratios are less than that of the index, except the Sharpe ratio of the period one sub-sample. This finding indicates that the samples underperform the market even when adjusted for risk. This result means that given the amount of risk associated with the samples, they would still be considered a worse investment than the overall market. The exception, as noted above, is the period 1 subsample when looking at the Sharpe ratios. This finding is also the only sample that did not produce a statistically significant result when comparing the raw return to the index above. This result indicates that the companies that announced the acceptance of cryptocurrency as a form of payment from 2014 through 2019 were not underperforming in the market with any statistical significance, nor were they underperforming when adjusted for risk under the Sharpe Ratio.

To compare the return of the whole sample with the sub-samples, we also calculate Jensen’s Alpha (1968) for each sample. Jensen’s Alpha measures the difference between the sample return and the return we calculated with the capital asset pricing model. In our calculation, Jensen’s Alpha is the intercept term of the regression of the excess returns of our sample of firms that announced the acceptance of cryptocurrency as a form of payment against the excess returns of the S&P 500. The equation used to calculate Jensen's Alpha can be seen below as Equation 5.

Equation 5: $R_{pt} - R_{ft} = \alpha + \beta(R_{mt} - R_{ft}) + e_{pt}$,

Our calculation of Jensen's Alpha allows us to assess whether our sample is undervalued or overvalued. A negative Jensen's Alpha indicates the sample is overvalued, while a positive Jensen's Alpha indicates it is undervalued. Our calculation results can be seen at the bottom of Table 4. These results show that the whole sample, small company subsample, and period 2 subsample all appear to be overvalued. The whole sample and period 2 subsample have results of -0.125 and -0.183, respectively, at the 1% significance level. At the same time, the small company subsample had a result of -0.159 at the 5% significance level.

We also test the risk-adjusted performance of the samples in the long term with the Fama-French 3-factor (1993) and 5-factor (2015) models. With the 3-factor model, we created a regression of the excess daily returns with three factors: excess return (MKTRF), size (SMB), and Book-to-Market (HML). With the 5-factor, we created a regression of the excess daily returns with the same three factors as the 3-factor and the addition of two more factors: profitability (RMW) and investment (CMA). The 5-factor model adds profitability because it has been found that companies reporting higher future earnings have higher returns. The investment factor is added because it has been found that companies who direct profits towards growth, so investing in themselves, are found to see more losses in the market. These additional factors allow for more factors to be considered when adjusting a firm's long-term return. Equations 7 and 8, listed below, show the equations for the Fama-French 3-factor and 5-factor models, respectively.

Equation 7: $R_{pt} - R_{ft} = a_i + b(R_{mt} - R_{ft}) + s\, SMB_t + hHML_t + e_t;$

Equation 8: $R_{pt} - R_{ft} = a_i + b(R_{mt} - R_{ft}) + s\, SMB_t + hHML_t + rRMW_t + cCMA_t + e_t;$

where:

R_{pt}	=	the simple return on the Whole sample
R_{ft}	=	the return on one-month T-bills
R_{mt}	=	the return on the market index
SMB_t	=	the return on small firms less the return on large firms
HML_t	=	the return on high book-to-market firms less the return on low book-to-market firms
RMW_t	=	the return on the most profitable firms less the return on the least profitable firms
CMA_t	=	the return on the firms that invest in growth conservatively less the return of firms that invest in growth aggressively

With both models, a positive and statistically significant intercept indicates that after accounting for all factors, the performance of the sample has added value. To calculate statistical significance, we calculated a t-statistic of each intercept for each regression factor using equation 1, defined previously. Our results for each of the regressions can be seen in Table 5. Our analysis of the 3-factor and 5-factor models shows that the whole sample and the small company subsample have statistically significant intercepts, both of which are negative—indicating that in the long run, with the previously discussed factors taken into account, the whole sample and that subsample is found to underperform the index. It is not unexpected that the small company subsample is found to underperform as smaller companies generally tend to underperform the index. Because of this, we cannot conclude that companies accepting cryptocurrency as a form of payment add to performance.

In summary, our results show that the whole sample's breakdown by subsample and sector is congruent with expectations we would have about companies that choose to accept cryptocurrency as a form of payment. Regarding our event study, the main day showing abnormal returns is the day before the event, which consistently showed multiple samples to underperform by a percent or so. This finding could indicate that there is news leakage a day before our sources which the market is reacting to a day earlier than expected. Alternatively, a confounding variable could be present, and further exploration would be required. Additionally, when adjusting our calculations for risk, we found that similar to our analysis of the raw return versus the index, almost every sample was underperforming by all tests with few exceptions.

Similarly, in our long-run tests of risk-adjusted returns with the Fama-French 3-factor and 5-factor models, almost all statistically significant results point to the samples underperforming. So, overall, the samples were found to underperform the index through numerous tests, both unadjusted and adjusted for risk in the short and long term. This finding does not mean that companies accepting cryptocurrency cause them to underperform then. It could just mean that most firms that announced their acceptance of cryptocurrency as a form of payment also happen to be firms that underperform the market in general. The only indicator that the announcement could affect returns is the three samples that showed negative abnormal returns the day before. However, operating under the assumption that our event dates are the first day this announcement was made, we would expect to see these abnormal returns on or after the event date.

Chapter 5

Conclusion

In this study, we seek to determine whether there is a market reaction to firms' announcement of accepting cryptocurrency as a form of payment for their goods or services. Our null hypothesis is that there will be no market reaction, and our alternative hypothesis is that there will be a negative market reaction. To test this, we conduct an eleven-day window event study encompassing the five days prior and five days following the announcement dates of thirty publicly traded firms to test for abnormal returns surrounding the event date. The only statistically significant abnormal returns resulting from our study fell one day before the event date on three of our five samples, one of which was the whole sample and two subsamples. Two other statistically significant results were found in two subsamples on the third and fourth days following the event date. Because there are no abnormal returns on or directly following the event date in any of the samples, we conclude that announcing a firm's acceptance of cryptocurrency as a form of payment does not generate a market reaction.

We also analyzed our samples' performance by evaluating the samples' risk-adjusted returns in the short and long term. Our results are robust in consistently indicating the samples underperform the index. Because this is true even for the subsamples, we cannot attribute any specific characteristic as the reason for this underperformance. Our sample generally consists of smaller firms that commonly underperform the market. However, we observed even our subsample of larger firms consistently underperformed the market on multiple tests. We also analyze our samples by three common financial ratios to assess size, profitability, and value. We find that with a few exceptions, all the samples have a negative return on assets, small market capitalization, and low book-to-market ratios. From this, we conclude that our sample consists mainly of small, unprofitable firms that could be considered overvalued. Lastly, we categorized our samples by market sector and found that almost all of the firms fell into two categories: consumer discretionary and information technology.

We believe that further testing can be done on the numerous unexplored features of our samples, like the size or sector classification, to explore whether they also commonly underperform their indexes. If this is not the case, there may be an unexplained characteristic of firms that accept cryptocurrency as a form of payment that explains their underperformance. Additionally, our research cannot explain the trend of negative abnormal returns one day before our event dates. Further testing can be done in search of an explanation for this observation.

Table 1: Sample Sector Distribution

Sector	Name	Whole Sample	Large Sample	Small Sample	2014 - 2019	2020 - 2022
		28	11	17	12	16
25	Consumer Discretionary (Consumer Cyclical)	10	4	6	4	6
35	Health Care	1	0	1	1	0
40	Financials	1	0	1	0	1
45	Information Technology	6	6	5	4	7
50	Communication Services	5	1	4	3	2

Table 2: Statistics and Distributions of Financial Measures

	Number of Observations	Mean	Standard Deviation	Percentile Min	25	50	75	Max
Whole Sample								
Market capitalization	29	108,642.81	181,819.58	23.35	732.34	14,004.76	125,519.63	677,443.20
Return on assets	28	-4.97	26.46	-93.22	-8.32	4.89	7.10	24.23
Book to market ratio	26	0.34	0.36	0.02	0.05	0.23	0.47	1.12
Large Companies Sample								
Market capitalization	11	276,341.84	206,408.81	42,204.87	83,675.34	255,311.90	464,582.52	677,443.20
Return on assets	11	5.66	18.13	-43.82	3.96	5.90	17.04	24.23
Book to market ratio	10	0.27	0.34	0.02	0.04	0.07	0.47	0.89
Small Companies Sample								
Market capitalization	18	6,160.07	8,354.96	23.35	475.59	2,640.63	9,033.93	26,542.82
Return on assets	17	-11.85	29.11	-93.22	-17.99	2.91	6.48	12.34
Book to market ratio	16	0.39	0.37	0.02	0.17	0.25	0.56	1.12
Year 2014 - 2019								
Market capitalization	12	63,514.24	150,792.43	23.35	99.19	4,327.79	17,788.38	504,476.48
Return on assets	12	-4.69	22.04	-57.48	-13.35	4.28	6.03	24.23
Book to market ratio	12	0.42	0.38	0.04	0.18	0.24	0.63	1.12
Year 2020 - 2022								
Market capitalization	17	140,498.27	199,032.35	475.59	4,500.61	42,204.87	255,311.90	677,443.20
Return on assets	16	-5.18	30.06	-93.22	-2.86	5.73	9.71	23.11
Book to market ratio	14	0.27	0.33	0.02	0.03	0.07	0.47	0.90

Table 3: Abnormal Returns Surrounding Event Date

	Whole Sample		Large Companies		Small Companies		Year 2014 - 2019		Year 2020 - 2022	
Panel A. Abnormal returns (%) around event date										
Day	AR	t-stat	AR	t-stat	AR	t-stat	AR	t-stat	AR	t-stat
-5	0.07	0.15	0.45	1.03	-0.19	-0.28	-0.57	-1.40	0.54	0.79
-4	-0.91	-1.52	-0.53	-0.95	-1.16	-1.25	-1.40	-1.40	-0.55	-0.73
-3	-0.45	-0.96	-0.39	-0.53	-0.48	-0.78	0.40	0.75	-1.08	-1.58
-2	0.06	0.12	-0.23	-0.43	0.25	0.33	0.97	1.43	-0.62	-0.93
-1	-1.11	-2.27*	-0.21	-0.67	-1.69	-2.24**	-0.75	-0.97	-1.38	-2.14**
0	0.57	0.78	-0.11	-0.17	1.00	0.89	2.02	1.53	-0.52	-0.75
1	-0.59	-0.77	-0.51	-0.83	-0.64	-0.53	0.03	0.02	-1.05	-1.63
2	-0.22	-0.44	-0.39	-0.61	-0.11	-0.15	-0.49	-0.61	-0.02	-0.02
3	0.03	0.06	0.65	0.90	-0.37	-0.49	-1.10	-1.92*	0.89	1.12
4	-0.56	-0.77	-0.15	-0.72	-0.83	-0.69	-0.50	-0.30	-0.61	-1.82*
5	-0.17	-0.26	0.17	0.35	-0.40	-0.38	-0.47	-0.39	0.05	0.07
Panel B. Cumulative abnormal returns (%) around event date										
Interval	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat	CAR	t-stat
(-5, -2)	-1.23	-1.15	-0.70	-0.61	-1.58	-0.97	-0.60	-0.46	-1.70	-1.04
(-1, 0)	-0.54	-0.52	-0.31	-0.36	-0.68	-0.42	1.22	0.71	-1.78	-1.43
(+1, +5)	-1.50	-0.83	-0.19	-0.15	-2.27	-0.82	-2.75	-0.74	-0.67	-0.37
(-5, +5)	-3.29	-1.18	-1.24	-0.58	-4.61	-1.05	-1.87	-0.48	-4.34	-1.09

Table 4: Monthly Raw and Risk-Adjusted Returns

	Whole Sample	Large Companies Sample	Small Companies Sample	Year 2014 - 2019	Year 2020 - 2022
Monthly raw return (%)	(Not Risk adjusted)				
Test sample (1)	-10.247	-1.977	-9.531	-0.878	-34.283
S&P 500 Index (2)	0.432	1.160	-0.275	1.023	-1.084
(1) - (2)	-10.679**	-3.137*	-9.256**	-1.900	-33.199**
Sharpe Ratio					
Test sample (1)	-0.029	-0.016	-0.034	-0.005	-0.045
S&P 500 Index (2)	0.002	0.017	-0.007	-0.015	-0.007
Treynor Ratio					
Test sample (1)	-0.096	-0.034	-0.128	-0.022	-0.134
S&P 500 Index (2)	0.002	0.020	-0.008	0.017	-0.008
Jensen's Alpha					
Test sample (1)	-0.125***	-0.064	-0.159**	-0.038	-0.183***

Table 5: Fama-French 3-Factor and 5-Factor Models

		Whole Sample	Large Companies Sample	Small Companies Sample	Year 2014 - 2019 Sample	Year 2020 - 2022 Sample
Panel A. Fama-French 3-factor model						
Intercept	Coefficient	-0.0013	-0.0004	-1.0013	-0.0010	-0.0011
	t-stat	-2.19**	-0.81	-1.92*	-1.31	-1.37
MKTRF	Coefficient	1.0724	1.0221	1.1511	0.9414	1.1905
	t-stat	22.68***	32.64***	20.52***	15.43***	17.36***
SMB	Coefficient	0.4167	0.1243	0.7542	0.1677	0.6855
	t-stat	4.39***	1.96**	6.36***	1.3	6.04***
HML	Coefficient	-0.3444	-0.3278	-0.2065	0.1133	-0.6014
	t-stat	-4.97***	-7.53***	-2.39**	1.00	-8.20***
Panel B. Fama-French 5-factor model						
Intercept	Coefficient	-0.0012	-0.0003	-0.0012	-0.0010	-0.0009
	t-stat	-2.04**	-0.63	-1.78*	-1.31	-1.2100
MKTRF	Coefficient	1.0512	1.0251	1.0951	0.9578	1.1757
	t-stat	20.80***	31.29***	18.16***	14.54***	17.15***
SMB	Coefficient	0.2867	-0.0092	0.6200	0.1918	0.3926
	t-stat	2.82***	-0.13	4.91***	1.43	3.08***
HML	Coefficient	-0.2294	-0.2457	0.0090	0.0624	-0.4615
	t-stat	-2.35**	-3.74***	0.07	0.46	-4.0***
RMW	Coefficient	-0.4999	-0.4889	-0.3887	0.0642	-0.6183
	t-stat	-3.87***	-5.72***	-2.59***	0.29	-4.91***
CMA	Coefficient	0.0107	0.1828	-0.3487	0.1746	0.1277
	t-stat	0.06	1.48	-1.58	0.61	0.6800

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ACADEMIC VITA

JANE A. BRENC

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Education

Pennsylvania State University, Behrend **August 2018 – May 2023**

Bachelors of Science in Finance

Minor in Accounting

Honors and Scholarships

- Schreyer Honors College Scholar
- Behrend's Dean's List
- Academic Merit Scholarship
- Behrend's Academic Achievement Presidents Award
- Beta Gamma Sigma member
- FMA Member

Work Experience **June 2021 – July 2022**

Legal Assistant

Experience with:

- Secretarial duties
- Preparing/editing legal documents
- Interactions in courthouse and courtroom setting
- Online document retrieving and filing
- Proficient Word and Excel skills.
- Email and In-Person Formal Communication

Other Work Experience **July 2019 – June 2021**

Full time supervisor at retail store

- Managing 5 – 10 associates at a time
- Collaborating with other management
- Handling technical, functional, and customer related problems
- Developed leadership skills as well as team building skills
- Advanced multitasking and coordination skills between work and school

Projects

CAS 252 Civility Project

- Making Behrend Greener
- Project to encourage students to reduce waste

Volunteer Work

Erie Animal Network

- Cleaning, Animal Care, Desk Work