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Adaptive calendar effects and volume of extra returns in the cryptocurrency market

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Abstract

Purpose – This study broadly attempts to explore adaptive or dynamics patterns of calendar effects existed in the cryptocurrency market as per the adaptive market hypothesis (AMH) framework. Another agendum of this study is to investigate the quantum of extra returns which may result from the presence of calendar effects.

Design/methodology/approach – The present study considers both parametric and non-parametric approaches to verify calendar effects empirically. Specifically, this study has implemented Generalised Autoregressive Conditional Heteroscedasticity (1, 1) and Kruskal–Wallis tests in the rolling window approach to reveal adaptive patterns of calendar effects. Additionally, the present study has used the implied trading strategy to evaluate the volume of excess returns resulted from calendar effects than buy-and-hold (BH) strategy.

Findings – The overall results of the current study exhibit that calendar effect in the cryptocurrency market is dynamic rather than static which indicates the calendar effect is a time-varying phenomenon. Moreover, this study also confirmed that ITS is not suitable to obtain extra returns despite the existence of calendar effects.

Research limitations/implications – The present study has covered some broad aspects of calendar anomalies in the cryptocurrency market, keeping aside certain other limitations which need to be addressed in the following dimensions. Future studies may aim at addressing issues like, Turn-of-the-Year effect, Halloween effect, weather effect, and Month-of-the-Year effects, and try to explore the reasons of presence of dynamic patterns of calendar effects.

Practical implications – The significant implication of this study is that it alerts investors about market return predictability due to calendar patterns or effects in different periods. It also suggests the period in which the ITS can perform better than the BH strategy.

Originality/value – It is the first study in the cryptocurrency literature which has adopted the AMH framework to verify adaptive calendar effects or anomalies. Furthermore, this study, instead of a mere examination of the presence of calendar effects, has evaluated the potential of calendar effects to produce extra returns through trading strategies.

Keywords Calendar anomalies, Adaptive market hypothesis, Market efficiency, Cryptocurrency, Bitcoin

Paper type Research paper

1. Introduction

The market efficiency fundamentals debar investors to obtain any form of extra market returns based on information. The concept of market efficiency formalised by Fama (1970) in the form of the efficient market hypothesis (EMH) proclaimed that market movement is unbiased and flow of information has no function in forecasting market signals. Hence, an efficient financial market makes no delay in acknowledging the arrival of any information and subsequently squeezes scope for excess returns. However, the reality is that financial market exhibits certain anomalies in EMH – indicating prospects of predictability in asset price movements (see Roberts, 1959; Milonas, 1991; Brusa *et al.*, 2000; Gunasekarage and Power, 2006). The voluminous literature of the EMH portrays that out of several anomalies, calendar anomalies have garnered substantial research attention because of their commonality and importance for investors and policymakers (see Kumar, 2017; Harshita *et al.*, 2018; Plastun *et al.*, 2019).

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Calendar anomaly or effect implies a mismatched behaviour of market movement during a particular time in a calendar period to the rest of the calendar period. Existing studies suggest that the Monday effect, the January effect, and the turn-of-the-month (TOTM) effect are the most prominent anomalies among the other calendar anomalies reported in various studies (see Urquhart and McGroarty, 2014; Kumar, 2016). Hence, the present study focuses on the presence of these anomalies along with Saturday and Sunday (S&S) effect and is crucial to the market which operates round the week.

The Monday effects convey that asset returns on Monday are significantly inconsistent with the returns of other days of the week. The common perception and extensively acknowledged fact about the Monday effect is that asset price returns are substantially negative on Mondays. Kelly (1930) was the first to discover about Monday anomalies. The January anomalies refer to the trend of higher asset returns in January than the remaining months of the year. Rozeff and Kinney (1976) were the first to detect January anomalies. The TOTM effect asserts that returns during the final trading day of a month to the initial few days of the immediate next month are positive compared to other days of the month. Ariel (1987) got credit for exploring the TOTM phenomenon. The S&S effect can cause more returns on Sunday compared to other day-of-the-week (DoW) as Sunday is the last trading day. In the case of other financial markets, the literature suggests that last trading DoW (Friday) returns are positive, and first trading DoW (Monday) returns are negative. Usually, in earlier studies, the evidence is absent about the S&S effect as the markets are generally closed for trading on S&S. However, few studies have tested the Saturday effect in the stock market, which follows the Islamic calendar than the western calendar (see, for instance, Abalala and Sollis, 2015).

Past studies examined calendar effects in financial markets, mostly by adopting the conventional EMH approach (see Aydogan and Booth, 2003; Kumar, 2016) and concluded that calendar anomalies are a static phenomenon. However, the existence of a perfectly efficient market is unrealistic due to the presence of behavioural bias. The behavioural economists oppose the all-or-nothing approach of the EMH and advocate that due to emergence of various economic or non-economic events and consequent changes in the market environment and market microstructure, there is every possibility of evolution of efficiency in due course of time (see Hiremath and Kumari, 2014). Therefore, to bring unity between supporters of EMH and behavioural economist, Lo (2004) proposed the “Adaptive Market Hypothesis (AMH)”.

1.1 Adaptive market hypothesis

The AMH proposed by Lo (2004) reconciles the EMH framework with its critiques in the behavioural domain. The conceptual framework of the AMH stands on the evolutionary principles of biology. Following the principles of biological evolution, bounded rationality and satisficing, Lo (2004) argued that market participants try to learn from their mistakes and adapt to different market conditions as behavioural biases move through specific evolutionary path. Lo (2004) postulates that a market agent who uses the previous experience to design the investment strategy is meant for survival rather than to maximise value. Lo (2005) also attached the degree of market efficiency to environmental factors, distinguishing market ecology into the number of competitors, the magnitude of profit opportunities available, and the adaptability of market participants. In contrast to the conventional approach of the EMH that market efficiency is like all-or-nothing conditions, the AMH holds that efficiency evolves due to changing market conditions (for example, business cycles, scams, bubbles, crises and political instability). These dynamic market conditions have substantial implications for the behaviour of market participants, resulting in a time-varying pattern of returns.

AMH being an alternative approach to EMH coexists with EMH in an intellectually consistent manner. This alternative explanation to the market theory of EMH from behavioural perspective interprets financial markets as adaptable, and it switches between efficiency and inefficiency at different points of time (see Lo, 2004; Urquhart and Hudson, 2013; Hiremath and Kumari, 2014; Khuntia and Pattanayak, 2018).

Deviating from the EMH, the AMH framework operates through six primary components, namely, individuals behave and act on their interest; they commit mistakes; they learn from mistakes and adapt; competition guides their adaptation and innovation; natural selection balances market ecology and evolution that determines market dynamics (Lo, 2005). As these components of AMH indicates that investors commit mistakes and then learn to adapt to different situations, then there is every possibility that market efficiency cannot be static. Instead, a market can be efficient as well as predictable. It indicates that profit opportunities get created from time to time and also get exploited.

Lo (2005) identified the number of practical implications of AMH on an investment management perspective. First, the risk premium in the financial market varies with the emergence of market events and changes in demographic compositions of investors. Second, the evolving nature of market efficiency leads to creation of arbitrage opportunities from time to time. Therefore, an investment strategy that was successful earlier may not work again. Thus, to survive and compete in different market conditions, one needs innovation. Third, due to the adaptability of investors, change in business conditions, the number of competitors, etc. the financial asset price undergoes either bearish or bullish trend. Realising the advanced approach of the AMH to explain market efficiency there are number of studies exclusively focused on the AMH to describe market efficiency in different financial market (see Katusiime *et al.*, 2015; Hiremath and Narayan, 2016; Khuntia and Pattanayak, 2018; Shahid *et al.*, 2019). However, there are no studies till date which has employed the AMH to measure comprehensively evolution of calendar effects in the cryptocurrency market. Hence, given the importance and practical implications of the AMH, this study is motivated to investigate adaptive calendar effects as per the AMH approach in the cryptocurrency market.

1.2 Why cryptocurrency market?

Cryptocurrency, as a new asset class, had garnered tremendous attention within a decade of its emergence when the Bitcoin was introduced in a white paper by Nakamoto (2008) following the sub-prime crisis in 2007. Subsequently, following the overwhelming acceptance of the Bitcoin, other cryptocurrencies were gradually evolved. In fact, as of March 2018, the crypto market hosted 1,568 cryptocurrencies, compared to just 40 cryptocurrencies in December 2013 (Global Cryptocurrency Exchange Trends, Reports and Statistics, 2018). The increasing popularity of the Bitcoin and other cryptocurrencies also gets reflected in terms of the trade volume and extraordinary levels of returns. However, despite the popularity of the cryptocurrencies, there are some severe concerns associated with different perspectives (Kumar and Ajaz, 2019).

For instance, abnormal volatility is a kind of usual phenomena in the cryptocurrency market compared to the mainstream financial market (Corbet *et al.*, 2018). Although the cryptocurrencies were developed for a peer-to-peer transaction without involving the third parties, it is now more involved with investment and speculations despite repeated warnings of different regulators (Katsiampa, 2019). Furthermore, Dyhrberg (2016) and Bouri *et al.* (2017) viewed that cryptocurrencies have no commonality with classical assets. Besides, it is also evidenced that the cryptocurrency market being relatively young has no strong fundamentals and is also not deep-rooted (Bohme *et al.*, 2015). Hence, a market with weak fundamentals can be more exposed to shock, and any impact on the market leader can also be transmitted to others. Subsequently, the market may collapse.

Apart from above, other concerns for cryptocurrencies include the cyber criminalities (Corbet *et al.*, 2020 and money laundering (Dupuis and Gleason, 2020). Cyber criminality is a major concern for crypto investments. Although cryptocurrency is a major technological innovation, still it is not free from hacking and other technical complexities. Repeated hackings and other technical difficulties may impair trading in a massive chunk of crypto assets which will subsequently impact liquidity and shall result in thin trading. Moreover, considering the regulatory weakness, cryptocurrency may act as an ideal instrument for illegal cross-border transactions, money laundering activities and financing terrorism. Eventually, these activities will lead to imposition of sanctions or strict regulations, ultimately affecting adversely on the volumes of trade and in the behaviour of investors.

Besides, cryptocurrencies are intangible assets and infinitely divisible, whereas traditional currencies are tangible. No monetary authorities and central banks are involved in the controlling of cryptocurrencies. Moreover, the value of cryptocurrency is not associated with any economy, which is the case for fiat currencies. Furthermore, cryptocurrencies with their fastest rising growth rate, increasing attention, decentralised controlling framework and innovative features attract higher capital inflows. However, a sharp decline in the price of the Bitcoin during 2018 drop the growth rate to 1,077%, on December 31, 2018. In 2019, again, the cost of the Bitcoin followed growth trajectory and led to improvement in growth rate from 1,077%, on December 31, 2018, to 2,318%, on May 25, 2019. Consequently, the trade volume (in terms of USD) had increased by 1,22,779%, on May 25, 2019, in comparison to October 25, 2014. Like the Bitcoin, other cryptocurrencies also witnessed notable growth in terms of returns and trade volume in the last five year except the year 2017 [Figures reported here are estimated by authors from the raw data of Bitcoin and other cryptocurrency prices sourced from “coinmarketcap.com”].

Given the uniqueness of the cryptocurrency market in terms of dynamic market sentiment, continuous technological changes, regulatory reforms this study believes that the AMH can better capture evolution or adaptive patterns of calendar anomalies. Hence, by doing this the current study has broadly contributed to the concerned literature on the AMH, calendar anomalies and cryptocurrencies (a detailed description about the contribution of this study is presented in Section 4.6).

2. Literature review

The core idea of the EMH precludes any form of trend, correlation and patterns (Fama, 1970). Appending to the seminal work of Fama (1970), a standard volume of studies were undertaken with a fundamental focus to explore chances of predictability in asset price movement of the different conventional financial markets including, stock, foreign exchange, oil, commodities and precious metals (Pesando, 1978; Fama and French, 1988; Crowder and Hamed, 1993; Jegadeesh and Titman, 1993; Huang, 1995; Liu *et al.*, 1997; Lee *et al.*, 2001; Smith, 2002; Nakamura and Small, 2007; Downing *et al.*, 2009; Worthington and Higgs, 2009; Narayan *et al.*, 2010; Alvarez-Ramirez *et al.*, 2012; Kristoufek *et al.*, 2016). However, there was no consensus regarding the outcomes of those studies owing to the existence of mixed results. Some studies documented the presence of market efficiency or random walk (Liu *et al.*, 1997; Lee *et al.*, 2001; Nakamura and Small, 2007; Alvarez-Ramirez *et al.*, 2012) and some others found the absence of market efficiency (Huang, 1995; Worthington and Higgs, 2009; Al-Yahyaee *et al.*, 2018).

The magnitude of studies paid attention to the EMH in the literature of financial economics exhibited the importance of the EMH. However, the framework of the EMH has been opposed because of its unrealistic assumption – which broadly says that investors are always rational and there are no market frictions (Grossman and Stiglitz, 1980; Westerhoff, 2003). There are several studies revealed various anomalies associated with EMH. For instance, Basu (1977) documented the “value effect”; French (1980) explored “weekend effect”; Banz (1981) reported “size effect”; Harris and Gurel (1986) recorded “index inclusion effect” and Saunders (1993) exhibited the “weather effect” in stock returns. Besides these, some studies also have identified that over-reaction and under-reaction to market information are the most common anomalies in EMH. For instance, De Bondt and Thaler (1985) examined the over-reaction phenomenon and Jegadeesh and Titman (1993) investigated under-reaction phenomenon and concluded that both the events produced extra returns for investors with the help of contrarian and momentum strategies. The evidence of inconsistencies and anomalies supported the study of Grossman and Stiglitz (1980), who documented that adequate profit opportunities must need to exist to compensate for the cost of information gathering. They also inferred that if information gathering by traders is not rewarded, then the existence of an informationally efficient market becomes nearly impossible as each trader remains uninformed. Moreover, there cannot be the persistence of either efficiency or inefficiency. However, findings of EMH studies corroborate that market efficiency is like a zero-or-one condition. Whereas in reality, changing dynamics of the market comprising of technological changes, behavioural changes, regulatory changes and institutional changes may cause an evolving or time-varying nature of market efficiency. Hence, Campbell *et al.* (1997) suggested for the examination of relative efficiency would be more realistic, given the presence of market frictions and behavioural bias.

Previous studies did never emphasise on time-varying nature of market efficiency (see Lim and Brooks, 2011). Moreover, as there was no consensus on the debate between proponents of the EMH and behavioural economists, the demand for an alternative explanation for the EMH started to grow over the years (Malkiel, 2005). Subsequently, bringing reconciliation between two opposing schools of thought, Lo (2004) has formulated the AMH.

2.1 Studies on AMH

The practical approach of AMH attracts a great deal of attention in the literature of market efficiency on the stock market (Urquhart and Hudson, 2013; Verheyden *et al.*, 2015; Hiremath and Narayan, 2016); precious metal market (Charles *et al.*, 2015; Urquhart, 2017); forex market (Katusiime *et al.*, 2015; Khuntia and Pattanayak 2017); interest rates (Hiremath *et al.*, 2019) and cryptocurrency market (Khuntia and Pattanayak 2018).

Todea *et al.* (2009) were the first such study which had exclusively used the AMH approach in six Asia–Pacific stock markets and explored that performance of moving average strategies fluctuated over time. Kim *et al.* (2011) and Lim *et al.* (2013) adopted the AMH approach in predicting the daily returns of the US stock market utilising the battery of linear and nonlinear tests and viewed in favour of time-varying predictability. Further, Urquhart and Hudson (2013), Ghazani and Araghi (2014), Hiremath and Kumari (2014), Urquhart and McGroarty (2014) and Manhov and Hudson (2014) investigated the relevance of EMH in several emerging and developed stock markets using varieties of testing tools and advocated that market efficiency is context-dependent.

Furthermore, Katusiime *et al.* (2015) and Khuntia and Pattanayak (2017) examined the AMH in Uganda and Indian forex markets, respectively and endorsed that evidence of dynamic market efficiency consistent with the implications of the AMH. Other than stock and forex markets, several other financial market asset price returns have been examined following the paradigm of the AMH (see, for instance, Zhou and Lee, 2013; Hall *et al.*, 2017; Urquhart, 2017).

Urquhart and McGroarty (2014) and Xiong *et al.* (2019) are the available literature which documented the use of AMH framework to evaluate evolving calendar anomalies in US and Chinese stock market, respectively. They concluded that calendar anomalies are not a static phenomenon, as it varies with time and emergence of events. The literature indicates that there is no studies pertaining to the AMH and calendar anomalies of cryptocurrencies – which provides an opportunity to explore the same.

2.2 Studies on cryptocurrencies

Initial studies on the cryptocurrency market primarily focused on the technical and legal aspects (Corbet *et al.*, 2020). However, recent studies started focusing on financial and economic issues of cryptocurrencies and are witnessing an increasing trend (Balcilar *et al.*, 2017; Munim *et al.*, 2019). In a systematic literature survey, Corbet *et al.* (2020) evidenced that a good number of studies is devoted towards informational efficiency. Urquhart (2016) in a seminal work on the cryptocurrency market efficiency, mainly focusing on Bitcoin returns, documented that Bitcoin return movement was initially inefficient, and over the period, it became efficient. However, Nadarajah and Chu (2017) using a different set of tests opined that Bitcoin return movement was efficient during the entire period of the study.

Bariviera (2017) revisited the concept of market efficiency and inferred that return movement was more efficient across the period, and the volatility was predictable. Similarly, Tiwari *et al.* (2018) noted that the Bitcoin movement was efficient in terms of long-range dependence except fewer period informational inefficiency. However, Jiang *et al.* (2018) re-examined the Bitcoin returns long-memory using generalised Hurst exponent and revealed that the Bitcoin returns was not efficient over time; instead, it displayed a continuous period of long-memory during the period of study. Furthermore, Cheah *et al.* (2018) recorded similar findings in consonance with the findings of Jiang *et al.* (2018) by concluding that the Bitcoin return movement exhibited long-memory during the period. Recently, Zargar and Kumar (2019) using intraday day Bitcoin returns confirmed that the Bitcoin market was not adhering to random behaviour.

Sliding the individual attention from the Bitcoin, some studies have examined the informational efficiency of altcoins. For instance, Caporale *et al.* (2018) verified the efficiency of four valuable cryptocurrencies (Bitcoin, Litecoin, Ripple, and Dash) by employing fractional integration and R/S analysis and exhibited the evidence of persistence in their return series. In a similar direction, Zhang *et al.* (2018) explored the presence of inefficiency in nine cryptocurrencies using a battery of efficiency tests. Caporale and Plastun (2019), in a different note, scrutinised the presence of calendar anomalies in four valuable cryptocurrencies and documented that Litecoin, Ripple and Dash showed no evidence of calendar effects. Besides these studies, Kochling *et al.* undertook a study in 2019 by measuring the event impact, i.e. the introduction of the Bitcoin futures on market efficiency of cryptocurrencies and concluded that implementation of Bitcoin futures had improved the Bitcoin efficiency but did not have any effect on other cryptocurrencies.

2.3 Studies on calendar effects

In this regard, calendar effects or anomalies which violates the principles of the EMH also witnessed several studies in different domain of financial markets (Milonas, 1991; Brusa *et al.*, 2000; Aydogan and Booth, 2003; Lucey and Tully, 2006; Zaremba and Schabek, 2017; Kumar, 2018; Plastun *et al.*, 2019). Specifically, previous researches have explored the likelihood of abnormal returns caused by a trend or pattern of asset price movement during a particular time of the calendar period – which includes DoW (Dicle and Levendis, 2014), the month of the year (Floros and Salvador, 2014; Plastun *et al.*, 2020a), TOTM (Kumar, 2015), Halloween period (Plastun *et al.*, 2020b) and holidays (Vergin and McGinnis, 1999). Irrespective of the financial market investigated, the Monday, January, and the TOTM effect received considerable attention, and the prime focus of this study is on these effects. Related research specific to Monday, January, and the TOTM effect in addition to the S&S is presented as follows.

2.3.1 Monday effect. The prominence of the Monday effect displayed by several studies in different financial markets (Wang *et al.*, 1997; Mehdian and Perry, 2001; Lucey and Tully, 2006; Keef *et al.*, 2009; Alt *et al.*, 2011) after the same was reported first by Kelly (1930).

Gibbons and Hess (1981) observed that Monday returns are comparatively lesser than other DoW for the S&P 500 indices. Keim (1983) also captured evidence of significant lower Monday returns than non-Mondays by analysing 55-year long data ranging from 1928 to 1982 for the US stock market. Furthermore, Lakonishok and Smidt (1988) revealed similar findings for the Dow Jones Industrial Average (DJIA) indices returns. However, Marquering *et al.* (2006) examined four decades of DJIA movement and divulged shrink in Monday effects in the recent period. In a different note, Urquhart and McGroarty (2014) evaluated DJIA index returns and disclosed that the Monday effect is not static, and it changes with time. Bush and Stephens (2016) explored the Monday effect for the EUR/USD exchange rate and described that the Monday effect depends on the relative strength and weakness of the domestic currency. However, many other studies advocated that there is no presence of the Monday effect (Prokop, 2010; Hui *et al.*, 2014; Xiong *et al.*, 2019).

While explaining the cause of lower Monday returns, Lakonishok and Maberly (1990) commented that the possible reason for lower Monday return could be due to little institutional trading. Lyroudi *et al.* (2004) accorded that investor's psychology lies in the background of negative Monday returns. Investors are generally optimistic on Fridays and Pessimistic on Mondays. Hence, higher selling pressure evidenced on Monday. Furthermore, Damodaran (1989) viewed that negative Monday returns might be the result of the conventional practice by firms to declare negative news on a close post-period followed by Fridays – which eventually causes negative returns on Monday. Although a standard volume of literature proclaims the presence of lower returns during Monday, still there is no consensus (Jebran and Chen, 2017).

2.3.2 January effect. The prevalent notion of the January effects indicates that generally asset returns in January significantly higher than the remaining month of the year. The January effect was detected by Rozeff and Kinney (1976), for the first time, in New York Stock Exchange (NYSE) returns. Rozeff and Kenny (1976) explored that January stock returns (3.48%) of NYSE were significantly higher than the remaining month of the year (0.48%). Following Rozeff and Kenny (1976), several other scholarly works have verified January effect across the financial market and reported the presence of the January effect (Gultekin and Gultekin, 1983; Bharadwaj and Brooks, 1992; Dbouk *et al.*, 2013; Hui and Chan, 2015, Kumar, 2016). For instance, Lucey and Whelan (2004) examined the Irish stock market and documented the presence of significant and constant January effects. Similarly, Sun and Tong (2010) had confirmed the strong presence of the January effect in the CRSP monthly returns, which draws supports from Agnani and Aray (2011) with similar findings for the US stock market. In the case of the UK stock market, Zhang and Jacobsen (2013) using three century-long data explored prominent January effect in the 18th century; however, the same disappears since mid of the 20th century. Further, Urquhart and McGroarty (2014) evaluating DJIA index returns for a century-long data noted that January effects are still alive, but it fluctuates with time. In a similar vein, Kumar and Pathak (2016) recorded the glaring presence of the January effect for the Indian currency market. In a recent study, Plastun *et al.* (2020a) have also drawn similar findings for the US stock market. The plausible causes for the presence of the January effect mostly lie with a change in the tax year (Gluetekin and Gluetekin, 1983), Window Dressing Hypothesis [1] (Lakonishok and Smidt, 1988), and liquidity (Ligon, 1997).

Notwithstanding the evidence of the strong January effect, some studies registered that the January effect is no longer significant (Mehdian and Perry, 2002; Marquering *et al.*, 2006; Depenchuk *et al.*, 2010; Zhang and Jacobsen (2013); Jebran and Chen, 2017).

2.3.3 TOTM effect. The TOTM effect refers to the higher likelihood of maximum returns during the last trading day of a month to the initial three trading days of the subsequent month (Lakonishok and Smidt, 1988). Following the scholarly work of Ariel (1987), the TOTM effect became the subject of discussion in sizeable literature. As a case in point, Cadsby and

Ratner (1992) enquired the FT 500 share index and reached at a conclusion which follows Lakonishok and Smidt (1988). Furthermore, Kunkel *et al.* (2003) have explored the crucial companionship of the TOTM effect in fifteen countries out of nineteen countries verified. Similarly, Bildik (2004) has identified significant evidence of the TOTM effect for the Turkish stock market. Besides these studies, many other scholarly works also captured the spirit of the TOTM effects (Lean *et al.*, 2007; Sharma and Narayan, 2014; Kayacetin and Lekpek, 2016; Jebran and Chen, 2017). However, few studies had noted a lack of proof for the TOTM effects (Kunkel *et al.*, 2003; Al-Jarrah *et al.*, 2011).

Parting away from the conventional approach, Urquhart and McGroarty have evaluated the dynamic or time-varying behaviour of the TOTM effect in the DJIA index in 2014 and observed flimsy evidence of the TOTM effect. Apart from the stock market, Liano and Kelly (1995) inspected the currency futures market and unveiled that the evidence is mixed. The Japanese yen exhibited significant TOTM effect, whereas the British pound demonstrated no such phenomenon against the US dollar. However, Kumar (2015) assessed the TOTM anomalies or effect in the Indian currency market and draws that the Indian rupee against the US dollar and Japanese yen exhibits significant TOTM effect. There are several reasons associated with TOTM effects. Zehr (1989) argued that portfolio managers at the end of each month usually revise their portfolio by converting cash into equities. Ogden (1990) viewed that in the US perspective, dividend and interest on debt usually paid during – the TOTM periods.

2.3.4 S&S effect. The S&S effect generally missed out from the agenda of previous similar studies. The reason for such ignorance is quite apparent as the S&S are non- trading days in the conventional financial market. However, there are only a couple of studies that have examined Saturday effect where instead of western calendar Islamic or other regional calendars are followed. For instance, Al-Khazali and Zoubi (2010) estimated the Saturday effect in the three Gulf (Bahrain, Kuwait, and Saudi Arabia) stock markets. They observed that there is no symptom of such effect. However, Abalala and Sollis (2015) concluded that a positive Saturday effect is prevalent in the Saudi Arabia stock market. Moreover, the findings of Abalala and Sollis (2015) contrasted to prior studies on financial markets that follow the western calendar and confirmed negative returns on the first working day of the week, i.e. Monday [2].

2.3.5 Cryptocurrency and calendar effects. Recently, there are few studies which have evaluated the calendar anomalies with particular focus on the DoW (see Table 1) in the Bitcoin and other cryptocurrency markets – which operate in relatively different set-ups. Ma and Tanizaki (2019a) detected positive Sunday effect in the Bitcoin returns when priced in the Australian dollar. However, Caporale and Plastun (2019) documented no DoW anomalies for most of the cryptocurrencies (Litecoin, Ripple and Dash). A list of papers verified calendar anomalies in the cryptocurrency market is displayed in Table 1.

3. Data and methods

3.1 Data

This study has employed daily closing price data of Bitcoin and eight other emerging cryptocurrencies, namely, Ripple, Litecoin, Monero, Dash, Dogecoin, Bitshares, Verge and Bytecoin for verification of calendar effects.

The rationale for the selection of different cryptocurrencies is based on the fact that they have distinctive features (see Appendix). Besides, though there are more than 2000 cryptocurrencies, most of them are less accepted, newly born and have a shorter trading history which is insufficient for measuring the time-series properties. Therefore, we implement two filtering criteria to consider only selected cryptocurrencies. The first filtering principles aim at excluding the crypto assets, which have not come under the best fifty

Authors	Sample	Anomalies	Methods	Findings
Durai and Paul (2018)	Bitcoin (2010–2018)	DoW	OLS	DoW effect is present in Bitcoin returns and varies with time
Aharon and Qadan (2019)	Bitcoin (2010–2017)	DoW	OLS, GARCH	Detected initial evidence of the DoW effect
Caporale and Plastun (2019)	Bitcoin, Litecoin, Ripple, Dash (2013–2017)	DoW	Student's *t*-test, ANOVA, Kruskal–Wallis and Mann–Whitney tests and regression analysis with dummy variables	Except for Bitcoin, other cryptocurrencies do not exhibit the DoW anomaly
Ma and Tanizaki (2019a)	Bitcoin (2014–2018)	DoW	GARCH	Dynamic patterns of the DoW effect
Ma and Tanizaki (2019b)	Bitcoin (2013–2018)	DoW	OLS, Stochastic Volatility	DoW effect in Bitcoin return varies with the sample period
Kinateder and Papavassiliou (2019)	Bitcoin	Halloween, DoW, MoY	GARCH	No Halloween effect is detected. Reverse January effect evidenced

Table 1.
List of studies on calendar anomalies or effects of the cryptocurrency market

cryptocurrencies in terms of market capitalisation. Selecting cryptocurrencies with higher market capitalisation decreases the chances for selecting crypto assets which have infrequent trading, less liquid and not a standard asset class for investment. The second criteria exclude those currencies which have less than four years of trading history. The idea of selecting at least a four-year trading history is to get sufficient data points for time-series related estimation to avoid possible spurious outcomes. After filtration, there are only nine cryptocurrencies left, including the Bitcoin.

The span of the study period ranges from October 25, 2014, to May 25, 2019. To have the homogeneous number of observations for all cryptocurrencies is the basis for selection of this particular study period. As the date October 25, 2014, is the cutoff date from where data for all cryptocurrencies are available, this study has chosen that particular date as the beginning period of the study. "Coinmarketcap.com" is the data source for all cryptocurrencies. All analysis in this study is performed on logarithmic returns.

3.2 Methods

To examine calendar effects this study has adopted both parametric (i.e., OLS with GARCH(1, 1)) and non-parametric (Kruskal–Wallis test) approaches widely followed in similar literature and also implemented in recent studies (see, for instance, Urquhart and McGroarty, 2014; Kumar, 2016; Kumar, 2018; Xiong *et al.*, 2019; Ma and Tanizaki, 2019a).

To evaluate the calendar effects, this study estimated the linear regression as follows:

$$R_{it} = \alpha_i + \beta_i C_{it} + \varepsilon_{it} \tag{1}$$

where R_{it} is the cryptocurrency return of cryptocurrency i on the day $(t = 1, \ldots.., T)$. C_{it} is the calendar anomaly dummy/indicator for currency i on day t. ε_{it}, is the error term. For Monday effects, the coefficient C in Equation (1) Includes all Monday returns assigned as one and other days of the week denoted as zero. Similarly, for January effect days coming under January indicated with one and remaining month have given zero; for TOTM effect final day of a month and the first three days of subsequent month appointed one and rest of the period as zero; for the S&S effect all S&S are denoted with one and other days are indicated as zero.

Following Urquhart and McGroarty (2014), we use the Generalised Autoregressive Conditional Heteroscedasticity (GARCH) model instead of the ordinary least square method as it is most robust and straightforward among volatility models (Engle, 2001). The GARCH (p, q) model is flexible to model the variance as conditional on past variance and error. The GARCH (1, 1) regression equation which takes account of the time-varying nature of cryptocurrency returns are as follows:

$$h_{it} = \lambda_0 + \lambda_1 \varepsilon_{t-1}^2 + \vartheta h_{it-1} \tag{2}$$

where h_{it} and h_{it-1} are the conditional variances of cryptocurrency returns of crypto-coin i at time t and $t-1$ respectively. λ_0, λ_1 and ϑ are coefficients of the GARCH (1, 1) model.

Further, we use the Kruskal–Wallis (KW) test as the GARCH model is not able to capture the non-normality of data. The KW test examines whether the populations from which samples are drawn have identical distributions and are particularly sensitive to means (Urquhart and McGroarty, 2014). In this study, the difference between cryptocurrency returns on calendar effects days and non-calendar effect days verified using the KW test as:

$$H = \left(\frac{12}{N(N+1)} \sum_{j=1}^{k} \frac{R_j^2}{n_j} \right) - 3N(N+1) \tag{3}$$

where R_j^2 is the mean rank of observations in the jth category. n_j is the overall sample in the jth category. k is the number of groups, and N stands a total number of observations. The KW estimates follows χ^2 distribution with K-1 degrees of freedom.

4. Results and analysis

4.1 Descriptive statistics of calendar effects

Table 2 exhibits the descriptive statistics of several calendar effects (Monday, January, TOTM and S&S effects) investigated in this study. Before proceeding to estimate the descriptive statistics, this study detaches presence of possible statistical bias due to unequal data range for different calendar and non-calendar effect periods by calibrating the data length of both calendar effects and non-calendar effect days [3].

In the case of Monday effects, it is evident that the sign of average Monday returns of cryptocurrencies compared to non-Monday returns are mixed (see Table 2). Notably, unlike a traditional financial asset like a stock, all cryptocurrencies excluding Litecoin, Dash, Bitshares, Verge, and Bytecoin exhibits significant positive Monday returns. The t-statistics and the KS-statistics have confirmed the same.

For the January effect, Table 2 portrays that except Bytecoin, all other cryptocurrencies show negative January returns, which received further attestation from the student's t and the KS-statistics (see Table 2). This particular evidence related to the January effect in the cryptocurrency market does not imitate the traditional financial asset markets.

Further, the TOTM mean returns like conventional assets are positive for all cryptocurrencies also got the approval of the student's t-statistics and the KS-statistics except for Dash, Dogecoin and Bitshares (see Table 2).

The S&S mean returns, as expected, show positive returns but found to have no significant differences with the non- S&S gains. The same has been further strengthened by insignificant student's t-statistics and the KS-statistics except for Monero, Verge and Bytecoin.

Besides, mean returns of different calendar anomalies Table 2 also portrays the standard deviation of several calendar anomaly and non-anomaly days. Surprisingly, it is evident that

Anomalies	Mean	SD	*t*-statistics	KS-statistics	Observations	Adj. Obs
Panel A: Bitcoin						
Monday	0.523	0.246	1.526***	0.167*	239	238
Non-Monday	0.131	0.101			1,435	238
January	−0.606	0.239	−7.202*	0.800***	155	5
Non-January	0.347	0.201			1,519	5
TOTM	0.729	0.249	2.307*	0.309*	220	55
Non-TOTM	0.115	0.103			1,454	55
S&S	0.191	0.131	0.027	0.067	479	239
Non- S&S	0.186	0.122			1,195	239
Panel B: Ripple						
Monday	0.220	0.023	−0.586	0.518*	239	238
Non-Monday	0.353	0.230			1,435	238
January	−0.847	0.474	−2.823**	0.600	155	5
Non-January	0.270	0.386			1,519	5
TOTM	0.546	0.530	0.578	0.145	220	55
Non-TOTM	0.222	0.237			1,454	55
S&S	−0.100	0.313	−1.219	0.087	479	239
Non- S&S	0.408	0.239			1,195	239
Panel C: Litecoin						
Monday	−0.001	0.338	−0.662	0.146*	239	238
Non-Monday	0.224	0.153			1,435	238
January	−0.567	0.262	−5.281*	0.600	155	5
Non-January	0.406	0.317			1,519	5
TOTM	0.776	0.324	1.891**	0.236***	220	55
Non-TOTM	0.118	0.153			1,454	55
S&S	0.409	0.219	1.095	0.083	479	239
Non- S&S	0.113	0.168			1,195	239
Panel D: Monero						
Monday	0.166	0.500	−0.252	0.230*	239	238
Non-Monday	0.297	0.174			1,435	238
January	−0.411	0.201	−5.217*	0.800***	155	5
Non-January	0.442	0.289			1,519	5
TOTM	0.839	0.349	1.405***	0.272**	220	55
Non-TOTM	0.219	0.215			1,454	55
S&S	0.846	0.293	2.280*	0.101	479	239
Non- S&S	0.059	0.187			1,195	239
Panel E: Dash						
Monday	−0.428	0.386	−1.850**	0.238*	239	238
Non-Monday	0.384	0.161			1,435	238
January	−0.110	0.460	−1.639***	0.400	155	5
Non-January	0.367	0.315			1,519	5
TOTM	0.552	0.379	0.818	0.218	220	55
Non-TOTM	0.233	0.161			1,454	55
S&S	0.474	0.275	0.886	0.096	479	239
Non- S&S	0.178	0.165			1,195	239
Panel F: Dogecoin						
Monday	0.174	0.378	0.064	0.171*	239	238
Non-Monday	0.148	0.185			1,435	238
January	−0.237	0.575	−0.757	0.600	155	5
Non-January	0.239	0.247			1,519	5
TOTM	0.361	0.409	0.529	0.145	220	55

(*continued*)

Table 2.
Descriptive statistics of several calendar anomalies

Anomalies	Mean	SD	*t*-statistics	KS-statistics	Observations	Adj. Obs
Non-TOTM	0.120	0.197			1,454	55
S&S	0.267	0.296	0.459	0.104	479	239
Non- S&S	0.102	0.186			1,195	239
Panel G: Bitshares						
Monday	−0.203	0.508	−0.572	0.209*	239	238
Non-Monday	0.109	0.229			1,435	238
January	−0.588	0.340	−3.261*	0.400	155	5
Non-January	0.205	0.389			1,519	5
TOTM	0.080	0.440	0.001	0.145	220	55
Non-TOTM	0.080	0.252			1,454	55
S&S	0.297	0.284	0.930	0.046	479	239
Non- S&S	−0.032	0.231			1,195	239
Panel H: Verge						
Monday	−2.060	0.946	−2.827*	0.255*	239	238
Non-Monday	0.916	0.398			1,435	238
January	−0.292	0.915	−1.342	0.200	155	5
Non-January	0.590	0.563			1,519	5
TOTM	1.106	0.888	0.601	0.254**	220	55
Non-TOTM	0.512	0.342			1,454	55
S&S	1.371	0.639	1.624***	0.129**	479	239
Non- S&S	0.066	0.394			1,195	239
Panel I: Bytecoin						
Monday	−0.269	0.490	−1.095	0.230*	239	238
Non-Monday	0.354	0.271			1,435	238
January	0.086	0.196	−1.062	0.400	155	5
Non-January	0.393	0.278			1,519	5
TOTM	0.813	0.693	0.712	0.272**	220	55
Non-TOTM	0.278	0.257			1,454	55
S&S	0.544	0.444	0.978	0.121*	479	239
Non- S&S	0.172	0.274			1,195	239

Note(s): This table presents descriptive statistics of different calendar periods. Here TOTM is turn-of-the-month, and S&S is Saturday and Sunday. KS refers to Kolmogorov–Smirnov. Adj. Obs denoted in the last column of this table indicate Adjusted Observations. *, ** and *** indicates level of significance at 1%, 5% and 10%, respectively

Table 2.

Verge delineates the highest variability in the case of all calendar anomalies (Monday, January, TOTM and S&S). However, Ripple has the least variance in the case of Monday returns and Bytecoin for January returns. Similarly, Bitcoin represents minimal volatility in the case of January; and S&S returns.

4.2 Adaptive calendar effects

The rolling window approach appraises the adaptive or time-varying calendar effects of different cryptocurrencies. The GARCH (1, 1) model is primarily estimated in the rolling window framework to explore dynamic patterns of calendar effects in select cryptocurrencies.

The rolling window set-up implemented in this study mainly followed a 350 days window length, which subsequently spun by 30 observations. In this way, the same exercise is repeated until there is adequate data to form 350 representations. Figures 1 and 2 exhibits estimates of the GARCH (1, 1) model for different cryptocurrencies. Figure 1 represents p-values of the β coefficient (representing calendar anomalies) and Figure 2 delineates the corresponding coefficient values (which denotes calendar anomalies) for each

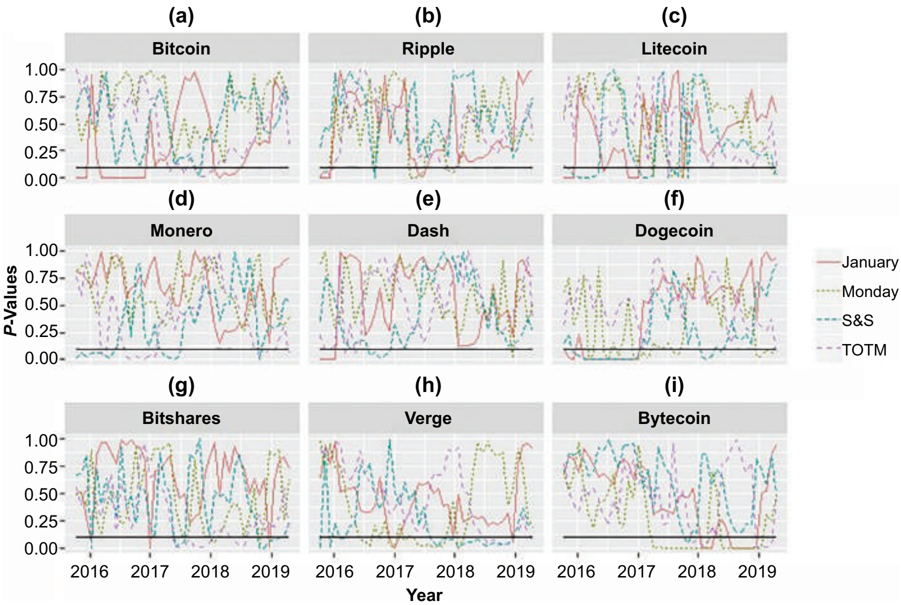

Figure 1. Rolling p-values of the GARCH (1, 1) estimates of different cryptocurrencies

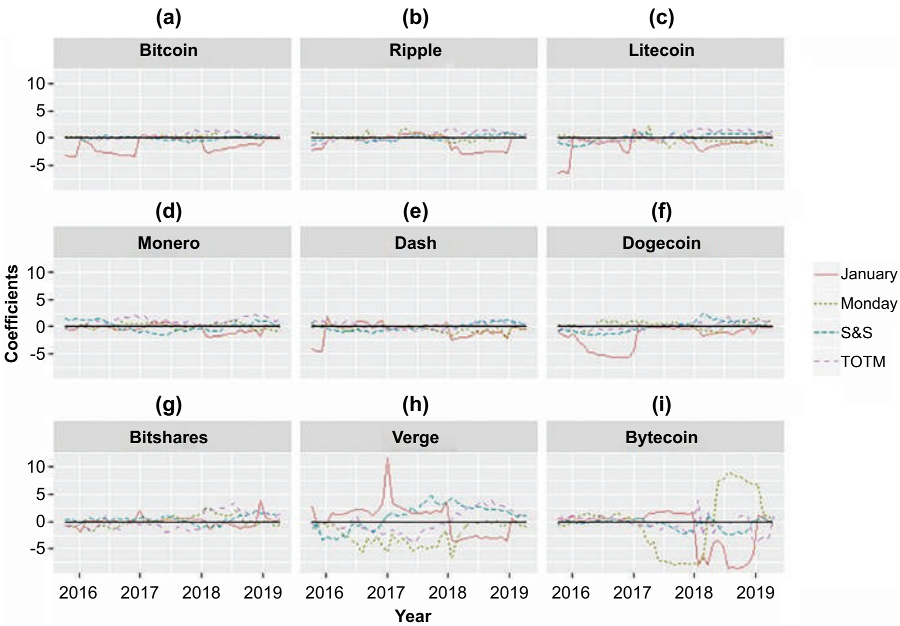

Figure 2. Rolling coefficient of the GARCH (1, 1) estimates of different cryptocurrencies

cryptocurrency. For the Monday effect, Figure 1 outlines except Bitcoin, Monero, and Dash all other cryptocurrencies evident prominent periods of variation in the Monday effects. However, the fact is mixed over the period, as the coefficient represents the Monday effect in Figure 2 which exhibits mixed evidence of positive and negative coefficients. Surprisingly, the Verge reveals that for the whole period, the coefficients of Monday effects are negative, which indicates a weakening Monday effect (see Figure 2(h)). However, at the same time, Bytecoin displays a heterogeneous significant Monday effect from the 2nd quarter of 2017 to the 3rd quarter of 2019 (see, Figure 1(i) and 2 (i)). Apart from, the Verge and the Bytecoin, other cryptocurrencies coefficient, representing the Monday effects meander around zero or ± 1, which indicates that despite the presence of the prominent Monday effect, the magnitude of the effect is not so significant.

Nevertheless, the evidence of swings in the Monday effect over the period validates the premise of the AMH. For January effects, Figure 1 confirms the existence of significant and adaptive January effect for all cryptocurrencies except for Monero and Bitshares. The corresponding coefficient value reveals a diversified effect for the cryptocurrencies. Unlike the Monday effect, the January effect shows little higher coefficients both in positive and negative form – which indicates strong or weakening January effect, respectively. However, unlike other cryptocurrencies Bitcoin, Dogecoin and Bytecoin who have recorded a comparatively long period of unusual January effect at different times, are associated with a significant negative coefficient (see Figure 2 (a), (f), (i)). This indicates that the January effect is weakening for these cryptocurrencies. Despite all these facts, it is evident that the January effect moved with time, which satisfies the principles of the AMH.

The TOTM effects estimates, represented in Figure 1, exhibits significant adaptive TOTM effect in all cryptocurrencies (except Litecoin and Dogecoin) as their p-values obtained are less than equal to 0.10. However, excluding the Bitcoin, Monero and Bitshares other cryptocurrencies portray trivial episodes of the TOTM effect. The corresponding period of the significant TOTM effect apparent from Figure 1, recorded a positive coefficient, as evident in Figure 2. Like other calendar effects, the TOTM effects also time-variant which comply with the AMH paradigm.

Finally, for the S&S effect, the Bitcoin, Ripple and Bytecoin observed a comparatively insignificant period of noticeable S&S effect (see Figure 1(a), (b), (i)). However, Litecoin, Monero and Dogecoin registered substantial S&S effect in the initial period, i.e. 2015–2016 (see Figure 1(c), (d), (f)). In contrast, Verge documented a relatively extensive stretch of the S&S effect at the end of the study period, i.e. mid-2017–2018 (see Figure 1(h)). The sign of the coefficient during significant S&S effect for Litecoin and Dogecoin indicate about weakening impact as it is negative (see Figure 2 (c), (f)); however, the same is influential for Monero as it is positive (see Figure 2 (d)). Similarly, the significant S&S effect period of the Verge is market with positive coefficients which pronounce vigorous effect. Moreover, Litecoin and Monero depict notable S&S effect at the middle point of the study period, i.e. 2017 (see Figure 1(c), (d)), where Litecoin reveals positive coefficients and Monero displays negative coefficients (see Figure 2 (c), (d)).

4.3 Estimates of KW test

Furthermore, this study has estimated the KW test following the same rolling window set-up to check the robustness of the findings of the GARCH (1, 1) model. As the return distribution of cryptocurrencies shows non-normality, there is a possibility that GARCH (1, 1) model might produce spurious outcomes. Thus, the KW test, which is robust to non-normality, can provide better results. Estimates of the KW test presented in Figure 3 communicate qualitatively similar findings like the GARCH (1, 1).

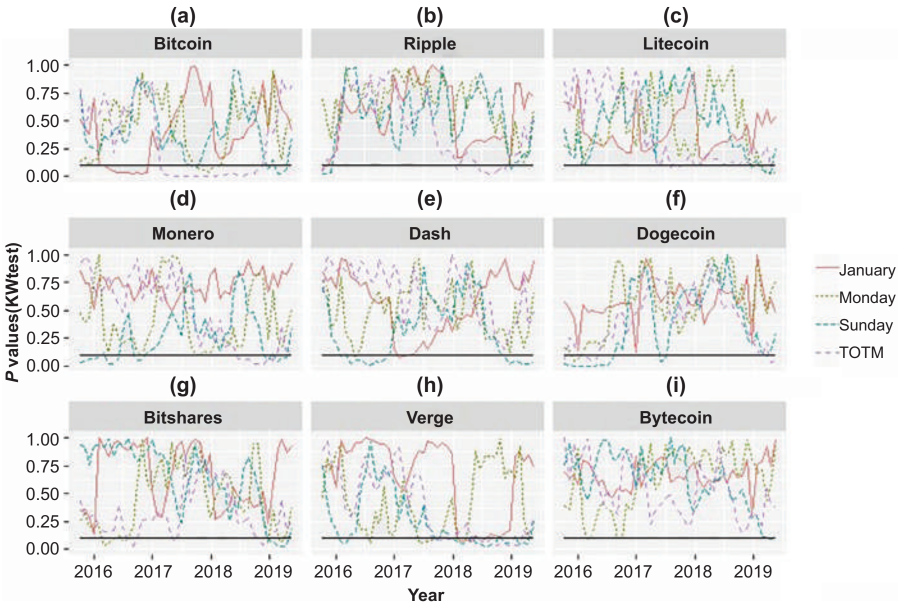

Figure 3.
Rolling p-values of KW estimates of different cryptocurrencies

4.4 Calendar effects ratio

In this section, the calendar effects ratio (CER) [4] is estimated to make a relative comparison of anomalies in the cryptocurrency markets. To measure the CAR, we have used the following method:

$$\mathrm{CER} = \frac{\Sigma\text{Number of windows accepts the presence of } CE}{N} * 100 \tag{4}$$

where CER is calendar anomalies ratio, CE is calendar effects and N is the total number of sub-samples in the rolling window.

Estimates of CER presented in Table 3 show that Bitcoin and Monero have no Monday effect. However, Bytecoin with CER of 47.73 % demonstrates the highest Monday effect followed by the Verge which documents CER of 36.36%. It implies that technical trading

Cryptocurrencies	Monday	January	TOTM	S&S	Average
Bitcoin	00.00	43.18	15.91	02.27	15.34
Ripple	20.45	11.36	13.64	02.27	11.93
Litecoin	11.36	18.18	06.82	36.36	18.18
Monero	00.00	00.00	31.82	31.82	15.91
Dash	02.27	09.09	09.09	11.36	07.95
Dogecoin	34.09	34.09	04.55	40.91	28.41
Bitshares	11.36	06.82	25.00	22.73	16.47
Verge	36.36	09.09	15.91	47.73	27.27
Bytecoin	47.73	20.45	20.45	02.27	22.72

Note(s): This table delineates calendar anomalies ratio of different cryptocurrencies. Where TOTM indicates turn-of-the-month, and S&S is Saturday and Sunday

Table 3.
Calendar anomalies ratio of cryptocurrencies

strategies could benefit investors in terms of excess market returns by exploiting the presence of significant Monday anomalies in Bytecoin and Verge. On the contrary, Bitcoin and Monero offer no such possibility as they exhibit zero percentage of Monday effects. In the case of the January effect, Monero is most efficient with CER of 0.00 % followed by Bitshares, which has recorded CER of 6.82. However, the Bitcoin manifests a higher magnitude (43.18%) of the January effect followed by the Dogecoin (34.09%). The CER of Bitcoin and Dogecoin conveys that trading strategies can outperform than simple buy-and-hold strategies to obtain extra market returns, which is not possible in the case of the Monero. For the TOTM effect, the CER reveals that the Dogecoin is the most efficient as there is a lesser proportion of time, which demonstrates TOTM effects. However, comparatively higher CER for the Monero indicates the possibility of earning abnormal returns due to TOTM effects. For the S&S effects, the CER of the Bitcoin, Ripple and Bytecoin pronounce that, for these crypto-coins, it is nearly impossible to get abnormal gains using S&S anomalies. On the other hand, the CER of the Verge (47.73%) and Dogecoin (40.91%) suggests chances of acquiring extra market returns using the S&S anomalies.

4.5 Possible excess returns from trading strategy

The presence of adaptive calendar effects indicates that the cryptocurrency market offers an opportunity for abnormal gains from time to time. However, every anomaly is not economically significant, and implementation of technical trading strategy may not perform superior to simple buying-and-hold (BH) strategy. Therefore, in this section, this present study evaluates possible excess returns by comparing the returns from simple BH strategy and implied trading strategy (ITS).

The BH strategy follows the idea of acquiring cryptocurrencies at the beginning of the study period (i.e., October 25, 2014) and selling at the end of the study period (i.e., May 25, 2019). However, the ITS operates strategically by incorporating an exclusive mechanism for each calendar anomaly. For this study, the ITS used for different calendar anomalies as follows:

Monday effect: Following Urquhart and McGroarty (2014), the ITS for the Monday effect involves long position on Tuesday and liquidation on the immediate Monday and the process imitated until May 25, 2019.

January effect: in this case long position is made at the closing price of the last trading day of the December and short position is done at the closing price of the final trading day of the immediate January, and the similar operation is repeated until May 25, 2019.

TOTM effect: for this effect, ITS is designed to purchase cryptocurrencies at the closing price of the finishing trading day of a month and sell cryptocurrencies at the closing price of the third trading day of the immediate next month. Similarly, this process is mimicked until the last day of the study period.

S&S effect: to capture the benefits of the S&S anomaly the ITS equipped with buying cryptocurrencies at the closing price of the Monday and selling at the closing price of the immediate Sunday, and the process runs until concluding day of the study period.

This study has examined the difference of returns between ITS and BH strategy for the full sample and two sub-samples – which equally divides the entire study period into two parts [5]. Estimates of excess returns obtained from ITS over BH strategy for each cryptocurrency and each calendar anomalies are presented in Table 4 for the full sample, Table 5 for first sub-sample and Table 6 for second sub-sample. For the whole sample, it is observed that for none of the cryptocurrencies, the ITS is able to outperform the BH strategy as thedifference is significantly negative except for a couple of instances of Bitshares (see Table 4). For example, in the case of the Bitcoin, the difference valu e of −1822 for Monday effect indicates that by following the ITS instead of BH can cause loss of −1822% on the

Table 4. Trading strategies and difference of returns for the full sample of different cryptocurrencies

	Bitcoin				Ripple				Litecoin			
Anomalies	Trade	ITS	BH	Difference	Trade	ITS	BH	Difference	Trade	ITS	BH	Difference
Monday	480	396.8	2218.8	−1822.0	480	921.8	8101.7	−7179.9	480	482.3	2697.5	−2215.2
January	10	41.6	2218.8	−2177.2	10	−77.4	8101.7	−8179.1	10	157.9	2697.5	−2539.6
TOTM	110	139.1	2218.8	−2079.7	110	148.1	8101.7	−7953.6	110	191.1	2697.5	−2506.4
S&S	474	289.3	2218.8	−1929.5	474	1304.8	8101.7	−6796.9	474	587.1	2697.5	−2110.4

	Monero				Dash				Dogecoin			
Anomalies	Trade	ITS	BH	Difference	Trade	ITS	BH	Difference	Trade	ITS	BH	Difference
Monday	480	749.5	11,658	−10909.0	480	671.5	8031.3	−7359.8	480	692.8	1115.9	−423.1
January	10	28.8	11,658	−11629.2	10	114.5	8031.3	−7916.8	10	44.6	1115.9	−1071.3
TOTM	110	23.9	11,658	−11634.1	110	105.7	8031.3	−7925.6	110	80.9	1115.9	−1035.0
S&S	474	751.1	11,658	−10906.9	474	836.1	8031.3	−7195.2	474	652.2	1115.9	−463.7

	Bitshares				Verge				Bytecoin			
Anomalies	Trade	ITS	BH	Difference	Trade	ITS	BH	Difference	Trade	ITS	BH	Difference
Monday	480	762.4	193.9	568.5	480	3302.9	157,414	−154,111	480	1031.4	7,650	−6618.6
January	10	2.9	193.9	−191.0	10	93.3	157,414	−157,321	10	67.1	7,650	−7582.9
TOTM	110	68.4	193.9	−125.5	110	454.1	157,414	−156,960	110	78.5	7,650	−7571.5
S&S	474	788.3	193.9	594.4	474	2020.5	157,414	−155,394	474	1644.4	7,650	−6005.6

Note(s): This table illustrates returns generated through implied trading strategy (ITS) and buy-and-hold (BH) trading strategies for the full sample. Difference denotes the gap between returns through ITS and BH strategy. S&S is Saturday and Sunday

Table 5.
Trading strategies and difference of returns for the first sub-sample of different cryptocurrencies

Anomalies	Trade	Bitcoin ITS	Bitcoin BH	Bitcoin Difference	Trade	Ripple ITS	Ripple BH	Ripple Difference	Trade	Litecoin ITS	Litecoin BH	Litecoin Difference
Monday	238	156.7	205.6	−48.9	238	112.8	35.8	77.0	238	71.3	10.1	61.2
January	6	−45.7	205.6	−251.3	6	−37.6	35.8	−73.4	6	−49.4	10.1	−59.5
TOTM	56	32.9	205.6	−172.7	56	−3.74	35.8	−39.5	56	−11.7	10.1	−21.8
S&S	236	83.4	205.6	−122.2	236	137.8	35.8	102.0	236	58.2	10.1	48.1

Anomalies	Trade	Monero ITS	Monero BH	Monero Difference	Trade	Dash ITS	Dash BH	Dash Difference	Trade	Dogecoin ITS	Dogecoin BH	Dogecoin Difference
Monday	238	511.6	1558.8	−1047.2	238	349.7	792.7	−443.0	238	3.2	−15.4	18.6
January	6	−37.5	1558.8	−1596.3	6	50.8	792.7	−741.9	6	50.2	−15.4	65.6
TOTM	56	55.3	1558.8	−1503.5	56	34.2	792.7	−758.5	56	−56.3	−15.4	−40.9
S&S	236	355.9	1558.8	−1202.9	236	351.9	792.7	−440.8	236	70.7	−15.4	86.1

Anomalies	Trade	Bitshares ITS	Bitshares BH	Bitshares Difference	Trade	Verge ITS	Verge BH	Verge Difference	Trade	Bytecoin ITS	Bytecoin BH	Bytecoin Difference
Monday	238	−48.1	−81.9	33.8	238	1141.3	200.0	941.3	238	502.2	341.7	160.5
January	6	−38.6	−81.9	43.3	6	101.3	200.0	−98.7	6	32.9	341.7	−308.8
TOTM	56	−74.2	−81.9	7.7	56	−8.38	200.0	−208.4	56	−23.96	341.7	−365.6
S&S	236	50.6	−81.9	132.5	236	869.1	200.0	669.1	236	296.2	341.7	−45.5

Note(s): This table illustrates returns generated through implied trading strategy (ITS) and buy-and-hold (BH) trading strategies for the first sub-sample. Difference denotes the gap between returns through ITS and BH strategy. S&S is Saturday and Sunday

Table 6. Trading strategies and difference of returns for second sub-sample of different cryptocurrencies

Anomalies	Bitcoin Trade	Bitcoin ITS	Bitcoin BH	Bitcoin Difference	Ripple Trade	Ripple ITS	Ripple BH	Ripple Difference	Litecoin Trade	Litecoin ITS	Litecoin BH	Litecoin Difference
Monday	242	240.1	657.5	−417.4	242	809	5911.8	−5102.8	242	411.1	2453.9	−2042.8
January	4	87.4	657.5	−570.1	4	−164.7	5911.8	−6076.5	4	78.9	2453.9	−2375.0
TOTM	54	106.2	657.5	−551.3	54	154.4	5911.8	−5757.4	54	202.8	2453.9	−2251.1
S&S	238	206	657.5	−451.5	238	1167.1	5911.8	−4744.7	238	529.5	2453.9	−1924.4

Anomalies	Monero Trade	Monero ITS	Monero BH	Monero Difference	Dash Trade	Dash ITS	Dash BH	Dash Difference	Dogecoin Trade	Dogecoin ITS	Dogecoin BH	Dogecoin Difference
Monday	242	237.9	575.2	−337.3	242	321.7	799.9	−478.2	242	689.6	1317.5	−627.9
January	4	−30.5	575.2	−605.7	4	131.6	799.9	−668.3	4	61.7	1317.5	−1255.8
TOTM	54	126.4	575.2	−448.8	54	71.5	799.9	−728.4	54	137.2	1317.5	−1180.3
S&S	238	395.1	575.2	−180.1	238	484.1	799.9	−315.8	238	581.5	1317.5	−736.0

Anomalies	Bitshares Trade	Bitshares ITS	Bitshares BH	Bitshares Difference	Verge Trade	Verge ITS	Verge BH	Verge Difference	Bytecoin Trade	Bytecoin ITS	Bytecoin BH	Bytecoin Difference
Monday	242	810.4	1548.3	−737.9	242	2161.5	52404.8	−50243.3	242	529.2	1654.7	−1125.5
January	4	−68.5	1548.3	−1616.8	4	126.1	52404.8	−52278.7	4	100.4	1654.7	−1554.3
TOTM	54	142.6	1548.3	−1405.7	54	462.5	52404.8	−51942.3	54	102.5	1654.7	−1552.2
S&S	238	737.4	1548.3	−810.9	238	1151.5	52404.8	−51253.3	238	1,345	1654.7	−309.7

Note(s): This table illustrates returns generated through implied trading strategy (ITS) and buy-and-hold (BH) trading strategies for the second sub-sample. Difference denotes the gap between returns through ITS and BH strategy. S&S is Saturday and Sunday investment. However, the Monday and S&S anomalies of Bitshares reveals significant excess positive returns of 568.5 and 594.4%, respectively from ITS against BH strategy (see the lower-left corner of Table 4). It implies that although there is evidence of different calendar anomalies for various cryptocurrencies, it is not economically exploitable except Bitshares. Additionally, as expected anomaly Bitshares reveals positive excess returns in case of the S&S effect. It denotes that the possible reason for such S&S effect could be due to increasing buying pressure on the weekend, i.e. S&S for Bitshares.

For the first sub-sample, which represents a calm and steady upward period of the cryptocurrency market it is evident that Ripple, Litecoin, Dogecoin, Bitshares, and Bytecoin reveals significant excess returns through ITS (see Table 5). Mainly, Ripple and Litecoin display excess returns from Monday and S&S anomalies as the difference of ITS and BH return is positive. Dogecoin exhibits additional returns from ITS over BH for Monday (18.6%), January (65.6%) and S&S (86.1%) anomalies. Interestingly, Bitshares confirms the possibility of excess returns through ITS from all anomalies (see the lower-left corner of Table 5). However, Bytecoin delineates positive excess returns through ITS for Monday anomalies only, i.e. 160.5%. The probable reason for such excess returns by ITS over BH strategy can be due to the slow movement and minimal variability of alternative cryptocurrency prices in their introduction phase. Slow inter-day movement and minimal variability kept the BH strategy return at a lower level, which ultimately helped the active ITS to acquire excess gains from short-term changes. However, other cryptocurrencies (Bitcoin, Monero, Dash and Verge) recorded no positive rewards of ITS for any of the anomalies examined (see Table 5) as the difference value from ITS and BH are negative.

For the second sub-sample, which represents an extreme volatility period attached with sudden ups and downs in cryptocurrency prices marked no evidence of any positive excess returns by ITS (see Table 6). The possible cause for such failure of ITS to obtain extra gains from different calendar anomalies could be associated with abnormal growth and fall in cryptocurrencies. Unusual movement in cryptocurrencies during this period restricted ITS to outperform.

4.6 Contribution of this study

This study supplements the existing literature in the following ways. First, this study has examined a wide range of possible calendar anomalies in a broader spectrum of the cryptocurrency market, unlike other studies undertaken in this context. Existing studies in the cryptocurrency market primarily have tested the day-of-the-week effect only, and the focus centered only on the Bitcoin market. However, other anomalies like January, TOTM, and S&S effects are left untouched. Moreover, Bitcoin has lost its weightage after the substantial development of alternative cryptocurrencies. Hence, the examination of a wide array of calendar effects in prominent cryptocurrencies will enrich the available literature.

Second, this study implements the AMH approach exclusively to explore the dynamics of several calendar anomalies in cryptocurrency returns. Pragmatically, presence of behavioural bias, market frictions, and change in market conditions can cause the evolution of calendar effects and thus the static approach of EMH cannot explain such dynamics. Therefore, following the AMH framework, this study has explored evolving calendar anomalies in cryptocurrency returns. Finally, this study also has estimated the relative calendar anomalies ratio over the period for different cryptocurrencies.

Third, none of the studies on cryptocurrency market has ever addressed whether the existence of any anomaly has the potential to produce excess returns through trading strategy. It may not hold good that mere presence of calendar anomalies would always cause abnormal gains. Hence, this particular study fills this void by comparing the volume of returns generated through a simple buy-and-hold strategy and implied investment trading strategy.

4.7 Research implications

The outcome of the present study suggests two-fold possible practical implications for investment decisions. First, this study has indicated that the calendar effect is not persistent; it is created with the emergence of events and movement of time. Hence, any assumption or to trade with the belief that the calendar effect is a continuous phenomenon may back-fire. In this regard, the safest way to deal with different calendar anomalies is to trace down events (economic or non-economic) which lead to the creation of calendar effects or pattern due to change in the market environment.

Second, the experiment made in this study to reap the calendar effects by trading strategies suggests crucial implications in practice. Specifically, an investment strategy (ITS in this study) which is successful in one condition to exploit the presence of calendar effects may not work in another condition because of the abnormal market volatility and dynamic movement of calendar effect. This outcome hints that trusting solely on the technical analysis and select trading strategies to predict cryptocurrency movement may be unproductive given the continuous changes in the market environment. Thus, in the canvas of dynamic market ecology, the investment manager must need to have a prime focus on survival strategy along with the objective of wealth maximisation. Moreover, timely and innovative active portfolio management strategies are of utmost importance to deal with changing market conditions.

5. Conclusion

The present study has explored adaptive calendar effects in the newly emerged cryptocurrency market to explain market efficiency. Instead of the traditional EMH approach, this study has followed the fundamentals of the AMH, which better interprets changes in efficiency. Mainly, Monday, January, TOTM and S&S effects were vital points of investigation. Although Monday, January and TOTM effects are commonly observed in the conventional financial market, the S&S effect could only be related to the cryptocurrency market – as it operates around the year. This study has implemented GARCH (1, 1) and KW-test in rolling window framework to verify adaptive calendar effects. Further, a straight forward ITS is adopted to check whether the presence of calendar effects is supplying any extra returns compared to simple BH strategy.

Findings of this study confirm that calendar effects over the period fluctuate and adapt with times. It adheres to the core values of the AMH – which views market efficiency cannot be a motionless phenomenon. The findings from ITS convey that except for Bitshares no other cryptocurrencies depicts extra returns through ITS. However, in case of sub-samples, the first sub-sample which represents relatively less volatile period documents that the ITS can generate additional return than BH strategy for the Ripple, Litecoin, Dogecoin, Bitshares, and Verge. On the other hand, the second sub-sample which is associated with a comparatively volatile period conveys that implementation of ITS could be a futile task as there is no evidence of abnormal gain from ITS over BH strategy. Furthermore, the CER estimated speaks that the Bytecoin is more inefficient in case of Monday anomalies; Bitcoin for the January anomalies; Monero for the TOTM effects; and Verge for the S&S anomalies.

The present study has covered some broad aspects of calendar anomalies in the cryptocurrency market, keeping aside certain other limitations which need to be addressed in the following dimensions. Future studies may aim at addressing issues like, Turn-of-the-Year effect, Halloween effect, weather effect, and Month-of-the-Year effects, and try to explore the reasons of presence of dynamic patterns of calendar effects.

Notes

1. It indicates that portfolio managers used to sell their weak or inferior stocks from their portfolio so that they can avoid them while presenting the annual reports.

2. As per the Islamic calendar, Saturday is the first working day of the week (Abalala and Sollis, 2015).
3. For example, the Monday series comprises all Mondays and, non-Monday series is the average of all days excluding Monday. Similarly, for other calendar effects, the average returns of non-calendar effect periods are considered to get similar data length.
4. CER refers to the proportion of the time exhibits the presence of studied calendar anomalies or effects concerning the total study period.
5. The rationale for such division is related to divide the entire study period with homogenous market characteristics. In the case of our study period, it is observed that the leading cryptocurrency "Bitcoin" has relatively steady growth before 2017. Since the beginning of 2017, it witnessed substantial volatility in price movements. Thus, equal division of our full sample falls around the beginning of 2017 (i.e. February 07, 2017), and each part can better capture the calendar effects unbiasedly.

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Appendix

Bitcoin is one of the earliest forms of cryptocurrency founded by the pseudonym Satoshi Nakamoto in 2009. The core technical composition of the Bitcoin comprehensively stands on the blockchain technology. Crucial economic and technological features of the Bitcoin entail that the maximum supply of the BTC could be 21 million, and currently there is more than 17 million BTC is in supply. The approximate time to create a block in case of the Bitcoin is 10 min, and it is capable of processing seven transactions per second. On the other hand, the Ripple–the third-largest cryptocurrency in terms of market capitalisation was founded in the year 2012. The maximum supply of the Ripple is prefixed at 100 billion, and currently, there is more than 40 billion of Ripple currency is in circulation. A new block can be created instantly in the Ripple network, and it can process 1,500 transaction per second. Litecoin – the fifth-largest cryptocurrency in terms of the market capitalisation was launched in the year 2011. The upper limit of the Litecoin supply is fixed at 84 million, and currently, there is more than 58 million of Litecoin is in supply. As far as block creation is concerned, Litecoin requires 2 min 30 s approximately to add a new block. Moreover, Litecoin facilitates the processing of 56 transactions per second. Monero – the 13th largest cryptocurrency as per the market capitalisation began its trading in the year 2014. The maximum supply of the Monero can be 18.4 million, and as of now, there is more than 15 million of the Monero under circulation. The average time required to create a new block in Monero is about 2 min only, and it is capable of processing about 1700 transactions per second. Dash is the 14th best cryptocurrency in terms of the total market capitalisation which was founded in the year 2014. The maximum limit of Dash can be mined or supplied is fixed at 18.9 million, and currently, there is more than 9 million is in supply. Dash requires 2 min 39 s to add a new block and can process 56 transactions per second. Dogecoin is ranked as 28th best cryptocurrency as per the market capit alisation, which started its operation in the year 2013. Interestingly, the Dogecoin has no maximum supply, and currently, there are more than 100 billion of the Dogecoin is available. To create a new block, Dogecoin consumes only one minute; however, the processing timing of transaction per second is comparatively slow, i.e. less than one transactions approximately per second. Bitshares – one of the leading cryptocurrency in terms of the market capitalisation (ranked as 48th) was launched in the year 2014. At the time of launch of Bitshares, the maximum supply of this cryptocurrency was fixed, which is about 3.6 billion, and at present, there are more than 2 billion of Bitshares in the collection. The Bitshares needs only 3 s to create an additional block. Similarly, Verge – which is positioned as 49th best in terms of the market capitalisation came to existence in the year 2014. The maximum Verge coin can be supplied 16.6 billion, which has currently touched at higher than 14 billion. The Verge can add a new block in the existing chain of blocks within 30 s. Bytecoin – which stands at the position of 50th best in terms of the market capitalisation was started functioning in the year 2012. The maximum level of supply of the Bytecoin cannot exceed 184 billion, which has currently crossed 140 billion. To accommodate a new block Bytecoin network system requires only 2 min (Information given in this section are collected from coingecko.com, accessed on October, 1, 2020).

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