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Do birds of a feather flock together? Evidence from time-varying herding behaviour of bitcoin and foreign exchange majors during Covid-19

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\textbf{ABSTRACT}

This paper analyses herding behaviour within bitcoin and foreign exchange majors before and during the Covid-19 pandemic. We utilise both static and time-varying parameter regression herding measures to assess herding intensity based on hourly and daily frequencies, covering the period from 1 March 2018 to 28 February 2022. Our hourly static and time-varying model results indicate the absence of herding (hence, the presence of anti-herding behaviour) within bitcoin and the foreign exchange majors before and during Covid-19. In daily herding analyses, however, while we do not find evidence of herding within bitcoin or the foreign exchange majors, we do observe strong time-varying herding within the foreign exchange majors after excluding bitcoin both before and during Covid-19, and during both up- and down-market days. We conclude that herding behaviour between foreign exchange majors tends to be time-varying and horizon-dependent. Our results could be useful for bitcoin and foreign exchange investors, traders, researchers and regulators, helping them to strengthen their understanding of herding behaviour before and during periods of market stress such as the period of Covid-19.

1. Introduction

Do investors herd, and why? These very questions have perhaps been asked ever since the infamous Dutch tulip bulb mania of the 1630s, the South Sea bubble of the 1720s and various market bubbles thereafter, including the late 1990s’ Dotcom tech bubble and the ‘big short’ of the US 2008 housing market collapse. Over the past decades and even centuries, these crashes may have had a common theme – investors jumping on the bandwagon and following other investors’ actions, either by buying or selling certain instruments, for fear of missing out on an investment opportunity or chance to cut their losses from trading. The extant literature generally asserts that herding happens when investors behave irrationally by suppressing their own private information, beliefs and judgment, and instead choosing to follow the market consensus.

Similarly, one could argue that investing in bitcoin may be rational and irrational within the cryptocurrency market. Some researchers contend that bitcoin lacks fundamentals, and its trading behaviour may be driven by informative signals from exogenous dynamics that contribute to herding (Bouri et al., 2019; Philippas et al., 2020). Notwithstanding the divergence among both public and
government opinion, bitcoin’s decentralised nature has attracted mass followers, investors, holders and whales (big investors), resulting in its price exploding exponentially. Before the advent of bitcoin, herding research had been undertaken within the scope of the equity and foreign exchange markets. The currency market is the world’s largest financial market, with transactions amounting to trillions of US dollars daily, and major currency pairs including EURUSD, GBPUSD, JPYUSD and CHFUSD (Kumar, 2014). Herding in the currency market is of particular interest to many researchers because its volatility can be caused by non-fundamental economic factors (Belke & Setzer, 2004), stop-loss orders resulting in price cascades (Osler, 2005), time-varying risk aversion that leads to currency excess returns (Demirer et al., 2022), and carry trades undertaken by currency traders (Demirer et al., 2020). However, very recently, Sibande et al. (2021) failed to find evidence of herding during periods of market stress in the currency market.

Our motivation to examine herding between bitcoin and foreign exchange majors are threefold. First, although one might argue that bitcoin, being a cryptocurrency, is different from foreign exchange as it may not be used by customers (as a proper currency) in making purchases, and while we agree that bitcoin is different from foreign exchange as it is decentralised in nature, and not backed by any government, it was adopted as legal tender by El Salvador in June 2021.1 Besides that, Tesla also bought $1.5 billion of bitcoin in February 2021 and started accepting bitcoin as payment for its cars in May 2021.2 Second, one might contend that bitcoin is mainly used as a speculative asset. We reiterate that speculation is also a common trait for foreign exchange, which has been traded by speculators, hedgers and arbitrageurs for decades. In many foreign exchange trading platforms, bitcoin is offered as a trading products alongside foreign exchange.3 Third, bitcoin may serve as a safe-haven asset (Urquhart & Zhang, 2019), as do currencies such as the dollar, euro, yen and Swiss franc (Chan et al., 2018; Cho et al., 2020; Fatum & Yamamoto, 2016). To this end, since both bitcoin and foreign exchange can be used as a medium of exchange, traded as speculative assets and serve as a safe haven, we argue that examining herding behaviour between bitcoin and the foreign exchange majors during periods of market stress such as that during Covid-19, is worth doing as market players are dealing with emotions full of fear, uncertainty and doubt. Hence, it would be interesting to know whether investors suppress their own beliefs and judgment in favour of the crowd at such times. Thus, our economic rationale for examining herding or anti-herding behaviour is essentially to ascertain the possibility of the assets under study serving as hedge instruments or diversifiers in a risky portfolio. For example, the lack of herding between bitcoin and the foreign exchange majors implies that these assets do not move together during extreme market movements, and hence have the potential to reduce portfolio risk.

Theories of herding go back a very long time and can be traced back to Keynes (1936), who argues that the notion of the stock market as a beauty contest where judges pick winners based on other judges’ opinions, thereby suppressing their own beliefs, is evidence against the efficient markets hypothesis. Early theoretical papers suggest that imitations and herding are human intuitions that can be found in fashion and fads (Bikhchandani et al., 1992; Devenow & Welch, 1996), and in financial markets (Bikhchandani & Sharma, 2000). Investors in the financial markets tend to learn from the behaviour of others. When they start to disregard their private information to imitate others, this process can result in informational cascades or herding behaviour (Bikhchandani et al., 1992, 1998; Welch, 1992). There are a few root causes of conformity or convergent trading behaviour. First, investors herd because they have similar payoffs, even if they have different information initially. By observing others (observational or social learning), rational investors utilise the information gained to help them make decisions (Bikhchandani et al., 1998). Second, investment managers mimic others’ actions to maintain their reputations and compensation. Scharfstein & Stein (1990) consider multiple herding equilibria and propose that, under principal-agent circumstances, investment managers may follow the decisions of other senior managers to protect their reputations, as they believe senior managers possess superior information—hence the herding behaviour. Third, interestingly, Froot et al. (1992) also compare multiple herding equilibria and argue that it is the short-term speculators in the financial markets, who attempt to learn from other traders, that causes herding, although the information that the short-term traders accumulate from other traders may not be related to fundamentals.

Herding can be measured in different ways. Lakonishok et al. (1992), Sias (2004) and Wermers (1999) were among the first to examine whether institutional investors follow each other’s trades or chase the trend. By making use of the institutional transaction data of 769 equity funds spanning from 1985 to 1989, and obtaining the numbers of active money managers or institutional buyers who are net buyers and sellers, Lakonishok et al. (1992) calculate cross-sectional temporal dependence between trades to determine whether institutional investors are following other earlier institutional investors within a particular period, only finding weak evidence of institutional herding. In a similar vein, Wermers (1999) scrutinises mutual fund herding behaviour based on a 1975 to 1994 dataset, uncovering weak institutional herding in small and growth stocks. On the other hand, Sias (2004) computes the cross-sectional correlation between current and next-period trades to establish whether institutional investors mimic other institutional investors in the following period. Based on a dataset covering all Fidelity funds’ institutional ownership filings from 1983 to 1997, the author reports evidence of institutions mimicking their own and other institutions’ trades from the previous quarter. One disadvantage of these measures of herding (Lakonishok et al., 1992; Sias, 2004; Wermers, 1999) is the need to access datasets of institutional transactions, which may not be available to many researchers.

The herding measures developed by Chang et al. (2000) and Christie & Huang (1995) are aimed at assessing market participants’ asymmetric herding behaviour during periods of market stress or extreme volatility. Christie & Huang (1995) propose a different approach to measuring the presence of herding behaviour, as compared to prior work (Lakonishok et al., 1992; Sias, 2004; Wermers,

1 See https://www.bloomberg.com/news/articles/2021-06-09/el-salvador-president-says-nation-adopts-bitcoin-as-legal-tender.
2 See https://www.cnbc.com/2021/02/08/tesla-buys-1-point5-billion-in-bitcoin.html.
3 See https://www.reuters.com/business/autos-transportation/tesla-will-most-likely-restart-accepting-bitcoin-payments-says-musk-2021-07-21/.
4 See, for example, https://www.fxcm.com/markets/forex/ and https://www.fxcm.com/markets/cryptocurrency/.
They contend that, if equity investors follow the market consensus (the herd) during market stress, equity returns will not digress too much from the broad market return; hence, the cross-sectional standard deviations (CSSDs) of returns should be low. Using daily data from the New York Stock Exchange and American Stock Exchange from 1962 to 1988, the authors find no evidence of equity returns herding or clustering during market stress. Taking a cue from their herding model, Hwang & Salmon (2004) introduce a beta herding approach to measure herding behaviour – in the event of herding, the cross-sectional dispersion of estimated betas will drop to reflect the market consensus. Due to the focus on the cross-sectional dispersion of betas instead of returns, the authors argue that the model should not be affected by the non-systematic risk component. Based on a 1993 to 2002 daily dataset, their results indicate herding during market stress in the US and South Korean equity markets. Phillips & Sul (2007) develop an attractive non-linear factor model to identify what they term convergence clubs or clusters across a panel dataset of cost-of-living indices for US cities. Their procedure can uncover herding behaviour and behavioural changes between groups. Perhaps the most popular approach to measuring herding behaviour was developed by Chang et al. (2000), inspired by the model of Christie & Huang (1995). According to Chang et al. (2000), the relationship between dispersion and the market return is linear, based on the Capital Asset Pricing Model (CAPM). Whenever there is herding during market stress, however, the linear relationship could transform into a non-linear one – and their non-linear specification captures this effect. Their first step is to calculate cross-sectional absolute deviations (CSADs) and test their asymmetric behaviour during up- and down-market days. Hence, their approach is known as the CSAD model. Based on about 20 years of daily equity data, ending between 1995 and 1997, they document significant herding behaviour in South Korea and Taiwan, partial herding in Japan, and no herding behaviour in either the US or Hong Kong. The increase in equity return dispersion is also higher for all samples during up- than down-market swings.

Whereas early herding research tends to focus on the equity market, of late, it has started to look at the cryptocurrency market. The latter has gained worldwide attention since Nakamoto (2008) published a white paper on bitcoin. It attracted the interest of the masses when its value reached an all-time high of $68,000 in 2021, from close to zero in 2009 (at its inception). While research on herding behaviour in the foreign exchange market appears to be scarce, studies on such behaviour in cryptocurrencies have been flourishing, particularly since 2018. Sibande et al. (2021) examine herding behaviour in nine currency pairs, using CSSD, CSAD and investor happiness analysis with a daily dataset from July 2003 to July 2019, and report anti-herding in highly bullish market periods. Earlier, Frenkel et al. (2020) tested for herding behaviour among foreign exchange forecasters in EURUSD, GBPUSD and JPYUSD. Using a monthly dataset from 1995 to 2014 for 67 forecasters, anti-herding was reported over different monthly horizons: foreign exchange forecasters tend to differentiate themselves from each other, mainly when dealing with short-term forecasts. Meanwhile, using five-minute data, Shahzad et al. (2021) scrutinise the interdependence between foreign exchange pairs and observe a strong positive relationship between the volatilities of pairs over the medium and long term.

The bulk of herding behaviour research in the cryptocurrency market uses a daily dataset, with the exceptions of Yarovaya et al. (2021), Mandaci & Cagli (2021) and Choi et al. (2021). Utilising CSAD and Markov-switching regressions on a 14-month hourly dataset of cryptocurrencies traded in the US dollar, euro, yen and won, from January 2019 to March 2020, Yarovaya et al. (2021) record that herding in the cryptocurrency markets is conditional upon whether it is an up- or down-market day. Further, the authors assert that herding does not appear to intensify during the Covid-19 period. Mandaci & Cagli (2021) exploit a Binance intraday order book dataset spanning from January 2019 to January 2021 and measure the herding intensity of nine cryptocurrencies using Patterson & Sharma (2006)’s specification. They observe a higher herding intensity during the Covid-19 pandemic. Choi et al. (2021) apply CSADs to eight cryptocurrencies traded on the Korean market across different hourly intervals, using a one-year dataset from January 2019 to May 2020. Their results show that herding is more pronounced over longer time intervals during down-market days.

Apergis et al. (2020) and Papadamou et al. (2021) apply Phillips & Sul (2007)’s convergence model to a daily dataset to test for the presence of clustering in cryptocurrencies. The former’s dataset spans from August 2015 to May 2020 (for eight cryptocurrencies), while the latter’s covers the period from January to December 2018 for all available cryptocurrencies in the market. Both studies generally observe the presence of convergence ‘clubs’, suggesting that herding exists in both bull and bear markets, but in clusters. Based on a daily dataset of 10 cryptocurrency pairs, and comments in public forums, from January 2017 to April 2019, Gurdgiev & O’Loughlin (2020) uncover the presence of herding bias when there is positivity amongst cryptocurrency speculators. King & Koutmos (2021), meanwhile, examine nine cryptocurrencies from roughly December 2013 to June 2020, employing Sentana & Wadhwani (1992)’s specifications, and document heterogeneity in herding patterns across cryptocurrencies.

One strand of research studies herding behaviour in the cryptocurrency market using Hwang & Salmon (2004)’s state-space beta herding model (Da Gama Silva et al., 2019; Kaiser & Stöckl, 2020; Raimundo Júnior et al., 2020). Da Gama Silva et al. (2019) run CSSD, CSAD and Hwang & Salmon (2004) specifications on 50 cryptocurrencies from March 2016 to November 2018. They report a weak herding result based on CSADs and find that herding exists during extreme periods, based on the state-space model. Similarly, using the beta herding measure to look at 80 cryptocurrencies from July 2015 to March 2020, Raimundo Júnior et al. (2020) record the presence of herding behaviour, particularly during periods of market stress. In the same manner, Kaiser & Stöckl (2020) report a strong herding pattern when they apply CSADs and the beta herding measure to a daily dataset of all cryptocurrencies available in the market from January 2015 to March 2019.

CSADs have been a popular measure of herding intensity within the cryptocurrency markets. Rubbani et al. (2021) and Shrotryia & Kalra (2021) employ it on daily datasets of 101 and 83 cryptocurrencies respectively, from 2015 to 2020, and reveal the presence of herding during bullish and high-volatility periods. Using CSADs and GARCH on six cryptocurrencies from January 2015 to March 2019, Ballis & Drakos (2020) conclude that herding is present during both up- and down-market days. Vidal-Tomás et al. (2019) examine a daily dataset of 65 cryptocurrencies from January 2015 to December 2017 using CSSDs and CSADs, and infer that the smallest cryptocurrencies are herding with the largest ones. Correspondingly, Philippas et al. (2020) explore signal herding in 100 cryptocurrencies from January 2016 to May 2018. Their findings seem to suggest that herding intensity is asymmetric and impacted by
| No | Paper | Data | Method | Herding or anti-herding? |
|----|-------|------|--------|-------------------------|
| 1  | Apergis et al. (2021, FRL) | Daily dataset of eight cryptocurrencies from Aug 2015 to May 2020. | Test for clustering (convergence clubs) following Phillips and Sul (2007). | Convergence occurs between cryptocurrencies with distinct technological functions. |
| 2  | Choi et al (2021, AE) | Hourly dataset of eight cryptocurrencies in the Korean market from Jan 2019 to May 2020. | CSAD on different hourly intervals. | Herding behaviour varies and is more pronounced in longer than shorter time intervals, and in down market. |
| 3  | Da Gama Silva et al. (2021, JBEF) | Daily dataset of 50 cryptocurrencies & CRX from Mar 2015 to Nov 2018. | CSSD, CSAD, Hwang & Salmon (2004) state-space model with Kalman filter. | Weak herding (CSAD). Herding during extreme periods (state-space model). |
| 4  | King & Koutmos (2021, AOR) | Daily dataset of nine main cryptocurrencies, roughly from Dec 2013 to Jun 2020. | Sentana & Wadhwani (1992) herding model. | Herding behaviours are not consistent across cryptocurrency market. |
| 5  | Kumar (2021, RBF) | Daily dataset of 100 cryptocurrencies from Aug 2013 to Apr 2019. | CSAD, quantiles and rolling window regression. | Presence of herding in both static and rolling window model, and herding is pronounced when market is either passing through stress. |
| 6  | Mandaci & Gagl (2021, FRL) | Binance intraday orderbook dataset for nine cryptocurrencies from Jan 2019 to Jan 2021 (2 years). | Herding intensity measure and Granger causality with Fourier approximation. | Herding behaviour intensified by the COVID-19 outbreak. |
| 7  | Papadamou et al (2021, JBEF) | Daily dataset of 216 cryptocurrencies from Jan to Dec 2018. | Test for clustering (convergence clubs) following Phillips and Sul (2007). | Herding is very intense during bull market. Herding also exists in bear market but in clusters. |
| 8  | Raimundo et al. (2021, JBF) | Daily dataset of 80 cryptocurrencies and VCRIX from July 2015 and March 2020. | Hwang & Salmon (2004) beta herding measure. | Presence of herding toward the market, particularly during market stress. |
| 9  | Rubbany et al (2021, Econ Lett) | Daily dataset of 101 cryptocurrencies and VCRIX from Jan 2015 to Jun 2020. | CSAD. | Presence of herding asymmetry during (extreme) bearish and bullish market conditions. |
| 10 | Shortyria & Kalra (2021, RBF) | Daily dataset of 83 cryptocurrencies and three stock indexes from June 2015 to May 2020. | CSAD and quantile regression. | Presence of herding during bullish and high volatility periods. |
| 11 | Sibande et al. (2021, JBF) | Daily dataset of nine currency pairs (foreign exchange) from July 2003 to July 2019. | CSSD, CSAD, rolling window, QQR (investor happiness analysis). | Anti-herding is generally stronger in extreme bullish sentiment states |
| 12 | Varovolta et al. (2021, JBFMIM) | Hourly dataset of cryptocurrencies traded in USD, Euro, JPY and KRW, from Jan 2019 to Mar 2020. | CSAD, Markov-switching regressions. | Herding is contingent on up or down markets days. |
| 13 | Ballis & Draksos (2020, FRL) | Daily dataset of six top cryptocurrencies, from Jan 2015 to Mar 2019 | CSAD & GARCH model. | Herding exists (CSAD), herding is present during both up and down markets. |
| 14 | Coskun et al. (2020, RIBAF) | Daily dataset of 14 cryptocurrencies and Daily News Index from Apr 2013 and Nov 2018. | CSAD and Hamilton (1989) time varying Markov-switching model. | Overall, there is a presence of anti-herding behaviour. |
| 15 | Fenkel et al (2020, EM) | Monthly foreign exchange forecasts dataset for EUR, JPY and GBP, from 1995 to 2014 - about 36,000 forecasts from 67 forecasters. | Bernhart et al. (2006) forecast clustering approach, for the 1-, 3-, 12-, and 24-month horizons. | Foreign exchange forecasters strategically differentiate from each other, especially when issuing short-term forecasts. Forecasters tend to anti-herd |
| 16 | Gourdie & O’Longlin (2020, JBEF) | Daily dataset of 10 cryptocurrencies and public comments in cryptocurrency forum from Jan 2017 to Apr 2019. | Generalised least squares (GLS) with robust standard errors & Generalised method of moments (GMM). | When there is overall positivity amongst cryptocurrency investors, cryptocurrency prices tend to rise, indicating a presence of herding biases amongst crypto assets investors. |
| 17 | Kaiser & Stockl (2020, FRL) | Daily dataset of all cryptocurrencies (between 395 and 2026) from Jan 2015 to Mar 2019 | CSAD & Hwang & Salmon (2004) beta herding measure. | Stronger beta herding of cryptocurrencies to bitcoin. |
| 18 | Philippas et al. (2020, JIFMIM) | Daily data of 100 cryptocurrencies from Jan 2016 to May 2018. | CSAD & Park & Sabourian (2011) model. | Herding intensity is affected by extracted signals, and the impact is asymmetric. |
| 19 | Youssef (2020, JBF) | Daily dataset of 18 cryptocurrencies from April 2013 to Nov 2019. | CSAD & Kalman filter. | Presence of anti-herding behaviour (static model). However, herding is present (time-varying analysis). |
| 20 | Kalinski & Wang (2019, FRL) | Daily dataset of 296 cryptocurrencies from Dec 2013 to Jul 2018. | CSAD, using equal and value weight, and quantile regression. | Herding exhibits asymmetric properties. Equal-weighted herding is stronger than value-weighted herding. |
| 21 | Stavros & Vassiliou (2019, JBEF) | Daily dataset of eight cryptocurrencies from Aug 2015 to Feb 2018. | CSAD & time-varying parameter (Markov chain Monte Carlo) regression by Nakajima (2011). | Presence of herding (static model), but herding is absence based on time-varying parameter regression. |
| 22 | Bouri et al (2018, FRL) | Daily dataset of 14 cryptocurrencies from Apr 2013 to May 2018. | CSAD, and Stavroyiannis and Babalos (2017) rolling window model. | Presence of herding (static model), but herding varies over time based on rolling window. |
| 23 | Vidal-Tomas et al. (2018, FRL) | Daily dataset of 65 cryptocurrencies from Jan 2015 to Dec 2017. | CSSD & CSAD. | Presence of herding during down markets. The smallest cryptocurrencies are herding with the largest ones. |

Note: This table shows the herding behaviour in cryptocurrency and foreign exchange literature.
extracted signals. Similarly, Kallinterakis & Wang (2019) measure the herding behaviour of 296 cryptocurrencies from December 2013 to July 2018. Their CSAD results indicate that the herding pattern exhibits asymmetric properties.

A few herding studies on the cryptocurrency market apply both the static and time-varying models of CSADs. Coskun et al. (2020) apply both CSAD and time-varying Markov-switching models to 14 cryptocurrencies from April 2013 to November 2018 and find both models generally suggest the presence of anti-herding behaviour. By the same token, Youssef (2020) explores herding behaviour in 18 cryptocurrencies from April 2013 to November 2019 using CSADs and the Kalman filter. The time-varying model indicates the presence of herding, while the static model suggests herding is absent. Bouri et al. (2019) employ CSADs and a rolling-window regression for 14 cryptocurrencies from April 2013 to May 2018. The authors detect the presence of herding in the static model, but herding appears to vary based on the rolling-window regression. Lastly, utilising CSAD and Nakajima (2011)’s time-varying parameter (TVP) regression with Markov chain Monte Carlo (MCMC) estimation and a stochastic volatility model, for eight cryptocurrencies from August 2015 to February 2018, Stavroyiannis & Babalos (2019) show that, while herding seems to be present based on the static model, it is not detected by the TVP regression model. The authors further assert the importance of applying a time-varying model to detect herding because such behaviour tends to be time-varying. We present a summary of the literature on herding behaviour in cryptocurrencies and foreign exchange in Table 1.

Some researchers have argued that the Covid-19 pandemic could have had an adverse ‘black swan’ impact on cryptocurrency, resulting in behavioural anomalies and investors following each other (herding) in the cryptocurrency markets (Yarovaya et al., 2021). Other research on the cryptocurrency markets include that on the relationship between bitcoin and the international stock markets, which is found to be stronger in the medium and long term (Li, Ao, et al., 2021), determinants of bitcoin volatility such as investors’ attention, speculation and market interoperability (Li, Dong, et al., 2021), and bitcoin reactions to shocks and related events (Li, Chen, et al., 2021).

In this paper, meanwhile, utilising an hourly dataset, we ask whether herding is present within bitcoin and the foreign exchange majors before and during Covid-19, whether any herding behaviour is asymmetric across quantiles, and whether its intensity is contingent upon up- and down-market hourly periods. Secondly, we omit bitcoin from the dataset, to explore whether the herding, asymmetries and conditional behaviour persist within the foreign exchange majors’ hourly dataset. Thirdly, we investigate whether the main hourly herding results for bitcoin and the foreign exchange majors still hold if we change the data frequency from hourly to daily. Fourthly, we conduct a robustness test based on hourly data using a different Covid-19 start date. Finally, we examine pairwise relationships between bitcoin and the foreign exchange majors across different time periods and horizons (or scales).

To address these empirical questions, we use Chang et al. (2000)’s baseline and asymmetric models, also known as CSAD models, and run them across quantiles. These CSAD estimations are specified using Newey & West (1987) heteroskedasticity- and autocorrelation-corrected standard errors (HACSEs). Further, to attest that the static model results hold across time, we employ TVP regression with stochastic volatility, first introduced by Nakajima (2011). The TVP approach is a Bayesian model; we use the MCMC algorithm to estimate the posterior distribution. According to Nakajima (2011), a time-varying model like the TVP stochastic model is capable of detecting coefficients’ time variation or structural changes, thereby yielding more precise and robust results.

We add to the burgeoning herding literature in several ways. First, we acknowledge that research on herding behaviour is extensive, but primarily confined within individual equity, foreign exchange or cryptocurrency markets. To the best of our knowledge, this research is among the first to explore herding behaviour within the realm of bitcoin and the foreign exchange majors by using an intraday hourly dataset. Recent studies (Choi et al., 2021; Mandaci & Cagli, 2021; Yarovaya et al., 2021) also examine the existence of herding within the scope of the cryptocurrency market using an hourly and intraday order book dataset. On the other hand, Sibande et al. (2021) scrutinise herding within the foreign exchange market using a 16-year daily dataset. Accordingly, we aim to address the empirical gap in terms of the analysis of both the cryptocurrency and foreign exchange markets together. Second, we attempt to compare and contrast the herding reactions within bitcoin and the foreign exchange majors in two periods: before and during a period of market stress. Yarovaya et al. (2021) identify the Covid-19 pandemic as a black swan event that should have a colossal impact on herding. Choi et al. (2021) and Mandaci & Cagli (2021) also probe into herding behaviour, but all these studies are restricted to just one period, that is, during the Covid-19 pandemic. Finally, our paper is one of the few studies to show the time-varying behaviour of herding coefficients according to hourly periods, besides Yarovaya et al. (2021). Previous studies (e.g., Geweke, 1992; Nakajima, 2011; Stavroyiannis & Babalos, 2019) have advocated the use of Bayesian inference with stochastic volatility, as it can deliver more solid and reliable results.

Our main hourly results from the static and time-varying models show that herding is not present within bitcoin and the foreign exchange majors either before or during the Covid-19 outbreak. We then run the same herding tests but exclude bitcoin from the dataset. Based on hourly data, we still arrive at the same conclusion regarding the non-existence of herding and during the period of market stress (Covid-19). We further re-estimate both static and time-varying models on a daily dataset comprising bitcoin and the foreign exchange majors, and we uncover interesting results. Herding is absent, but once we exclude bitcoin, we observe strong time-varying herding behaviour before and during the Covid-19 pandemic. Not only is herding time-varying, but it is also horizon-dependent. Subsequently, as a robustness check, we run hourly herding analyses based on a different Covid-19 dates and find similar results persist. Finally, we analyse the pairwise coherency (relationship) between bitcoin and the foreign exchange majors using wavelet coherence. We observe strong coherence between the foreign exchange majors in the medium term, thus strengthening our TVP regression results; herding between the foreign exchange majors is time-varying and horizon-dependent.

The remainder of our paper is arranged as follows. Section 2 describes the data and methodology. Empirical results are discussed in Section 3, and Section 4 offers our conclusions.
2. Data and methodology

Our dataset consists of hourly closing prices of bitcoin and the foreign exchange majors priced in US dollars, namely EURUSD, GBPUSD, JPYUSD and CHFUSD, obtained from Thomson Reuters Eikon, spanning the period from 1 March 2018 to 28 February 2022. Following Goodell & Goutte (2021), we identify 1 March 2020 as the start of the Covid-19 pandemic.\(^5\) We then divide the dataset into two subperiods of equal length, the 24 months before Covid-19 started and the 24 months after it started, to compare the herding behaviour of bitcoin and the foreign exchange majors between the two periods. The 24-month period was chosen to enable us to cover the longest study period possible during the pandemic, i.e., from 1 March 2020 to 28 February 2022. Yarovaya et al. (2021) state that an hourly timeframe is an ideal intraday frequency in herding intensity research, as it minimises microstructural bias and noise compared to a minute-by-minute frequency.

We utilise an hourly dataset and a daily dataset for three reasons. First, we compute the bitcoin coefficient of variation (CoV = std dev of return/mean return) as a relative volatility measure and compare the 1-, 5-, 15- and 60-minute (hourly) relative volatilities of bitcoin. We observe an 81.3 % decrease from the 1-minute CoV of 2,130.15 to the 5-minute CoV of 398.30, a further 43 % fall to the 15-minute CoV of 227.7, and finally a 99 % fall to the hourly CoV of 0.535. Second, we apply a time-varying herding approach – using TVP regression (Nakajima, 2011) and MCMC estimation with a stochastic volatility model – using a 15-minute dataset, and present the results in Fig. A1. We notice that the 15-minute frequency result is a bit noisy, although we do not detect any herding pattern before or during the Covid-19 period, as shown by the graphs of coefficients \( \alpha_1 - \alpha_4 \). Third, the majority of the empirical work on herding intensity in the cryptocurrency and foreign exchange markets uses a daily dataset, with the exception of a couple of studies (Choi et al., 2021; Yarovaya et al., 2021) that use hourly datasets. As an hourly frequency is more granular than a daily timeframe, we believe it will also enable us to capture the presence of intraday herding patterns more accurately, and ascertain whether herding behaviour is horizon-dependent.

Fig. 1 shows the time evolution, and Table 2 the descriptive statistics, of the hourly bitcoin and foreign exchange majors’ prices and returns used in this study. It appears that, after March 2020, at the start of the pandemic, both the bitcoin and foreign exchange majors’ prices experienced up-trends for about 12 months before they started to decline slightly, with the exception of JPYUSD and CHFUSD, which dropped as far as the pre-pandemic price levels. It is evident that the volatility of the bitcoin and foreign exchange majors, measured by the standard deviation, has been higher during Covid-19. The Jarque-Bera tests indicate that all variables under study are non-normally distributed. The unconditional correlations of the returns, presented in Table 3, generally suggest that the correlations measured by the standard deviation, has been higher during Covid-19. The Jarque-Bera tests indicate that all variables under study are horizon-dependent.

### 2.1. CSAD static model

The extant literature defines herding as behaviour in which traders imitate, mimic or follow the actions of other traders, thereby disregarding their own judgment. Christie & Huang (1995) were among the first to argue that herding intensity could be captured by the CSSDs of assets’ returns during periods of market stress – hence departing from the need to use institutional data to measure herding behaviour.\(^6\) Further, Chang et al. (2000) propose transforming the linear relationship in Christie & Huang (1995)’s CSSD into a non-linear relationship, and define this non-linear herding intensity as CSAD as follows:

\[
CSAD_t = \frac{1}{N} \sum_{i=1}^{N} |R_i - R_{\text{m}}| \tag{1}
\]

where \( R_i \) is the natural log return of each instrument and \( R_{\text{m}} \) is the market return of all constituent instruments, namely bitcoin, EURUSD, GBPUSD, JPYUSD and CHFUSD.

Then, following Chang et al. (2000), we use these CSAD values calculated in Eq (1) to investigate the presence of herding behaviour by running the following regression:

\[
CSAD_t = \alpha_1 + \alpha_2 |R_{\text{m}}| + \alpha_3 R_{\text{m}}^2 + \varepsilon_t \tag{2}
\]

where \( |R_{\text{m}}| \) is the absolute market return for all constituent instruments namely bitcoin, EURUSD, GBPUSD, JPYUSD and CHFUSD. In the presence of herding, \( \alpha_3 \) is expected to be negative, suggesting that the CSAD declines during periods of market stress, reflecting the

\(^5\) On 30 January 2020, the World Health Organization (WHO) reported 7,818 Covid-19 cases worldwide, prompting its Director-General to declare the outbreak a public health emergency of international concern. For robustness, we also use 1 February 2020 as the Covid-19 start date in one of our analyses in this paper.

\(^6\) Christie & Huang (1995) define CSSD as follows:\(CSSD_t = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (R_i - R_{\text{m}})^2} \) where \( R_i \) is natural log return of each asset and \( R_{\text{m}} \) is the market return of all constituent assets in the portfolio. One disadvantage of the CSSD as computed above is that it might be severely affected by outliers in the dataset. Further, to measure herding, based on the values derived in the previous CSSD equation, Christie & Huang (1995) estimate the following model:\( CSSD_t = a + \beta_1 D_{t}^u + \beta_2 D_{t}^l + \varepsilon_t \) where \( D_{t}^u \) and \( D_{t}^l \) represent the assets’ returns at time \( t \), equalling 1 if they lie in the upper and lower tails, respectively, of the returns distribution, and 0 otherwise. The above CSSD model specifies a linear relationship between dispersion and the market return, proxied by the CAPM.
Fig. A1. Time-varying herding between bitcoin and foreign exchange majors based on 15-min data using CSAD and Eq (3).

Fig. 1. Time evolution of bitcoin and foreign exchange majors’ hourly prices and returns.
### Table 2
Descriptive statistics.

|                   | Before Covid-19          | During Covid-19          |
|-------------------|--------------------------|--------------------------|
|                   | Bitcoin | EURUSD | GBPUSD | CHFUSD | JPYUSD | Bitcoin | EURUSD | GBPUSD | CHFUSD | JPYUSD |
| Mean              | −0.0020 | −0.0008 | −0.0006 | −0.0002 | −0.0001 | 0.0101  | 0.0001 | 0.0004 | −0.0006 | 0.0003 |
| Median            | 0.0044  | 0.0000  | 0.0000  | −0.0010 | −0.0018 | 0.0173  | 0.0009 | 0.0008 | −0.0009 | 0.0000 |
| Maximum           | 13.0279 | 0.8143  | 2.2239  | 0.7710  | 2.0170  | 18.6378 | 0.8703 | 1.1654 | 1.8483  | 0.7252 |
| Minimum           | −13.5873 | −0.7466 | −1.1240 | −0.5816 | −1.2647 | −17.5878 | −1.0855 | −1.8622 | −0.7968 | −0.9496 |
| Std Dev           | 0.8698  | 0.0774  | 0.1058  | 0.0756  | 0.0791  | 0.9655  | 0.0908 | 0.1197 | 0.0876  | 0.0913 |
| Skewness          | 0.5532  | 0.1051  | 1.0623  | 0.2713  | 1.4287  | −1.2134 | −0.2819 | −0.3606 | 0.7006  | −0.2597 |
| Kurtosis          | 40.4236 | 12.5569 | 28.8459 | 9.0571  | 48.6364 | 52.1117 | 14.9000 | 18.2816 | 31.1353 | 11.168 |
| Jarque-Bera       | 723070*** | 47136*** | 346910*** | 19077*** | 1078528*** | 1253152*** | 73559*** | 121304*** | 411295*** | 34286*** |
| ADF               | −113.9*** | −113.3*** | −113.1*** | −114.4*** | −113.6*** | −81.9*** | −112.8*** | −116.8*** | −112.3*** | −114.4*** |
| ARCH 1-S          | 10.95*** | 58.05*** | 17.35*** | 72.56*** | 29.32*** | 313.8*** | 104.9*** | 290.5*** | 223*** | 222.8*** |
| # Obs             | 12,380  | 12,380  | 12,380  | 12,380  | 12,380  | 12,439  | 12,439  | 12,439  | 12,439  | 12,439  |

Note: This table presents the descriptive statistic of bitcoin and foreign exchange majors hourly percentage returns. *** denotes significance at 1%. ADF stands for Augmented Dickey-Fuller unit root test.
herding is not present but anti-herding is, then traders’ herding behaviour of following the market consensus (other traders) and disregarding their own judgment. However, if herding is not present but anti-herding is, then $\alpha_3$ will be positive. Further, to examine herding behaviour during up- and down-market periods, following Chang et al. (2000), we specify the following model:

$$CSAD_t = \alpha_1 + \alpha_2 |R_{m_t}| + \alpha_3^+ (R_{m_t}^+ - R_{m_t}^-) + \alpha_4^- (R_{m_t}^+ - R_{m_t}^-) + \epsilon_t$$  \hspace{1cm} (3)

where $R_{m_t}^+$ and $R_{m_t}^-$ denote market returns during up and down periods, respectively, taking values of 1 if the market registers positive (upturns) or negative (downturns) returns, respectively, and 0 otherwise. Coefficients $\alpha_3^+$ and $\alpha_4^-$ will take negative values if herding is present and positive values if anti-herding is present.

We estimate Eqs (2) and (3) using Bartlett kernel weights as specified in Newey & West (1987), with HACSEs. Eqs (2) and (3) are then estimated across quantiles to test for asymmetries.

### 2.2. Time-varying parameter (TVP) model with stochastic volatility

To complement the CSAD static model analysis, inspired by Nakajima (2011) and Stavroyiannis & Babalos (2019), we employ TVP regression with stochastic volatility. The advantage of TVP regression is its ability to capture potential changes in herding behaviour, which varies with time. Nakajima (2011) applies the TVP regression model with MCMC estimation to a Japanese quarterly dataset from 1977 to 2007 to show the time-varying behaviour of Japanese macroeconomic dynamics, and argues for the importance of integrating stochastic volatility into the TVP model. Hence, following Nakajima (2011) and Stavroyiannis & Babalos (2019), we specify our TVP regression model as follows:

$$y_t = \beta_0 + \beta_1 x_t + \beta_2 z_t + \epsilon_t$$  \hspace{1cm} (4)

where $y_t$ is a scalar of response; $x_t$ and $z_t$ are $(k \times 1)$ and $(p \times 1)$ vectors of covariates respectively; $\beta$ is a $(k \times 1)$ vector of constant coefficients, $\alpha_t$ is a $(p \times 1)$ vector of time-varying coefficients; $h_t$ is the stochastic volatility.

The dynamics of the system are given by:

$$\alpha_{t+1} = \alpha_t + u_t$$  \hspace{1cm} (5)

where $\alpha_t$ represents a vector of time-varying coefficients.

And the stochastic volatility is described as follows:

$$\sigma_t^2 = \gamma \exp(h_t); h_{t+1} = \phi h_t + \eta_t; \eta_t \sim N(0, \sigma_t^2); t = 0, \ldots, n - 1$$  \hspace{1cm} (6)

where $h_t$ indicates stochastic volatility; it is assumed that $\alpha_0 = 0, u_0 \sim N(0, \Sigma_0), \gamma > 0$, and $h_0 = 0$.

The time-varying coefficients $\alpha_t$ specified in Eq (5) follow a first-order random walk process, which enables the detection of temporary and permanent shifts. At the same time, the drifting coefficient allows us to uncover any non-linearity, such as a gradual change or structural break. For the log-volatility function in Eq (6), we assume the initial condition for the stationary distribution to be $h_0 \sim N(0, \sigma_0^2/(1 - \phi^2))$ and $|\phi| < 1$. $\Sigma$ (in the output) represents a positive definite matrix.

Within the context of Bayesian inference, we apply MCMC to estimate the posterior distribution of the parameters in the TVP model with stochastic volatility. According to Nakajima (2011), MCMC is one of the most powerful algorithms researchers can use to recursively sample from a posterior distribution.

### 2.3. Wavelet coherence and phase difference

We further employ wavelet coherence to examine whether the relationship between bitcoin and the foreign exchange majors is time-varying and horizon-dependent. A wavelet can be described as a smaller form of a wave with its focal energy expressed in terms of time, scale and position, allowing an analysis of similar time-series graphs which display pendular phenomena across frequencies (Burrus et al., 1998). A wavelet can also be expressed as a function with a mean of zero, localised in both time and frequency elements (Grinsted et al., 2004). In and Kim (2013) describe a continuous wavelet transform (CWT) as an integral over the signal (for all time) multiplied by the scaled form of the wavelet function $\psi$, giving rise to wavelet coefficients as a function of scale, time and position. A
CWT can be used to observe values within a dimensionless time–frequency domain. Following Burrus et al. (1998), the CWT can be expressed as:

$$F(a,b) = \int f(t)\psi\left(\frac{t-a}{b}\right)dt$$

(7)

followed by an inverse transform of:

$$f(t) = \int \int F(a,b)\psi\left(\frac{t-a}{b}\right)dadb$$

(8)

where \(\psi(t)\) denotes the basic wavelet, while \(a, b \in \mathbb{R}\) represent real continuous variables. In essence, increasing (decreasing) variable \(a\) causes the wavelet to advance (delay) across the time series, thus changing its position, while increasing (decreasing) variable \(b\) causes the wavelet to expand (compress) in scale length. This continuous wavelet process is run to capture the infinite levels of granularity in the time–frequency domain.

The idea of wavelet coherence is to measure the signal responses between two instruments. There is a growing debate on the similarity between ‘correlation’ and ‘coherence’ and what they examine. According to In & Kim (2013), correlation is more sensitive to the signal differences between two variables, while coherence is relatively more stable regardless of these signal differences. Hence, we

### Table 4

Bitcoin and foreign exchange majors’ CSAD quantile regression (hourly).

Panel A: Baseline model Eq (2): \(\text{CSAD}_t = \alpha_1 + \alpha_2|\text{R}_{mt}| + \alpha_3\text{R}_{mt}^2 + \epsilon_t\)

| Parameter | Quantile | Before Covid-19 | During Covid-19 |
|-----------|----------|----------------|-----------------|
| \(\alpha_1\) | 0.2 | 0.0063 | 4.29 | 0 | 0.0074 | 5.42 | 0 |
| 0.4 | 0.0115 | 8.08 | 0 | 0.0152 | 13.85 | 0 |
| 0.5 | 0.0171 | 12.34 | 0 | 0.0214 | 22.66 | 0 |
| 0.6 | 0.0246 | 25.06 | 0 | 0.0310 | 4.85 | 0 |
| 0.8 | 0.0509 | 26.74 | 0 | 0.0620 | 48.92 | 0 |

| \(\alpha_2\) | 0.2 | 0.8252 | 26.68 | 0 | 0.8171 | 35.87 | 0 |
| 0.4 | 1.1318 | 35.46 | 0 | 1.1570 | 65.36 | 0 |
| 0.5 | 1.2782 | 39.85 | 0 | 1.2640 | 100.16 | 0 |
| 0.6 | 1.3523 | 68.09 | 0 | 1.3241 | 9.10 | 0 |
| 0.8 | 1.4413 | 35.10 | 0 | 1.4125 | 107.23 | 0 |

| \(\alpha_3\) | 0.2 | 0.3751 | 17.08 | 0 | 0.2140 | 34.61 | 0 |
| 0.4 | 0.2947 | 5.09 | 0 | 0.1542 | 9.60 | 0 |
| 0.5 | 0.2640 | 4.47 | 0 | 0.1398 | 12.24 | 0 |
| 0.6 | 0.2263 | 7.69 | 0 | 0.1364 | 0.37 | 0.709 |
| 0.8 | 0.1738 | 2.11 | 0.0346 | 0.1182 | 8.90 | 0 |

Panel B: Augmented model Eq (3): \(\text{CSAD}_t = \alpha_1 + \alpha_2|\text{R}_{mt}| + \alpha_3|\text{R}_{mt}^2| + \alpha_4\text{R}_{mt}^2 + \epsilon_t\)

| Parameter | Quantile | Before Covid-19 | During Covid-19 |
|-----------|----------|----------------|-----------------|
| \(\alpha_1\) | 0.2 | 0.0063 | 4.29 | 0 | 0.0074 | 5.42 | 0 |
| 0.4 | 0.0115 | 8.08 | 0 | 0.0152 | 13.85 | 0 |
| 0.5 | 0.0171 | 12.34 | 0 | 0.0214 | 22.66 | 0 |
| 0.6 | 0.0246 | 25.06 | 0 | 0.0310 | 4.85 | 0 |
| 0.8 | 0.0509 | 26.74 | 0 | 0.0620 | 48.92 | 0 |

| \(\alpha_2\) | 0.2 | 0.8252 | 26.68 | 0 | 0.8171 | 35.87 | 0 |
| 0.4 | 1.1318 | 35.46 | 0 | 1.1570 | 65.36 | 0 |
| 0.5 | 1.2782 | 39.85 | 0 | 1.2640 | 100.16 | 0 |
| 0.6 | 1.3523 | 68.09 | 0 | 1.3241 | 9.10 | 0 |
| 0.8 | 1.4413 | 35.10 | 0 | 1.4125 | 107.23 | 0 |

| \(\alpha_3\) | 0.2 | 0.3751 | 17.08 | 0 | 0.2140 | 34.61 | 0 |
| 0.4 | 0.2947 | 5.09 | 0 | 0.1542 | 9.60 | 0 |
| 0.5 | 0.2640 | 4.47 | 0 | 0.1398 | 12.24 | 0 |
| 0.6 | 0.2263 | 7.69 | 0 | 0.1364 | 0.37 | 0.709 |
| 0.8 | 0.1738 | 2.11 | 0.0346 | 0.1182 | 8.90 | 0 |

| \(\alpha_4\) | 0.2 | 0.4737 | 24.44 | 0 | 0.2298 | 33.12 | 0 |
| 0.4 | 0.3483 | 7.78 | 0 | 0.1549 | 19.67 | 0 |
| 0.5 | 0.3039 | 5.62 | 0 | 0.1391 | 15.68 | 0 |
| 0.6 | 0.2442 | 4.05 | 0 | 0.1315 | 8.95 | 0 |
| 0.8 | 0.1979 | 4.48 | 0 | 0.1227 | 8.17 | 0 |

Note: This table shows the cross-sectional absolute deviation (CSAD) quantile regression results for bitcoin and foreign exchange majors based on hourly data.
can conclude that correlation is sensitive to noise, while coherence remains steady, when examining the signal feedback of two energy commodities. Correlation and coherence are constantly used together for robustness purposes because the former is based on the maximal overlap discrete wavelet transform specification. In contrast, coherence is based on the CWT. The two measures complement each other as procedures for quantifying the signal connectedness of time series.

We calculate wavelet coherence as the squared absolute value of the smoothed cross wavelet spectra, \( W_{xy}(u, s) = W_x(u, s)W_y(u, s) \). The value or \( R \rightarrow R^2 \) is normalised by the product of the smoothed series of individual wavelet power spectra. The estimated coherence spectra of instrument\(_1\)-instrument\(_2\) for various frequencies are specified as follows:

\[
R^2 = \frac{|S[x^{-1}W_{xy}(u, s)]|^2}{S[x^{-1}|W_x(u, s)|^2]S[y^{-1}|W_y(u, s)|^2]}
\tag{9}
\]

where \( R^2 \) is the wavelet coherence, \( S \) is the smoothing operator, and hourly and daily commodity\(_1\) and commodity\(_2\) are denoted by \( x \) and \( y \) respectively. The magnitude of wavelet coherence is \( 0 \leq R^2(u, s) \leq 1 \), which can be interpreted as the Pearson correlation coefficient.

Wavelet coherence is also equipped with a phase difference, which provides the details on the oscillation between the two instruments. The vectored rotary arrows show the phase difference: a clockwise arrow means that instrument\(_1\) and instrument\(_2\) are in phase, thus indicating that instrument\(_1\) is leading (predicting) instrument\(_2\). On the other hand, an arrow that points anti-clockwise implies that instrument\(_1\) and instrument\(_2\) are in anti-phase, thus indicating the opposite, i.e., instrument\(_2\) is leading (predicting) instrument\(_1\).

3. Empirical results

3.1. Herding between bitcoin and the foreign exchange majors (hourly data)

We first estimate Eq (2) using ordinary least squares (OLS) on the hourly dataset for both periods, before Covid-19 and during Covid-19, to detect the existence of herding behaviour between bitcoin and the foreign exchange majors. The results are shown below, with the coefficients’ \( t \)-statistics in square brackets [ ] . In Eq (2), if herding is present, the CSAD will decline as the market return increases, thus the coefficient \( \alpha_3 \) will be negative. Interestingly, we find the coefficient \( \alpha_3 \) to be positive in both periods, suggesting the presence of anti-herding behaviour based on the baseline CSAD model.

\[
\text{CSAD}_t = \alpha_1 + \alpha_2|R_{mt}| + \alpha_3 R_{mt}^2 + \epsilon_t \tag{Eq (2)}
\]

| Before Covid-19 | \( \text{CSAD}_t = 0.016 + 1.336 |R_{mt}| + 0.142 R_{mt}^2 \) |
|----------------|----------------------------------|
|                | \( = [12.25] [68.84] [6.67] \) |
| During Covid-19| \( \text{CSAD}_t = 0.027 + 1.235 |R_{mt}| + 0.108 R_{mt}^2 \) |
|                | \( = [14.77] [63.53] [9.06] \) |

We run a quantile regression on Eq (2) and present the results in Panel A of Table 4. Here, the coefficient \( \alpha_3 \) is positive across quantiles in both periods, indicating the absence of herding and asymmetry across quantiles. The results point to the presence of anti-herding behaviour. We also estimate Eq (3) using OLS on the hourly dataset for both periods. In this augmented CSAD model, we examine whether herding persists during up- or down-market periods, which would be shown by negative values of the coefficients \( \alpha_3 \) and \( \alpha_4 \). The coefficients \( \alpha_3 \) and \( \alpha_4 \) do not show negative values in either period, suggesting there is anti-herding behaviour in both periods, whether the market is bullish or bearish. We further estimate Eq (3) using quantile regression. The results presented in Panel B of Table 4 reveal no herding asymmetries across quantiles. The CSAD results based on Eq (3) are as follows:

\[
\text{CSAD}_t = \alpha_1 + \alpha_2|R_{mt}| + \alpha_3 \left( R_{mt}^2 + \epsilon_t \right) + \alpha_4 \left( R_{mt}^2 - \epsilon_t \right) \tag{Eq (3)}
\]

| Before Covid-19 | \( \text{CSAD}_t = 0.016 + 1.333 |R_{mt}| + 0.0135 R_{mt}^2 + 0.156 R_{mt}^2 \) |
|----------------|----------------------------------|
|                | \( = [11.47] [63.1] [6.73] [4.56] \) |
| During Covid-19| \( \text{CSAD}_t = 0.027 + 1.236 |R_{mt}| + 0.064 R_{mt}^2 + 0.122 R_{mt}^2 \) |
|                | \( = [15.75] [68.15] [3.99] [10.45] \) |

Our hourly CSAD static model results imply that herding between bitcoin and the foreign exchange majors is absent during up- and down-market periods both before and during the Covid-19 pandemic, even when estimated across quantiles. Particularly, our hourly CSAD static model results agree with those of Sibande et al. (2021), who observe anti-herding behaviour in the currency market with their CSAD static measure. One might argue that herding behaviour is very likely to be time-varying (Babalos et al., 2015; Gebka & Wohar, 2013; Stavroyiannis & Balabos, 2017, 2020; Yarovaya et al., 2021). To depict its potentially vigorous and fluctuating nature,
Fig. 2. Time-varying herding between bitcoin and foreign exchange majors (hourly).
we implement Nakajima (2011)’s TVP model with stochastic volatility.

Following prior work (Nakajima, 2011; Stavroyiannis & Babalos, 2019), we use the TVP regression model to model volatility as a stochastic process by applying Bayesian MCMC estimation. We obtain 20,000 samples (iterations), after discarding the initial 2,000 samples from the burn-in period, assuming the following subsequent priors:

\[ \beta \sim N(0, 10 \times I); \]
\[ \Sigma \sim IW(4, 40 \times I); \]
\[ \alpha, \beta \sim N(0, 10 \times I); \]
\[ \phi + 1 \sim \text{Beta}(20, 1.5); \]
\[ \sigma^2 \sim IG(2, 0.02); \]
\[ \gamma \sim IG(2, 0.02) \]

where IW and IG refer to the inverse-Wishart and inverse-Gamma distributions, while \( \Gamma_p() \) represents a multivariate Gamma distribution, specified as follows:

\[
W^{-1}(\Psi, v) = \frac{\left| \Psi \right|^{-\frac{v+1}{2}}}{2^{v} \Gamma(v)} |X|^{\frac{v+1}{2}} \exp\left(-\frac{1}{2} tr(\Psi^{-1}X)\right) \tag{10}
\]

\[
f(x; a, \beta) = \frac{\beta^n}{\Gamma(n)} x^{n-1}\exp(-\beta/x) \tag{11}
\]

Fig. 2 shows the time-varying herding behaviour between bitcoin and the foreign exchange majors, using hourly data, for the periods before and during Covid-19, based on Eqs (2) (Panel A) and (3) (Panel B). As our dataset covers periods before and during Covid-19 equally, the centre of each chart signifies the start of the Covid-19 pandemic. If herding were present, we would expect coefficient \( \alpha_3 \) in Panel A to be negative, but surprisingly, the few instances where it becomes negative are very brief. From Panel A, we can observe that the coefficient remains above 0 more than 95% of the time in both periods. The MCMC sampling results illustrate the sample autocorrelations (top), sample paths (middle) and posterior densities (bottom) for some of the parameters. After discarding the first 2,000 samples, the sample paths appear to stabilise, and the sample autocorrelations seem to drop steadily, implying that the MCMC algorithms provide sampling efficiency. Meanwhile, the stochastic volatility pattern appears to be clustering at the onset of the pandemic. The TVP estimation results, including posterior means, standard deviations, 95% credible intervals, convergence diagnostics (CDs) based on Geweke (1992), and inefficiency factors based on MCMC estimation are provided in the bottom-right section of Panel A. Based on a 95% credible interval, which is derived from the CD statistics, the null hypothesis of convergence to the posterior distribution is not rejected, as the estimated posterior mean is within the credible intervals for all parameters in all four quadrants. The inefficiency factors are quite low; the highest inefficiency factor is about 300, which implies about 70 uncorrelated samples for each quadrant; hence, this analysis should be adequate for posterior inference.

The top-left section of Panel B of Fig. 2 sketches the time evolution of coefficients \( \alpha_1, \alpha_2, \alpha_3, \text{and} \alpha_4 \) based on Eq (3). If herding behaviour between bitcoin and the foreign exchange majors existed during up- and down-market days, respectively, the coefficients \( \alpha_3, \text{and} \alpha_4 \) should carry negative signs. We find that, before and during the Covid-19 pandemic, both coefficients, \( \alpha_3, \text{and} \alpha_4 \), are positive, indicating the absence of herding during both up- and down-market days, before and during the pandemic. In short, our hourly data suggest the absence of herding. Instead, we observe the presence of anti-herding behaviour between bitcoin and the foreign exchange majors.

### 3.2. Herding between the foreign exchange majors (hourly data)

One might argue that the absence of herding in our results could be due to combining bitcoin and the foreign exchange majors in our dataset. Perhaps, if we discarded bitcoin from the analysis, we might detect herding between the foreign exchange majors. To this end, we exclude bitcoin from the dataset and run a quantile regression of Eqs (2) and (3). The CSAD static regression results based on Eqs (2) and (3) are as follows:

\[
\text{CSAD}_t = \alpha_1 + \alpha_2 |R_{m,t}| + \alpha_3 R_{m,t}^2 + \epsilon_t \quad \text{Eq (2)}.
\]

| Period          | CSAD, \( \beta = 0.114 + 0.358 |R_{m,t}| - 0.172 R_{m,t}^2 \) |
|-----------------|----------------------------------|
| Before Covid-19 | \([15.43] \quad [4.53] \quad [-1.42]\) |
| During Covid-19 | \([20.97] \quad [3.54] \quad [1.85]\) |
The CSAD regression results based on Eqs (2) and (3) generally indicate an absence of herding. In both Panel A of Table 5 and Panel A of Fig. 3, we are particularly interested in checking whether the coefficients \(\alpha_3\) are negative in the baseline model of Eq (2). In both Panel B of Table 5 and Panel B of Fig. 3, we test whether coefficients \(\alpha_3\) and \(\alpha_4\) carry negative signs in the asymmetric or augmented model of Eq (3). In contrast with hourly herding results between bitcoin and foreign exchange majors shown in Table 4, the quantile regression results presented based on foreign exchange majors herding are outlined in Fig. 3. The TVP regression and MCMC sampling results based on the foreign exchange majors’ hourly data are shown in Table 5. Taking results presented in Table 5 and Fig. 3 together, interestingly although the static herding analyses show that

### Table 5

**Foreign exchange majors’ CSAD quantile regression (hourly).**

| Parameter | Quantile | Before Covid-19 | During Covid-19 |
|-----------|----------|-----------------|-----------------|
|           |          | Coefficient | t-Stat | Prob | Coefficient | t-Stat | Prob |
| \(\alpha_1\) | 0.2 | 0.0346 | 5.58 | 0.000 | 0.0533 | 11.51 | 0.000 |
|           | 0.4 | 0.0652 | 8.66 | 0.000 | 0.0837 | 13.41 | 0.000 |
|           | 0.5 | 0.0936 | 9.67 | 0.000 | 0.1008 | 13.87 | 0.000 |
|           | 0.6 | 0.1158 | 7.91 | 0.000 | 0.1268 | 14.31 | 0.000 |
|           | 0.8 | 0.1938 | 13.53 | 0.000 | 0.2065 | 13.61 | 0.000 |
| \(\alpha_2\) | 0.2 | 0.3127 | 3.59 | 0.000 | 0.1142 | 4.89 | 0.000 |
|           | 0.4 | 0.3837 | 5.94 | 0.000 | 0.1831 | 5.64 | 0.000 |
|           | 0.5 | 0.3753 | 5.15 | 0.000 | 0.2050 | 5.72 | 0.000 |
|           | 0.6 | 0.3510 | 1.96 | 0.050 | 0.2009 | 4.87 | 0.000 |
|           | 0.8 | 0.2565 | 2.65 | 0.008 | 0.0884 | 1.02 | 0.309 |
| \(\alpha_3\) | 0.2 | -0.2196 | -1.22 | 0.225 | 0.0570 | 3.97 | 0.000 |
|           | 0.4 | -0.2471 | -2.60 | 0.010 | 0.0181 | 1.01 | 0.314 |
|           | 0.5 | -0.2581 | -2.51 | 0.012 | 0.0041 | 0.21 | 0.832 |
|           | 0.6 | -0.1661 | -0.44 | 0.661 | 0.0048 | 0.22 | 0.825 |
|           | 0.8 | 0.0058 | 0.07 | 0.947 | 0.2313 | 4.16 | 0.000 |

| Parameter | Quantile | Before Covid-19 | During Covid-19 |
|-----------|----------|-----------------|-----------------|
|           |          | Coefficient | t-Stat | Prob | Coefficient | t-Stat | Prob |
| \(\alpha_1\) | 0.2 | 0.0348 | 6.67 | 0.000 | 0.0545 | 11.73 | 0.000 |
|           | 0.4 | 0.0650 | 8.38 | 0.000 | 0.0857 | 13.09 | 0.000 |
|           | 0.5 | 0.0928 | 9.52 | 0.000 | 0.1008 | 9.36 | 0.000 |
|           | 0.6 | 0.1157 | 10.57 | 0.000 | 0.1277 | 10.36 | 0.000 |
|           | 0.8 | 0.2021 | 14.24 | 0.000 | 0.1941 | 13.69 | 0.000 |
| \(\alpha_2\) | 0.2 | 0.3922 | 5.64 | 0.000 | 0.1042 | 4.42 | 0.000 |
|           | 0.4 | 0.3809 | 4.97 | 0.000 | 0.1705 | 4.76 | 0.000 |
|           | 0.5 | 0.3543 | 4.10 | 0.000 | 0.1811 | 1.53 | 0.126 |
|           | 0.6 | 0.1517 | 1.81 | 0.071 | 0.2167 | 2.66 | 0.008 |
| \(\alpha_3\) | 0.2 | -0.2693 | -2.91 | 0.004 | 0.0786 | 5.20 | 0.000 |
|           | 0.4 | -0.2903 | -1.58 | 0.114 | 0.0334 | 1.40 | 0.163 |
|           | 0.5 | -0.2666 | -1.69 | 0.091 | -0.0949 | -0.09 | 0.926 |
|           | 0.6 | -0.1047 | -0.51 | 0.612 | 0.0153 | 0.19 | 0.847 |
|           | 0.8 | 0.2548 | 2.37 | 0.018 | -0.0236 | -0.54 | 0.589 |
| \(\alpha_4\) | 0.2 | -0.1103 | -1.56 | 0.119 | 0.0615 | 4.64 | 0.000 |
|           | 0.4 | -0.2552 | -2.44 | 0.015 | 0.0236 | 1.35 | 0.177 |
|           | 0.5 | -0.2632 | -2.53 | 0.012 | 0.0165 | 0.11 | 0.914 |
|           | 0.6 | -0.2391 | -1.93 | 0.054 | 0.0656 | 0.18 | 0.855 |
|           | 0.8 | 0.0751 | 0.93 | 0.352 | 0.1605 | 3.39 | 0.001 |

Note: This table shows the cross-sectional absolute deviation (CSAD) quantile regression results for foreign exchange majors based on hourly data.
Fig. 3. Time-varying herding between foreign exchange majors (hourly).
herding is present in two or three quantiles, from a time-varying analyses standpoint, herding appears to be less pronounced. We observe weak herding or stronger anti-herding behaviour based on hourly data. We posit that our static and time-varying herding results for the foreign exchange majors using hourly data are generally consistent with Frenkel et al. (2020) and Sibande et al. (2021), who conclude that foreign exchange forecasters and currency pairs tend to exhibit anti-herding behaviour.

3.3. Herding between bitcoin and the foreign exchange majors (daily data)

In a very recent study, Choi et al. (2021) run a CSAD analysis on Korean cryptocurrencies over different intervals and conjecture that herding behaviour is more pronounced over longer time intervals and during down-market periods. Motivated by their contention, we decided to run both the static CSAD and TVP models on our dataset of bitcoin and the foreign exchange majors but to use a daily frequency as well. We thus re-estimate the CSAD using Eqs (2) and (3) across quantiles and tabulate the results in Table 6. Again, to demonstrate herding, coefficient $\alpha_3$ in Eq (2) and coefficients $\alpha_3$ and $\alpha_4$ in Eq (3) must be negative. Although coefficient $\alpha_3$ has a negative sign in one of the quantiles during Covid-19, this negative coefficient is not statistically significant. In essence, we discover no herding behaviour during up- or down-market days based on the static model using the lower, daily frequency.

We also replicate the TVP regression and MCMC procedure on the daily data and show the results of the baseline model from Eq (2) and the augmented model from Eq (3) in Fig. 4. At a glance, coefficient $\alpha_3$ appears to be less noisy, more stable, and generally positive before and during the Covid-19 pandemic. This pattern is a clear indication of a lack of herding or a presence of anti-herding behaviour.

Table 6

| Parameter | Before Covid-19 | During Covid-19 |
|-----------|-----------------|-----------------|
| $\alpha_1$ | 0.2 | 0.6700 | 2.36 | 0.018 | 0.0145 | 0.54 | 0.590 |
| $\alpha_1$ | 0.4 | 0.122 | 6.09 | 0.000 | 0.0166 | 2.93 | 0.004 |
| $\alpha_1$ | 0.5 | 0.1548 | 7.03 | 0.000 | 0.1056 | 5.20 | 0.000 |
| $\alpha_1$ | 0.6 | 0.189 | 8.58 | 0.000 | 0.1672 | 7.29 | 0.000 |
| $\alpha_1$ | 0.8 | 0.3653 | 10.86 | 0.000 | 0.2979 | 11.49 | 0.000 |
| $\alpha_2$ | 0.2 | 0.6320 | 6.07 | 0.000 | 0.9129 | 11.02 | 0.000 |
| $\alpha_2$ | 0.4 | 0.9258 | 11.87 | 0.000 | 1.1857 | 22.43 | 0.000 |
| $\alpha_2$ | 0.5 | 1.0691 | 13.00 | 0.000 | 1.2697 | 29.49 | 0.000 |
| $\alpha_2$ | 0.6 | 1.2168 | 17.58 | 0.000 | 1.3165 | 27.86 | 0.000 |
| $\alpha_2$ | 0.8 | 1.168 | 12.66 | 0.000 | 1.4574 | 31.48 | 0.000 |
| $\alpha_3$ | 0.2 | 0.2601 | 6.33 | 0.001 | 0.0531 | 6.92 | 0.000 |
| $\alpha_3$ | 0.4 | 0.2033 | 6.52 | 0.000 | 0.0267 | 5.32 | 0.000 |
| $\alpha_3$ | 0.5 | 0.1550 | 4.95 | 0.000 | 0.0184 | 4.37 | 0.000 |
| $\alpha_3$ | 0.6 | 0.1043 | 3.76 | 0.000 | 0.0134 | 3.00 | 0.003 |
| $\alpha_3$ | 0.8 | 0.1359 | 2.88 | 0.000 | $-0.0012$ | $-0.29$ | 0.769 |

Note: This table shows the cross-sectional absolute deviation (CSAD) quantile regression results for bitcoin and foreign exchange majors based on daily data.
Fig. 4. Time-varying herding between bitcoin and foreign exchange majors (daily).
Overall, we observe anti-herding behaviour between bitcoin and the foreign exchange majors, and the hourly data results are consistent with those of the daily data.

3.4. Herding between the foreign exchange majors (daily data)

For good measure, we re-estimate both the static CSAD and TVP models on our foreign exchange majors’ daily data. The CSAD Eqs (2) and (3) are re-estimated again across quantiles and the results are presented in Table 7. Interestingly, we observe negative $\alpha_3$ coefficients in quantiles 2 and 3 in Panel A. A few negative $\alpha_3t$ and $\alpha_4t$ coefficients are also detected in Panel B. These negative static CSAD coefficients, which are presented in bold in Table 7, suggest that the foreign exchange majors herd together about 40% of the time during upturns and downturns, and these behaviours appear to be asymmetric.

We re-run the TVP regression and MCMC sampling algorithms on the foreign exchange majors’ daily data and present the results from Eqs (2) and (3) in Fig. 5. Panel A shows an interesting result—the time-varying coefficient $\alpha_3$ hovers steadily below zero both before and during Covid-19. In a similar vein, Panel B presents negative time-varying $\alpha_3t$ and $\alpha_4t$ coefficients which consistently dip below zero throughout the sample period, i.e., before and during Covid-19. Our TVP results are indicative of strong herding behaviour between the foreign exchange majors, putting them at odds with those of Frenkel et al. (2020) and Sibande et al. (2021). These conflicting findings may be due to differences in data frequency and sample size. For instance, Frenkel et al. (2020) utilise 20-year monthly foreign exchange forecasts, about 36,000 in total, sourced from 67 forecasters, spanning from 1995 to 2014. Correspondingly, Sibande et al. (2021) employ a 16-year daily dataset of nine foreign exchange currency pairs from 2003 to 2016. In contrast, this study uses a four-year dataset of hourly and daily data covering the two years before and during Covid-19 pandemic.

| Parameter | Quantile | Before Covid-19 | During Covid-19 |
|-----------|----------|-----------------|-----------------|
| $\alpha_1$ | 0.2 | 0.0346 | 5.58 | 0.000 | 0.0533 | 11.51 | 0.000 |
| | 0.4 | 0.0652 | 8.66 | 0.000 | 0.0837 | 13.41 | 0.000 |
| | 0.5 | 0.0936 | 9.67 | 0.000 | 0.1008 | 13.87 | 0.000 |
| | 0.6 | 0.1158 | 7.91 | 0.000 | 0.1268 | 14.31 | 0.000 |
| | 0.8 | 0.1938 | 13.53 | 0.000 | 0.2065 | 13.61 | 0.000 |
| $\alpha_2$ | 0.2 | 0.3127 | 3.59 | 0.000 | 0.1142 | 4.89 | 0.000 |
| | 0.4 | 0.3837 | 5.94 | 0.000 | 0.1831 | 5.64 | 0.000 |
| | 0.5 | 0.3753 | 5.15 | 0.000 | 0.2050 | 5.72 | 0.000 |
| | 0.6 | 0.3510 | 1.96 | 0.050 | 0.2009 | 4.87 | 0.000 |
| | 0.8 | 0.2565 | 2.65 | 0.008 | 0.0884 | 1.02 | 0.309 |
| $\alpha_3$ | 0.2 | –0.2196 | –1.22 | 0.225 | 0.0570 | 3.97 | 0.009 |
| | 0.4 | –0.2471 | –2.60 | 0.010 | 0.0181 | 1.01 | 0.314 |
| | 0.5 | –0.2581 | –2.51 | 0.012 | 0.0041 | 0.21 | 0.832 |
| | 0.6 | –0.1661 | –0.44 | 0.661 | 0.0048 | 0.22 | 0.825 |
| | 0.8 | 0.0058 | 0.07 | 0.947 | 0.2313 | 4.16 | 0.000 |
| $\alpha_4$ | 0.2 | –0.2508 | –2.33 | 0.018 | 0.0206 | 1.62 | 0.050 |
| | 0.4 | –0.2993 | –1.58 | 0.114 | 0.0334 | 1.40 | 0.163 |
| | 0.5 | –0.2666 | –1.69 | 0.091 | –0.0094 | –0.09 | 0.926 |
| | 0.6 | –0.1047 | –0.51 | 0.612 | 0.0153 | 0.19 | 0.847 |
| | 0.8 | 0.2548 | 2.37 | 0.018 | –0.0236 | –0.54 | 0.589 |
| $\alpha_5$ | 0.2 | –0.1103 | –1.56 | 0.119 | 0.0615 | 4.64 | 0.000 |
| | 0.4 | –0.2552 | –2.44 | 0.015 | 0.0236 | 1.35 | 0.177 |
| | 0.5 | –0.2632 | –2.53 | 0.012 | 0.0165 | 0.11 | 0.914 |
| | 0.6 | –0.2391 | –1.93 | 0.054 | 0.0056 | 0.18 | 0.855 |
| | 0.8 | 0.0751 | 0.93 | 0.352 | 0.1605 | 3.39 | 0.001 |

Panel B: Augmented model Eq (3):$CSAD_t = \alpha_1 + \alpha_2R_{\text{maj}} + \alpha_3(R_{\text{maj}})|t - 1 + \alpha_4(R_{\text{maj}})|t - 2 + \epsilon_t$

Note: This table shows the cross-sectional absolute deviation (CSAD) quantile regression results for foreign exchange majors based on daily data.
Fig. 5. Time-varying herding between foreign exchange majors (daily).
Fig. 6. Time-varying herding between bitcoin and foreign exchange majors (robustness check; hourly, Covid-19 start date: 1 February 2020).
Fig. 7. Time-varying herding between foreign exchange majors (robustness check; hourly, Covid-19 start date: 1 February 2020).
At this stage, our hourly herding analyses show the absence of herding within bitcoin and the foreign exchange majors, as well as within the foreign exchange majors, based on both static and time-varying herding models. Our daily herding analyses, however, yield interesting findings. A weak herding pattern (about 40%) is detected between the foreign exchange majors based on the daily static herding model, in the period before the Covid-19 pandemic. However, we observe a strong intensity of herding between the foreign exchange majors when using the TVP regression model, throughout the sample period. We posit that, not only is herding within the foreign exchange majors time-varying, but it is also horizon-dependent, as the time-varying herding is only observed based on the daily frequency but not at the hourly frequency. Specifically, our hourly and daily time-varying herding results provide some support to Choi et al. (2021), who document that herding intensity varies, being more pronounced over longer than shorter time intervals, and Shahzad et al. (2021), who uncover a strong positive relationship between foreign exchange’s volatilities over the medium and long horizons.

3.5. Herding between (a) bitcoin and the foreign exchange majors and (b) the foreign exchange majors, using hourly data, and an altered Covid-19 start date (robustness check)

One might argue that the absence of herding in our hourly analyses could be due to the choice of the start date of the Covid-19 pandemic. As mentioned earlier, the WHO declared the Covid-19 outbreak as a public health emergency of international concern on 30 January 2020. While in the earlier analyses, we analysed time-varying herding using 1 March 2020 as the Covid-19 start date, we now re-estimate the TVP regression model with MCMC algorithms based on a start date of 1 February 2020. The hourly TVP regression results between bitcoin and the foreign exchange majors are visualised in Fig. 6. The time-varying coefficient \( \alpha_3 \) in Panel A of Fig. 6 appears to be positive both before and during Covid-19. Similarly, the time-varying coefficients \( \alpha_{3,3} \) and \( \alpha_{4,4} \) in Panel B of Fig. 6 seem to be positive throughout the sample period. These results are very similar to those presented in Fig. 2 based on a Covid-19 start date of 1 March 2020.

Next, we scrutinise the herding between the foreign exchange majors using hourly data based on the start date of 1 February 2020 and show the results in Fig. 7. The time-varying coefficient \( \alpha_3 \) in Panel A of Fig. 7 generally floats above zero both before and during Covid-19. Likewise, the time-varying coefficients \( \alpha_{3,3} \) and \( \alpha_{4,4} \) in Panel B of Fig. 7 remain above zero throughout the sample period. Generally speaking, these time-varying herding results are almost identical to those in Fig. 3. Comparing Figs. 6 and 7 with Figs. 2 and 3 enables us to conclude that our hourly herding results hold and are not influenced by the choice of Covid-19 start date.

3.6. Wavelet coherence and phase difference

Earlier discussions in Sections 3.3 and 3.4 point out that, while we observe no herding between the foreign exchange majors based on the hourly data, we do uncover strong herding patterns based on the daily data, which indicates that the herding behaviour is essentially time-varying and horizon-dependent. To further examine the potentially horizon-dependent nature of herding between bitcoin and the foreign exchange majors, we utilise wavelet coherence and report the findings in Fig. 8. The blue colour in the wavelet coherence figure indicates a lack of association between the two series, while the red colour signifies a strong relationship (coherency) between the two instruments. Since our dataset covers periods of equal length before and during Covid-19, the centre of each chart marks the start of the Covid-19 pandemic. The wavelet coherence for bitcoin-EURUSD, bitcoin-GBPUSD, bitcoin-CHFUSD and bitcoin-JPYUSD shows a weak coherency intensity, as denoted by the bluish colour in each diagram throughout the sample period. Bitcoin appears to have almost zero coherency intensity against EURUSD, GBPUSD, CHFUSD and JPYUSD, particularly over a short horizon, i.e., below the 256-hour scale. Meanwhile, we can observe a mild coherency intensity between bitcoin and the four foreign exchange majors over the medium horizon, i.e., above the 256-hour scale. These wavelet coherence patterns explain the absence of herding between bitcoin and the foreign exchange majors in both our hourly and daily analyses.

The coherency intensity between the foreign exchange majors is considerably stronger, as depicted by the reddish colour in the wavelet coherence charts. The strongest coherency intensity is shown by the EURUSD-GBPUSD, EURUSD-CHFUSD and CHFUSD-JPYUSD pairs. There are strong relationships between these three currency pairs over short, medium and long horizons (scales). The wavelet coherence of these three currency pairs also shows that the two series are perfectly in phase at the onset of the Covid-19 pandemic. We also provide a description of the wavelet coherence phase difference at the bottom of Fig. 8. A considerable coherence intensity is also observed for the remaining pairs, EURUSD-JPYUSD, GBPUSD-CHFUSD and GBPUSD-JPYUSD, particularly between the 16-hour and 256-hour scales. For these three remaining pairs, their wavelet coherence generally exhibits arrows pointing northeast at the centre of the diagram, implying that the second leads the first instrument, i.e., JPYUSD leads EURUSD, CHFUSD leads GBPUSD, and JPYUSD leads GBPUSD at the onset of Covid-19 pandemic. Our wavelet coherence results between JPYUSD and other foreign exchange majors are generally in line with the results of our unconditional correlation presented earlier in Table 3 which reveal that JPYUSD records a higher correlation with other foreign exchange majors during the pandemic. Our wavelet coherence findings also provide some support to the growing debate in academics over similarities (versus differences) between ‘correlation’ and ‘coherence’.

By and large, our wavelet coherence results presented in Fig. 8 are consistent with both the hourly and daily herding analyses between the foreign exchange majors shown earlier in Figs. 3 and 5. Specifically, these results show that the foreign exchange majors tend to exhibit a strong intensity of coherency beyond a 16-hour horizon – which means the relationships between the foreign exchange majors are generally not detected over a shorter horizon, i.e., using hourly data. However, the relationships could be found when looking at a longer horizon, such as when using daily data. Overall, our findings point to a very important inference – not only is herding between the foreign exchange majors time-varying, but it is also horizon-dependent, a pattern that can be ascertained using wavelet coherence analysis.
4. Conclusion

In this paper, we explore whether herding behaviour exists within the bitcoin market and the foreign exchange majors’ markets of EURUSD, GBPUSD, CHFUSD and JPYUSD before and during the Covid-19 pandemic. Our dataset spans the period from March 2018 to February 2022. We run both static CSAD and TVP regressions with MCMC to assess herding. Specifically, we ask whether herding is present before and during the Covid-19 period, whether herding intensity is asymmetric across quantiles, and lastly, whether herding is contingent upon bullish or bearish market cycles.

Our main hourly analyses generally reveal no herding behaviour before or during the Covid-19 pandemic. We then exclude bitcoin from our analyses and find the hourly herding results persist. Further, we run the herding test on a daily dataset and, while we observe the absence of herding between bitcoin and the foreign exchange majors, we do find time-varying herding within foreign exchange majors during up- and down-market days. Subsequently, we undertake hourly herding analyses using a different Covid-19 start date than in the main analyses as a robustness check and we still find that similar results prevail. In essence, this means our main results are not dependent upon our Covid-19 start date of choice. It also means that, while bitcoin and the foreign exchange majors do not herd together, the foreign exchange majors do move together based on a daily frequency. Finally, we undertake wavelet coherence analyses to examine the pairwise relationships between all the instruments under study, and the wavelet coherence results are in line with the findings regarding time-varying herding. Herein, we reiterate that, not only is herding between the foreign exchange majors time-varying, but it is also horizon-dependent.
We believe our results have important implications for foreign exchange and bitcoin investors, academics and policymakers. First, the lack of herding between bitcoin and the foreign exchange majors generally implies that they could be used to create a safe portfolio, as they typically do not move together during extreme market movements. Although, in a sense, bitcoin can be considered electronic cash, as per Nakamoto (2008)’s white paper, its herding behaviour indicates that it is a bird of a different feather to the foreign exchange majors. Second, within our foreign exchange majors’ dataset, all the currencies in our sample are priced in US dollars. We detect daily herding patterns among them, which implies that, when the US dollar appreciates, the other major currencies tend to depreciate relative to it. This outcome also suggests that, if investors hold foreign exchange majors other than the US dollar, they will not be well-diversified, as these foreign exchange majors will herd under market stress based on a daily frequency. Third, our daily static and time-varying herding analyses yield quite dissimilar results, hence we would advocate using the TVP regression alongside the static model to analyse herding behaviour. The most significant advantage of a TVP model with stochastic volatility is its ability to capture the time variation in the coefficient, even in the presence of structural changes within the underlying variables, and hence provide a more accurate herding analysis. Fourth, our results essentially suggest that herding behaviour between the foreign exchange majors is time-varying and horizon-dependent, which necessitates the use of wavelet coherence. Our economic interpretation of herding’s horizon-dependent nature is that foreign exchange traders are taking trading positions based on different scales or frequencies; short-term traders may be trading based on an hourly frequency, while longer-term traders may be looking at daily data, causing the discrepancy and horizon-dependent herding behaviour. Fifth, our research reveals an important implication. Bitcoin is considered a phenomenon within the sphere of the cryptocurrency market, regarded as a new asset class by many, and even perceived as one of the biggest influencers in the financial markets, with moves dictated by ‘whales’. However, in our study, bitcoin appears to be detached from foreign exchange, despite the fact that it is also offered by forex brokers to be traded alongside foreign exchange. We argue that one reason why bitcoin behaves like a bird of a different feather that does not flock together with the foreign exchange majors may be its different volatility, such that it is associated with different margin requirements. As could be seen from the descriptive statistics in Table 2, bitcoin shows a standard deviation of 96.5 % during the Covid-19 pandemic, in contrast to GBPUSD’s 12 %. Moreover, FXCM, for instance, offers leverage of 400:1 to trade foreign exchange but only one of 4:1 to trade bitcoin.7

Last but not least, our study is not free from limitations. Our hourly and daily dataset covers two years before and two years during the pandemic. As a previous herding study by Sibande et al. (2021) utilised a 16-year daily currency dataset, future research should attempt to obtain a longer intraday and daily foreign exchange dataset to achieve more comparable herding results.

CRediT authorship contribution statement

Azhar Mohamad: Conceptualization, Methodology, Formal analysis, Resources, Writing – original draft, Writing – review & editing, Funding acquisition. Stavros Stavroyiannis: Conceptualization, Methodology, Software.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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