# Industry Herding in Crypto Assets

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August 1, 2022

**Abstract**

The aim of this paper is to investigate if herd behaviour is present in crypto assets at industry level. Using price information extracted from coinmarketcap.com between 29 April 2013 and 9 May 2022, we find evidence of herding and reverse herding in the crypto assets market. Concentrated periods of herding and reverse herding are particularly evident in the January 2020-April 2022 Covid period. At industry level, herding is more profound in large sectors with higher volatility. In smaller sectors where ventures are backed by 'real assets', very short periods of herding with marginal significance are detected. Reverse herding is present in all industries except Real Estate between June 2021 and May 2022, implying that strategies such as excessive 'flight to quality' or/and token picking are at play during the recent crypto crash. We also detect varying asymmetric herding at industry level. This paper further examines the factors that drive such industry herding and reverse herding in the crypto assets market, and our results show that industry concentration and investor sentiments contribute to the probability of herding/reverse herding. Our study provides further insights to the forces that drive the dispersion in crypto assets prices and contribute to the behavioural studies of the crypto market.

**Keywords**: Asymmetric herding, Crypto assets, Industry herding, Investor behaviour, Sentiment

**JEL Classification**: C22, E42, G40

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# 1 Introduction

Herding refers to a phenomenon where market participants mimic the action of others while suppressing their own private information. Herd behaviours in cryptocurrencies have merited the attention of scholars, as the booms and busts in crypto assets are not always backed by fundamentals (Ajaz and Kumar, 2018; Ballis and Drakos, 2020; Bouri et al., 2019; da Gama Silva et al., 2019; Gurdgiev and O'Loughlin, 2020; Kallinterakis and Wang, 2019; King and Koutmos, 2021; Senarathne and Wei, 2020; Vidal-Tomás et al., 2019).

While previous studies show evidence of asymmetric herding in cryptocurrencies under different market conditions (Ajaz and Kumar, 2018; Ballis and Drakos, 2020; Bouri et al., 2019; Calderón, 2018; da Gama Silva et al., 2019; Haryanto et al., 2020; Kaiser and Stöckl, 2020; Kallinterakis and Wang, 2019; Raimundo Júnior et al., 2020; Vidal-Tomás et al., 2019) and among different sizes of assets (Ajaz and Kumar, 2018; Kallinterakis and Wang, 2019), these studies have treated cryptocurrencies and tokens as one type of asset. We argue that as the crypto assets market evolves, the blockchain based assets have been developed to have different functionalities. For example, the issuing of utility tokens, known as the 'initial coin offering' (ICO) permits a venture to raise financing from future users (Howell et al., 2020); there are also security tokens, which may offer token holders certain financial incentives such as interest or dividends. Along with the development of different functionalities, crypto assets have gone far beyond the payment and finance sectors. Companies in a wide range of industries have deployed blockchain based crypto assets. Our data shows that additional to the Payment sector, crypto assets spread across IT, Financials, Communication Service, Consumer Discretionary as well as 'real asset' sectors such as Industrial, Real Estate, Healthcare, Utilities. Contrary to the argument that 'cryptocurrencies do not have underlying assets to justify whether the trading occurs due to firm-specific (or underlying asset-specific) factors' (Senarathne and Wei, 2020, p. 21), some of these tokens are linked to projects with potential values (Lo, 2020).

Industry herding has been investigated in many finance studies previously. Style investing theories suggest that investors allocate funds into styles/industries that have performed well in the past while withdrawing funds from under-performing styles (Barberis and Shleifer, 2003). Such herding at industry level could be a result of information cascades (Bikchandani et al., 1992; Choi and Sias, 2009; Welch, 1992), or industry momentum (Barberis et al., 1998; Moskowtiz and Grinblatt, 1999), or simply fads (Choi and Sias, 2009). Industry herding is evident in the financial markets, but little is known if investors exhibit herd behaviour in different industries in the crypto assets market.[1] We argue that it is important to differentiate amongst industries when examining investors behaviours in the crypto market. For example, do investors invest in cryptocurrencies because they believe in the underlying business model or do they simply follow others in and out of an industry?

Against this background, this paper aims to address the following questions: Do investors herd in the crypto asset markets? Is herding asymmetric? Do investors herd across industries? What are the determinants of industry herding? The first two questions have been investigated by a number of studies, we aim to contribute to the existing literature by

[1] Ren and Lucey (2022) categorise cryptocurrencies from a sustainability perspective (i.e. green vs dirty coins), but not according to industry per se.

including a larger sample with longer analysis time period. To our knowledge, this paper is the first that examines herding in crypto asset market at industry level. Furthermore, it has been argued that investors may share similar fears during crisis such as Covid and herding intensifies as a result (Mandaci and Cagli, 2022). Empirical results in herding in the crypto market over the Covid period however, are mixed. As our data includes a longer Covid period (January 2020 to May 2022), we also examine the potential changes in behaviours in the unprecedented period.

The remainder of the paper is structured as follows. Existing literature in herd behaviour in finance market and crypto markets are reviewed in Section 2. Section 3 provides the details of our empirical strategies, followed by data description in Section 4. We present and interpret our empirical findings in Section 5. Finally, Section 6 concludes this paper.

## 2 Literature review

Behavioural economists view investors' rationality as bounded (Conlisk, 1996; Selten, 1990). To reduce the cost of information processing, people rely on heuristics (Tversky and Kahneman, 1974), which in turn tends to cause behavioural bias such as herding (Banerjee, 1992). The phenomenon of herding has been widely studied in the financial literature. While empirical findings on herding are mixed, in general studies show that herd behaviour tends to be manifested when market participants are dominated by individual amateur investors; when important macro data are released (Galariotis et al., 2015); and when there is a coordination mechanism, by which investors can observe other decision-makers and price movements (Devenow and Welch, 1996). Furthermore, it has been argued that during market upturn, 'investors become enthusiastic and optimistic, neglecting their own information and follow each other in buying transactions. Conversely, when market declines, driven by panic and fear, investors follow the market consensus and engage in overselling transactions' (Pochea et al., 2017, p. 400). In line with this, empirical studies have found herding in up and/or down markets (Chiang et al., 2010; Chiang and Zheng, 2010; Pochea et al., 2017).[2]

Given the ambiguity surrounding the fundamentals of crypto assets (Cheah and Fry, 2015), the fact that crypto assets are noise-prone (Chueng et al., 2015) and that the market has a large proportion of individual investors (Wang et al., 2022),[3], herding is expected in the crypto markets. Empirically, studies have shown mixed findings in asymmetric herding in up and/or down markets depending on the time period analysed (Ajaz and Kumar, 2018; Ballis and Drakos, 2020; Bouri et al., 2019; Calderón, 2018; da Gama Silva et al., 2019; Haryanto et al., 2020; Kallinterakis and Wang, 2019; Raimundo Júnior et al., 2020; Vidal-Tomás et al., 2019). Furthermore, Ajaz and Kumar (2018) capture the effect of herding in the extreme quantiles in major cryptocurrencies. Vidal-Tomás et al. (2019) find that the smallest cryptocurrencies herd with the largest ones. The authors explain that due to the

[2]While some suggest that herding asymmetry is more profound in rising markets in certain stock markets (Chang et al., 2000; Chiang and Zheng, 2010; Lee et al., 2013; Tan et al., 2008; Zheng et al., 2021), others find more intensive herding during market downswings or crisis (Galariotis et al., 2016; Goodfellow et al., 2009; Lao and Singh, 2011; Philippas et al., 2013; Yao et al., 2014).

[3]Although studies also show institutional investors are involved in ICOs (Boreiko and Risteski, 2020; Bourveau et al., 2018; Howell et al., 2020).

scant information about the smallest cryptocurrencies, traders only invest in the smaller coins/tokens according to the information provided by the largest ones. We follow these previous studies and first investigate such potential characteristics of herd behaviours in the crytpo asset market.

Industry herding is defined as a group of investors following each other into and out of the same industry over a period (Choi and Sias, 2009; Sias, 2004). There are a number of explanations to industry herding. One strand relates to information cascades within industries. As investors receive valuation signals containing private information regarding future firm performance, they may infer information about a given firm based on the information of other firms within the same industry (Lang and Lundholm, 1996), or follow correlated signals at different times within the industry (Choi and Sias, 2009). Zheng et al. (2017) assert that investors tend to focus on industry-specific information and invest in sectors that they are familiar with. Information is easier to collect in smaller sectors with fewer companies, whereas firms in larger industries face a more competitive environment and thus their success is less certain, such uncertainty leads to herding.

Another theoretical framework is based on style investing, referring to investors allocating funds into styles/industries that have performed well in the past while withdrawing funds from under-performing styles (Barberis and Shleifer, 2003).Wahal and Yavuz (2013) find that past style returns help explain future stock returns after controlling for size, book-to-market and past stock returns, hence style investing plays a role in the predictability of asset returns. Industry-wide style investing behaviour of retail investors is found in Jame and Tong (2014). Moskowtiz and Grinblatt (1999) also document such strong industry momentum effect in stock returns, which could be a result of overconfidence and self-attribution biases in certain industries, a conservatism bias related to new information, representativeness bias triggered by industry specific news rather than firm-specific news (Barberis et al., 1998), or slow information diffusion among industry leaders (Hong and Stein, 1999; Hong et al., 1999). Last but not least, the fads argument proposes that investors may herd to industries simply due to the increasing popularity of the industries (Choi and Sias, 2009). Chen et al. (2021) for example, show that under imperfect markets and the constraints of regulations, fads induced herding can be used as a short-term safe haven under uncertainty.

Industry herding is evident in the finance markets (see BenSaïda (2017), Celiker et al. (2015), Dehghani and Sapian (2014), Litimi et al. (2016), Ukpong et al. (2021), Yao et al. (2014) and Zheng et al. (2017) and more). As highlighted earlier, crypto assets now have spread into a wide range of industries providing investors with different rights associated with the underlying ventures. Crytpo studies have made an attempt to categorise crypto assets to better understand the market. Yarovaya and Zięba (2022) utilise the qualitative characteristics of crypto assets and find that such categorisation helps explain the volume-return relationship within the asset. Corbet, Larkin, Lucey, Meegan and Yarovaya (2020) classify digital assets into three broad categories: currencies, Protocols and Decentralised Applications and study the spillover and feedback effects of momentary policies on these digital assets. Using similar categorisation, Katsiampa et al. (2022) find unique co-movement patterns amongst digital asset class categories. Benedetti and Nikbakht (2021) emphasise that tokens vary according to their functions (such as crypto currencies, platform tokens, utility tokens, security tokens, assets) and find such characteristics affect crypto asset returns. Similar categorisation is also found in Cong and Xiao (2021). Aspris et al. (2021) investigate the crypto markets by segmenting tokens listed on centralised exchanges and decentralised exchanges. Notably, the above studies categorise crypto assets according to their digital functionalities and herding was not a focus. From a sustainability perspective, Ren and Lucey (2022) distinguish between 'dirty' and 'clean' cryptocurrencies and find that herding is evident in the 'dirty' crypto sector particularly in market downturns. 'Clean' cryptos only herd with dirty ones when both markets are positive. We contribute to the existing literature by categorising crypto assets according to the underlying business venture's industry. Given that the crypto industry is still in its infancy, we hypothese that the effect of information cascades, style investing and fads are likely to be present at industry level.

Scholars further investigate the factors that drive herding over a specific period. A number of studies report more pronounced herd behaviours during periods of high liquidity (BenSaïda et al., 2015; Chang et al., 2000; Chiang and Zheng, 2010; Indãrs et al., 2019; Lam and Qiao, 2015; Litimi et al., 2016). Similarly in the cryptocurrency market, Kallinterakis and Wang (2019) find that herding is stronger during high volume days. Extensive literature in finance also conjectures that investor sentiment may be another important factors in explaining herding (Barberis et al., 1998; De long et al., 1990; Lakonishok et al., 1992). This is supported by empirical studies in mutual fund managers (Hudson et al., 2020; Liao et al., 2011) and in the stock markets (Economou et al., 2018). In the context of crypto assets market, Bouri et al. (2019) find that Economic Policy Uncertainty (EPU) index[4] is positively associated with the probability of herding in cryptocurrencies. The authors suggest that 'the overall cryptocurrency market exhibit(s) a safe-haven property that prevent crypto traders from engaging in "flight to safety" during the presence of economic policy uncertainty, which is contrary to the case of equity markets' (Bouri et al., 2019, p. 219). The findings on the safe haven properties of cryptocurrencies remain mixed, particularly during Covid period. Goodell and Goutte (2021), Le et al. (2021) and Mariana et al. (2021) suggest that crypto currencies can be considered as a safe haven asset during the first months of the pandemic, whereas Corbet, Larkin and Lucey (2020), Conlon and McGee (2020) and Conlon et al. (2020) show contrary results. Katsiampa et al. (2022) show that the Covid crisis have spiked interest in the crypto assets among retail investors particularly in altcoins and new crypto assets, which could in turn explain the potential changes in herd behaviours in this time period. Furthermore, da Gama Silva et al. (2019) relate herding and reverse herding with major events in the financial and political worlds and find that investors are more affected by negative information than positive information and Bitcoin drives the investment flows in crypto assets. Motivated by the existing studies, we further investigate the factors that drive herd behaviour at industry level in the crypto market.

# 3 Methodology

There are two major strands of empirical studies of herding in the financial markets, one relies on aggregate price and market activity data and investigates herding towards the market consensus in international stock markets (Chang et al., 2000; Christie and Huang,

[4] Developed by Baker et al. (2016).

1995; Hwang and Salmon, 2004) and national equity markets (Bhaduri and Mahapatra, 2013; Chiang et al., 2010; Dang and Lin, 2016; Dehghani and Sapian, 2014; Indãrs et al., 2019; Lam and Qiao, 2015; Litimi et al., 2016; Yao et al., 2014). The other group of studies relies on microdata and investigates whether specific investor types herd (Choi and Sias, 2009; Hsieh, 2013; Lakonishok et al., 1992; Sias, 2004). Due to the nature of our data, we adopt methods in the first strand.

## 3.1 Basis of the estimated model for herd behaviour

First we calculate the daily return for each crypto asset as:

$$R_{i,t} = ln\frac{P_{i,t}}{P_{i,t-1}} \tag{1}$$

Where $i$ denotes each crypto asset, $t$ is the time period and $P$ is the closing price for each asset.

Rational asset pricing models predict that stock return dispersion is an increasing function of market returns (Christie and Huang, 1995). If herding is present however, stock returns could deviate from this relation. We follow Chang et al. (2000) cross-sectional absolute standard deviation (CSAD) measure to quantify return dispersion:

$$CSAD_t = \frac{1}{N}\sum_{i=1}^{N}|R_{i,t} - R_{m,t}| \tag{2}$$

Where $R_{i,t}$ is the observed daily return for crypto asset $i$ at time $t$; $R_{m,t}$ is the value-weighted average of all returns in our sample at time $t$; and $N$ is the number of crypto assets included in the market portfolio at time $t$. In this study, we also consider the use of CCi30[5] (Senarathne and Wei, 2020), Bitcoin (BTC) and Ethereum (ETH)[6] as proxies for market return (Kallinterakis and Wang, 2019; Lo, 2020; Vidal-Tomás et al., 2019). Bitcoin is considered as the primary means of buying and selling tokens (Kaiser and Stöckl, 2020; Lo, 2020) and Ethereum smart contracts are the main technological basis of many of the tokens (Lo, 2020).

Christie and Huang (1995) empirically examine whether stock return dispersion is significantly lower than the average during periods of extreme market movements to indicate the presence of herd behaviour using a linear model. Chang et al. (2000) argue that if market participants herd, the relationship between dispersion and market return can become non-linear. The authors therefore examine the potential non-linear relationship between CSAD and $R_{m,t}$ to detect herd behaviour as in Equation 3. If market participants estimate asset prices in accordance with the Capital Asset Pricing Model (CAPM), the relationship between CSAD and $R_{m,t}$ should be linear and increasingly positive. However, if investors exhibit herd behaviour, $\gamma_2$ will be significantly negative.

$$CSAD_t = \alpha + \gamma_1|R_{m,t}| + \gamma_2 R^2_{m,t} + \varepsilon_t \tag{3}$$

[5]The CCi30 index tracks the 30 largest cryptocurrencies by market capitalisation, excluding stablecoins, the index starts from 1 January 2015.

[6]Ethereum price data starts from 8 August 2015.

### 3.2 Robustness check

Equation 3 is our baseline Ordinary Least Square (OLS) model.[7] We further include a number of time-varying approaches, including a combination of an autoregressive (AR) term and a GARCH model (Ballis and Drakos, 2020; Tan et al., 2008); a rolling window of 365 observations[8] (Bouri et al., 2019; Clements et al., 2017; Stavroyiannis and Vassilios, 2017), and a three-state Markov-Switching Model (Babalos et al., 2015; Calderón, 2018; Klein, 2013).

Equation 3 could potentially suffer from a high level of multicollinearity between the two explanatory variables $R_{m,t}$ and $R_{m,t}^2$ and a high level of serial correlation in high frequency time series market data. Following Yao et al. (2014), as robustness check, $R_{m,t}^2$ in Equation 3 is replaced with $(R_{m,t} - \bar{R}_m)^2$ and we also add a 1-day lag of the dependent variable:

$$CSAD_t = \alpha + \gamma_1 |R_{m,t}| + \gamma_2 (R_{m,t} - \bar{R}_m)^2 + \gamma_3 CSAD_{t-1} + \varepsilon_t \quad (4)$$

Where $\bar{R}_m$ is the arithmetic mean of $R_{m,t}$ and $CSAD_{t-1}$ is the 1-day lag of CSAD. Again, a negative and statistically significant $\gamma_2$ indicates the presence of herding.

To detect the potential asymmetric herd behaviour under different market conditions, we follow Chiang and Zheng (2010) and modify Equation 3 as:

$$CSAD_t = \alpha + \gamma_{1,U} R_{m,t}(1-D) + \gamma_{1,D} D R_{m,t} + \gamma_{2,U}(1-D) R_{m,t}^2 + \gamma_{2,D} D R_{m,t}^2 + \varepsilon_t \quad (5)$$

Where $D$ is a dummy variable with value of 1 when $R_{m,t} < 0$ and 0 otherwise. Asymmetric herding in upward or downward market condition is captured by $\gamma_{2,U}$ and $\gamma_{2,D}$ respectively (Chiang and Zheng, 2010). A Wald coefficient equality test is further applied to see if $\gamma_{2,U} = \gamma_{2,D}$ (Chiang and Zheng, 2010; Lee et al., 2013).

Extreme outliers can significantly affect the tail values of a distribution, but such information could be lost in the OLS models as the least squares estimators focus on the mean as a measure of location (Chiang et al., 2010). To address this, following Chiang et al. (2010) and Pochea et al. (2017), we also employ a quantile regression to estimate the interrelationship between CSAD and $R_{m,t}^2$ at 75, 50 and 25 quantiles respectively:

$$CSAD_{\tau,t} = \alpha + \gamma_{1U,\tau} R_{m,t}(1-D) + \gamma_{1D,\tau} D R_{m,t} + \gamma_{2U,\tau}(1-D) R_{m,t}^2 + \gamma_{2D,\tau} D R_{m,t}^2 + \varepsilon_{\tau,t} \quad (6)$$

Where $\tau$ represents a specific quantile.

As this paper aims to investigate herding among different industries, we repeat the above models by industry sectors. The categorisation of industries is discussed in Section 4.

[7] We use the Newey-West HAC robust standard errors to compute coefficient t-statistics.

[8] The crypto market operates throughout the whole week, therefore there are 365 data points for each year.

### 3.3 Determinants of herding

Last, we investigate the determinants of herding and reverse herding in crypto assets market using a panel Probit model with robust standard errors as in Equation 7.

$$Pr(y_{j,t} = 1|X_{j,t}) = \Phi(\alpha_j + X_{j,t}\beta + \epsilon_j) \tag{7}$$

We define a binary herding (reverse-herding) variable $y_{j,t} = 1$ when the time-varying herding coefficient $\gamma_2$ is negative (positive) and statistically significant for each industry $j$ at $t$; and 0 otherwise. $\Phi(\cdot)$ is the cumulative distribution function of the standard normal distribution, and $X_{j,t}$ is a vector of determinant variables explained below.

We first include a set of industry specific variables as proxies for industry characteristics, including the Herfindahl index($Herfindahl$)[9], industry liquidity measured by daily trading volume scaled by daily market cap ($Liquidity$), industry market size measured by daily market cap in millions ($MktcapMil$), and industry institutional investment percentage ($Institution$)[10]. The values of $Herfindahl$, $Liquidity$, $MktcapMil$ and $Institution$ are calculated using data from coinmarketcap.com. Previous studies use put/call ratio, the Chicago Board Options Exchange Volatility Index (CBOE VIX), and the economic policy uncertainty (EPU) index as proxies for market sentiment. A rising (falling) put/call ratio suggests that investors expect the market to decline (rise) (Gurdgiev and O'Loughlin, 2020; Qian, 2009). CBOE VIX is a benchmark index reflecting investors' expectations of the 30-days forward volatility in the S&P 500 equity index (BenMabrouk and Litimi, 2018). A higher VIX level indicates a higher level of uncertainty in the market (Economou et al., 2018). EPU index also measures uncertainty and is based on newspaper coverage frequency. $Put/Call$, $VIX$ and $EPU$ are obtained from Bloomberg. We further include crypto specific sentiment measures such as Google trend search data on Bitcoin ($GoogleBTC$) and top 30 cryptocurrency price index ($CCi30$).[11]

# 4 Data

Sample selection bias may be present in the previous studies that investigate herding in crypto assets, as only the large and mature crypto coins are selected (Kaiser and Stöckl, 2020). We collected daily prices, market capitalisation and volume of all listed cryptocurrencies from www.coinmarketcap.com from 29 April 2013 to 9 May 2022. The sample consists of 10,059 assets traded on a daily basis over the time period with a total number of 4,629,118 observations.

The challenge in categorising industry sectors is that most crypto assets listed on coinmarketcap.com are under more than one industry sector and many sectors are not explicitly

[9] $Herfindahl = \sum_{i=1}^{N}(mktcap_i/mktcap_{industry})^2$, where $N$ is the number of crypto assets for each industry.As an industry is growing to include more assets, the industry becomes less concentrated, Herfindahl index value becomes lower.

[10] coinmarketcap.com identifies the crypto assets that are included in institutional investors' portfolios, we use this information to calculate the proportion of institutional investors in each industry.

[11] We also run a panel regression of Eq 3 on $CSAD_t$ at industry level over determinants, and find the coefficients for majority of determinants remain robust.

labelled (for example, coinmarketcap has over 180 industry segments, but over 73% of the observations are categorised as 'others'). We use the more simplified industry segmentation by Coinlore (https://www.coinlore.com/crypto-sectors) and match crypto assets on Coinlore with those listed on Coinmarketcap. The procedure results in 818 crypto assets being matched and the sample with industry classification in our study consists of 1,344,037 observations. In order to have sufficient sample size for each industry sector, we assign each industry in our sample to the broader Global Industry Classification Standard (GICS) (see https://www.msci.com/gics). For those crypto assets that belong to more than one industry, we categorise them as 'Multi Sector'. The industry categories used in this study are: Communication Services, Consumer Discretionary, Financials, Healthcare, Industrials, Information Technology (IT), Payments[12], Real Estate, Utilities and Multi sector. More details on the industry segmentation are discussed in Appendix.

Descriptive statistics are presented in Table 1. As shown, Payments and IT have the largest numbers of assets, the highest transaction volumes and the largest market caps. Amongst other industries that could potentially be backed by business ventures, Industrials, Multisector, Financials and Communication Services are the largest sectors. The 'real asset' sectors such as Real Estate, Healthcare, Utilities are small in terms of both transaction volume and number of assets. All sectors have negative average returns over the whole time period. Volatility in Consumer Discretionary is significantly higher compared to other industries. As expected, Herfindahl index value is relatively low for large industries such as Financials, IT and Communication Services, suggesting that these sectors are the least concentrated. These sectors are also more liquid and have a larger proportion of institutional investors compared to other sectors. Notably, the Payment sector's Herfindahl index value is high. A possible explanation is that the sector is dominated by a few cryptocurrencies (such as Bitcoin) with large market cap.

[Table 1 here]

# 5 Empirical Results

## 5.1 Herding

Results of models 3, 4, 5, 6 and other robust checks are presented in Table 2. $\hat{\gamma}_2$ appears to be positive and statistically significant in static models 3 and 4. $\hat{\gamma}_2$ is also statistically positive in the OLS+AR+GARCH specification, but is negative (but insignificant) with in the rolling window model. A positive $\hat{\gamma}_2$ indicates reverse herding, an evidence of market participants behaviour characterised by performing contrary to market consensus, leading to a higher degree of cross sectional return dispersion. We will discuss this in more detail below. In the Markov Switching model, $\hat{\gamma}_2$ is significantly negative in the first two states (indicating herding behaviour) but significantly positive in state 3.

[12] For 'payments only' type of crypto assets, we treat them as cryptocurrencies as opposed to tokens that are linked to a specific venture.

[Table 2 here]

To demonstrate the results further, we plot the time-varying t-statistics of $\hat{\gamma}_2$ in the OLS rolling window specification against the 95% critical values (illustrated by the dotted lines) in Figure 1.[13] In line with previous studies discussed in Section 2, herding is present in our sample when such time-varying approach is adopted. Herding is detected in similar time periods using 'All' market return, BTC and CCi30, these are periods of June 2013-August 2016 (a period of increase of Bitcoin price; also in July 2016, the reward for BTC miners was halved); July 2017- February 2018 (during this period, Bitcoin price saw a sharp increase and reached a peak in December 2017 as its futures contracts began trading on the CBOE and Chicago Mercantile Exchange); and December 2018- February 2019 (a period with much regulatory uncertainty in the crypto assets markets). Unlike some of the previous studies that suggest herding is not Bitcoin bound (Kallinterakis and Wang, 2019; Lo, 2020; Vidal-Tomás et al., 2019), this implies that Bitcoin was the dominating crypto asset in these time periods and changes in Bitcoin price may have triggered herding behaviour amongst investors. Reverse herding appeared to be present during July 2017-July 2018 if ETH is used as a proxy for market return, presumably due to less maturity of Ethereum during the earlier period.

[Figure 1 here]

We now turn attention to the Covid period specifically. Unlike previous studies, where Covid period tends to be constrained to the early months of the pandemic, we define Covid period as from January 2020 (when the virus started to spread worldwide) and May 2022 (the end of our data series, including a time period of the Omicron variant and the lockdown of Chinese cities in Spring 2022). With all four measures, herding is detected between July 2019 and March 2021 (including the first 12 months of the Covid pandemic period), this is in line with findings in Mandaci and Cagli (2022); Shrotryia and Kalra (2021); Susana et al. (2020); Vidal-Tomás (2021); Yarovaya et al. (2021). Furthermore, Mandaci and Cagli (2022) find intensified herding during the Covid outbreak, and assert that such altered investing behaviour is 'due to the halted industrial production process and precautions taken by policymakers' (p. 2). One could also argue that major positive developments in the crypto market during 2020-first half of 2021[14] could also drive herding behaviour. We will investigate this further in the section below when asymmetric herding is specifically examined.

Notably, reversing herding (measured against the overall market) is present during the later period of the pandemic since June 2021. Gębka and Wohar (2013) summarise three potential reasons for reverse herding: localised herding, where a subset of investors move into a

[13] 'All' and BTC as market return have longer time period but not shown in Figure 1, due to the shorter time periods of CCi30 and Ethereum.

[14] For example, the trading of options on BTC futures in January 2020, the permission of nationally chartered banks to custody crypto currencies in July 2020, the announcement by MicroStrategy of the adoption of BTC as primary Treasury reserve assets in August 2020, PayPal's announcement of accepting BTC in October 2020, the 18.5 million USD Thether settlement in February 2021, and Coinbase IPO in April 2021.

subset of assets increased dispersion in returns across the overall market (we will investigate this further below in the context of industry herding); excessive 'flight to quality' during market stress, whereby investors shift their capital from risky positions to more secure ones during high volatile period, resulting in opposite price movements in risk markets compared to safe ones; and overconfidence of investors, who overemphasis their own views and downplay the importance of market signals, particularly following periods of high positive returns (Philippas et al., 2020). Contrary to Gębka and Wohar (2013)'s excessive 'flight to quality' argument, Calderón (2018) argues that when cryptocurrency market faces extreme negative returns individuals do not 'flight to safety' but adopt the "HODL" strategy. Nevertheless, such behaviour can also lead to reverse herding measured return dispersion. Indeed, since November 2021, several major crypto currencies including Bitcoin and Ethereum saw significant declines in values. The average overall market return in our data decreased from 33% in January 2020 and March 2021 to -35% in June 2021-May 2022. Furthermore, the market dominance of BTC and ETH, measured as the ratio between market cap of BTC or ETH and market cap of all crypto assets, has significantly dropped from approximately 80% (70% for BTC and 10% for ETH) in January 2021 to around 60% (40% for BTC and 20% for ETH) in June 2021. Such decline in the dominance of BTC&ETH, as an indication of crypto-picking/overconfidence in altcoins (as suggested by Gębka and Wohar (2013)) may contribute to the increasing dispersion from market.

The above finding also implies that herding/reverse-herding asymmetry in upward and downward markets. To investigate this further, results of Models 5 and 6 are presented in the last two columns in Table 2. In general, $\hat{\gamma}_{2,D}$ is negative but statistically insignificant. $\hat{\gamma}_{2,U}$ however, is significantly positive in both C&Z (2010) model and quantile regression. To highlight the periods with asymmetric herding/reverse herding, we plot the estimated coefficients $\hat{\gamma}_{2,U}$ and $\hat{\gamma}_{2,D}$ in the 365-day rolling window with 1-day step specification (blue solid line) along with their 95% confidence intervals (red dotted lines) in Figure 2.

[Figure 2 here]

We find significantly negative $\hat{\gamma}_{2,D}$ during time periods in which 'negative' events took place in the crypto market, for example in September 2017-February 2018, following the Chinese ban on ICOs; from December 2018 to February 2019, when several crypyocurrency exchange hacks took place; and December 2019-January 2020, following the launch of crackdown on cryptocurrencies by the People's Bank of China. $\hat{\gamma}_{2,D}$ is also significantly negative during March 2020-March 2021, the first half of the Covid period, which is also consistent with the findings in literature that herding amplifies during crisis periods or market turmoil (BenSaïda, 2017; Litimi et al., 2016).

We do not find time periods of herding in upward market, hence the positive developments in the crypto market mentioned above may not have resulted in herding. $\hat{\gamma}_{2,U}$ however, is significantly positive in June 2021-May 2022, suggesting that during the recent 2021-2022 crypto crash, investors exhibit reverse herding behaviours even when market returns are positive. A possible explanation could excessive 'flight to quality' during market stress proposed by Gębka and Wohar (2013) as opposed to Calderón (2018)'s HODL hypothesis during market stress. The Wald test results in Figure 2 (c) show that $\hat{\gamma}_{2,U}$ and $\hat{\gamma}_{2,D}$ are significantly different during February and June 2015, February to June 2020, and

January, April-July 2021 Covid period, further confirming such asymmetric herding(reverse herding) in downward (upward) markets. Our findings are partially in line with findings in literature (Bouri et al., 2019; Ballis and Drakos, 2020; Kallinterakis and Wang, 2019) that herding is asymmetric in downward market. What is also interesting in our finding is that investors herd when the market returns are negative, even during a period of price increase in the overall market; reversing herding takes place during market stress even when market returns are positive, a behavioural change in the crypto markets that was not shown in previous studies before.

## 5.2 Industry herding

Models 3, 4, 5, 6 and other robust checks are repeated at industry level. Results are consistent across all models, we present the estimated coefficients of Model 3 with dynamic rolling window approach in Table 3. As shown in Table 3, the average $\hat{\gamma}_2$ is negative in most cases, however the average t-statistic appears to be insignificant, except the multi sector, which is marginally significant when CCi30 is used as a proxy for market return.

[Table 3 here]

The time-varying t-statistics of $\hat{\gamma}_2$ against the 95% critical values for each industry are plotted in Figures 3, where market returns are measured as the value weighted average of all crypto assets.[15] Each industry specific series are highlighted in orange, and the grey series represent the rest of industries for comparison.

[Figure 3 here]

The results confirm that herding in the crypto assets market is not uniform across different sectors. Herding is more profound in larger sectors with higher volatility (such as Payment, Information, Financial and multisector), which is in line with the argument that investors tend to herd in large industries due to higher level of uncertainty (Zheng et al., 2017). Interestingly, out of the four sectors with the largest returns, there is little evidence of herding in the Healthcare sector and very short time period in the Industrial sector, but strong evidence of herding in the Financial sector and Multisector. This implies that the style investing theory (that investors allocate funds in styles/industries that have performed well) only holds for the large sectors that are not back by 'real assets'. For smaller sectors with ventures that are backed by 'real assets', such as Real Estate, Utilities and Healthcare, investors appear to exhibit a minimum level of herding. This is contrary to findings in Vidal-Tomás et al. (2019) that small assets herd with large ones. Given that such crypto assets often have some functionality linked to the underlying assets and the sectors consist of a small number of assets, investors are more likely to follow their private information rather than mimicking others. Turning attention to reverse herding in June 2021-May 2022. If reverse herding is caused by a subset of investors moving into a subset of assets (i.e. an industry sector) as indicated by Gębka and Wohar (2013), we would expect more herding

[15] BTC, CCi30 and ETH as proxies for market return are also investigated, the results are kept in Appendix.

behaviours at industry level for this time period. Our results however, show that reverse herding is present in all industries except Real Estate. This further implies that other strategies such as excessive 'flight to quality' or asset picking at industry level are at play during the recent crash.

We repeat Equation 5 at industry level to test potential asymmetric herding. The results of OLS estimation with rolling window are presented in Table 4. In general, $\hat{\gamma}_{2,U}$ and $\hat{\gamma}_{2,D}$ are negative, but insignificant, apart from $\hat{\gamma}_{2,D}$ in the Multi sector. As before, we plot the t-statistics of $\hat{\gamma}_{2,U}$ and $\hat{\gamma}_{2,D}$ for each industry with 95% confidence levels in Figure 4 and Figure 5.

[Table 4 here]

[Figure 4 and 5 here]

Figures 4 and 5 show that asymmetric behaviours vary across industries. In the earlier periods between 2013 and earlier 2016, substantial periods of herding (longer than 3 months) in down markets is only detected in the Healthcare and Information sectors. In the Industrial sector, reversing herding is present when market return is positive in 2014; while herding in both up and down markets is present during 2015. From 2016, we observe more periods of herding and reverse herding periods across all sectors. For example, in the largest sector Payment, herding in down market is detected in September 2017-February 2018 following a few 'negative' events in the crypto market such as the Chinese ban on ICOs and the subsequent order of determination of mining operations. Interestingly, during such negative period, investors in Communications, Financials, IT, and utilities also herd, but only herd when market returns are positive. A possible explanation could be that as the fundamentals for Payment cryptos are difficult to determine, investors are likely to herd when markets are down. For other industries, where tokens may be linked to a more 'tangible' venture, investors herd when there is a positive signal in the market (Philippas et al., 2020).

Turning attention to the latest period, including the Covid pandemic, a mix of up and downward market herding is evident from October 2019 to May 2021 in many sectors but not the 'real' asset related sectors (Healthcare, Industrial, Real Estate and Utilities). Coupled with results in Figure 2, this implies that herding is predominately driven by investors in the 'non-real' asset related sectors, presumably due to increasing popularity altcoins and the increased crypto asset co-movements during this period evident in Katsiampa et al. (2022).

Figures 4 and 5 also confirm that reverse herding between June 2021 and May 2022 is driven by market upswings only. During this later period of the Covid pandemic, the crypto asset markets saw significant price falls, many countries experienced (and are still experiencing) a high level of inflation, the uncertainty of the Omicron variant and increased energy costs, investor in all sectors but Real Estate invest against market consensus even when the market is up. One possible explanation is consistent with the hypothesis of excessive 'flight to quality', that under extreme uncertainty and during market decline, investors exit the overall crypto market (and ignore the sector differences) and move to less risky assets even when the overall market returns are positive. An alternative/additional explanation is that at industry level, investors predominately rely on their own private information and asset-pick during high level of market uncertainty.

Finally, we conduct a Wald test under rolling window context to see if $\hat{\gamma}_{2,U}$ and $\hat{\gamma}_{2,D}$ are significantly different for each industry and the results are show in Figure 6. The test results further confirm asymmetric herding in both upward and downward markets at industry level in line with findings in in the previous section.

[Figure 6 here]

## 5.3 Herding Determinants

The estimated coefficients and t-statistics of Equation 7 are presented in Table 5. As our results indicate reverse herding, we also run Equation 7 for reverse herding, where the dependent variable is a binary variable $y_{j,t} = 1$ when the time-varying herding coefficient $\gamma_2$ is positive and statistically significant for each industry $j$ at $t$ and 0 otherwise. Probit model results for herding and reverse herding are presented in Panel A and B respectively.

[Table 5 here]

As expected the coefficients in Panels A and B generally have opposite signs. Investors are more (less) likely to herd (reverse herd) if the industry is less concentrated (indicated by the negative coefficient of $Herfinhadl$ in Panel A and positive coefficient in Panel B). This finding is in line with the existing literature discussed in Section 2, that herd behaviours may be induced by the increasing popularity of certain industries. Liquidity, market cap and institutional investors yield insignificant coefficients [16]. Amongst crypto assets related sentiment measures, $GoogleBTC$ yielded a significantly positive coefficient in Panel A and negative coefficient in Panel B, further implying the dominating influence on investor behaviours by Bitcoin. Consistent with the excessive 'flight to quality' hypothesis, the probability of herding (reverse herding) appears to be reduced (increased) when $CCi30$ increases, although the magnitudes appear to be very small. In terms of general investors sentiment measures, all three variables $EPU$ and $Put/Call$ yield significant coefficients. Stock market uncertainty measured by $VIX$ appear to induce both herding and reverse herding behaviours. The higher $EPU$ value, the more (less) likely crypto traders herd (reverse herd), due to the increased confidence about the (upward) direction of cryptocurrencies (Bouri et al., 2019). $Put/Call$ coefficients show that when the stock market is expected to rise (falling put/call ratio), the probability of herding (reserve herding) in the crypto assets market is also higher (lower). These findings imply that the general stock market sentiment also influence behaviours in the crypto assets market - a possible explanation to the short periods of herding in sectors that are backed by 'real assets'.

[16]Except in the first column in Panel B, where it is marginally significant.

# 6 Conclusion

Amongst recent empirical studies, there is a consensus that investors herd in the cryptocurrency market. Herding can result in mispricing and inefficiency in the asset market. As cryptocurrencies are evolving, they provide investors with a range of rights, some of which are directly related to the underlying business ventures. In this paper, We argue that the crypto market should not be seen as a whole, but categorised into different sectors in order to understand the forces that drive the dispersion in crypto assets' prices.

Empirically, we adopt method in Chang et al. (2000) with the inclusion of time varying approaches to crypto assets price data extracted from coinmarketcap. At the overall market level, we find evidence of concentrated herd behaviours and reverse herding during periods of market stress and erratic price changes. This is particularly evident in the 2020-2022 Covid period. Further investigation in asymmetric herding shows that herding is predominately driven by the downturn market not upward movements. Investors however exhibit reverse herding behaviour during June 2021-May 2022, even when market return is positive. At industry level, our results confirm varying herding behaviour across industry. Particularly, herding is more profound in larger sectors with higher volatility. In smaller sectors with ventures backed by 'real assets', such as Real Estate, Utilities and Healthcare, investor appear to exhibit a minimum level of herding. Reverse herding however, is evident across all sectors during the later period of Covid.

To our knowledge, this paper is the first that analyses crypto investors' behaviours at industry level. Our findings have important implications, first, our findings support the view in financial literature that investors of crypto assets are also likely to herd across different industries. However, herding in large sectors or style investing is predominately present in assets whose fundamentals are difficult to define (for example the Payment and IT sectors). A potential categorisation of digital asset is to group them according their digital functionalities (as in Benedetti and Nikbakht (2021) and Yarovaya and Zięba (2022), we will investigate this in our next research project. Second, we find strong evidence of reverse herding in upward market across most industries, which has not been documented before. This implies fundamental changes in investment behaviour in the crypto market (such as excessive 'flight to quality' or asset picking proposed by asset picking arguments proposed by Gębka and Wohar (2013)). This also provides some indirect evidence against the safe haven property hypothesis of crypto assets suggested by previous studies. Third, asymmetric herding is different among industries, while the overall market shows evidence of herding in down market, upward market herding is present in certain industries. This further confirms the importance to segment the crypto industry. Last but not the least, the probability of herding and reverse herding is not only associated with industry characteristics and crypto asset market sentiment, but is also affected by the general investment market sentiments. This paper contributes to the behavioural studies of crypto assets investors by providing further insights in the forces that drive the dispersion in crypto assets' prices.

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## Tables and Figures

**Table 1: Cryptocurrency overview:** Number ($n$), returns and standard deviations ($\mu_{r_it}$, $\sigma_{r_it}$), average volume in millions of shares ($Vol$), average market capitalisation in millions ($MktcapMil$) of \$, industry concentration measured by daily Herfindahl index ($H$), liquidity measured by average daily trading volume scaled by daily market cap ($Liq$), and institutional investment percentage ($Inst$) for each industry for the period 2013-2022.

| Sector | $n$ | $\mu_{r,it}$ | $\sigma_{r,it}$ | $Vol$ | $MktcapMil$ | $H$ | $Liq$ | $Inst$ |
|---|---|---|---|---|---|---|---|---|
| Communication Services | 84 | -0.2085 | 0.2558 | 6.57 | 33.90 | 42.02 | 0.19 | 7.14% |
| Consumer Discretionary | 40 | -0.5423 | 2.8665 | 0.49 | 6.15 | 43.17 | 0.10 | 5.00% |
| Financials | 147 | -0.1576 | 0.3570 | 8.74 | 73.10 | 26.61 | 0.48 | 6.80% |
| Healthcare | 9 | -0.0176 | 0.2425 | 2.58 | 17.80 | 58.28 | 0.02 | 0.00% |
| Industrials | 42 | -0.1672 | 0.3314 | 32.20 | 93.90 | 95.12 | 0.09 | 0.00% |
| Information Technology | 183 | -0.2103 | 0.3822 | 25.10 | 117.00 | 34.48 | 0.12 | 6.56% |
| Multisector | 131 | -0.1650 | 0.2949 | 14.20 | 78.00 | 31.73 | 0.18 | 4.58% |
| Payments | 172 | -0.1809 | 0.6461 | 103.00 | 1280.00 | 81.89 | 0.04 | 2.91% |
| Real Estate | 4 | -0.2002 | 0.1804 | 0.04 | 9.09 | 65.58 | 0.01 | 0.00% |
| Utilities | 6 | -0.2045 | 0.1637 | 0.19 | 3.51 | 79.67 | 0.03 | 0.00% |
| All | 818 | -0.2054 | 0.5721 | 19.31 | 171.24 | 55.86 | 0.13 | 5.01% |

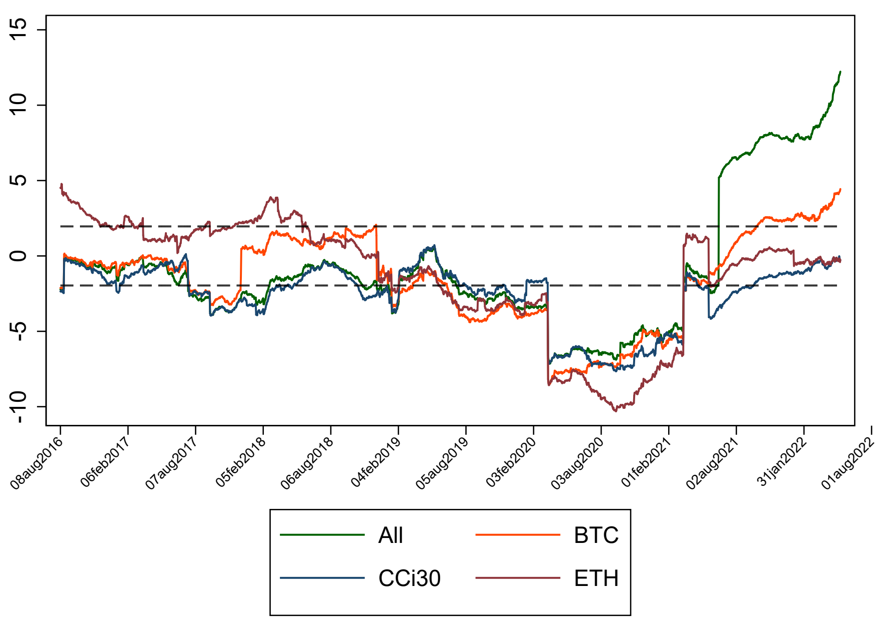



**Figure 1: Herding coefficients from the rolling window estimation:** The figure presents the t-statistics of $\hat{\gamma}_2$ in Eq. 3, estimated from the lagged 365-day rolling window. The value-weighted average (All), Bitcoin (BTC), CCi30 Index (CCi30), and Ethereum (ETH) returns are used as market returns respectively. Dates on the horizontal axis are the end dates of the rolling windows.

**Table 2: Model robustness check:** Model specifications consist of OLS estimation of Eq3 (OLS), linear model with additional autoregressive and heteroskedasticity terms (OLS+AR+GARCH), OLS under rolling window context (the average presented), Markov Switching model with three states (MS 3 States), and other model specifications in Eq. 4, 5, 6 for the period 2013-2022. The t-statistics are computed using Newey-West HAC robust standard errors.

| | OLS | OLS+AR+GARCH | Rolling OLS | MS 3 States | | | Yao et al. (2014) | C&Z (2010) | Qtl Regression Boots | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | S1 | S2 | S3 | | | Q25 | Q50 | Q75 |
| $\gamma_1$ | 0.2598 | 0.2359 | 0.4733 | 0.3586 | 0.3951 | -0.2841 | 0.1557 | | | | |
| $t$ | 11.50 | 27.23 | 7.520 | 12.97 | 11.92 | -2.92 | 8.51 | | | | |
| $\gamma_2$ | 0.0077 | 0.0077 | -0.0075 | -0.0030 | -0.0056 | 0.0116 | 0.0094 | | | | |
| $t$ | 11.69 | 46.47 | -0.44 | -2.35 | -3.02 | 8.90 | 17.63 | | | | |
| $\alpha$ | 9.0028 | 8.3796 | 8.6004 | 6.8918 | 10.8658 | 32.2841 | 4.0503 | 8.8714 | 6.9479 | 8.2459 | 10.7798 |
| $t$ | 117.54 | 65.42 | 55.23 | 79.88 | 114.71 | 35.40 | 31.03 | 115.03 | 118.29 | 80.14 | 119.59 |
| $\gamma_{CSAD,t-1}$ | | 0.7687 | | | | | 0.5269 | | | | |
| $t$ | | 56.08 | | | | | 42.96 | | | | |
| $\gamma_{1,U}$ | | | | | | | | 0.3733 | 0.2897 | 0.3637 | 0.3064 |
| $t$ | | | | | | | | 13.84 | 7.55 | 9.02 | 7.46 |
| $\gamma_{1,D}$ | | | | | | | | -0.2956 | -0.3132 | -0.2957 | -0.2594 |
| $t$ | | | | | | | | -8.78 | -11.58 | -5.34 | -3.23 |
| $\gamma_{2,U}$ | | | | | | | | 0.0075 | 0.0083 | 0.0071 | 0.0113 |
| $t$ | | | | | | | | 10.67 | 3.10 | 2.95 | 4.49 |
| $\gamma_{2,D}$ | | | | | | | | -0.0009 | -0.0017 | -0.0014 | 0.0011 |
| $t$ | | | | | | | | -0.56 | -1.01 | -0.31 | 0.24 |
| $ARCH$ | | 0.1374 | | | | | | | | | |
| $t$ | | 13.46 | | | | | | | | | |
| $GARCH$ | | 0.8451 | | | | | | | | | |
| $t$ | | 100.19 | | | | | | | | | |
| $Prob_{State}$ | | | | | | | | | | | |
| $p11$ | | | | 0.9847 | | | | | | | |
| $p12$ | | | | 0.0123 | | | | | | | |
| $p21$ | | | | | 0.0134 | | | | | | |
| $p22$ | | | | | 0.9844 | | | | | | |
| $p31$ | | | | | | 0.1777 | | | | | |
| $p32$ | | | | | | 0.2925 | | | | | |
| Loglikeihood | | -6756.5040 | | | -6784.8607 | | | | | | |
| $Adj-R^2$ | 24.19% | | 33.90% | | | | 51.38% | 26.34% | 8.97% | 7.74% | 8.33% |
| $\gamma_{2U}=\gamma_{2D}$ p-val | | | | | | | | 0.00 | 0.00 | 0.13 | 0.07 |
| $T$ | 3297 | 3297 | 3297 | | 3297 | | 3297 | 3297 | | 3297 | |

**Table 3: Rolling window regression by industry:** The table presents the average coefficients and associated average t-statistics of Eq. 3, estimated from rolling window OLS regression with Newey-West HAC robust standard errors for the period 2013-2022.

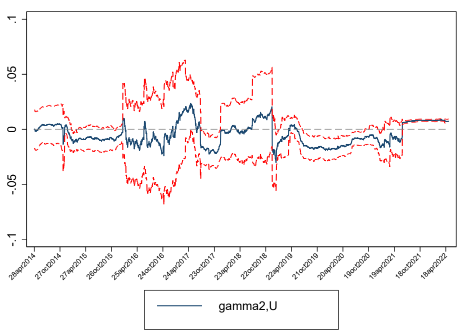
| | Communication Service Sector | | | | Consumer Discretionary Sector | | | | Financials Sector | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | All | BTC | CCi30 | ETH | All | BTC | CCi30 | ETH | All | BTC | CCi30 | ETH |
| $\gamma_1$ | 0.6415 | 0.6263 | 0.6056 | 0.4822 | -0.0734 | -0.0843 | 0.3626 | 0.5136 | 0.3185 | 0.2824 | 0.5016 | 0.3417 |
| $t$ | 4.23 | 3.78 | 4.26 | 5.33 | 2.20 | 1.96 | 2.86 | 3.99 | 4.34 | 3.74 | 5.00 | 5.55 |
| $\gamma_2$ | -0.0142 | -0.0112 | -0.0093 | -0.0005 | 0.0366 | 0.0371 | -0.0064 | -0.0028 | -0.0025 | 0.0010 | -0.0145 | 0.0047 |
| $t$ | -0.53 | -0.88 | -1.21 | -0.60 | 0.04 | -0.42 | -0.89 | -0.67 | 0.06 | -0.35 | -1.46 | 0.24 |
| $\alpha$ | 7.8400 | 7.8781 | 7.5550 | 7.9167 | 13.0490 | 13.0732 | 11.3934 | 10.9486 | 7.9456 | 8.0541 | 7.3041 | 7.6921 |
| $t$ | 26.31 | 25.77 | 27.14 | 28.55 | 21.46 | 20.88 | 22.43 | 23.58 | 30.27 | 29.55 | 30.17 | 31.85 |
| $Adj-R^2$ | 18.03% | 14.55% | 14.85% | 29.40% | 10.86% | 7.32% | 8.40% | 17.91% | 22.16% | 18.22% | 18.49% | 35.52% |
| $T$ | 3007 | 3007 | 2685 | 2466 | 3131 | 3131 | 2685 | 2466 | 3009 | 3009 | 2685 | 2466 |
| | Healthcare Sector | | | | Industrials Sector | | | | Information Technology Sector | | | |
| | All | BTC | CCi30 | ETH | All | BTC | CCi30 | ETH | All | BTC | CCi30 | ETH |
| $\gamma_1$ | 0.5299 | 0.5531 | 0.3222 | 0.3219 | 0.4052 | 0.4253 | 0.6373 | 0.4823 | 0.4260 | 0.4039 | 0.4203 | 0.3800 |
| $t$ | 1.49 | 1.29 | 1.41 | 1.71 | 2.13 | 1.94 | 3.10 | 3.38 | 4.53 | 3.99 | 4.83 | 6.08 |
| $\gamma_2$ | -0.0192 | -0.0204 | -0.0019 | 0.0060 | -0.0050 | -0.0093 | -0.0254 | 0.0025 | -0.0024 | 0.0008 | -0.0021 | 0.0027 |
| $t$ | -0.13 | -0.29 | -0.22 | 0.89 | 0.28 | -0.18 | -1.23 | 0.23 | 0.32 | -0.44 | -1.08 | -0.18 |
| $\alpha$ | 8.7269 | 8.7066 | 8.1810 | 8.6607 | 8.3288 | 8.3738 | 8.9590 | 9.2031 | 8.2712 | 8.3470 | 7.8545 | 7.7963 |
| $t$ | 13.21 | 12.93 | 13.26 | 13.47 | 18.70 | 18.24 | 20.01 | 20.56 | 34.69 | 33.56 | 36.55 | 36.92 |
| $Adj-R^2$ | 4.80% | 3.13% | 3.36% | 13.07% | 10.17% | 7.12% | 7.36% | 19.98% | 22.89% | 18.06% | 19.05% | 37.50% |
| $T$ | 3003 | 3003 | 2685 | 2466 | 3297 | 3297 | 2685 | 2466 | 3073 | 3073 | 2685 | 2466 |
| | Multisector Sector | | | | Payments Sector | | | | Real Estate Sector | | | |
| | All | BTC | CCi30 | ETH | All | BTC | CCi30 | ETH | All | BTC | CCi30 | ETH |
| $\gamma_1$ | 0.6477 | 0.6090 | 0.4811 | 0.5170 | 0.4846 | 0.4615 | 0.4966 | 0.4682 | 0.1852 | 0.1662 | 0.2277 | 0.4723 |
| $t$ | 5.81 | 5.11 | 5.82 | 7.54 | 4.92 | 4.39 | 5.52 | 7.24 | 1.67 | 1.07 | 1.56 | 1.70 |
| $\gamma_2$ | -0.0158 | -0.0138 | -0.0049 | -0.0020 | -0.0069 | -0.0052 | -0.0068 | 0.0011 | 0.0425 | 0.0317 | 0.0263 | -0.0044 |
| $t$ | -0.85 | -1.61 | -1.87 | -1.60 | 0.03 | -0.59 | -1.18 | -0.10 | 0.08 | 0.21 | -0.10 | -0.17 |
| $\alpha$ | 7.8360 | 7.9843 | 7.2282 | 7.2845 | 9.2332 | 9.2581 | 9.7978 | 9.9680 | 9.4178 | 9.6835 | 9.4844 | 9.0836 |
| $t$ | 29.28 | 28.18 | 31.13 | 31.24 | 41.47 | 40.89 | 44.05 | 43.96 | 10.39 | 10.23 | 9.91 | 9.85 |
| $Adj-R^2$ | 25.22% | 19.65% | 22.65% | 38.18% | 24.48% | 19.43% | 22.74% | 45.66% | 5.56% | 4.45% | 4.60% | 4.16% |
| $T$ | 3077 | 3077 | 2685 | 2466 | 3297 | 3297 | 2685 | 2466 | 1649 | 1649 | 1649 | 1649 |
| | Utilities Sector | | | | | | | | | | | |
| | All | BTC | CCi30 | ETH | | | | | | | | |
| $\gamma_1$ | 0.7477 | 0.7997 | 0.7083 | 0.4986 | | | | | | | | |
| $t$ | 1.86 | 1.69 | 1.59 | 1.91 | | | | | | | | |
| $\gamma_2$ | -0.0340 | -0.0412 | -0.0374 | -0.0004 | | | | | | | | |
| $t$ | -0.75 | -0.88 | -0.89 | 0.06 | | | | | | | | |
| $\alpha$ | 9.9496 | 9.9781 | 9.0100 | 8.6373 | | | | | | | | |
| $t$ | 11.14 | 10.83 | 10.86 | 10.75 | | | | | | | | |
| $Adj-R^2$ | 3.97% | 2.79% | 2.49% | 8.35% | | | | | | | | |
| $T$ | 2915 | 2915 | 2685 | 2466 | | | | | | | | |

**Table 4: Rolling window regression of asymmetric herding by industry:** The table presents the industry average coefficients and associated average t-statistics of Eq. 5, estimated from rolling window OLS regression with Newey-West HAC robust standard errors for the period 2013-2022.

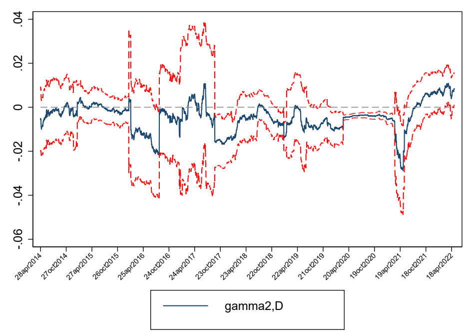
| | Communication Service | Consumer Discretionary | Financials | Healthcare | Industrials | Information Technology | Multisector | Payments | Real Estate | Utilities |
|---|---|---|---|---|---|---|---|---|---|---|
| $\gamma_{1,U}$ | 0.6359 | 0.1276 | 0.4700 | 0.4813 | 0.6377 | 0.4684 | 0.4006 | 0.5218 | 0.3629 | 0.7685 |
| $t$ | 3.10 | 1.89 | 3.51 | 1.20 | 2.30 | 3.40 | 3.61 | 3.82 | 1.52 | 1.47 |
| $\gamma_{1,D}$ | -0.6381 | 0.4848 | -0.2367 | -0.4487 | -0.2208 | -0.4181 | -0.7283 | -0.4567 | -0.0523 | -2.1763 |
| $t$ | -3.14 | -1.38 | -2.97 | -1.00 | -1.02 | -3.36 | -4.56 | -3.55 | -0.98 | -1.41 |
| $\gamma_{2,U}$ | -0.0105 | 0.0179 | -0.0168 | -0.0157 | -0.0199 | -0.0057 | 0.0103 | -0.0052 | 0.0201 | -0.0197 |
| $t$ | 0.00 | -0.01 | -0.07 | -0.05 | 0.01 | 0.61 | 0.77 | 0.35 | -0.32 | -0.29 |
| $\gamma_{2,D}$ | -0.0165 | 0.1805 | 0.0032 | -0.0111 | 0.0030 | -0.0029 | -0.0254 | -0.0076 | 0.0722 | -2.9178 |
| $t$ | -0.95 | -0.23 | -0.26 | -0.23 | 0.10 | -0.65 | -1.89 | -0.64 | 0.19 | -0.93 |
| $\alpha$ | 7.8387 | 13.0011 | 7.9057 | 8.7581 | 8.2715 | 8.2469 | 8.0733 | 9.2125 | 9.3140 | 9.8893 |
| $t$ | 25.32 | 20.60 | 29.09 | 12.73 | 17.93 | 33.35 | 28.33 | 40.15 | 9.86 | 10.68 |
| $Adj-R^2$ | 18.66% | 11.35% | 22.98% | 5.24% | 11.69% | 24.29% | 26.19% | 25.44% | 6.08% | 4.52% |
| $T$ | 3007 | 3131 | 3009 | 3003 | 3297 | 3073 | 3077 | 3297 | 1649 | 2915 |

**Table 5: Panel probit regression of herding determinants:** The table presents the coefficients and associated t-statistics of panel Probit regression of herding over determinants with robust standard errors and industry fixed effect. The dependent variable is a binary variable equals one when the herding (or reverse herding) coefficient is statistically significantly negative (or positive) and zero otherwise for each industry. The determinant variable consist of four sets of variables. The industry specific characteristic variables: industry concentration measured by daily Herfindahl index ($Herfindahl$), industry liquidity measured by daily trading volume scaled by daily market cap ($Liquidity$), industry market size measured by daily market cap in millions ($MktcapMil$), and industry institutional investment percentage ($Institution$). The crypto assets related variables: Google trend search data on Bitcoin ($GoogleBTC$), and top 30 cryptocurrency price index ($CCi30$). The market sentiment variables: CBOE VIX price index ($VIX$), EPU price index ($EPU$), and CBOE put/call ratio ($Put/Call$).

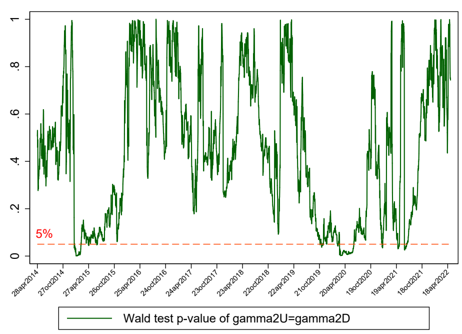
| | Panel A: Herding | | | Panel B: Reverse Herding | | |
|---|---|---|---|---|---|---|
| $Herfindahl$ | -0.0155 | -0.0180 | -0.0113 | 0.0302 | 0.0359 | 0.0367 |
| $t$ | -1.69 | -1.81 | -1.72 | 2.05 | 1.66 | 3.31 |
| $Liquidity$ | -0.0002 | 0.0007 | -0.0004 | 0.1755 | 0.0009 | 0.0029 |
| $t$ | -0.03 | 0.15 | -0.06 | 0.28 | 0.33 | 1.33 |
| $MktcapMil$ | -0.0001 | 0.0001 | 0.0001 | 0.0002 | -0.0001 | -0.0001 |
| $t$ | -0.17 | 0.32 | 1.20 | 1.02 | -0.56 | -0.93 |
| $Institution$ | 4.8450 | 3.5296 | 10.5252 | 31.2516 | 40.6870 | 41.6121 |
| $t$ | 0.38 | 0.27 | 0.36 | 1.70 | 1.59 | 1.60 |
| $GoogleBTC$ | 0.0106 | 0.0258 | 0.0260 | -0.0101 | -0.1736 | -0.1651 |
| $t$ | 2.93 | 9.71 | 7.18 | -1.71 | -17.47 | -15.53 |
| $CCi30$ | | -0.0001 | -0.0001 | | 0.0003 | 0.0003 |
| $t$ | | -4.33 | -4.02 | | 21.01 | 10.66 |
| $VIX$ | | | 0.0259 | | | 0.0663 |
| $t$ | | | 1.73 | | | 8.87 |
| $EPU$ | | | 0.0025 | | | -0.0065 |
| $t$ | | | 4.96 | | | -11.35 |
| $Put/Call$ | | | -2.1434 | | | 0.5355 |
| $t$ | | | -2.01 | | | 3.34 |
| $\alpha$ | -0.7856 | -0.5360 | -0.6149 | -3.2158 | -3.5232 | -4.4841 |
| $t$ | -0.92 | -0.63 | -0.80 | -1.91 | -1.43 | -1.67 |
| $\sigma_u$ | 0.55 | 0.53 | 0.61 | 0.77 | 1.22 | 1.24 |
| $\rho$ | 0.23 | 0.22 | 0.27 | 0.37 | 0.60 | 0.61 |
| N | 25537 | 25537 | 17484 | 25537 | 25537 | 17484 |




(a)




(b)




(c)

**Figure 2: Herding coefficients $\gamma_{2,U}$ and $\gamma_{2,D}$ from rolling window estimation:** The figure presents the $\hat{\gamma}_{2,U}$ and $\hat{\gamma}_{2,D}$ in Eq. 5 with associated confidence interval at 5% significance level, estimated from the lagged 365-day rolling window. The Wald coefficient equality test is applied to $\gamma_{2,U} = \gamma_{2,D}$ and its associated p-values are plotted. The value-weighted average of all cryptos is used as market. The dates shown are the end dates of the rolling windows.

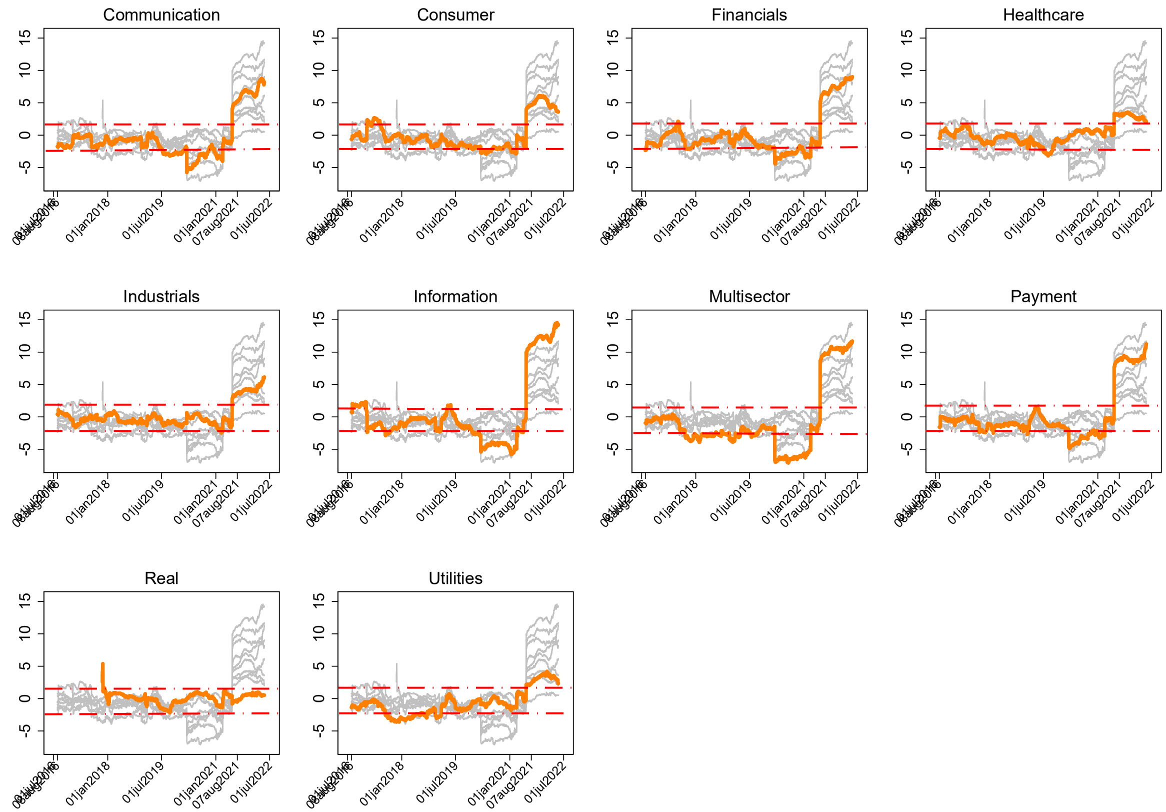
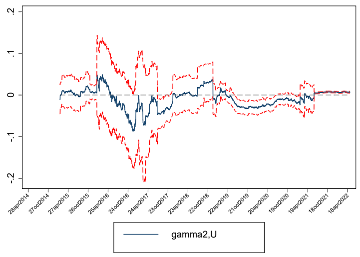
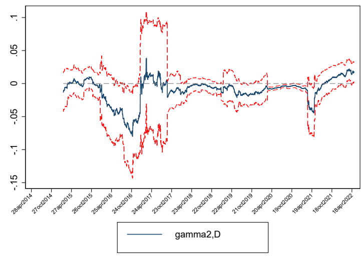


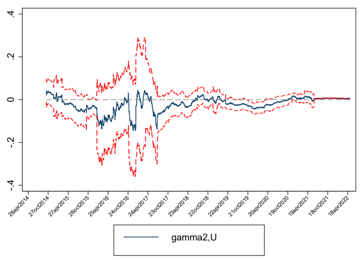

**Figure 3: Herding coefficient from rolling window estimation:** The figure presents the t-statistics of $\hat{\gamma}_2$ in Eq. 3, estimated from the lagged 365-day rolling window, for 10 industries respectively. The value-weighted average returns are used as market returns. 5% is used as significance level, shown in dashed line. The dates shown are the end dates of the rolling windows.



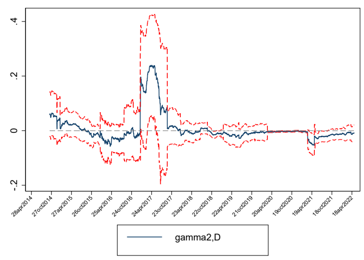

(a) Communication



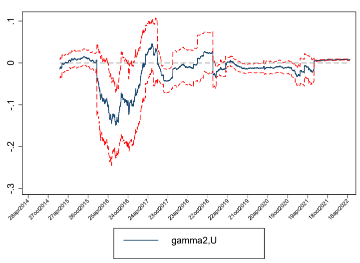

(b) Communication



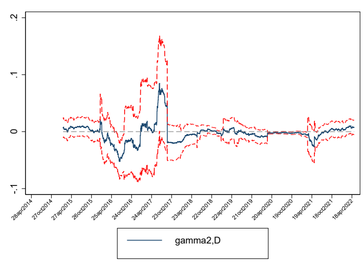

(c) Consumer



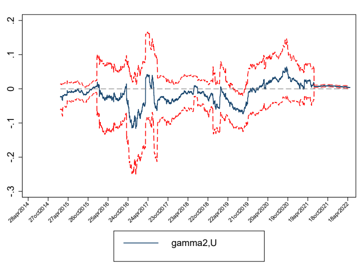

(d) Consumer



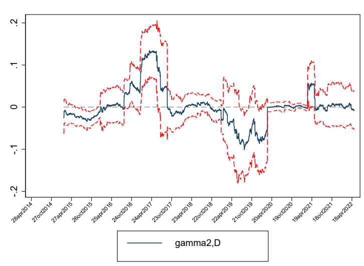

(e) Financials



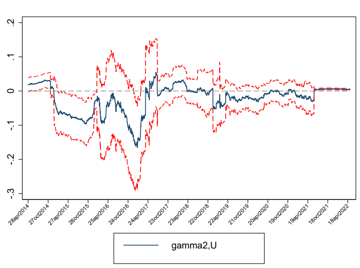

(f) Financials



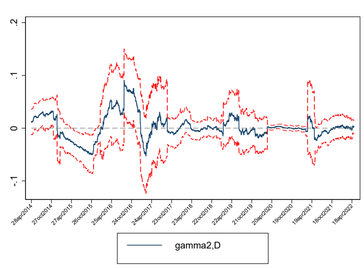

(g) Healthcare




(h) Healthcare

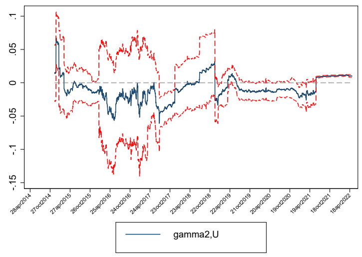



(i) Industrials

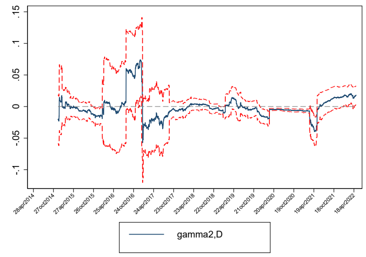



(j) Industrials

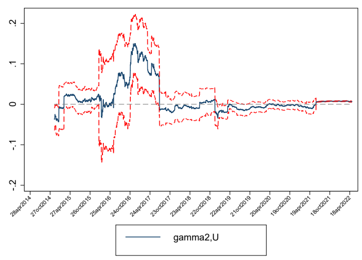
**Figure 4: Herding coefficients $\hat{\gamma}_{2,U}$ and $\hat{\gamma}_{2,D}$ from rolling window estimation part 1**



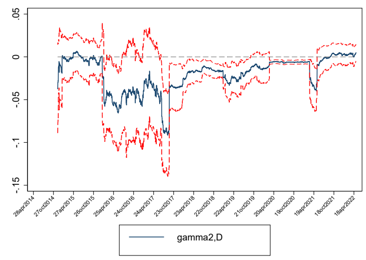

(a) Information



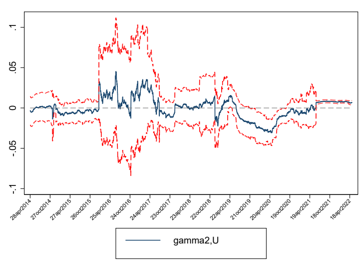

(b) Information



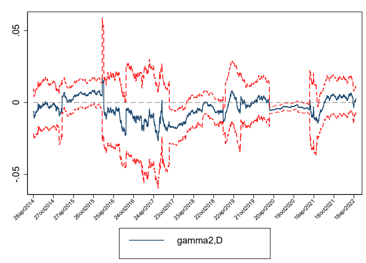

(c) Multisector



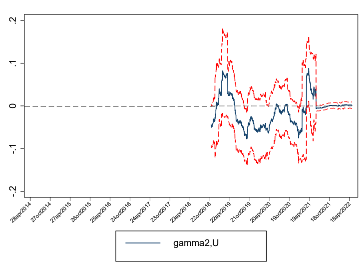

(d) Multisector



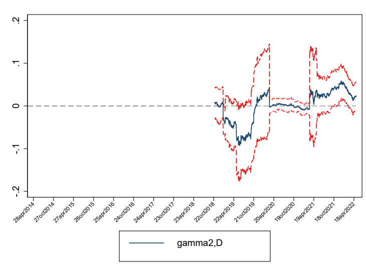

(e) Payment



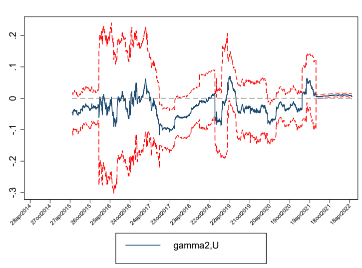

(f) Payment



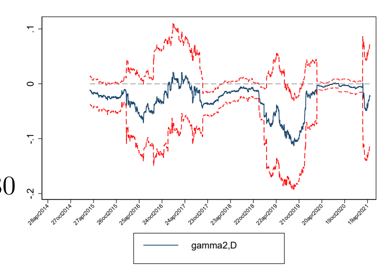

(g) Real Estate




(h) Real Estate




(i) Utilities




(j) Utilities

**Figure 5: Herding coefficients $\hat{\gamma}_{2,U}$ and $\hat{\gamma}_{2,D}$ from rolling window estimation part 2**

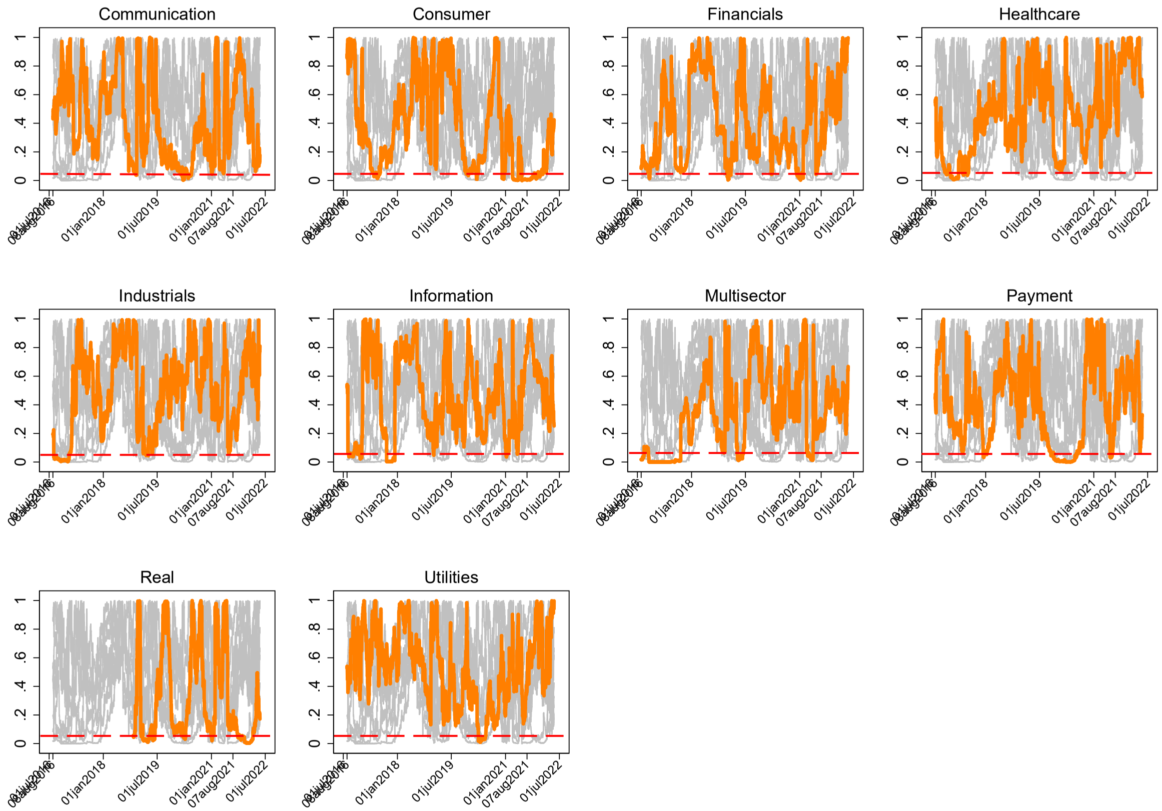



**Figure 6: The Wald coefficient equality test $\gamma_{2,U} = \gamma_{2,D}$ from rolling window estimation:** The Wald coefficient equality test is applied to $\gamma_{2,U} = \gamma_{2,D}$ and its associated p-values are plotted. $\hat{\gamma}_{2,U}$ and $\hat{\gamma}_{2,D}$ are estimated from Eq. 5 from the lagged 365-day rolling window, for 10 industries respectively. The value-weighted average returns are used as market returns. The dates shown are the end dates of the rolling windows.

# A Appendix

## A.1 Herding vs. Different Market Proxy

We examine the robustness of industry herding with respect to different choices of markets, including Bitcoin (BTC), CCi30 Index (CCi30), and Ethereum (ETH) returns, and present the results in Figure A1 and A2.

[Figure A1, A2 here]

## A.2 Industry Classification

The main purpose of this exercise is to assign each crypt asset in the dataset to a conventional industry classification according to the principal business activity of the underlying venture to examine industry herding. Similar to Liu et al. (2022), we collected trading data on all cryptocurrencies from www.coinmarketcap.com from 29 April 2013 to 9 May 2022.[17] The sample consists of 10,059 assets traded on a daily basis over the time period with a total number of 4,629,118 observations. Although coinmarketcap.com has industry categories (examples include Market, Asset Management, Commodities, Cybersecurity, Art, Gaming, Sports, Insurance and many more), as discussed previously, the challenge in using these categories directly is that most crypto assets are listed under more than one industry sector and a large proportion (73%) of the observations has ambiguous categorisation (for example, categorised as 'others').

We found the simplified industry segmentation by Coinlore is more in line with the conventional Global Industry Classification Standard (GICS) (see https://www.msci.com/gics). GICS is a hierarchical industry classification system in which companies are assigned to a sub-industry group according to its principal business activity. There are 158 sub-industries, which are subsequently categorised into 69 industries, 24 Industry groups, and 11 sectors (Energy, Materials, Industrials, Consumer Discretionary, Consumer Staples, Health Care, Financials, Information Technology, Communication Services, Utilities and Real Estate). There are over 50 industry categories in Coinlore which are very similar to the sub-industries/industries definitions by GICS. In order to have a sufficient sample size for each industry sector, we further assign these industries to GICS' broadest sectors.[18] We further introduced a Payment sector for 'payments only' cryptocurrencies as opposed to tokens that are linked to a specific venture. For those crypto assets that belong to more than one GICS sector, we categorise them as 'Multi Sector'. An illustration of the categorisation is presented in Table A1.

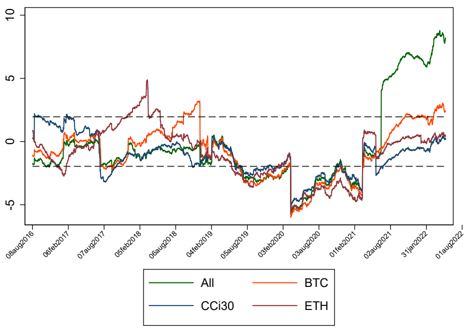
[Table A1 here]

[17] We are aware that the data may be subject to survivorship bias.

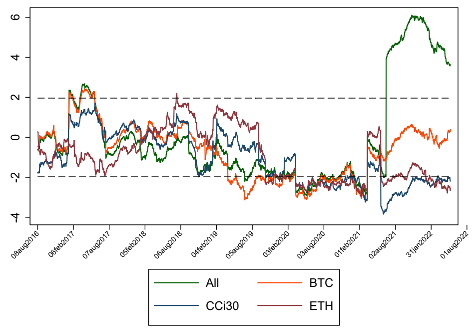
[18] We combined Energy with Utilities and, Consumer Discretionary with Consumer Stables due to the small number of observations in some of the categories.

**Table A1: Industry Specifications**

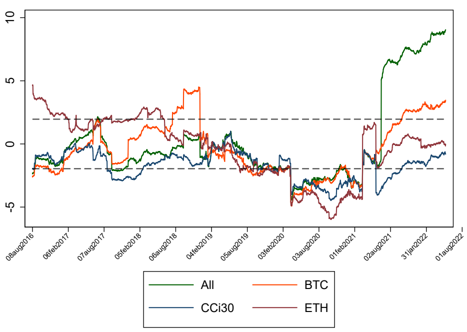
| **GICS Sector** | **Industry Coinlore** | **Crypto Example (largest 3)** |
|---|---|---|
| Communication Services | Commerce&Advertising; Communication; Events&Entertainment; Marketplace; Media&Publishing; Social Network | BitTorrent; Basic Attention Token; Horizen |
| Consumer Discretionary | Adult; Casino&Gambling; Education; Gaming; Retail; Sports; Tourism | FUNToken; AVINOC; Edgeless |
| Financials | Asset-backed Tokens; Assets Management; Decentralized Exchange; Exchange-based Tokens; Finance/Banking; Loans; Monetization; Trading&Investing; Wallet | Stellar; Huobi Token; Waves |
| Healthcare | Drugs&Healthcare | Dentacoin; Humanscape; SOLVE |
| Industrials | Business Services; Charity; Environment Friendly; Infrastructure; Lightning Network; Manufacturing; Recruitment; Supply&Logistics | Litecoin; v.systems; LTO Network |
| Information Technology | Artificial Intelligence; Big Data&Data Storage; Blockchain Service; Business Platform; Computing&Cloud Infrastructure; Cross-chain; Identity&Verification; Internet of Things (IOT); Mobile; Off-chain; Premine; Private Chains; Scalable; Sidechains; Software; Technology&Science | Chainlink; Cosmos; VeChain |
| Multisector | more than one GICS sectors | TRON; Theta Network; Decentraland |
| Payments | Payments | Bitcoin; XRP; Bitcoin Cash |
| Real Estate | Real Estate | Breezecoin; Ecoreal Estate; ATLANT |
| Utilities | Energy&Utilities | WePower; Robotina; Energycoin |



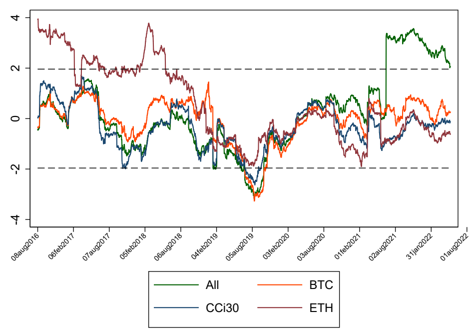

(a) Communication



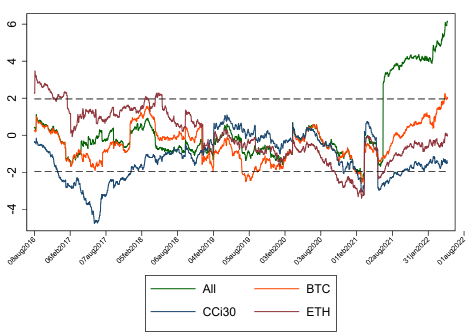

(b) Consumer




(c) Financials

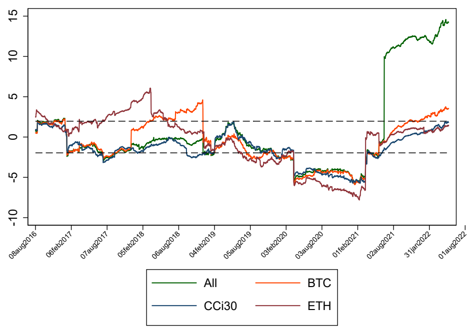



(d) Healthcare

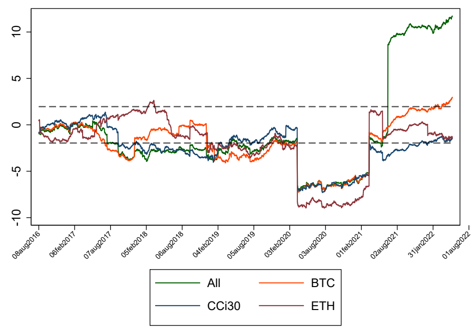



(e) Industrials

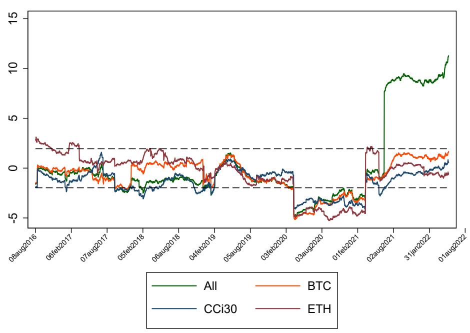
**Figure A1: Herding coefficient from rolling window estimation part 1:** The figure presents the t-statistics of $\hat{\gamma}_2$ in Eq. 3, estimated from the lagged 365-day rolling window. The value-weighted average (All), Bitcoin (BTC), CCi30 Index (CCi30), and Ethereum (ETH) returns are used as market returns respectively. The dates shown are the end dates of the rolling windows.



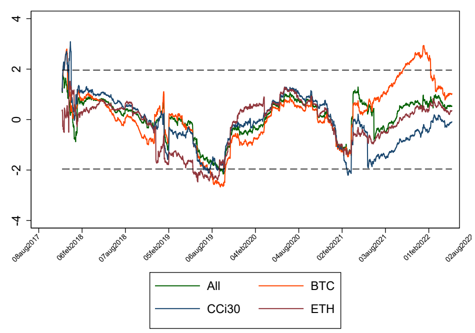

(a) Information



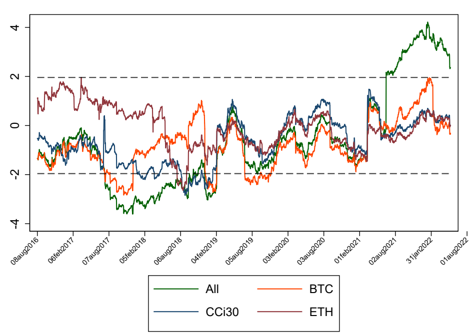

(b) Multisector




(c) Payment




(d) Real Estate




(e) Utilities

**Figure A2: Herding coefficient from rolling window estimation part 2:** The figure presents the t-statistics of $\hat{\gamma}_2$ in Eq. 3, estimated from the lagged 365-day rolling window. The value-weighted average (All), Bitcoin (BTC), CCi30 Index (CCi30), and Ethereum (ETH) returns are used as market returns respectively. The dates shown are the end dates of the rolling windows.