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Highlights

- We examine the influence of exogenous informative signals on herding detection.
- Extracted signals are endogenised by cryptocurrency investors.
- The signals can amplify or dampen herding behaviour in the cryptocurrency market.
- Extracted signals are found to have an asymmetric impact on herding intensity.

Signal-herding in cryptocurrencies

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Abstract

The paper examines the influence of informative signals derived from exogenous factors on herding intensity in the cryptocurrency market. We propose a novel approach whereby extracted signals are endogenized in investors' decision-making. The signals may induce investors to converge towards (depart from) the market consensus, contributing to herding amplification (dampening). The findings reveal substantial asymmetries with respect to the intensity of herding stemming from exogenous influences. We conclude that the evidenced diversity is indicative of the value that investors attach to the information embedded in the different external signals they receive.

Keywords: signal-herding; conditional herding; cryptocurrencies;

JEL classification: G11; G15; G40.

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1. Introduction

Herd behaviour is the tendency of investors to suppress their own beliefs and their private information in favour of the market consensus when trading individual assets. Conceptually, herd behaviour traces back to the works of Scharfstein and Stein (1990), Bikhchandani et al. (1992) and Froot et al. (1992). These studies argue that under certain circumstances, such as informational cascades, market inefficiency and so on, market agents may follow the investment decisions of others when concerned about their own reputation, potentially ignoring their private information. Putting the concepts above into the context of financial markets, herd behaviour is related to the notion of 'animal spirits', representing a switch in investors' opinion in the direction of the crowd.

Cryptocurrencies lack fundamentals (in contrast with conventional financial assets) and, given the high uncertainty in financial markets, investment behaviour in the cryptocurrency market is largely affected by signals derived from exogenous information flows (e.g., Vidal-Tomás et al., 2018; Bouri et al., 2018; Fang et al., 2019; Corbet et al., 2019). These signals are generated when volatility in a seemingly related market influences behaviour in the market of interest (Graham, 1999), i.e. in our case the cryptocurrency market. Potentially, information signals initially have the form of spillovers that are later translated into irrational herd behaviour, acting as collective signals. This paper proposes a novel approach whereby herding intensity in cryptocurrencies is influenced by informative signals extracted from convex patterns present in exogenous factors.

The role of informative signals extracted from the behaviour of exogenous factors and their influence on herding intensity has not received adequate attention. A considerable body of empirical literature has previously tested for herding behaviour across different financial markets and how it is influenced in the presence of exogenous factors (see Christie and Huang, 1995; Grinblatt et al., 1995; Chang et al., 2000; Gleason et al., 2004; Sias, 2004; Chiang and Zheng, 2010; Economou et al., 2011; Demirer et al., 2015; Bernales et al., 2016; Galariotis et al., 2016; Voukelatos and Verousis, 2019). These studies examine herding using the cross-sectional dispersion of asset returns (CSAD), providing mixed evidence. Dummy variables have also been used in some of these studies to test for the influence of certain news.

Park and Sabourian (2011) developed a theoretical model that analyses the sources of informational herding and contrarianism from signals that informed investors receive from the market. They argue that investors herd when information is sufficiently dispersed, therefore considering extreme outcomes more likely than moderate ones (U-shaped signals), while contrarianism is observed when moderate outcomes are considered more likely (hill-shaped signals). This is particularly relevant for markets which lack a solid basis of fundamentals, such as cryptocurrencies, where it is argued that trading is predominantly speculative (Baur et al., 2018). Given also the evidence on herding behaviour in cryptocurrencies (e.g. Vidal-Tomás et al., 2018; Corbet et al., 2019), it is important to examine how external influences are endogenized in the decisions of cryptocurrency investors, therefore *amplifying* or *dampening* herding. The implication arising from this paper is that the behaviour of exogenous factors generates signals that investors take into account for their decisions. We argue that there is a mechanism whereby these signals may amplify or dampen herding, focusing on the cryptocurrency market.

The study of herding behaviour among cryptocurrency investors is of great importance for several reasons. First, cryptocurrencies are receiving increasing attention in the recent literature due to their impressive historic returns, are speculative investment with extreme volatility and low correlation with other conventional assets such as stocks, bonds, commodities and currencies, in normal or turbulent times (see the studies of Baur et al., 2018; Ji et al., 2018b; Corbet et al., 2019; Shahzad et al., 2019). Secondly, cryptocurrency demand, though, can be determined by other factors other than its historical returns. The loose regulatory framework around cryptocurrencies and the anonymity that characterizes them means that they are undetectable and therefore preferred for illegal transactions such as arms and drug trafficking or money laundering (Yelowitz and Wilson, 2015). Hence, the imposition of additional controls on their use contributes to the closure of cryptocurrency exchanges due to the resulting decline in demand. Moreover, socioeconomic and political uncertainty motivates investors to seek alternatives which are outside governmental control and the sources of the underlying instability. Therefore, while the role of cryptocurrencies as a means of exchange is challenged, they may be viewed as a substitute for conventional assets during turbulent times.

Given the above, we argue that the presence of herding behaviour in cryptocurrencies can be justified from a number of viewpoints. On the one hand, their purported speculative nature suggests that their price behaviour cannot be attributed to changes in fundamentals but rather to the formation of behavioural patterns. The observed behaviour therefore depends on the reaction of uninformed investors to signals that are formed from patterns in the behaviour of exogenous factors. On the other hand, the popularity of cryptocurrencies during turbulent times indicates that external influences may play an important role in their pricing. This is supported by the strong evidence of market inefficiencies for cryptocurrencies (Urquhart, 2016). The scant literature on herding behaviour in cryptocurrencies suggests that smaller digital currencies tend to follow the larger ones (Vidal-Tomás et al., 2018), responding to negative news more than to positive (Fang et al., 2019), while herding tends to increase with economic policy uncertainty (Bouri et al., 2018).

This paper proposes a novel approach whereby herding intensity in cryptocurrencies is influenced by informative signals extracted from patterns present in exogenous factors. Following the notion of U-shaped and hill-shaped signals in Park and Sabourian (2011), we assume that market agents receive a signal from the market when such shapes are observed in exogenous factors (*signal-herding*). We therefore argue that herding amplification (dampening) is observed when signals from external factors induce more (less) herding compared to the standard unconditional herding model. Given our arguments that cryptocurrency trades seem to react to information arrivals in the market, we extract signals from information-rich indicators that can influence the behaviour of cryptocurrency investors and the intensity of herding. These informative signals extracted from consistent benchmark indicators can identify periods associated with triggering events, but also with cumulative flow of news over time. Consequently, in this paper, we include five main groups of indicators that generate information signals: (i) benchmark market-based indicators to capture expectations of market agents, (ii) risk (volatility) indicators as expectation of risk attitude, (iii) uncertainty indicators to account for the impact of released economic news, (iv) media attention indicators to capture information demand and supply and its cumulative sentimental influence, as well as, (v) commodities to capture any information derived when market agents shift to hedging diversification. To our knowledge, this is the first attempt to model signal extraction in the context of herding behaviour, while we also contribute to the scant literature on herding in cryptocurrencies.

Using daily data from 100 cryptocurrencies during the period from the beginning of January 2016 to the end of May 2018, we find strong evidence of conditional signal-herding, the strongest influencer of herding intensity being the information supply and demand due to relevant Twitter hashtags and Google searches, both of which amplify herding. An amplifying effect is also found in the volatility index and treasury yield volatility index, as well as the economic policy uncertainty factor, the latter highlighting the influence of economic fundamentals on bitcoin. In contrast, the connectedness of financial markets and foreign exchanges has a dampening effect through the presence of hill-shaped and U-shaped signals, respectively, while, a downward reversal of commodities' returns induces investors to form individual strategies.

Our paper contributes to the relevant literature in several ways. From a theoretical perspective, we contribute to close the gap in the herding literature by deriving predictions for aggregate herding intensity from the impact of heterogeneous exogenous factors derived as informative signals, translating conveniently into the conditional herding model. We provide insights into how herding aggregates across a set of assets that lack a solid fundamentals basis and over time, and how it is related to investors' herding intensity. We decompose the herding coefficient to the overall herding coefficient and the herding intensity coefficient, capturing different behaviours (cases) of herding, contrarianism and a hybrid case. We propose signal-herding which is shaped from exogenous factors which shift to herding amplification (dampening). In this way, we differ from the previous studies in that we investigate how informative signals can be endogenized in the decision-making of cryptocurrency investors. This can reflect the value of information an investor derives when updating her informative signals upon observing externalities and the behaviour of a crowd.

The remainder of the paper is organized as follows. Section 2 outlines the proposed herding detection framework we employ in our analysis. Section 3 describes the data, while section 4 presents the empirical results and discusses the implications along with a robustness check with the results provided in the accompanying Supplement. Finally, section 5 concludes.

2. Herding detection

A commonly used approach to detect herding is that proposed by Chang et al. (2000), who suggest that asset pricing models indicate a linear relationship between asset return dispersion and the absolute value of market returns. The linear model predicts that during periods of extreme market movement, the returns of any asset will deviate away from the market returns. Conversely, during stable periods, individual returns are dispersed closer to market returns. The cross-sectional absolute deviation (CSAD) is a common measure that captures the dispersion of individual asset returns from market returns and is calculated as follows:

$$CSAD_t = \frac{\sum_{i=1}^{n} \left| r_{i,t} - r_{m,t} \right|}{n-1} \tag{1}$$

where $r_{i,t}$ is the return of asset i at time t, $r_{m,t}$ is the market return at t, and n is the number of assets included in the cross-section at t. Chang et al. (2000) show that, under the capital asset pricing model's (CAPM) assumptions, CSAD is linear and is positively associated with contemporaneous market returns. Therefore, CSAD should be small during tranquil periods but considerably—though proportionately—higher when market returns exhibit extreme positive or negative values.

Herding in this context appears when investors decide to follow the market instead of their own beliefs or strategies, which introduces non-linearities in the relationship between CSAD and market returns. To capture herding, the following regression has been proposed (Chang et al., 2000; Chiang and Zheng, 2010):

$$CSAD_t = \beta_0 + \beta_1 \left| r_{m,t} \right| + \beta_2 r_{m,t}^2 + u_t \tag{2}$$

In the absence of herding, the CAPM-based market model predicts that variations in market returns in either direction should be linearly associated with CSAD, demonstrated by a positive and statistically significant β_1 coefficient. However, if herding exists, then investors switch from their own strategies to following the market consensus, pulling individual asset returns towards market returns. This obscures the linear relationship between CSAD and market returns and is reflected in a statistically significant and negative β_2 coefficient (Chang et al., 2000). If β_2 is positive and statistically significant, then market participants divert disproportionately from the market; this could be either due to overreaction to news or evidence of contrarian trading. Chiang and Zheng (2010) also proposed an extended form of

(2) to capture asymmetries in herding behaviour between days with a positive market return and days with a negative market return (up and down markets), using a dummy variable that takes the value of one if the market return is negative and zero otherwise. In this setting, and under the linear market term, CSAD should be higher where the magnitude of returns is higher, while the non-linear terms should be statistically insignificant. This specification allows examination of whether herding is stronger during periods of positive or negative market returns, thus revealing asymmetries in investors' behaviour.[1]

Herding behaviour can also be associated with external factors on an aggregate level which characterize periods of market stress and increased information flows (Bernales et al., 2016; Galariotis et al., 2016). To test for such influences, Eq. (2) can include a set of exogenous variables X_t:

$$CSAD_t = \beta_0 + \beta_1 |r_{m,t}| + \beta_2 r_{m,t}^2 + \beta_X X_t + u_t \tag{3}$$

Assuming that investors use the CAPM to price assets, under the null hypothesis of no herding, exogenous factors should not influence CSAD and β_X should be statistically insignificant. If the null hypothesis is rejected, then conditional herding describes the case where investors respond to market stress and/or increased information flow by pricing individual assets in a uniform way.

2.1 Herding amplification and dampening

An important issue that has not received adequate attention in the empirical literature relates to the external factors that may amplify or dampen herding activity. Park and Sabourian (2011) use a sequential Bayesian game framework to provide a formal definition of herding behaviour. In their framework, informed investors make trading decisions by interpreting signals that they receive from public information available to all market participants. A risky asset is assumed to take three possible values, $V_1 < V_2 < V_3$, at the end of time t, corresponding to three possible states. Therefore, the expected value of the asset depends on the probability attached to each state and hence the three possible

[1] Asymmetric effects due to positive (up) and negative (down) market returns would be elaborated on Eq.(2) as follows (Chiang and Zheng, 2010): $CSAD_t = \beta_0 + \beta_1(1 - D_t)r_{m,t} + \beta_2 D_t r_{m,t} + \beta_3(1 - D_t)r_{m,t}^2 + \beta_4 D_t r_{m,t}^2 + u_t$ where D_t is a dummy variable that takes the value of 1 when the market returns are negative and zero otherwise.

values. The signals that the informed investors receive induce their behaviour and ensure that their private asset valuation is different from the market one.

Informed investors choose to buy, hold or sell the asset (action) at time t, depending on the signal they receive from the market. Their private information set is defined as $I = \{\Pr(S_i|V_j)\}_{i,j=1,2,3}$, where $\Pr(S_i|V_j)$ is the probability that the investor receives signal S_i if the true value of the asset is V_j. They will buy the asset if their private valuation exceeds the ask price and sell if it falls short of the bid price, while they will hold the asset if their valuation lies between the bid and ask prices. Park and Sabourian (2011) distinguish the following cases for the shape of the conditional signal distribution:

- Increasing *iff* $\Pr(S|V_1) \leq \Pr(S|V_2) \leq \Pr(S|V_3)$
- Decreasing *iff* $\Pr(S|V_1) \geq \Pr(S|V_2) \geq \Pr(S|V_3)$
- U-shaped *iff* $\Pr(S|V_1) > \Pr(S|V_2)$ and $\Pr(S|V_2) < \Pr(S|V_3)$
- Hill-shaped *iff* $\Pr(S|V_1) < \Pr(S|V_2)$ and $\Pr(S|V_2) > \Pr(S|V_3)$

Park and Sabourian (2011) show that a necessary condition for herding (contrarian) behaviour is that there exists a U-shaped (hill-shaped) signal.

Our proposed model builds on similar principles to those in Park and Sabourian (2011) and primarily on the conceptual framework of the standard sequential trading setup of Glosten and Milgrom (1985). In Glosten and Milgrom (1985), risk-neutral investors trade units of financial assets with a market maker. Public information includes not only historical prices, but also past trades as well. The market maker adjusts the price after each transaction to reflect any new information incorporated. Rational investors should buy if their expectation, conditional to the information set, is above the price and sell if it is below. A recent development of this model is offered by Park and Sabourian (2011), who postulate that informative signals are manifested with three key types of *likelihood function* (LF): monotonic, hill-shaped and U-shaped. Investors who receive a signal with a monotonically increasing (decreasing) LF will always buy (sell). Investors who receive a signal with a hill-shaped LF will buy (sell) if prices substantially fall (rise), monetizing as contrarians against the trend. Finally, investors who receive a U-shaped LF will buy (sell) if prices substantially rise (fall), monetizing on the trend (herding).

Our framework has the distinctive difference that the signal emerges from exogenous influences instead of being determined endogenously. We argue in this paper that the degree of herding intensity is affected by signals extracted from exogenous factors and which investors endogenize in their trading strategies. We define as *herding amplification (dampening)* the situation where exogenously extracted signals intensify (weaken) herding behaviour in the market of interest. The interpretation of the signals is subjective and private for each investor, and therefore unobservable to other investors. However, some of the main strategy types can be identified through patterns observed in trading behaviour.

Suppose that in a market there are investors with different strategies which are unobservable, though influenced by internal or external signals. Internal signals can be interpreted differently by market participants, overall inducing herding, which can be examined using the models discussed in the previous section. Consider also that investors extract a set of signals from the history of an exogenous variable X at time t, denoted as $S(X^t)$, which influence their current strategy in the asset market. Investors have a short-term time window (τ, t) from which $S(X^t)$ is extracted, and they update or not their information set. In our model, we assume for simplicity that $\tau = t - 2$ and that the investor is interested in the value behaviour of X from $t - 2$ to t, although the analysis could extend to different time windows. We assume that the investor interprets monotonically increasing or decreasing values of X during the evaluation period as a signal of positive or negative market conditions, respectively. Similarly, swings in X indicate market volatility (risk) and a reversal of expectations. We therefore distinguish the following signals:

- Monotonically increasing when $X^{t-2} < X^{t-1} < X^t$
- Monotonically decreasing when $X^{t-2} > X^{t-1} > X^t$
- U-shaped when $X^{t-2} > X^{t-1}$ and $X^{t-1} < X^t$
- Hill-shaped when $X^{t-2} < X^{t-1}$ and $X^{t-1} > X^t$

Given that investors consider the behaviour in making trading decisions, a monotonically increasing or decreasing signal should not intensify or weaken herding in the main market, due to the fact that the signal from the exogenous factor is clear and will not make them revise their expectations for the asset price. However, as in Park and Sabourian (2011), we argue that swings in the value of X in the U-shaped or hill-shaped signals may encourage herding amplification or dampening, as they are considered as a form of information cascade with two steps: (i) a cascade begins when an individual encounter a scenario with a limited decision (i.e. a binary one) based on a previous information set; (ii) an individual makes a decision sequentially, influenced by outside factors that can affect this decision when observing collective signals and make inferences about this information from how other people acted earlier.[2]

To test for herding amplification (dampening), we first extract signals using an indicator $D_t^{S(X^t)}, S(X^t) = \{U, H, HU\}$, where the signal $S(X^t)$ can be U-shaped (D_t^U), hill-shaped (D_t^H) or hybrid (D_t^{HU}), where only the existence of value swings matters and not the shape. We therefore introduce the following definitions:

- $D_t^U = 1$ in the presence of a U-shaped signal and $D_t^U = 0$ otherwise
- $D_t^H = 1$ in the presence of a hill-shaped signal and $D_t^H = 0$ otherwise
- $D_t^{HU} = 1$ in the presence of either a hill-shaped or U-shaped signal and $D_t^{HU} = 0$ otherwise

Then, by augmenting Eq. (2), we have:

$$CSAD_t = \beta_0 + \beta_1 |r_{m,t}| + (\beta_2 + \gamma D_t^{S(X)}) r_{m,t}^2 + u_t \tag{4}$$

The extracted signal $S(X^t)$ is endogenized in the market trading behaviour, hence differentiating and extending from the exogenous effects type of model. In the presence of herding, β_2 should be negative and statistically significant as in Eq. (2). If there is evidence of herding amplification (dampening), then γ should be negative (positive) and statistically significant. If γ is positive and statistically significant, then market participants divert disproportionately from the market as a sign of contrarian trading. The fundamental difference of our definition of herding amplification (dampening) from that of the

[2] The informational cascade occurs when a market agent observes the actions of others and then, despite possible contradictions in her own private information beliefs, engages in the same acts inferred from other agents' actions. Information cascades can feed speculation and create excessive price moves. This is consistent with the idea that information cascades arise as irrational herd behaviour when people follow others regardless of their private information, pushed by collective signals that feed the cascade. This is in line with the study by Welch (2000), where information cascades are also observed in security analysts' recommendations, increasing the fragility of financial markets.

conditional herding model in Eq. (4) is that herding is influenced by the signal extracted from an exogenous factor rather than just the factor itself.

3. The data

The data come from various sources and include daily observations which span the period from the beginning of January 2016 to the end of May 2018. The chosen period is rich in financial and economic events, as well as those of socioeconomic and political significance originating in the USA, Europe and elsewhere, with potential impacts for the global financial industry and the financial markets.[3] Moreover, blockchain has been attracting increasing interest internationally since 2016, as captured by Google Trends.

The main market under consideration in this paper is cryptocurrencies. We use daily closing prices for the top 100 cryptocurrencies in terms of volume at the end of the study period.[4] Individual returns are calculated by taking the log-differences, while market returns are calculated as the simple average of the returns of the 100 cryptocurrencies. On each day of the sample period, we compute the cross-sectional dispersion of daily cryptocurrencies' returns (CSAD) using Eq. (1). Figure 1 plots the daily CSAD, on the primary axis, and market returns, on the secondary axis, for the cryptocurrency market. While the market returns show a trend of increasing uncertainty, especially after 2017, the behaviour of CSAD is not perfectly aligned. For example, we observe spikes in CSAD at the beginning of the study period, while the relatively high market volatility in 2018 coincides with a decreasing CSAD. We find some early evidence that the linear relationship between CSAD and market returns is violated, and the examination of herding behaviour is therefore justified.

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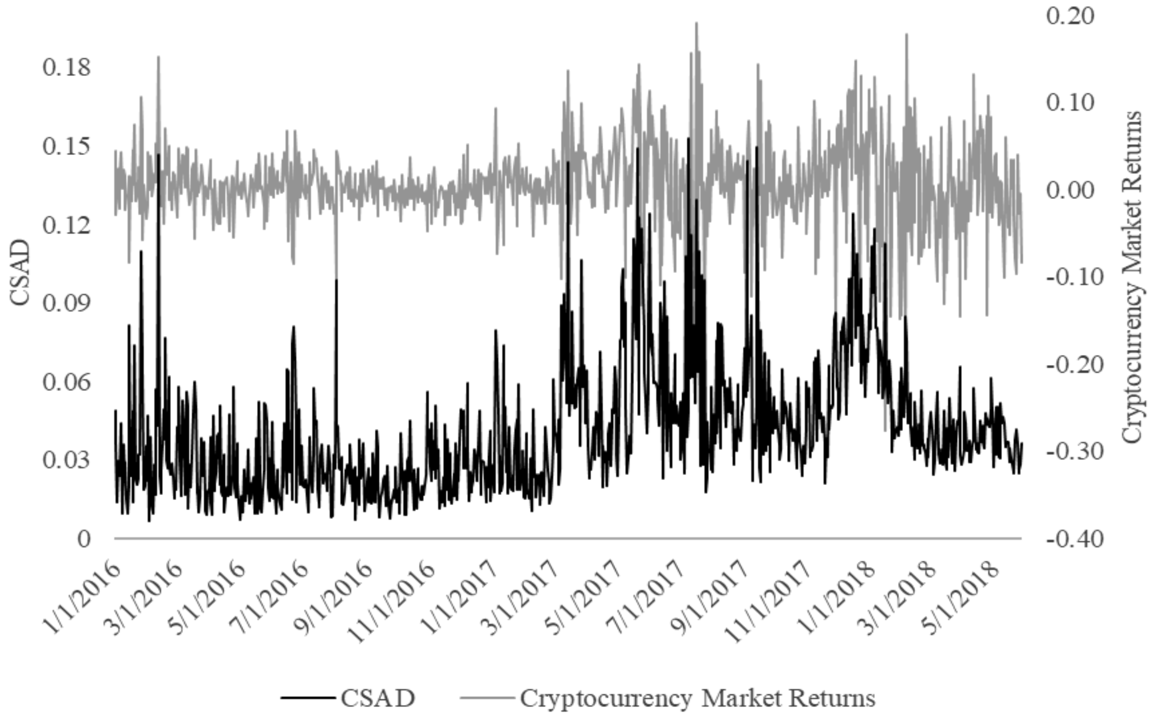
[3] Some examples that may influence investor sentiment include the Brexit referendum (June 2016), the US elections (November 2016), the US Tax Reform Bill (December 2017), the independence referendum in Catalonia (October 2017), OPEC increasing oil prices (November 2016), China's increasing debt, the ongoing turbulence in the Middle East related to the Syrian war, or the numerous ISIS terrorist attacks around the world, among others.

[4] Daily data on cryptocurrencies were downloaded from https://coinmarketcap.com.

Figure 1. CSAD and returns in the cryptocurrency market



Notes: The figure presents the daily cross-sectional absolute deviations (CSAD) on the primary axis and returns of the cryptocurrency market on the secondary axis during the period from 01/01/2016 to 28/05/2018. Market returns are calculated as the simple average of the returns of the top 100 cryptocurrencies in terms of volume at the end of the study period.

To examine exogenous influences on herding behaviour, we extract signals from market indices, media attention indices and risk and uncertainty indicators. Despite the fact that most of these indicators are associated with the US, they all have a global outreach since they are commonly used as benchmarks. Finally, it is important to note that our choice of a high frequency dataset is justified by the fact that the cryptocurrencies market is fast-paced and highly volatile. Even though higher frequency introduces noise, examining the behaviour of the market in longer horizons would not add value, given its nature. A direct implication of this is that signals from exogenous factors are expected to be short-lived and it would therefore make more sense to extract signals from the continuous time spectrum.

We split these indicators into broad groups to capture different types of signal related to the cryptocurrency market that can partially affect cryptocurrency price discovery.

Group I: Market indices

The first group includes benchmark market indices from the USA, since it is among the most liquidating markets globally, it may capture market portfolio performance, while events or news originating from the USA can influence other markets internationally, as well as bitcoin pricing. There is a vast literature studying the relationship between cryptocurrencies and conventional financial assets such as stocks, commodities and bonds, and it reports evidence of a very weak correlation (see Bouri et al., 2017; Baur et al., 2018; Guesmi et al., 2018). We firstly include in this group returns on the S&P500 index, which is a benchmark to capture the overall performance of the US economy and financial sector and is frequently used by portfolio managers to mimic a standard portfolio that an investor might be willing to invest in (such as equities, corporate bonds or commodities). We also include in this group the bitcoin to US dollar exchange rate, which can be considered an international proxy for Bitcoin price discovery at cryptocurrency exchanges (Brandvold et al., 2015), that reacts quickly to new information. Daily data for all indices in this group were downloaded from Bloomberg.

Group II: Volatility indices

The second group includes market volatility indicators, commonly used in empirical research. Information related to the risk attitude of market participants can indicate fluctuations in expectations and therefore a signal of overall economic unrest. We include in this group the volatility index (*VIX*) and the treasury yields volatility index (*TYVIX*) provided by the Chicago Board Options Exchange (CBOE). Even *VIX* is the most followed measure of implied volatility, the *TYVIX* is equally important for active market agents, because it covers the most liquid segment of the financial market, that is, the fixed-income market. While equity volatility (*VIX*) can be specified exogenously, government bond volatility needs to fulfil 'no-arbitrage' restrictions and to be consistent with the dynamics of the whole yield curve. Daily data for market volatility indices were downloaded from Bloomberg. We also include the volatility risk premium (*VP*) as a proxy for market sentiment, following Bollerslev et al. (2009). *VP* is defined as the difference between the ex-ante, risk-neutral expectation of the future returns' volatility and the ex-post realized volatility over a specific period (we chose this period to be n_m=30 days). The variance premium is given by $VP_{i,t} = IV_{i,t} - RV_{i,t}$. The first term ($IV_{i,t}$) is the implied volatility proxied by *VIX*. The second term is the S&P realized volatility calculated as $RV_{i,t} = \frac{252}{n_m}\sum_{t=1}^{n_m}(r_i)^2$, where r is the daily return of the underlying S&P500 equity index and $n_m = 30$ is the number of trading days in a year (i.e. we use the 252 days counting convention).

Group III: Media attention indices

The third group captures the behaviour of agents when exposed to news, events, hashtag trends and other online media-related factors. A strand of the literature discusses the effect of media coverage and social media on investing decisions (see Da et al., 2011; Engelberg and Parsons, 2011; Da et al., 2014). In the case of cryptocurrencies, social media are a prominent channel through which new information is diffused and discussed, especially by retail investors, being the majority of the cryptocurrency market (Kristoufek, 2015). However, not all social media have equal impact on cryptocurrencies, which might also depend less on economic and financial variables and more on a unique set of characteristics such as attractiveness, information diffusion rate, the nature of information and so on. We use two proxies for market trend information flow data: (i) the Google Trends daily data using the query term '*bitcoin*' that captures information demand, and (ii) the daily volume of Twitter hashtag '*btc*' that captures information supply (Philippas et al., 2019).[5]

Group IV: Uncertainty indicators

The fourth group includes indicators measuring uncertainty, derived from media (text) information. We first include in this group the Economic Policy Uncertainty (*EPU*) index, an uncertainty indicator proposed by Baker et al. (2016) which is based on the frequency of keywords appearing in the media.

[5] Google Trends data are quantitative data that capture the information demand for any keyword the user inputs. They are derived from the number of searches for the specific keyword divided by the total number of queries at that point in time and are scaled to the highest value for the requested period so that the highest value of the sample is 100. However, Google Trends data do not reflect the actual count of the number of searches for a given search term and cannot observe the precise piece of information the user acquires because the data include noise from random people searching for information other than investment, even if we assume that there is no systematic influence. What we extract is an index of users' propensity to search for a specific term. Daily data were downloaded from Google Trends (https://trends.google.com) and daily Twitter hashtags from https://bitinfocharts.com/.

Investors in the cryptocurrency market may use information about global economic uncertainty to enhance their predictions of cryptocurrency market volatility (Fang et al., 2019). However, there is no strong evidence of a connection between economic uncertainty and the hedging ability of cryptocurrencies, implying that investors cannot substantially enhance the hedging performance of cryptocurrencies under different states of economic uncertainty (Fang et al., 2019).

Moreover, Diebold and Yilmaz (2009, 2014) proposed a set of measures monitoring financial stress, commonly referred to as *connectedness*, and quantify the spillovers between financial intermediaries and financial markets. The inclusion of connectedness under the umbrella of uncertainty is that when markets are interconnected, a shock in one part of the components or geographies included, may propagate risks in other parts as well. Recent literature has shown that the importance of cryptocurrencies in return and volatility connectedness is not related to their market size (Ji et al., 2018a). In this paper, we use daily observations for the global equity markets' (denoted *ConnGL*) and global foreign exchange markets' (denoted *ConnFX*) connectedness measures.[6]

Group V: Commodities

In the last group, we use two commodities, the returns on gold and crude oil, which act as a safe haven investment during extreme market conditions (Dyhrberg, 2016; Shahzad et al., 2019). Since cryptocurrencies are uncorrelated with commodities (Baur et al., 2018), the aim is to examine whether the impact of commodities' extreme price movements shift investors to herd in cryptocurrencies in order to avoid risk exposure generated by commodities' extreme movements, i.e. cost push inflation, policy uncertainty which is incorporated into a short-run pricing model for gold and so on (Jones and Sackley, 2016; Maghyereh et al., 2017; Selmi et al., 2018). Daily data were downloaded from Bloomberg.

4. Empirical analysis

This section presents the empirical results of the modelling framework presented in section 2 and discusses the implications associated with the herding detection hypotheses. We first address our

[6] Daily data were downloaded from http://financialconnectedness.org/data.html.

findings on herding behaviour arising from the unconditional model in Eq. (2). Under the linear model, there is evidence of herding if β_2 is negative and statistically significant. Next, we discuss the herding behaviour arising from the conditional herding model in Eq. (3) and our proposed signal-herding model in Eq. (4). We use the same structure of panels in every table of results (i.e. panels A and B) to show the conditional herding and signal-herding respectively, providing also a comparative discussion.[7] Panel A reports the results on conditional herding from X regressor or X-matrix regressor, while panel B reports the results on signal-herding for the cases of U-shaped, hill-shaped and hybrid (both) exogenous signals.

If investors' herding behaviour for cryptocurrencies is also influenced by signals extracted from patterns of behaviour (U-shaped, hill-shaped or both) of exogenous factors, then the respective γ coefficient should be statistically significant. A negative (positive) and statistically significant γ is evidence of herding amplification (dampening). It is important to note, though, that it would not be possible to form predictions on individual cryptocurrency returns or form trading strategies using these results. Following a signal for herding amplification (dampening), it would be expected that cryptocurrency returns would converge to (diverge from) the market consensus. Therefore, while no inference could be made on the direction of returns in the presence of dampening signals, the opposite is true for the case of amplification signals. Amplification signals reinforce the estimations about the overall movements in the market, while for cryptocurrencies already exhibiting relatively high or low returns it would be possible to infer on the direction of their returns too (given the expected adjustment). Such predictions, though, would be very short-lived since information arrivals are updated very frequently (Philippas et al., 2019).

[7] A potential extension to our model would be as follows: $CSAD_t = \beta_0 + \beta_1(1 - D_t)r_{m,t} + \beta_2 D_t r_{m,t} + \left(\beta_3 + \gamma_1 D_t^{S(X)}\right)(1 - D_t)r_{m,t}^2 + \left(\beta_4 + \gamma_2 D_t^{S(X)}\right)D_t r_{m,t}^2 + u_t$, where γ_1 and γ_2 capture the effects of signal-herding when the market has positive or negative returns (i.e. γ_1<0 and/or γ_2<0), respectively. To account for extreme market movements, D_t could be specified accordingly. Experimenting with the alternative specifications, we did not observe any differences in the overall conclusions of the paper, presumably owing to the volatile nature of cryptocurrencies.

4.1 Empirical results

We start with the results for the unconditional herding model presented in Table 1. In the unconditional herding model, the coefficient of squared market returns is negative and statistically significant, and the null hypothesis of no herding is therefore rejected. This is not a surprising result since cryptocurrencies, as opposed to equities or fixed income securities, lack a fundamentals basis and therefore prices are more likely to be influenced by market sentiment and behaviour formation compared to other markets.

Table 1. Unconditional herding

β_0	β_1	β_2
0.019^{***}	0.743^{***}	-1.396^{***}
(0.001)	(0.032)	(0.186)

Notes: The table presents the results for unconditional herding for all cryptocurrency market, given from Eq. (2): $CSAD_t = \beta_0 + \beta_1 |r_{m,t}| + \beta_2 r_{m,t}^2 + u_t$. For each variable, we present the estimated coefficients, while Newey-West Heteroscedasticity and Autocorrelation consistent (HAC) standard errors are reported in parentheses. Three stars (***), two stars (**) and one star (*) denote statistical significance at the 1%, 5% and 10% level, respectively.

Results for Group I: Returns of market-based indices

Table 2 presents the results for the conditional herding and signal-herding derived from the returns on market-based indices (for each index or as a regressor matrix X). When examining the results for conditional herding in panel A of the table, we find mixed results. The S&P500 returns have a significant though small positive effect on CSAD. The bitcoin to dollar exchange rate has a significant and substantial positive impact on CSAD. These results are similar if we consider the regressor matrix X. Considering the cases of signal-herding in panel B, we do not find evidence of signal-herding, since γ is statistically insignificant. In contrast with panel A, which indicates that conditional herding exists from returns on the S&P500 index and the bitcoin to dollar exchange rate, the behaviour of the exogenous variables of this group is not endogenized in the herding behaviour of cryptocurrency investors. We therefore conclude that the influence of the market-based indicators is purely exogenous.

The findings show interesting patterns of herding influence derived from market-based indices. High returns on the S&P500 index are associated with less herding activity in the cryptocurrency market, while higher returns on the USD to bitcoin exchange rate are associated with reduced herding activity.

The latter also suggests that the higher the returns on bitcoin, the more inclined investors are to follow and to form strategies which are independent from the market.

Table 2. Conditional herding, signal-herding from market-based indicators

Panel A: Conditional herding from market-based indicators

Regressor	β_0	β_1	β_2	β_{SP500}	$\beta_{btc/\$}$
$X = [S\&P500]$	0.019***	0.741***	-1.379***	0.143*	
	(0.001)	(0.032)	(0.186)	(0.073)	
$X = [btc/\$\ rate]$	0.019***	0.732***	-1.235***		0.048***
	(0.001)	(0.032)	(0.188)		(0.012)
$X = [S\&P500 \quad btc/\$\ rate]$	0.018***	0.730***	-1.223***	0.127*	0.047***
	(0.001)	(0.032)	(0.188)	(0.072)	(0.012)

Panel B: Signal-herding from market-based indicators

Regressor	Signal	β_0	β_1	β_2	γ
$X = [S\&P500]$	U-shaped	0.019***	0.749***	-1.405***	-0.124
		(0.001)	(0.034)	(0.187)	(0.197)
	Hill-shaped	0.019***	0.742***	-1.405***	0.062
		(0.001)	(0.033)	(0.188)	(0.171)
	Hybrid	0.019***	0.745***	-1.394***	-0.265
		(0.001)	(0.034)	(0.187)	(0.158)
$X = [btc/\$\ rate]$	U-shaped	0.019***	0.742***	-1.511***	0.316**
		(0.001)	(0.032)	(0.194)	(0.153)
	Hill-shaped	0.019***	0.744***	-1.375***	-0.096
		(0.001)	(0.033)	(0.213)	(0.169)
	Hybrid	0.019***	0.741***	1.534***	0.237
		(0.001)	(0.032)	(0.221)	(0.159)

Notes: The table presents the estimation results of the two main models discussed in the paper, for the case of market-based indicators. Panel A presents the results of the conditional herding model, given by Eq. (3): $CSAD_t = \beta_0 + \beta_1|r_{m,t}| + \beta_2 r_{m,t}^2 + \beta_X X_t + u_t$, where X_t represents one market-based indicator or a regressor matrix of the market-based indicators considered. Panel B presents the results of the signal-herding model, given by Eq. (4): $CSAD_t = \beta_0 + \beta_1|r_{m,t}| + (\beta_2 + \gamma D_t^{S(X)}) r_{m,t}^2 + u_t$, where $D_t^{S(X)}$ represents signals extracted from the market-based indicators. The signals are extracted from the returns on the S&P500 index (S&P500) and the bitcoin to dollar exchange rate (btc/$). The correlation coefficient between the market-based indices is not statistically significant ($\rho = 0.055$) and it is reported at Table S1 in the Supplement. Results are reported for U-shaped signals, hill-shaped signals, and the hybrid case. For each variable, we present the estimated coefficients, while Newey-West Heteroscedasticity and Autocorrelation consistent (HAC) standard errors are reported in parentheses. Three stars (***), two stars (**) and one star (*) denote statistical significance at the 1%, 5% and 10% level, respectively.

Results for Group II: Volatility indices

Panel A in Table 3 shows evidence of conditional herding in the same direction in all three cases of volatility indicators (with similar results for the regressor matrix *X*). The treasury yield volatility index (*TYVIX*) and the 30-day VP induce a sizeable marginal reduction on herding, whereas the *VIX* has a significant effect but a smaller marginal reduction on herding. The results from panels B and C show evidence that signals extracted from *VIX* and *VP* are not endogenized in investors' herding behaviour despite our previous evidence on conditional herding for the two indices. In contrast, we find evidence of herding amplification in the presence of U-shaped signals from *TYVIX*, though there is stronger evidence of herding dampening when signals are hill-shaped.

Some important implications emerge from the results in Table 3. In the presence of higher implied volatility in equity and fixed income markets, cryptocurrency investors tend to herd less around the market returns. An implication arising from the result on *TYVIX* is that inflation risk, liquidity risk and fluctuations in macroeconomic fundamentals, which are common elements affecting the riskiness of fixed income securities, are considered by cryptocurrency investors. We also argue that the informational content in *TYVIX* generally encourages investors to adopt their own strategies. While herding intensity can increase when *TYVIX* swings down and then up (U-shaped), intensity reduces considerably if the opposite pattern is observed. One explanation could be that the swings in liquidity, inflation and other macroeconomic risks induce investors to update their expectations, reconsider their own strategies and follow the market (U-shaped), though predominantly to abstract from the market (hill-shaped).

Table 3. Conditional herding and signal-herding from volatility indices

Panel A: Conditional herding from volatility indices

Regressor	β_0	β_1	β_2	β_{VIX}	β_{TYVIX}	β_{VP30}
$X = [VIX]$	0.034***	0.742***	-1.374***	-0.105***		
	(0.004)	(0.057)	(0.296)	(0.023)		
$X = [TYVIX]$	0.038***	0.711***	-1.329***		-0.386***	
	(0.007)	(0.062)	(0.34)		(0.136)	
$X = [VP30]$	0.023***	0.739***	-1.326***			-0.274***
	(0.002)	(0.059)	(0.300)			(0.066)
	0.039***	0.729***	-1.350***	-0.091***	-0.156**	

$X = [\mathrm{VIX} \quad \mathrm{TYVIX}]$	(0.003)	(0.031)	(0.176)	(0.013)	(0.073)

Panel B: Signal-herding from volatility indices

Regressor	Signal	β_0	β_1	β_2	γ
$X = [VIX]$	U-shaped	0.019***	0.747***	-1.388***	-0.210
		(0.001)	(0.063)	(0.345)	(0.315)
	Hill-shaped	0.019***	0.744***	-1.397***	-0.042
		(0.001)	(0.061)	(0.348)	(0.499)
	Hybrid	0.019***	0.751***	-1.394***	-0.161
		(0.001)	(0.063)	(0.344)	(0.307)
$X = [TYVIX]$	U-shaped	0.019***	0.746***	-1.294***	-0.504**
		(0.003)	(0.062)	(0.321)	(0.286)
	Hill-shaped	0.019***	0.713***	-1.315***	0.909***
		(0.001)	(0.061)	(0.338)	(0.417)
	Hybrid	0.019***	0.746***	-1.386***	-0.082
		(0.001)	(0.061)	(0.338)	(0.318)
$X = [VP30]$	U-shaped	0.019***	0.744***	-1.438***	0.121
		(0.001)	(0.06)	(0.325)	(0.269)
	Hill-shaped	0.019***	0.739***	-1.389***	0.117
		(0.001)	(0.062)	(0.35)	(0.408)
	Hybrid	0.019***	0.739***	-1.443***	0.159
		(0.001)	(0.062)	(0.362)	(0.24)

Notes: The table presents the estimation results of the two main models discussed in the paper, for the case of volatility indicators. Panel A presents the results of the conditional herding model, given by Eq. (3): $CSAD_t = \beta_0 + \beta_1|r_{m,t}| + \beta_2 r_{m,t}^2 + \beta_X X_t + u_t$, where X_t represents one volatility indicator or a regressor matrix of the volatility indicators considered. Panel B presents the results of the signal-herding model, given by Eq. (4): $CSAD_t = \beta_0 + \beta_1|r_{m,t}| + (\beta_2 + \gamma D_t^{S(X)}) r_{m,t}^2 + u_t$, where $D_t^{S(X)}$ represents signals extracted from the volatility indicators. The signals are extracted from the volatility index (*VIX*), the treasury yield volatility index (*TYVIX*), the 30-day volatility premium (*VP30*). The correlation coefficient between the two volatility indices (*VIX* and *TYVIX*) is not statistically significant ($\rho = 0.34$) and it is reported at Table S1 in the Supplement. Results are reported for U-shaped signals, hill-shaped signals, and the hybrid case. For each variable, we present the estimated coefficients, while Newey-West Heteroscedasticity and Autocorrelation consistent (HAC) standard errors are reported in parentheses. Three stars (***), two stars (**) and one star (*) denote statistical significance at the 1%, 5% and 10% level, respectively.

Results for Group III: Media attention indices

Media attention indicators have a statistically significant impact on CSAD, providing evidence in favour of conditional herding. The β_{ex} estimates are both statistically significant but have different signs, highlighting the different nature and use of trending topics on Twitter hashtags and trends in

Google searches. The former are associated mostly, if not purely, with information supply whereas the latter are associated with information demand.

Media attention indicators also provide strong evidence of signal-herding, and in particular of herding amplification due to patterns formed for bitcoin Twitter hashtags and relevant trends in Google searches. Herding is intensified when bitcoin tweets form a U-shaped pattern and when Google searches form a hill-shaped pattern. This is an intuitive result based on our previous argument that bitcoin tweets reflect information supply and Google searches information demand. A hill-shaped signal from Twitter may be associated with an unexpected information supply peak reflecting bitcoin market information, amplifying herding effects. A U-shaped signal in Google searches indicates a dip and sudden resurgence of interest in bitcoin-related information, which can be used by investors to form strategies. In both cases, we observe that the hybrid signals are also statistically significant. We attribute this to the fact that in all cases of signal-herding, the γ coefficient is negative and therefore the results for hybrid signals merely carry interpretation.

Cryptocurrencies are very volatile assets; therefore, minor changes can influence their prices, manipulated by negative and positive publicity in the media. Since the market capitalization of cryptocurrency is not large when compared with the global economy, even the mildest rumours that circulate on the web can lead to fluctuations in the value. Our results suggest that the impact of information demand on cryptocurrency herding is weaker compared to information supply, shown in the smaller deviation of β_2 from its unconditional value. This may seem somewhat surprising, since investors demand information to form strategies, but bitcoin-related searches may also be conducted by non-traders, introducing noise. Google searches by active investors facilitate the formation of their private trading strategies, but they can also induce herding depending on the signals they receive. Our findings suggest that the herding effect dominates in this case. Conversely, information supply through Twitter hashtags is usually by users who have some familiarity or expertise with cryptocurrencies, providing less noisy signals compared to Google trends. We argue that information supply in cryptocurrencies reduces herding since investors have access to more information to form their strategies and divert from the market average (contrarian behaviour).

Table 4. Conditional herding and signal-herding from media attention indices

Panel A: Conditional herding from media attention indices

Regressor	β_0	β_1	β_2	β_{btc_tweets}	β_{Google_trends}
$X = [btc\ tweets]$	0.014***	0.697***	-1.321***	0.014***	
	(0.002)	(0.066)	(0.368)	(0.0001)	
$X = [Google\ trends]$	0.023***	0.748***	-1.418***		-0.009**
	(0.003)	(0.062)	(0.342)		(0.005)
$X =$	0.017***	0.703***	-1.339***	0.013***	-0.004*
[btc tweets Google trends]	(0.001)	(0.032)	(0.181)	(0.002)	(0.002)

Panel B: Signal-herding from media attention indices

Regressor	Signal	β_0	β_1	β_2	γ
$X = [btc\ tweets]$	U-shaped	0.019***	0.740***	-1.320***	-0.163
		(0.001)	(0.032)	(0.199)	(0.153)
	Hill-shaped	0.019***	0.746***	-1.308***	-0.437**
		(0.001)	(0.032)	(0.189)	(0.171)
	Hybrid	0.019***	0.739***	-1.060***	-0.505***
		(0.001)	(0.032)	(0.21)	(0.151)
$X = [Google\ trends]$	U-shaped	0.019***	0.728***	-1.122***	-0.431***
		(0.001)	(0.033)	(0.208)	(0.151)
	Hill-shaped	0.019***	0.742***	-1.360***	-0.193
		(0.001)	(0.032)	(0.19)	(0.198)
	Hybrid	0.019***	0.722***	-0.935***	-0.564***
		(0.001)	(0.033)	(0.223)	(0.153)

Notes: The table presents the estimation results of the two main models discussed in the paper, for the case of media attention indicators. Panel A presents the results of the conditional herding model, given by Eq. (3): $CSAD_t = \beta_0 + \beta_1 |r_{m,t}| + \beta_2 r_{m,t}^2 + \beta_X X_t + u_t$, where X_t represents one media attention indicator or a regressor matrix of the media attention indicators considered. Panel B presents the results of the signal-herding model, given by Eq. (4): $CSAD_t = \beta_0 + \beta_1 |r_{m,t}| + (\beta_2 + \gamma D_t^{S(X)}) r_{m,t}^2 + u_t$, where $D_t^{S(X)}$ represents signals extracted from the two media attention indicators. The signals are extracted from bitcoin-related tweets (#btc tweets) and google trends (keyword: *bitcoin*). The correlation coefficient between the media attention indicators is not statistically significant ($\rho = -0.25$) and it is reported at Table S1 in the Supplement. Results are reported for U-shaped signals, hill-shaped signals, and the hybrid case. For each variable, we present the estimated coefficients, while Newey-West Heteroscedasticity and Autocorrelation consistent (HAC) standard errors are reported in parentheses. Three stars (***), two stars (**) and one star (*) denote statistical significance at the 1%, 5% and 10% level, respectively.

Results for Group IV: Uncertainty indicators

When considering uncertainty indicators, we find partial evidence of conditional herding. While β_{ex} appears statistically significant for global equity connectedness (*ConnGL*) and foreign exchange connectedness (*ConnFX*), this is not true for Economic Policy Uncertainty (*EPU*). Our results indicate that greater market connectedness reduces CSAD, and at the same time reduces herding (β_2). Signals extracted from uncertainty monitoring have a significant effect on cryptocurrency herding behaviour. However, the signs and responses to signal patterns are mixed. For example, hill-shaped patterns in the connectedness of global equity and of foreign markets reduce the strength of herding, which is in line with earlier findings in this paper. In contrast, connectedness in foreign exchange markets induces herding dampening when generating U-shaped signals. Finally, swings in *EPU*, whether U-shaped or hill-shaped, have a hybrid influence on herding at the 10% level of significance.

Some interesting implications emerge from our findings. The uncertainty indicators included in this group are monitoring the systemic risk associated with sovereign economies in the globe, with an impact on investors' financial and economic stress. Unexpected stress events can help to popularize cryptocurrencies, including bad news or announcements with negative publicity, financial crises, governmental decisions which increase political risk, and so on. The financial crisis in Cyprus is a cited example. On the other hand, greater spillovers in the financial markets also induce investors to divert from the mainstream cryptocurrency market trends. As financial markets become more interconnected and hedging opportunities become harder to find, investors use cryptocurrencies for hedging purposes in their own portfolios.

An important economic factor contributing significantly to cryptocurrency exchanges is regulation and change in fiscal policies. Governments have the primary ability to regulate all market agents, which can be achieved by imposing high tariffs on businesses/households that cause negative externalities. Thus, investors are motivated to buy cryptocurrencies by the simple fact that they consider them a safe haven. Companies can also try to diversify from the market to gain a competitive edge. Such variation could take the form of transferring cryptocurrency as a means of currency exchange, which is not connected with any government body or policy decisions. However, governments should try to limit the use of these exchanges if the interchange is used to conduct illegal activity through the dark web.

Table 5. Conditional herding and signal-herding from uncertainty indicators

Panel A: Conditional herding from uncertainty indicators

Regressor	β_0	β_1	β_2	β_{ConnGL}	β_{ConnFX}	β_{EPU}
$X = [ConnGL]$	0.045***	0.696***	-1.320***	-0.042***		
	(0.007)	(0.065)	(0.350)	(0.010)		
$X = [ConnFX]$	0.038***	0.719***	-1.342***		-0.029***	
	(0.012)	(0.064)	(0.352)		(0.018)	
$X = [EPU]$	0.017***	0.742***	-1.396***			0.001
	(0.002)	(0.062)	(0.348)			(0.001)
$X =$	0.031***	0.707***	-1.362***	-0.065***	0.046***	
$[\mathrm{ConnGL} \quad \mathrm{ConnFX}]$	(0.005)	(0.032)	(0.178)	(0.009)	(0.013)	
$X =$	0.044***	0.695***	-1.320***	-0.042***		0.002*
$[\mathrm{ConnGL} \quad \mathrm{EPU}]$	(0.003)	(0.032)	(0.179)	(0.005)		(0.001)
$X =$	0.037***	0.716***	-1.339***		0.032***	0.002*
$[\mathrm{ConnFX} \quad \mathrm{EPU}]$	(0.005)	(0.033)	(0.185)		(0.009)	(0.018)
$X =$	0.031***	0.705***	-1.360***	-0.064***	0.043***	0.001
$[ConnGL \quad ConnFX \quad EPU]$	(0.005)	(0.032)	(0.178)	(0.009)	(0.013)	(0.001)

Panel B: Signal-herding from uncertainty indicators

Regressor	Signal	β_0	β_1	β_2	γ
$X = [ConnGL]$	U-shaped	0.019***	0.740***	-1.416***	0.119
		(0.001)	(0.033)	(0.188)	(0.164)
	Hill-shaped	0.019***	0.735***	-1.503***	0.562***
		(0.001)	(0.032)	(0.187)	(0.166)
	Hybrid	0.019***	0.723***	-1.598***	0.555***
		(0.001)	(0.032)	(0.192)	(0.149)
$X = [ConnFX]$	U-shaped	0.019***	0.750***	-1.683***	0.611***
		(0.001)	(0.059)	(0.3)	(0.188)
	Hill-shaped	0.019***	0.729***	-1.172***	-0.355**
		(0.001)	(0.062)	(0.363)	(0.22)
	Hybrid	0.018***	0.767***	-1.941***	0.495**
		(0.001)	(0.062)	(0.487)	(0.388)
$X = [EPU]$	U-shaped	0.018***	0.758***	-1.446***	-0.421
		(0.001)	(0.061)	(0.344)	(0.468)
	Hill-shaped	0.019***	0.738***	-1.293***	-0.164
		(0.001)	(0.061)	(0.381)	(0.223)
	Hybrid	0.019***	0.745***	-1.254***	-0.282**
		(0.001)	(0.061)	(0.383)	(0.148)

Notes: The table presents the estimation results of the two main models discussed in the paper, for the case of uncertainty indicators. Panel A presents the results of the conditional herding model, given by Eq. (3): $CSAD_t = \beta_0 + \beta_1|r_{m,t}| + \beta_2 r_{m,t}^2 + \beta_X X_t + u_t$, where X_t represents one uncertainty indicator or a regressor matrix of the uncertainty indicators considered. Panel B presents the results of the signal-herding model, given by Eq. (4): $CSAD_t = \beta_0 + \beta_1|r_{m,t}| + (\beta_2 + \gamma D_t^{S(X)}) r_{m,t}^2 + u_t$, where $D_t^{S(X)}$ represents signals extracted from the uncertainty indicators. The signals are extracted from the connectedness measures for global equity markets (*Conn GL*) and foreign exchange markets (*Conn FX*), as well as the Economic Policy Uncertainty (*EPU*) indicator. The correlation coefficients between all the uncertainty indicators are not statistically significant ($\rho_{EPU,ConnGL} = 0.02$ and $\rho_{EPU,ConnFX} = 0.09$) and they are reported at Table S1 in the Supplement. Results are reported for U-shaped signals, hill-shaped signals, and the hybrid case. For each variable, we present the estimated coefficients, while Newey-West Heteroscedasticity and Autocorrelation consistent (HAC) standard errors are reported in parentheses. Three stars (***), two stars (**) and one star (*) denote statistical significance at the 1%, 5% and 10% level, respectively.

Results for Group V: Commodities

Cryptocurrency investors do not seem to be affected to a great extent by the commodity returns on gold and crude oil, and the null hypothesis of no conditional herding cannot be rejected. The hypothesis that a limited supply of both cryptocurrencies and these two main commodities would induce a degree of substitutability is not confirmed by the results of the conditional model. Commodity prices are based on the principle that mining costs are primary influencing factors, just like the cryptocurrency prices are determined by the need for certain technology, also termed mining. This forms the supply side. The demand side is based on the investor's trust in the earnings that commodities or cryptocurrencies can give. These results highlight the fact that cryptocurrencies lack a fundamental basis and therefore herding is not conditionally influenced by the commodities considered in our paper.

However, the results on commodities in panel B show evidence that the commodities' behaviour is considered by cryptocurrency investors. Hill-shaped signals in gold amplify herding, while in the presence of downswings in gold returns, investors move closer to the average, gold not playing the role of substitute in this case. Crude oil returns generate mixed yet statistically significant signals, since in all cases there is strong evidence of herding dampening. Thus, crude oil return reversals induce the formation of individual trading strategies which go against the market average.

Table 6. Conditional herding and signal-herding from commodities

Panel A: Conditional herding for commodities

Regressor	β_0	β_1	β_2	β_{crude_oil}	β_{gold}
$X =$ [Crude oil]	0.019***	0.744***	-1.396***	0.025	
	(0.001)	(0.062)	(0.347)	(0.024)	

$X = [\text{Gold}]$	0.019***	0.742***	-1.390***		0.078
	(0.001)	(0.062)	(0.347)		(0.053)
$X =$	0.019***	0.739***	-1.372***	0.026	0.080
$[\text{Crude oil} \quad \text{Gold}]$	(0.001)	(0.061)	(0.340)	(0.024)	(0.068)

Panel B: Signal-herding from commodities

Regressor	Signal	β_0	β_1	β_2	γ
$X = [\text{Crude oil}]$	U-shaped	0.019***	0.727***	-1.436***	0.485***
		(0.001)	(0.033)	(0.186)	(0.159)
	Hill-shaped	0.019***	0.741***	-1.463***	0.348***
		(0.001)	(0.032)	(0.189)	(0.159)
	Hybrid	0.019***	0.719***	-1.571**	0.632**
		(0.001)	(0.032)	(0.188)	(0.149)
$X = [\text{Gold}]$	U-shaped	0.019***	0.740***	-1.339***	-0.093
		(0.001)	(0.033)	(0.207)	(0.15)
	Hill-shaped	0.018***	0.751***	-1.403***	-0.162**
		(0.001)	(0.034)	(0.186)	(0.187)
	Hybrid	0.018***	0.748***	-1.272***	-0.222
		(0.001)	(0.033)	(0.206)	(0.159)

Notes: The table presents the estimation results of the two main models discussed in the paper, for the case of commodities. Panel A presents the results of the conditional herding model, given by Eq. (3): $CSAD_t = \beta_0 + \beta_1|r_{m,t}| + \beta_2 r_{m,t}^2 + \beta_X X_t + u_t$, where X_t represents one commodity or a regressor matrix of the two commodities considered. Panel B presents the results of the signal-herding model, given by Eq. (4): $CSAD_t = \beta_0 + \beta_1|r_{m,t}| + (\beta_2 + \gamma D_t^{S(X)}) r_{m,t}^2 + u_t$, where $D_t^{S(X)}$ represents signals extracted from the returns of crude oil and gold. The correlation coefficient between the two commodities is not statistically significant ($\rho_{crude_{oil},gold} = 0.05$) and it is reported at Table S1, in the Supplement. Results are reported for U-shaped signals, hill-shaped signals, and the hybrid case. For each variable, we present the estimated coefficients, while Newey-West Heteroscedasticity and Autocorrelation consistent (HAC) standard errors are reported in parentheses. Three stars (***), two stars (**) and one star (*) denote statistical significance at the 1%, 5% and 10% level, respectively.

4.2 Robustness checks

To overcome concerns regarding the specifications used to model herding detection for cryptocurrencies conditional to informative exogenous signals, we employ a series of robustness checks. We start with the concerns about if investors are equally keen to seek information about cryptocurrencies with less media attention compared to the more popular ones. Are dominant cryptocurrencies, based on market capitalization, more (or less) susceptible to herding? This would reveal to what extent our findings are robust to separating out the popular cryptocurrencies from the less popular ones.[8] To address this, we follow the approach in Vidal-Tomás et al. (2018) and we examine whether minor cryptocurrencies (in terms of market capitalization) herd with the 5 major ones, namely Bitcoin (BTC), Ethereum (ETH), Ripple (XRP), Litecoin (LTC) and Bitcoin Cash (BTC cash). We test this with the following specification:

$$CSAD_{minor,t} = \beta_0 + \beta_1 \left| r_{minor,t} \right| + \beta_2 r_{minor,t}^2 + \beta_3 r_{major,t}^2 + u_t \tag{5}$$

Effectively, we treat the submarket of the 95 minor cryptocurrencies as separate from the major ones, to test for cross-(sub)market influences. The subscripts *minor* and *major* on returns, squared returns and the CSAD above, indicate that calculations are performed on each submarket, respectively. If the major cryptocurrencies herd with the minor ones, then the coefficient β_3 should be negative and statistically significant. We find that the major cryptocurrencies do not herd with the minor ones, given that the β_3 coefficient is positive (and statistically significant). We also observe that herding behaviour is also present in the minor group, even without the inclusion of the major ones, since β_2 is negative and statistically significant.

We moreover use an extension in the model specification of Eq. (4) and we replicate the empirical analysis, considering additively the exogenous factor X_t to examine whether it affects the CSAD in the main market. The specification has the following form:

$$CSAD_t = \beta_0 + \beta_1 \left| r_{m,t} \right| + (\beta_2 + \gamma D_t^{S(X)}) r_{m,t}^2 + \beta_X X_t + u_t \tag{6}$$

In this specification, if the signals extracted from an exogenous factor are endogenized in the herding behaviour then the γ coefficient should be statistically significant and, moreover, if β_X is statistically significant, it can be considered as the magnitude of evidence on conditional herding, since CSAD no longer solely depends linearly on the magnitude of market returns. The fundamental difference from the model specification in Eq. (4) is that an exogenous variable can only indirectly determine the outcome for herding in cryptocurrencies in the presence of adequate correlation with squared returns, hence allocating some of the variability in CSAD to the exogenous variable. The results report similar

[8] We thank the reviewer for this suggestion. The regression results of this exercise are presented in Table S2 in the Supplement.

findings with all the panels in our main tables indicating similar implications of how investors endogenize the signal herding from market, risk and uncertainty indicators.[9]

Finally, we check the findings when aggregating the indices within each group of the indicators considered.[10] For aggregation, we use principal component analysis (PCA) with varimax rotation, since alternative aggregation schemes are associated with significant limitations (i.e. same scaling and units of measurement, approaches based on multi-objective programming that require an optimization objective, and so on). To make the aggregation exercise more meaningful, we base our results on using only the first extracted component. Our results are qualitatively and intuitively similar with the results found within each group separately, and therefore can provide a general overview. However, we report weaker findings which we attribute to the fact that correlations between indicators of a group are not always high, combined with the potential information loss due to aggregating the indices.

5. Conclusion

The paper examines how informative signals from exogenous factors contribute to herding intensity in the cryptocurrencies market. We extend the conditional herding model, which is traditionally used to test for exogenous influences, and we introduce the notion of signal-herding, where such influences are endogenized in investors' decision-making. We use the terms 'U-shaped' and 'hill-shaped' signals, as in Park and Sabourian (2011), to associate non-monotonic behavioural patterns in the international financial markets with signals that cryptocurrency investors potentially identify. These signals may induce investors to further converge to (depart from) the market consensus compared to the case of no external influences, hence contributing to herding amplification (herding dampening).

Signal-herding offers a more detailed account of whether external influences are endogenized in the behaviour of cryptocurrency investors. We reveal the substantial diversity in the way information is valued and taken into account by cryptocurrency investors. We find that influences from equity-related

[9] The results of this robustness check are shown in Tables A1 to A5 in the Appendix.

[10] The authors would like to thank Reviewer 1 for suggesting this robustness check. Results on the correlation analysis are given in Table S1, in the Supplement. Results of the signal herding using aggregated indicators are presented in Table S3 in the Supplement.

indicators are all purely exogenous, since their behaviour does not generate signals that cryptocurrency investors seem to value. Finally, we find that behavioural patterns in bitcoin-related tweets and Google searches induce herding amplification, while patterns in policy uncertainty and connectedness of equity and foreign exchange markets induce herding dampening.

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Appendix

Table A1. Conditional signal-herding from market-based indicators

Regressor	Signal	β_0	β_1	β_2	β_X	γ
$X = [\text{S\&P500}]$	U-shaped	0.018***	0.751***	-1.393***	0.160**	-0.214
		(0.001)	(0.034)	(0.186)	(0.075)	(0.201)
	Hill-shaped	0.019***	0.739***	-1.388***	0.143**	0.066
		(0.001)	(0.033)	(0.188)	(0.073)	(0.17)
	Hybrid	0.018***	0.746***	-1.373***	0.148***	-0.077
		(0.001)	(0.034)	(0.186)	(0.074)	(0.16)
$X = [\text{btc/\$ rate}]$	U-shaped	0.018***	0.732***	-1.339***	0.045***	0.254*
		(0.001)	(0.033)	(0.198)	(0.012)	(0.152)
	Hill-shaped	0.018***	0.732***	-1.227***	0.048***	-0.041
		(0.001)	(0.032)	(0.2)	(0.012)	(0.162)
	Hybrid	0.018***	0.730***	-1.364***	0.047***	0.215
		(0.001)	(0.032)	(0.196)	(0.012)	(0.156)

Notes: The table presents the estimation results of the conditional signal-herding, given by Eq. (6): $CSAD_t = \beta_0 + \beta_1 |r_{m,t}| + (\beta_2 + \gamma D_t^{S(X)}) r_{m,t}^2 + \beta_X X_t + u_t$, where X_t represents one market-based indicator. The signals are extracted from the returns on the S&P500 index (S&P500) and the bitcoin to dollar exchange rate (btc/$). Results are reported for U-shaped signals, hill-shaped signals, and the hybrid case. For each variable, we present the estimated coefficients, while Newey-West Heteroscedasticity and Autocorrelation consistent (HAC) standard errors are reported in parentheses. Three stars (***), two stars (**) and one star (*) denote statistical significance at the 1%, 5% and 10% level, respectively.

Table A2. Conditional signal-herding from volatility indices

Regressor	Signal	β_0	β_1	β_2	β_X	γ
$X = [VIX]$	U-shaped	0.033***	0.747***	-1.362***	-0.106***	-0.291
		(0.001)	(0.031)	(0.176)	(0.012)	(0.204)
	Hill-shaped	0.034***	0.736***	-1.367***	-0.107***	0.233
		(0.001)	(0.031)	(0.176)	(0.012)	(0.22)
	Hybrid	0.033***	0.745***	-1.373***	-0.105***	-0.058
		(0.001)	(0.031)	(0.176)	(0.012)	(0.165)
$X = [TYVIX]$	U-shaped	0.038***	0.715***	-1.231***	-0.382***	-0.485***
		(0.003)	(0.032)	(0.184)	(0.066)	(0.169)
	Hill-shaped	0.040***	0.673***	-1.228***	-0.416***	1.077***
		(0.003)	(-0.033)	(-0.181)	(-0.066)	(0.252)
	Hybrid	0.038***	0.711***	-1.3283***	-0.386***	-0.006

		(0.003)	(0.032)	(0.183)	(0.067)	(0.157)
$X = [VP30]$	U-shaped	0.023***	0.739***	-1.331***	-0.274***	0.014
		(0.001)	(0.031)	(0.189)	(0.041)	(0.159)
	Hill-shaped	0.023***	0.730***	-1.312***	-0.279***	0.251
		(0.001)	(0.032)	(0.181)	(0.041)	(0.211)
	Hybrid	0.023***	0.736***	-1.366***	-0.273***	0.131
		(0.001)	(0.032)	(0.187)	(0.041)	(0.145)

Notes: The table presents the estimation results of the conditional signal-herding, given by Eq. (6): $CSAD_t = \beta_0 + \beta_1|r_{m,t}| + (\beta_2 + \gamma D_t^{S(X)})r_{m,t}^2 + \beta_X X_t + u_t$, where X_t represents one volatility indicator. The signals are extracted from the volatility index (*VIX*), the treasury yield volatility index (*TYVIX*) and the 30-day volatility premium (*VP30*). Results are reported for U-shaped signals, hill-shaped signals, and the hybrid case. For each variable, we present the estimated coefficients, while Newey-West Heteroscedasticity and Autocorrelation consistent (HAC) standard errors are reported in parentheses. Three stars (***), two stars (**) and one star (*) denote statistical significance at the 1%, 5% and 10% level, respectively.

Table A3. Conditional signal-herding from media attention indicators

Regressor	Signal	β_0	β_1	β_2	β_X	γ
$X = [\#\text{btc tweets}]$	U-shaped	0.014***	0.692***	-1.212***	0.015***	-0.230
		(0.001)	(0.032)	(0.194)	(0.002)	(0.149)
	Hill-shaped	0.014***	0.700***	-1.223***	0.015***	-0.480***
		(0.001)	(0.032)	(0.183)	(0.002)	(0.166)
	Hybrid	0.014***	0.688***	-0.910***	0.015***	-0.610***
		(0.001)	(0.032)	(0.205)	(0.002)	(0.147)
$X = [google\ trends]$	U-shaped	0.023***	0.733***	-1.159***	-0.008***	-0.406***
		(0.001)	(0.032)	(0.207)	(0.002)	(0.15)
	Hill-shaped	0.023***	0.747***	-1.384***	-0.009***	-0.185
		(0.001)	(0.032)	(0.188)	(0.002)	(0.196)
	Hybrid	0.023***	0.727***	-0.980***	-0.008***	-0.534***
		(0.001)	(0.032)	(0.19)	(0.002)	(0.152)

Notes: The table presents the estimation results of the conditional signal-herding, given by Eq. (6): $CSAD_t = \beta_0 + \beta_1|r_{m,t}| + (\beta_2 + \gamma D_t^{S(X)})r_{m,t}^2 + \beta_X X_t + u_t$, where X_t represents one media attention indicator. The signals are extracted from bitcoin-related tweets (#btc tweets) and google trends (keyword: *bitcoin*). Results are reported for U-shaped signals, hill-shaped signals, and the hybrid case. For each variable, we present the estimated coefficients, while Newey-West Heteroscedasticity and Autocorrelation consistent (HAC) standard errors are reported in parentheses. Three stars (***), two stars (**) and one star (*) denote statistical significance at the 1%, 5% and 10% level, respectively.

Table A4. Conditional signal-herding from uncertainty indicators

Regressor	Signal	β_0	β_1	β_2	β_X	γ
$X = [\text{Conn GL}]$	U-shaped	0.046***	0.693***	-1.343***	-0.042***	0.134
		(0.001)	(0.032)	(0.181)	(0.005)	(0.158)
	Hill-shaped	0.046***	0.687***	-1.435***	-0.042***	0.611***
		(0.003)	(0.032)	(0.18)	(0.005)	(0.16)
	Hybrid	0.047***	0.673***	-1.540***	-0.043***	0.608***
		(0.003)	(0.032)	(0.179)	(0.005)	(0.143)
$X = [\text{Conn FX}]$	U-shaped	0.038***	0.725***	-1.636***	-0.031***	0.629***
		(0.005)	(0.032)	(0.196)	(0.009)	(0.148)
	Hill-shaped	0.038***	0.704***	-1.103***	-0.030***	-0.375***
		(0.005)	(0.033)	(0.208)	(0.009)	(0.151)
	Hybrid	0.037***	0.743***	-1.884***	-0.029***	0.492**
		(0.005)	(0.034)	(0.292)	(0.009)	(0.08)
$X = [EPU]$	U-shaped	0.017***	0.759***	-1.451***	-0.002*	-0.453
		(0.001)	(0.034)	(0.189)	(0.001)	(0.276)
	Hill-shaped	0.017***	0.738***	-1.306***	0.001	0.144
		(0.001)	(0.033)	(0.208)	(0.001)	(0.151)
	Hybrid	0.017***	0.744***	-1.260***	0.001	-0.270*
		(0.001)	(0.033)	(0.207)	(0.001)	(0.148)

Notes: The table presents the estimation results of the conditional signal-herding, given by Eq. (6): $CSAD_t = \beta_0 + \beta_1|r_{m,t}| + (\beta_2 + \gamma D_t^{S(X)})r_{m,t}^2 + \beta_X X_t + u_t$, where X_t represents one uncertainty indicator. The signals are extracted from the connectedness measures for global equity markets (*Conn GL*) and foreign exchange markets (*Conn FX*), as well as the Economic Policy Uncertainty (*EPU*) indicator. Results are reported for U-shaped signals, hill-shaped signals, and the hybrid case. For each variable, we present the estimated coefficients, while Newey-West Heteroscedasticity and Autocorrelation consistent (HAC) standard errors are reported in parentheses. Three stars (***), two stars (**) and one star (*) denote statistical significance at the 1%, 5% and 10% level, respectively.

Table A5. Conditional signal-herding from commodities

Regressor	Signal	β_0	β_1	β_2	β_{ex}	γ
$X = [\text{Crude oil}]$	U-shaped	0.0192***	0.728***	-1.435***	0.017	0.470***
		(0.001)	(0.061)	(0.343)	(0.023)	(0.312)
	Hill-shaped	0.091***	0.741***	-1.467***	0.028	0.360**
		(0.001)	(0.06)	(0.325)	(0.025)	(0.176)
	Hybrid	0.0193***	0.719***	-1.570***	0.019	0.624***
		(0.001)	(0.059)	(0.297)	(0.023)	(0.226)
$X = [\text{Gold}]$	U-shaped	0.019***	0.739***	-1.320***	0.084	-0.115
		(0.001)	(0.033)	(0.208)	(0.068)	(0.151)

Hill-shaped	0.018***	0.748***	-1.397***	0.070	-0.132
	(0.001)	(0.034)	(0.187)	(0.068)	(0.189)
Hybrid	0.018***	0.747***	-1.267***	0.077	-0.220
	(0.001)	(0.033)	(0.206)	(0.068)	(0.159)

Notes: The table presents the estimation results of the conditional signal-herding, given by Eq. (6): $CSAD_t = \beta_0 + \beta_1|r_{m,t}| + (\beta_2 + \gamma D_t^{S(X)}) r_{m,t}^2 + \beta_X X_t + u_t$, where X_t represents the returns of one commodity. The signals are extracted from the returns of crude oil and gold. Results are reported for U-shaped signals, hill-shaped signals, and the hybrid case. For each variable, we present the estimated coefficients, while Newey-West Heteroscedasticity and Autocorrelation consistent (HAC) standard errors are reported in parentheses. Three stars (***), two stars (**) and one star (*) denote statistical significance at the 1%, 5% and 10% level, respectively.

Supplement

Signal-herding in cryptocurrencies

Dionisis Philippas, Nikolaos Philippas, Panagiotis Tziogkidis and Hatem Rjiba

Table S1. Contemporaneous correlations between exogenous factors within each group

Group I	*S&P 500*	*btc/$ rate*
S&P 500	1	
btc/$ rate	0.055	1

Group II	*VIX*	*TYVIX*	*VP30*
VIX	1		
TYVIX	0.347	1	
VP30	0.947	0.407	1

Group III	*google trends*	*#btc tweets*
google trends	1	-0.255
#btc tweets	-0.255	1

Group IV	*EPU*	*ConnGL*	*ConnFX*
EPU	1		
Conn GL	0.027	1	
Conn FX	0.098	0.793	1

Group V	*Crude oil*	*Gold*
Crude oil	1	
Gold	0.056	1

Notes: The table presents the correlation coefficients for all the exogenous factors included in our sample.

Table S2. Unconditional herding among "minor" and "major" groups of cryptocurrencies

β_0	β_1	β_2	β_3
0.012***	1.376***	-5.113***	0.440***
(0.0004)	(0.041)	(0.540)	(0.099)

Notes: The table presents the estimation results for unconditional herding among "minor" and "major" groups of cryptocurrencies, in terms of market capitalization, given in Eq. (5): $CSAD_{minor,t} = \beta_0 + \beta_1 |r_{minor,t}| +$

$\beta_2 r^2_{minor,t} + \beta_3 r^2_{major,t} + u_t$. For each variable, we present the estimated coefficients, while Newey-West Heteroscedasticity and Autocorrelation consistent (HAC) standard errors are reported in parentheses. Three stars (***), two stars (**) and one star (*) denote statistical significance at the 1%, 5% and 10% level, respectively.

Table S3. Signal-herding for first principal components by group

Panel A: Conditional herding

	β_0	β_1	β_2	β_X
Market: Principal component	0.019***	0.722***	-1.346***	0.001***
	(0.001)	(0.033)	(0.186)	(0.0004)
Volatility: Principal component	0.019***	0.728***	-1.325***	-0.002***
	(0.0008)	(0.031)	(0.177)	(0.0003)
Media attention: Principal component	0.019***	0.722***	-1.378***	-0.002***
	(0.0008)	(0.032)	(0.181)	(0.0004)
Uncertainty: Principal component	0.020***	0.705***	-1.320***	-0.002***
	(0.0008)	(0.032)	(0.183)	(0.0004)
Commodities: Principal component	0.019***	0.742***	-1.392***	0.0004
	(0.0008)	(0.032)	(0.186)	(0.0004)

Panel B: Signal-herding

		β_0	β_1	β_2	γ
Market: Principal component	U-shaped	0.019***	0.737***	-1.385***	0.148
		(0.0009)	(0.034)	(0.187)	(0.228)
	Hill-shaped	0.019***	0.747***	-1.456***	0.100
		(0.001)	(0.033)	(0.213)	(0.155)
	Hybrid	0.019***	0.743***	-1.477***	0.154
		(0.0009)	(0.032)	(0.202)	(0.148)
Volatility: Principal component	U-shaped	0.019***	0.747***	-1.385***	-0.225
		(0.0009)	(0.033)	(0.186)	(0.206)
	Hill-shaped	0.019***	0.736***	-1.387***	0.237
		(0.0009)	(0.033)	(0.186)	(0.239)
	Hybrid	0.019***	0.744***	-1.395***	-0.034
		(0.0009)	(0.033)	(0.186)	(0.173)
Media attention: Principal component	U-shaped	0.018***	0.756***	-1.575***	0.208
		(0.0009)	(0.034)	(0.229)	(0.155)
	Hill-shaped	0.018***	0.764***	-1.445***	-0.484**

		(0.0009)	(0.034)	(0.187)	(0.221)
	Hybrid	0.019***	0.742***	-1.373***	-0.029
		(0.0009)	(0.033)	(0.221)	(0.157)
Uncertainty: Principal component	U-shaped	0.019***	0.731***	-1.407***	0.485***
		(0.0009)	(0.033)	(0.186)	(0.205)
	Hill-shaped	0.019***	0.745***	-1.430***	0.059
		(0.0009)	(0.033)	(0.207)	(0.154)
	Hybrid	0.019***	0.746***	-1.583***	0.309**
		(0.0009)	(0.033)	(0.206)	(0.148)
Commodities: Principal component	U-shaped	0.019***	0.744***	-1.412***	0.027
		(0.0009)	(0.033)	(0.206)	(0.150)
	Hill-shaped	0.019***	0.741***	-1.332***	-0.119
		(0.0009)	(0.033)	(0.203)	(0.149)
	Hybrid	0.019***	0.732***	-1.092***	-0.271
		(0.0009)	(0.033)	(0.206)	(0.256)

Panel C: Conditional signal-herding

		β_0	β_1	β_2	β_X	γ
Market: Principal component	U-shaped	0.019***	0.716***	-1.333***	0.001**	0.176
		(0.0009)	(0.034)	(0.187)	(0.0004)	(0.228)
	Hill-shaped	0.019***	0.727***	-1.410***	0.001**	0.106
		(0.0009)	(0.034)	(0.208)	(0.0004)	(0.154)
	Hybrid	0.019***	0.722***	-1.436***	0.001***	0.172
		(0.0009)	(0.034)	(0.202)	(0.0004)	(0.147)
Volatility: Principal component	U-shaped	0.019***	0.734***	-1.311***	-0.002***	-0.307
		(0.0009)	(0.031)	(0.177)	(0.0003)	(0.196)
	Hill-shaped	0.019***	0.713***	-1.302***	-0.0002***	0.537**
		(0.0009)	(0.031)	(0.177)	(0.0003)	(0.229)
	Hybrid	0.019***	0.725***	-1.325***	-0.0002***	0.058
		(0.0009)	(0.034)	(0.177)	(0.0003)	(0.165)
Media attention: Principal component	U-shaped	0.019***	0.737***	-1.605***	-0.002***	0.263*
		(0.0009)	(0.033)	(0.223)	(0.0004)	(0.153)
	Hill-shaped	0.019***	0.748***	-1.439***	-0.003***	-0.605***
		(0.0009)	(0.033)	(0.182)	(0.0003)	(0.216)
	Hybrid	0.019***	0.721***	-1.353***	-0.002***	-0.032*
		(0.0009)	(0.034)	(0.216)	(0.0004)	(0.153)

Uncertainty: Principal component	U-shaped	0.020***	0.692***	-1.332***	-0.002***	0.508**
		(0.0009)	(0.033)	(0.182)	(0.0004)	(0.153)
	Hill-shaped	0.020***	0.707***	-1.360***	-0.002***	0.068
		(0.0009)	(0.033)	(0.203)	(0.0003)	(0.150)
	Hybrid	0.020***	0.708***	-1.519***	-0.002***	0.330**
		(0.0009)	(0.032)	(0.202)	(0.0004)	(0.145)
Commodities: Principal component	U-shaped	0.019***	0.743***	-1.396***	0.0004	0.008
		(0.0009)	(0.033)	(0.182)	(0.0004)	(0.151)
	Hill-shaped	0.019***	0.741***	-1.336***	0.0004	-0.104
		(0.0009)	(0.033)	(0.203)	(0.0003)	(0.150)
	Hybrid	0.019***	0.731***	-1.077***	-0.0004	-0.280
		(0.0009)	(0.032)	(0.202)	(0.0004)	(0.250)

Notes: The table presents the estimation results of the three models discussed in the paper, for the case of first principal component of each group of exogenous indicators. Panel A presents the results of the conditional herding model, given by Eq. (3): $CSAD_t = \beta_0 + \beta_1|r_{m,t}| + \beta_2 r_{m,t}^2 + \beta_X X_t + u_t$, where X_t represents the first principal component of each group of exogenous factors. Panel B presents the results of the signal-herding model, given by Eq. (4): $CSAD_t = \beta_0 + \beta_1|r_{m,t}| + (\beta_2 + \gamma D_t^{S(X)}) r_{m,t}^2 + u_t$, where $D_t^{S(X)}$ represents signals extracted from the first principal component of each group of exogenous factors. Panel C presents the results of the conditional signal-herding, given by Eq. (6): $CSAD_t = \beta_0 + \beta_1|r_{m,t}| + (\beta_2 + \gamma D_t^{S(X)}) r_{m,t}^2 + \beta_X X_t + u_t$, $D_t^{S(X)}$ represents signals extracted from the first principal component of each group of exogenous factors. The signals are extracted from the first principal component on the market-based indicators, the volatility indicators, the media attention indicators, the uncertainty indicators and the commodities. The eigenvalues derived from PCA for each group are the following: group I with $\lambda = 1.7$, group II with $\lambda = 2.24$, group III with $\lambda = 1.25$, group IV with $\lambda = 1.8$ and group V with $\lambda = 1.88$. Results are reported for U-shaped signals, hill-shaped signals, and the hybrid case. For each variable, we present the estimated coefficients, while Newey-West Heteroscedasticity and Autocorrelation consistent (HAC) standard errors are reported in parentheses. Three stars (***), two stars (**) and one star (*) denote statistical significance at the 1%, 5% and 10% level, respectively.