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Intraday herding and attention around the clock

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ABSTRACT

This paper analyzes the relationship between investor herding and attention in the decentralized cryptocurrency market with its continuous, around the clock trading and large share of retail investors. Herding behavior is stronger when market returns are positive but is negatively related to both the level and cross-sectional dispersion of investor attention. Moreover, there are pronounced intraday variations: Herding exhibits similar patterns as attention and blockchain activity and is strongest during the overlap of hours when traders in major economic centers are likely awake.

1. Introduction

Herding in financial markets describes the inclination of individual investors to mimic the investment decisions of other investors instead of trading on their own information. There are many reasons for such behavior, some of which are rational while others may indicate behavioral biases. Documented in practically all financial markets, herd behavior might lead to inefficient prices as investors disregard fundamental information, thereby creating irrational bubbles. Understanding such behavior and its underlying drivers is thus important for investors and regulators alike.

In this paper, we analyze investor herding at the intraday level in the decentralized cryptocurrency market, where herding behavior is particularly interesting. Contrary to most other markets, cryptocurrency markets are decentralized and open around the clock, allowing for an analysis of herding patterns throughout the day. Additionally, because there is relatively little fundamental information available or, where available, might be complex to evaluate due to the novelty of the assets, there are potentially higher levels of herding as investors follow the market instead of relying on coin-specific information. Similarly, because the market for cryptocurrencies is still young and developing, price inefficiencies might be more pervasive than in other markets. Finally, with a large fraction of retail traders (Dyhrberg et al., 2018), the investor base of cryptocurrencies is different from other, more mature asset classes, making an analysis of how investor attention affects herding especially relevant.

While there is already a rich literature on herding in cryptocurrencies, there is no consensus on the size or even presence of such behavior. We make several contributions: Firstly, using intraday data allows us to detect short-term herding by investors, which might go undetected when using lower frequencies as pointed out by Gleason et al. (2004). Moreover, the higher frequency of our dataset allows us to look at variations in herding behavior throughout the day. Secondly, we provide evidence on how investors' limited attention and the way they distribute their limited attention across different assets impact herding while controlling for general market trends. To the best of our knowledge, we are the first to apply the concept of attention dispersion to herding in any financial market. Thirdly, we relate herding to both on- and off-blockchain trading activity.

In our empirical analysis, we first document substantial herding behavior that is stronger when market returns are positive, which we attribute to a fear-of-missing-out during times of increasing prices. Herding is negatively related to both the level and cross-sectional dispersion of investor attention, suggesting that these are also important factors for herd behavior. Moreover, we uncover pronounced intraday variations in investor herding. Market return herding exhibits similar intraday patterns as attention and blockchain activity and is strongest during the overlap of hours when traders in major economic centers are likely awake.

This paper contributes to multiple streams within the literature: We add to the literature on investor herding, in particular that of retail investors, by providing novel evidence on the intraday patterns of herding in a global and continuously open market. By focusing on the cryptocurrency market, we also contribute to the understanding of price

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formation and investor behavior in this growing market. Additionally, we relate to the literature on investor attention by linking intraday herding to both the level and dispersion of investor attention.

Herding behavior and informational cascades have been studied extensively both theoretically and empirically across many different markets and asset classes. In their seminal empirical works, Christie and Huang (1995) and Chang et al. (2000) suggest using measures of the dispersion of returns to capture herd behavior. The general idea of their measures is that less dispersion of individual asset returns around the market return indicates investor herding across assets. While both studies do not find evidence for significant herding in the United States, Chang et al. (2000) observe this behavior in other countries. Analyzing equity markets in 35 countries, Chen et al. (2022) show that around the time of earnings disclosures, stronger herding is associated with greater price informativeness. Regarding other asset classes, investor herding has been analyzed for exchange traded funds (Gleason et al., 2004), foreign exchange (Park and Sabourian, 2011; Sibande et al., 2023), corporate bonds (Cai et al., 2019), options (Bernales et al., 2020), and commodities (Youssef, 2022a; Liu et al., 2023). Furthermore, there is evidence that herding is a global phenomenon (Chiang and Zheng, 2010) and differs between sectors and industries (Choi and Sias, 2009; Gebka and Wohar, 2013). Herding behavior is not limited to retail investors (Hsieh et al., 2020; Zheng et al., 2021), but has also been documented for institutional investors (Sias, 2004; Kremer and Nautz, 2013). While most previous studies measure herding at a daily frequency, some analyze herding using intraday data (Gleason et al., 2004; Hsieh, 2013; Andrikopoulos et al., 2017; Cai et al., 2019; Wang et al., 2022).

The literature looking specifically at herding in cryptocurrencies so far does not agree on the prevalence of the behavior. Bouri et al. (2019), Youssef (2022b), and Yousaf and Yarovaya (2022) find significant but time-varying herding behavior. da Gama Silva et al. (2019) find overall weak evidence of herding. Depending on the methodology, herding is found to be more significant during down markets. Vidal-Tomás et al. (2019) observe that, while extreme price movements can generally be explained by a rational asset pricing model, there is significant herding during down markets. By considering sentiment expressed in online forums, Gurdgiev and O'Loughlin (2020) find cryptocurrency-market specific herding which is more prevalent in bear markets. In contrast, Papadamou et al. (2021), Kallinterakis and Wang (2019), and Ballis and Drakos (2020) conclude that herding is more pronounced during up markets. Using a large cross-section of cryptocurrencies, Kaiser and Stöckl (2020) discover strong evidence for herding in both bull and bear markets. Closely related to our study, Philippas et al. (2020) look at how potentially informative signals affect herding activity. They find heterogeneity in how information from various external factors is taken into account by investors. For example, media attention related to Bitcoin increases herding, while high equity returns are associated with reduced herding in the cryptocurrency market. As in other markets, most studies on herding in cryptocurrency markets focus on daily data. While there are some studies that use intraday data (Yarovaya et al., 2021; Mandaci and Cagli, 2022; Choi et al., 2022; Mohamad and Stavroyiannis, 2022; Blasco et al., 2022), none focus on the intraday patterns of herding behavior or how these relate to investor attention.

Our paper also relates to the literature on intraday patterns in cryptocurrency trading activity and on the importance of using higher-frequency data. For example, Dyhrberg et al. (2018) and Eross et al. (2019) document intraday patterns in cryptocurrency trading activity that resemble those found in foreign exchange markets. They additionally find significant intraday patterns in both volatility and liquidity. Hu et al. (2019) show that price clustering at round numbers is relatively stable throughout the day. Baur et al. (2019) do not find substantial intraday patterns in returns but in the trading volume of various exchanges. Petukhina et al. (2021) find intraday patterns in volatility and trading volume that are not consistent with a full automation of trading by algorithms. Instead, they conclude that much of trading is driven by human traders. Brauneis et al. (2023) document intraday patterns in trading activity, liquidity, and volatility. These patterns are similar to each other and across exchanges located in different geographic regions, suggesting that they are partially explained by common global factors. Finally, Aslan and Sensoy (2020) highlight that conclusions regarding the efficiency of cryptocurrency prices depend on the sampling frequency, which further motivates our study.

Investor herding may be related to limited attention resulting from cognitive limitations in information processing so that investors only exhibit "approximate rationality" (Simon, 1955, 1956). Herding around the market consensus might then be a heuristic to simplify the investment decision process as in Tversky and Kahneman (1974). Investor herding is particularly related to "illusory correlation", i.e., the overestimation of the frequency of the co-occurrence of events closely related to each other, and the resulting overconfidence in prediction. Heuristic learning in financial markets is also discussed by Hirshleifer (2015), in which the tendency of extrapolation is particularly related to investor herding. Moreover, Hirshleifer and Teoh (2003) examine the consequences of limited attention regarding firm disclosures and its impact on market prices.

Since attention is generally not directly observable, many proxies for investor attention have been proposed in the literature, for example based on extreme returns (Barber and Odean, 2008). However, a more direct proxy for investor attention and deliberate information demand is given by internet search volume. In early work, Da et al. (2011) use Google search volume to proxy for investor attention and find evidence that it likely captures the attention of less sophisticated retail traders and helps predict price movements in the following weeks. Building on these results, Joseph et al. (2011) also use Google search volume to find that it reflects buy pressure by retail traders. Similar to our study, Meshcheryakov and Winters (2020) do not rely on Google search volume at daily or lower frequencies but instead use hourly data. Higher search activity is followed by increased trading volume and smaller order sizes. They posit that the increase in trading activity is driven by retail traders who mistakenly think they are informed.

Whereas internet search volume captures the informational demand aspect of investor attention, the supply of new information might also affect herding behavior. A particularly active platform of information exchange in the context of cryptocurrencies are internet message boards (Phillips and Gorse, 2018). Antweiler and Frank (2004) analyze messages posted to two internet stock message boards and find that messages regarding particular stocks lead to increases in volatility. The more strongly the content of different messages disagrees, the larger the subsequent increases in trading volume. Sabherwal et al. (2011) analyze pump-and-dump behavior related to message board posts when there is no new fundamental information. Their results suggest that message boards can be used to induce investor herding to drive up prices.

With a substantial fraction of retail traders and some extreme price movements in the past, cryptocurrencies tend to be particularly affected by investor attention. Phillips and Gorse (2018) proxy for investor attention by considering various online and social media factors. Among them are Google search volume and posts and comments on Reddit, a message board popular among cryptocurrency traders. They find particularly strong correlations between the factors and prices during periods of bubble-like price increases. Zhang and Wang (2020) find that high investor attention is associated with positive returns. Similarly, Jafarinejad and Sakaki (2018) show that Bitcoin-related search volume is significantly positively related to the conditional volatility of Bitcoin returns. Philippas et al. (2020) document that Bitcoin-related tweets and Google search volume amplify return herding. Similarly, Gurdgiev and O'Loughlin (2020) use sentiment expressed on Bitcointalk.org forum to find presence of cryptocurrency-market specific herding.

While most studies focus on the level of investor attention, only few look at cross-sectional relationships of attention across individual assets. Drake et al. (2017) introduce the concept of attention co-movement, which measures the extent to which firm-specific attention is related to the attention paid to the industry or to the whole market. They then show that the co-movements of attention and of returns are positively related. Similarly, See-To and Yang (2017) consider investor sentiment dispersion, which is measured using textual analysis of tweets that contain stock tickers. While sentiment dispersion does not appear to affect future returns, there is an almost immediate increase in realized volatility which then decreases during the subsequent days. To the best of our knowledge, our study is the first to relate the concept of attention dispersion to the context of investor herding.[1]

We conclude that the literature linking attention to herding is scarce, particularly when it comes to attention dispersion. Furthermore, most previous studies investigate investor attention at lower frequencies, potentially missing some of the finer dynamics of how attention affects trading behavior. We attempt to fill that gap.

The remainder of this paper proceeds as follows: Section 2 develops our hypotheses. Section 3 describes the dataset and the empirical approach. Section 4 discusses the results for herding and its intraday patterns before presenting some robustness tests, while Section 5 concludes.

2. Hypotheses

In this part we develop the hypotheses which are then tested below. There are several reasons to expect that cryptocurrency investors exhibit herding behavior. With relatively little fundamental information available, it is likely that investors follow the market more strongly than in conventional financial markets. Similarly, because the market for cryptocurrencies is still developing, there might be stronger price inefficiencies than in other markets. Finally, with a large fraction of retail traders, the investor base of cryptocurrencies is different from other, more mature asset classes (Dyhrberg et al., 2018). Given the large number of available cryptocurrencies, investors are likely to use simplifying heuristics when trading due to limited information processing capabilities (Tversky and Kahneman, 1974). We therefore hypothesize that investor herding is prevalent in the cryptocurrency market.

Hypothesis 1. Cryptocurrency investors show herding behavior

Previous studies have shown that the strength of herding behavior is not constant, but rather conditional on the market environment (see e.g. Chang et al., 2000; Kallinterakis and Wang, 2019; Raimundo Júnior et al., 2022; Wang et al., 2022; Vidal-Tomás et al., 2019). While it is mostly hypothesized that herding is more pronounced during times of market stress, the same might not hold for cryptocurrency markets. In particular, a fear-of-missing-out might induce traders to herd during times of extreme price increases (see e.g. Piccoli and Chaudhury, 2019). We are hence agnostic on the direction of the effect and consider this to ultimately be an empirical question.

Hypothesis 2a. Herding is asymmetric and stronger when prices are increasing.

Hypothesis 2b. Herding is asymmetric and stronger when prices are decreasing.

The demand for both on- and off-blockchain transactions in cryptocurrencies likely fluctuates over time.[2] In the long run, it should be correlated with the size of the investor base and the popularity of the currency, whereas any short-term fluctuations might reflect trading based on newly available information or stem from arbitrage activities. However, high levels of transaction activity might also result from speculation and the formation of bubbles. We hence hypothesize that both exchange trading volume and the number of transactions recorded on the blockchain are related to herding activity, but the direction of the effect is, again, an empirical question.

Hypothesis 3a. Trading volume and blockchain transaction activity are positively related to herding behavior

Hypothesis 3b. Trading volume and blockchain transaction activity are negatively related to herding behavior

Herding can be the result of limited attention (as in Hirshleifer, 2015). High levels of investor attention might then be associated with lower market herding because investors seek — and find — more private information. This especially holds when attention is measured via internet search volume since this is a direct proxy for informational demand. Likewise, informational supply as measured by posts on internet message boards is positively associated with investor attention. While we expect that higher levels of aggregate attention already have a negative effect on herding, we anticipate an additional negative effect when the cross-sectional dispersion of attention is high. The reason is that high dispersion indicates that attention is directed towards specific currencies and does not solely reflect an increase in interest in cryptocurrencies in general.

Hypothesis 4. Herding is negatively related to both the level and the dispersion of investor attention

Contrary to most other financial markets, cryptocurrencies trade around the clock, allowing for an analysis of differences in herding behavior throughout the day. We hence hypothesize that herding behavior varies throughout the day, but interpreting the exact pattern is complicated by the fact that the cryptocurrency market is global, decentralized, and anonymous, so that it is unclear in which time zones traders are located. However, because prior studies have documented distinct patterns in global cryptocurrency trading activity and liquidity, we expect herding to be most prevalent when global activity is strongest. According to Brauneis et al. (2023), this would be the afternoon in Coordinated Universal Time (UTC).

Hypothesis 5. Herding activity varies throughout the day and is strongest when global trading activity is high

3. Methodology and data

3.1. Cryptocurrency data

We obtain hourly intraday data on 12 cryptocurrencies: Bitcoin (BTC), Cardano (ADA), Dash (DASH), Dogecoin (DOGE), Ethereum (ETH), Ethereum Classic (ETC), Litecoin (LTC), Monero (XMR), Ripple (XRP), Stellar (XLM), Tronix (TRX), and Zcash (ZEC). All prices are in USD. The sample spans from July 1st, 2017, to March 31st, 2022. At the beginning (end) of our sample, the included cryptocurrencies represent more than 85% (75%) of the total cryptocurrency market capitalization.[3]

Data quality and reliability is a particular concern when analyzing cryptocurrency markets. For example, Alexander and Dakos (2020)

[1] We note that the literature on cross-sectional differences in attention is also closely related to the more general question of disagreement between market participants, see e.g. Carlin et al. (2014).

[2] Depending on the cryptocurrency, on-blockchain transactions include for example payments for goods and services, but more commonly settlement of transactions at centralized exchanges or transactions related to decentralized applications such as decentralized exchanges, lending and borrowing, or gaming.

[3] Our choice of sample cryptocurrencies is motivated by their listing at the exchange Kraken and the length of available data. Furthermore, we exclude stablecoins.

warn that using non-traded prices from so-called "coin-ranking" websites might lead to inconsistent results. Our sample is hence based on trade data from Kraken, which has been identified as one of the trustworthy crypto exchanges (Härdle et al., 2020). For example, there is no evidence that it reports inflated trading volume.[4]

We then calculate logarithmic returns for cryptocurrency i at time t based on hourly closing prices C and, similarly to Chang et al. (2000), use these to construct an equally weighted market portfolio:

$$R_{i,t} = \ln\left(\frac{C_{i,t}}{C_{i,t-1}}\right) \qquad R_{m,t} = \frac{1}{N_t}\sum_{i=1}^{N_t} R_{i,t} \tag{1}$$

For robustness we also use a value weighted index and a market index solely based on Bitcoin returns. As in Kaiser and Stöckl (2020), we allow the number of included cryptocurrencies N to change over time, in particular as newer cryptocurrencies enter the sample. We require the market index to be based on at least five currencies at each point in time, but typically the number is substantially larger. On average, about ten of the twelve cryptocurrencies are part of the market index, and more than 95% of the time there are at least eight.

We additionally obtain the number of transactions recorded on the blockchain of each cryptocurrency in the sample. The data is collected by connecting to publicly available APIs for the various currencies. The number of transactions contained in every block is counted and aggregated to one-hour intervals to match the trading data. We then normalize the transaction data by winsorizing at the 99.5% level, dividing each time series by their respective maximum transaction count, and multiplying the result by 100. Analogously to the attention measure below, we then aggregate the individual transaction counts Tx to the market level:

$$\text{BlockchainTransactions}_t = \frac{1}{N_t}\sum_{i=1}^{N_t} \ln\left(1 + \text{Tx}_{i,t}\right) \tag{2}$$

3.2. Investor attention and information demand and supply

Following Da et al. (2011) and Joseph et al. (2011), we use the search volume index (SVI) from Google Trends to measure investor attention and information demand. As search keywords, we use the full name of the cryptocurrency, unless the name does not unambiguously return results related to the cryptocurrency. In those cases, we use the ticker or add the word "coin" to the name of the cryptocurrency. The keywords are thus Bitcoin, Cardano, Ethereum, Ethereum Classic, Dash coin, Dogecoin, Litecoin, Monero, Ripple, Tron coin, XLM, and Zcash.[5] Our measure of market-wide search activity and thus attention is given by the average of the logarithms of relative search volume S across all currencies that are part of the market portfolio for a given hour:

$$\text{SearchVolumeLevel}_t = \frac{1}{N_t}\sum_{i=1}^{N_t} \ln\left(1 + S_{i,t}\right) \tag{3}$$

Additionally, we measure the cross-sectional dispersion of investor attention similarly to the return dispersion measure below by taking the average absolute deviation from the market search volume level:

$$\text{SearchVolumeDispersion}_t = \frac{1}{N_t}\sum_{i=1}^{N_t} \left|\ln\left(1 + S_{i,t}\right) - \text{SearchVolumeLevel}_t\right| \tag{4}$$

We further obtain data on messages posted on Reddit as a proxy for information supply. The platform is especially popular with retail and cryptocurrency investors (Phillips and Gorse, 2018). We collect all submissions and comments (called posts henceforth) from the Pushshift archives (Baumgartner et al., 2020). We then count the number of posts on the respective main message board ("Subreddit") for each cryptocurrency. The data is aggregated to market-wide measures of the level and cross-sectional dispersion of the number of Reddit posts analogously to the internet search volume measures.

A noteworthy point about the measures of attention and information supply is that they are based on data that is normalized in the time series. Dispersion hence does not measure differences in absolute search volume or Reddit posts, but rather differences in relative values. We employ this approach to address the vastly different levels of attention the larger cryptocurrencies such as Bitcoin receive compared to some of the smaller altcoins. This approach is thus consistent with using an equally weighted market portfolio.[6]

3.3. Measuring herding behavior

Following Chang et al. (2000) and many subsequent studies on investor herding, we consider the cross-sectional absolute deviation (CSAD) of individual cryptocurrency returns from the market return.

$$\text{CSAD}_t = \frac{1}{N}\sum_{i=1}^{N} \left|R_{i,t} - R_{m,t}\right| \tag{5}$$

CSAD itself is not yet a measure of herding around the market consensus, but a non-linear relationship between this measure and the market return may be consistent with the presence of herding behavior. To formally test this notion, Chang et al. (2000) suggest regressing the CSAD on absolute and squared market returns. If investors exhibit return herding behavior, we expect a significantly negative coefficient for the squared market returns. The intuition is that a rational and linear asset pricing model like the CAPM would predict a linear relationship between return dispersion and market returns. However, if there is herding around the market consensus during periods of market stress, return dispersion will decrease in the market return or at least increase at a decreasing rate.[7]

[4] However, to additionally verify that the data is representative of the overall cryptocurrency market and that our results do not depend on our specific data source, we compare it to prices determined by coinmarketcap.com. Differences are generally small: The average (median) difference between these two prices is 0.52% (0.37%) and similar across the various currencies, though some price differences between exchanges are expected due to differences in trading fees and liquidity. To filter any remaining outliers, we drop observations where the absolute difference is larger than 10%.

[5] Google Trends only returns hourly data for relatively short time spans. For a given keyword-timeframe combination, the raw data is always expressed relative to the highest search volume in that timeframe which is set to a value of 100. The other relative values are rounded to the nearest integer and set to zero if below an unknown threshold. To obtain a long hourly sample with consistent scaling in the time series, we start with the first week of the sample and then move forward in time by six days, leaving 24 observations per keyword as an overlap which we use to consistently scale the data in the time series. Finally, we winsorize the data at the 99.5% level, divide every time series by the maximum SVI of the respective currency, and multiply by 100.

[6] In untabulated analyses we find that our conclusions also hold when applying value weighting to the attention measures.

[7] Note that Bohl et al. (2017) and Stavroyiannis et al. (2019) present evidence that the methodology of Chang et al. (2000) likely underestimates the presence and magnitude of herding behavior. The reason is that when using realized returns with idiosyncratic components as opposed to expected CAPM returns, under the null hypothesis of no herding, the true coefficient for the squared market returns β_2 is actually expected to be some positive — but generally unknown — value. By testing against a coefficient of zero, one underestimates herding and overestimates anti-herding behavior, which has frequently been documented in the empirical literature on herding (e.g. Bouri et al., 2019; Coskun et al., 2020). We never document any anti-herding

Formally, we use various specifications of the following regression equation:

$$\begin{aligned}\text{CSAD}_t = \alpha &+ \beta_1 \left|R_{m,t}\right| + \beta_2 R_{m,t}^2 \\ &+ \beta_3 \text{TradingVol}_t + \beta_4 \text{BlockchainTrans}_t \\ &+ \beta_5 \text{SearchVol}_t + \beta_6 \text{RedditPosts}_t \\ &+ \sum_d \tau_d D_{(t\in d)} + \varepsilon_t\end{aligned} \quad (6)$$

where $D_{(t\in d)}$ indicates the date d and is used to capture date-fixed effects. We use this equation to test for the overall presence of herding behavior in intraday returns, which are likely more sensitive to short-lived herding.

Firstly and as a baseline specification, we only include the market return measures. While the coefficient for absolute market returns is of lesser interest and primarily controls for the expected return dispersion under a rational asset pricing model such as the CAPM, the coefficient for squared market returns indicates herding behavior when significantly negative. Importantly and as mentioned above, this approach captures herding around the market consensus, i.e., around the market return, during times of market stress, i.e., when returns are large in magnitude.

We then include additional variables in the model. This approach follows Bernales et al. (2020) who postulate that additional variables (called "herd variables" in their study) included in such a regression should not have an impact on return dispersion as measured by CSAD under the null hypothesis of no herding. The authors consider significant coefficients for these additional variables a case of "conditional herding". Specifically, we then include variables related to trading volume and blockchain activity to see if herding is impacted by the level of both off- and on-blockchain activity. *BlockchainTrans* captures the transaction activity in the currencies of the market portfolio. *TradingVol* is the hourly trading volume at Kraken across all included cryptocurrencies. While this variable only captures a fraction of global trading activity in cryptocurrencies, it still proxies for the trading intensity of investors using US Dollars, especially when we consider intraday variations. Furthermore, Brauneis et al. (2023) show that trading activity is generally highly correlated across exchanges and geographical regions. In the next step, we include variables related to investor attention: *SearchVol* is a vector containing the measures for the level and dispersion of information demand as measured by internet search volume and *RedditPosts* similarly contains measures for the level and dispersion of information supply as measured by submissions and comments on the message board Reddit. Finally, the use of intraday data allows us to add fixed effects for every day in the sample, which controls for general trends in the data and thus focuses the analysis on shorter-term variations in herding behavior. Following Chang et al. (2000), we repeat these regressions separately for up and down markets, i.e., when market returns are positive or negative, to study any asymmetry in herding behavior.

As is commonly done in the literature, we use (Newey and West, 1987) standard errors to account for the potential heteroscedasticity and autocorrelation in the residuals. We set the number of lags equal to $\lceil T^{0.25} \rceil$ where T is the number of observations in the regression. In the regressions with date fixed effects, we cluster the standard errors by date, though the exact choice of standard errors does not seem to meaningfully impact our results.[8]

Previous studies have shown that return herding behavior may be time-varying (Bouri et al., 2019; Yarovaya et al., 2021). The intraday data allows us to test for another type of time-variation: Patterns in intraday herding behavior. To investigate such patterns, we estimate

$$\text{CSAD}_t = \alpha + \sum_{h=0}^{23} \beta_{1,h} \left|R_{m,t}\right| D_{h,t} + \sum_{h=0}^{23} \beta_{2,h} R_{m,t}^2 D_{h,t} + \varepsilon_t \quad (7)$$

where D_h is a set of binary variables for each one-hour window of the day. The vector of regression coefficients β_2 then shows how herding behavior fluctuates throughout the day.

4. Results

4.1. Summary statistics

In Table 1 we provide summary statistics, first for the total sample and then split into periods where the market return is positive or negative, respectively. The average cross-sectional absolute deviation of hourly returns around the market is about 48 basis points. For comparison, the (untabulated) time series average absolute deviation of the hourly market return from its mean is about 60 basis points. Market return volatility and cross-sectional dispersion are thus both economically meaningful and at comparable levels. Both show signs of fat tails with substantial excess kurtosis.

While on average return dispersion is similar in up and down markets, there are more extreme values when prices are increasing as evidenced by the larger maximum and minimum values, respectively, and the higher excess kurtosis. We observe a similar pattern for trading volume: While still similar on average during up and down markets, it exhibits more extreme values for up markets. Market returns are more volatile during down markets, suggesting the presence of asymmetric volatility. The measures for attention and blockchain activity behave quite similarly during both market states.

Untabulated augmented Dickey–Fuller tests reject the null hypothesis of a unit root for all variables. Likewise, multicollinearity does not appear to pose a problem as all variance inflation factors are well below five in any of the estimated models below.

4.2. Baseline herding analysis

We now investigate herding behavior and its potential determinants. The baseline results can be found in Table 2. In the first model we apply the basic specification of Chang et al. (2000) to our hourly data. We find a significantly negative coefficient for the squared market returns, suggesting that investors exhibit return herding behavior and confirming our first hypothesis. This result thus agrees with several previous studies that find herding in cryptocurrency markets (e.g. Kaiser and Stöckl, 2020; Ballis and Drakos, 2020), though the size and significance of the effect appear to support the notion of Gleason et al. (2004) that higher frequency returns may be better able to detect short-term herding by investors.

We then include the trading volume at Kraken and the number of transactions recorded on the blockchains. For the exchange-specific trading volume we find a positive and significant coefficient. This means that the higher the aggregate demand to exchange these specific currencies (in particular against the USD), the less investors herd around the market, consistent with the finding by Youssef (2022b), who find that investors herd less as the trading volume increases. For the number of transactions, we find a negative coefficient. This indicates that over the course of the sample period, a higher demand in blockchain transactions is associated with more herding, though neither the adjusted R^2 nor the size of the return herding coefficient meaningfully change after including the transaction count. On a longer horizon, the transaction count correlates with the popularity of a currency and how broad the investor base is. Taken together, the negative coefficient

behavior, so in our study this bias can only work against finding significant return herding. Since in almost all of our specifications we in fact find significant herding even when testing the coefficient against zero, we conclude that while we might underestimate the magnitude of herding, our general conclusions are not affected by this bias.

[8] To further address concerns about autocorrelation in the dependent variable, in untabulated analyses we repeat all regressions by including lagged values of CSAD as in Alexakis et al. (2023). The results are very similar and our conclusions remain unaffected.

Table 1
Descriptive statistics.

	Mean	SD	Min	P5	P50	P95	Max	Skew.	Kurt.	N
Panel A: Full sample										
CSAD	0.48	0.31	0.00	0.18	0.39	1.06	7.75	2.7	20.5	40,799
Market Return	−0.00	0.94	−10.81	−1.45	0.02	1.33	11.29	−0.6	13.2	40,799
Trading Volume	7.92	13.60	0.00	0.56	3.22	30.99	361.44	6.3	85.4	40,799
Blockchain Transactions	3.02	0.42	1.70	2.39	2.95	3.72	4.22	0.3	2.1	40,799
Search $\text{Volume}_{\text{Level}}$	2.00	0.69	0.43	1.09	1.88	3.35	4.55	0.8	3.2	40,799
Search $\text{Volume}_{\text{Dispersion}}$	0.82	0.22	0.07	0.42	0.84	1.17	2.13	−0.2	3.2	40,799
Reddit $\text{Posts}_{\text{Level}}$	2.13	0.59	0.40	1.23	2.12	3.15	4.62	0.3	2.8	40,799
Reddit $\text{Posts}_{\text{Dispersion}}$	0.66	0.16	0.04	0.40	0.65	0.92	1.55	0.2	3.4	40,799
Panel B: Up markets										
CSAD	0.49	0.32	0.01	0.18	0.40	1.10	7.75	2.8	24.0	21,107
Market Return	0.58	0.64	0.00	0.03	0.38	1.77	11.29	3.2	23.1	21,107
Trading Volume	7.87	13.18	0.00	0.58	3.29	30.64	361.44	6.6	101.4	21,107
Blockchain Transactions	3.03	0.42	1.70	2.39	2.97	3.72	4.22	0.2	2.1	21,107
Search $\text{Volume}_{\text{Level}}$	2.01	0.70	0.43	1.09	1.89	3.36	4.55	0.7	3.2	21,107
Search $\text{Volume}_{\text{Dispersion}}$	0.82	0.22	0.07	0.42	0.84	1.17	1.74	−0.2	3.2	21,107
Reddit $\text{Posts}_{\text{Level}}$	2.13	0.59	0.64	1.24	2.12	3.15	4.62	0.3	2.8	21,107
Reddit $\text{Posts}_{\text{Dispersion}}$	0.66	0.16	0.04	0.40	0.65	0.92	1.40	0.2	3.4	21,107
Panel C: Down markets										
CSAD	0.46	0.30	0.01	0.18	0.38	1.02	4.32	2.6	15.0	19,645
Market Return	−0.63	0.78	−10.81	−2.12	−0.38	−0.03	−0.00	−3.3	21.0	19,645
Trading Volume	8.00	14.04	0.00	0.55	3.18	31.23	333.88	6.1	71.4	19,645
Blockchain Transactions	3.01	0.42	1.80	2.39	2.94	3.72	4.17	0.3	2.1	19,645
Search $\text{Volume}_{\text{Level}}$	1.98	0.69	0.47	1.09	1.86	3.32	4.51	0.8	3.3	19,645
Search $\text{Volume}_{\text{Dispersion}}$	0.82	0.22	0.10	0.42	0.84	1.17	2.13	−0.2	3.3	19,645
Reddit $\text{Posts}_{\text{Level}}$	2.13	0.59	0.40	1.23	2.11	3.14	4.46	0.3	2.8	19,645
Reddit $\text{Posts}_{\text{Dispersion}}$	0.66	0.16	0.11	0.40	0.65	0.92	1.55	0.2	3.4	19,645

This table shows summary statistics for our key variables. *CSAD* is the cross-sectional absolute deviation of returns in percent. *Market Return* is the hourly logarithmic return of the market index in percent. *Squared Market Return* is the squared hourly logarithmic return of the market index in basis points. *Blockchain Transactions* is the equally weighted cross-sectional average of the log normalized number of transactions recorded on the blockchain within an hour. *Search* $\textit{Volume}_{Level}$ is the equally weighted cross-sectional average of the log normalized Google search volume within an hour. Similarly, *Search* $\textit{Volume}_{Dispersion}$ is its cross-sectional absolute deviation. $\textit{Reddit}_{Level}$ and $\textit{Reddit}_{Dispersion}$ are constructed analogously using the number of submissions and comments on Reddit. *Trading Volume* is the total hourly trading volume of all currencies in the market in 1mn USD. In Panel A, the full sample is used. In Panels B and C, the sample is split into observations with positive and negative market returns, respectively.

Table 2
Baseline herding analysis.

	(1)	(2)	(3)	(4)	(5)	(6)
|Market Return|	0.242***	0.225***	0.227***	0.158***	0.146***	0.144***
	(36.50)	(33.30)	(33.37)	(26.16)	(24.62)	(24.31)
Market Return^2	−1.238***	−1.260***	−1.377***	−0.457**	−0.608***	−0.589***
	(−6.59)	(−6.84)	(−7.29)	(−2.42)	(−3.34)	(−3.21)
Trading Vol.		0.002***	0.003***		0.004***	0.003***
		(7.93)	(9.81)		(12.41)	(11.74)
Blockchain Trans.			−0.059***			0.108***
			(−5.96)			(7.08)
Date FE	–	–	–	✓	✓	✓
Observations	40 799	40 799	40 799	40 798	40 798	40 798
Adj. R^2	0.212	0.222	0.227	0.533	0.543	0.544

This table shows time-series regression results based on variations of Eq. (6). The dependent variable is the CSAD. A significantly negative coefficient for the squared market return indicates herding. The variables are as defined in Table 1, except CSAD which is here given in basis points. Newey and West (1987) standard errors are reported in parentheses, except for in the fixed effects model, where the standard errors are clustered by date. ***, **, * denotes significance at the 1%, 5%, 10%-level, respectively.

would thus indicate that the more popular the currencies in the sample get, the more investors herd around the market.

The hourly data allows us to include date fixed effects to control for overall trends in the data. The identification of herding behavior and how it relates to market returns and the other investigated potential determinant of herding now comes from their intraday variation. Including date fixed effects thus focuses the analysis on short-term herding, whereas the overall analysis before includes both short-term and longer-term effects. The results are presented in the rightmost three columns of Table 2. Overall, our conclusion of significant market return herding behavior proves robust in all models. In the baseline model, we find that the size of the effect of squared market returns on cross-sectional dispersion reduces to about one third but stays highly statistically significant. The biggest difference from including date fixed effects can be found in the effect of the number of transactions. While in the analysis without date-fixed effects, more transactions are associated with less return dispersion, the opposite is true when focusing on intraday variations by including these fixed effects. This suggests that the short and long run effects of transaction activity go in opposite directions. In the long run, the measure likely picks up the currencies' popularity and broadness of investor base, while at short horizons it is more likely to capture the activity of roughly the same investor base.

4.3. Herding and investor attention

We then study how investor attention relates to herding. The results are presented in Panel A of Table 3. First, we include the level of internet search volume as a proxy for information demand by investors and find a significantly positive relationship with the dispersion of returns. In other words, a higher level of investor attention as measured by the aggregate search activity across different cryptocurrencies is associated with lower levels of herding around the market consensus, contrary to the results found for stock markets by Hsieh et al. (2020). The magnitude of the return herding coefficient is reduced by about 25% while the adjusted R^2 increases slightly, indicating that investor information demand is indeed an important determinant of investor herding. Similarly, we then include search volume dispersion and find a positive effect on return dispersion. In fact, the effect of the level of attention is stronger when dispersion is additionally included, which implies that they capture two different dimensions of attention. This is further verified by the time-series correlation of about −40% between the level and dispersion of search volume.[9] Interpreting these

[9] See Table A.1 in the Appendix for all time-series correlations.

Table 3
Herding and investor attention.

	(1)	(2)	(3)	(4)	(5)
Panel A: No fixed effects					
|Market Return|	0.194***	0.192***	0.198***	0.198***	0.190***
	(30.44)	(30.44)	(30.26)	(30.25)	(29.70)
Market Return^2	−0.937***	−0.912***	−1.021***	−1.021***	−0.891***
	(−5.11)	(−5.02)	(−5.46)	(−5.46)	(−4.85)
Trading Vol.	0.002***	0.002***	0.002***	0.002***	0.002***
	(5.41)	(5.10)	(6.91)	(6.90)	(5.09)
Blockchain Trans.	−0.155***	−0.170***	−0.072***	−0.072***	−0.149***
	(−18.17)	(−17.83)	(−8.37)	(−8.19)	(−15.33)
Search Vol.$_{Level}$	0.160***	0.176***			0.131***
	(24.04)	(23.81)			(18.82)
Search Vol.$_{Dispersion}$		0.077***			0.058***
		(6.13)			(4.67)
Reddit Posts$_{Level}$			0.151***	0.151***	0.058***
			(20.54)	(20.50)	(8.72)
Reddit Posts$_{Dispersion}$				0.002	0.033**
				(0.11)	(2.09)
Date FE	–	–	–	–	–
Observations	40 799	40 799	40 799	40 799	40 799
Adj. R^2	0.318	0.320	0.303	0.303	0.326
Panel B: Date fixed effects					
|Market Return|	0.144***	0.144***	0.144***	0.144***	0.144***
	(24.34)	(24.38)	(24.19)	(24.21)	(24.28)
Market Return^2	−0.587***	−0.590***	−0.581***	−0.578***	−0.579***
	(−3.19)	(−3.22)	(−3.14)	(−3.13)	(−3.15)
Trading Vol.	0.003***	0.003***	0.003***	0.003***	0.003***
	(11.54)	(11.38)	(11.25)	(11.15)	(10.81)
Blockchain Trans.	0.104***	0.118***	0.077***	0.070***	0.083***
	(6.90)	(7.70)	(4.97)	(4.57)	(5.35)
Search Vol.$_{Level}$	0.024***	0.052***			0.049***
	(5.69)	(8.11)			(7.80)
Search Vol.$_{Dispersion}$		0.063***			0.068***
		(6.16)			(6.64)
Reddit Posts$_{Level}$			0.046***	0.045***	0.044***
			(7.99)	(7.65)	(7.67)
Reddit Posts$_{Dispersion}$				0.057***	0.057***
				(5.73)	(5.73)
Date FE	✓	✓	✓	✓	✓
Observations	40 798	40 798	40 798	40 798	40 798
Adj. R^2	0.545	0.545	0.545	0.546	0.547

This table shows time-series regression results based on variations of Eq. (6). The dependent variable is the CSAD. A significantly negative coefficient for the squared market return indicates herding. Panel A does not include fixed effect, whereas Panel B includes day fixed effects. The variables are as defined in Table 1, except CSAD which is here given in basis points. Newey and West (1987) standard errors are reported in parentheses, except for in the fixed effects model, where the standard errors are clustered by date. ***, **, * denotes significance at the 1%, 5%, 10%–level, respectively.

results jointly, we find evidence that the more investors search for cryptocurrency information, the more idiosyncratic information they incorporate into their trading decisions and thus prices. Likewise, the more dispersed their searches are across the individual currencies, the less their trading decisions reflect the market consensus since their searches are less likely to solely reflect an increase in general interest in cryptocurrencies, leading to less herding. Overall, we thus find strong support for Hypothesis 4.

We then turn to the investor attention measures capturing the supply of information, where we proceed similarly as with search volume. In models 3–4, we include the level and dispersion of the number of posts on the message boards for the different cryptocurrencies on the platform Reddit. The results generally mimic those found for search volume, though they are smaller in magnitude. The level of attention is significantly negatively associated with herding around the market return. However, in this specification, the effect of dispersion is insignificant. Note that the results regarding Reddit posts do not necessarily imply that investors receive correct fundamental information through this channel. As pointed out by Sabherwal et al. (2011), pump-and-dump schemes facilitated by message boards might lead investors to drive prices of individual currencies further away from the market, thus increasing the cross-sectional dispersion of returns.

In model 5, we include both groups of attention measures. While the magnitudes of the coefficients for search volume and the level of Reddit posts decrease, the effect of dispersion in Reddit posts now turns significant. This suggests that search volume and message board posts indeed capture different dimensions of investor attention and that both are negatively related to herding around the market portfolio, further confirming Hypothesis 4.

In Panel B we repeat the analysis by including date fixed effects so that the identification comes from the intraday variation in the data. Again, all results prove robust to controlling for long-term trends. Contrary to before, the coefficient for squared market returns now is hardly affected by the inclusion of the different attention measures. Interpreting these results jointly, this suggests that long-term changes in market consensus herding behavior (as defined in Chang et al., 2000) are partially explained by long-term changes in aggregate attention, but only to a lesser extent by short-term fluctuations in attention.

Generally speaking, the coefficients for the level of attention decrease in magnitude while those for attention dispersion increase compared to the results without date fixed effects, in particular when including all four variables in model 5. Overall, these findings suggest that intraday variations in attention are strongly related to conditional herding behavior (as defined in Bernales et al., 2020), which will be investigated in more detail below.

4.4. Herding across different market states

Because several prior studies have proposed asymmetries in herding behavior in various markets (Chang et al., 2000; Chiang and Zheng, 2010; Vidal-Tomás et al., 2019), we proceed by splitting the sample into periods of positive and negative market returns. The results in Table 4 show that investors particularly herd in bull market states. For down markets, the herding coefficients are negative and significant when not controlling for attention or date fixed effects, but otherwise insignificant. Our results thus agree with Ballis and Drakos (2020), who also find some herding behavior by cryptocurrency investors in both up and down markets, but a stronger effect when prices are increasing. When compared to non-cryptocurrency markets, our results resemble those found for many Asian equity markets in Chiang and Zheng (2010): Herding exists in both market states, but there is an overall stronger effect during up markets. This behavior is consistent with the idea that cryptocurrency investors are prone to trading based on a fear-of-missing-out. Observing that market prices are increasing, the average investor does not want to miss out on bullish markets and hence similarly invests across the cryptocurrency universe. This effect is potentially aggravated by short-sell restrictions so that investors with opposing views may find it difficult to trade on their information. We thus find support for Hypothesis 2a and reject Hypothesis 2b.

The other estimated coefficients stay at similar levels and significances compared to the unconditional model. In particular, this suggests that the effects of investor attention on herding do not materially depend on the market state. Likewise, in the descriptive statistics we found virtually identical levels and dispersions of attention for up and down markets. The differences in return herding behavior between up and down markets are thus unlikely to be driven by differences in attention, but rather indicate that investor attention and the direction of market returns are two distinct determinants of investor herding.

Furthermore and similarly to Kallinterakis and Wang (2019), we split the sample into high and low volatility periods. High market volatility periods are defined as those where the estimated volatility is larger than its moving average of the previous two weeks, where we estimate volatility for every hour using the forward-looking asymmetric

Table 4
Herding in up and down markets.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Up markets						
|Market Return|	0.290***	0.266***	0.229***	0.203***	0.187***	0.187***
	(30.92)	(27.33)	(25.47)	(24.51)	(22.20)	(22.40)
Market Return^2	−2.031***	−1.955***	−1.515***	−1.143***	−1.151***	−1.151***
	(−6.12)	(−5.79)	(−4.64)	(−3.24)	(−3.26)	(−3.30)
Trading Vol.		0.004***	0.002***		0.004***	0.004***
		(7.73)	(4.22)		(8.95)	(8.29)
Blockchain Trans.		−0.069***	−0.159***		0.125***	0.100***
		(−5.27)	(−12.52)		(6.44)	(5.05)
Search Vol.$_{Level}$			0.135***			0.056***
			(15.06)			(5.88)
Search Vol.$_{Dispersion}$			0.043***			0.074***
			(2.69)			(4.75)
Reddit Posts$_{Level}$			0.055***			0.041***
			(6.28)			(5.11)
Reddit Posts$_{Dispersion}$			0.040*			0.068***
			(1.92)			(4.71)
Date FE	–	–	–	✓	✓	✓
Observations	21 107	21 107	21 107	21 104	21 104	21 104
Adj.R^2	0.210	0.228	0.325	0.521	0.534	0.538
Panel B: Down markets						
|Market Return|	0.197***	0.188***	0.150***	0.114***	0.103***	0.104***
	(24.15)	(21.78)	(18.87)	(15.53)	(13.97)	(13.91)
Market Return^2	−0.470**	−0.677***	−0.168	0.261	0.049	0.061
	(−2.29)	(−3.18)	(−0.83)	(1.28)	(0.24)	(0.29)
Trading Vol.		0.003***	0.001***		0.003***	0.003***
		(7.32)	(3.27)		(11.25)	(10.48)
Blockchain Trans.		−0.051***	−0.138***		0.084***	0.061***
		(−4.07)	(−11.58)		(4.36)	(3.11)
Search Vol.$_{Level}$			0.128***			0.041***
			(15.59)			(6.05)
Search Vol.$_{Dispersion}$			0.070***			0.062***
			(4.42)			(4.98)
Reddit Posts$_{Level}$			0.063***			0.043***
			(8.32)			(6.19)
Reddit Posts$_{Dispersion}$			0.021			0.047***
			(1.12)			(3.64)
Date FE	–	–	–	✓	✓	✓
Observations	19 645	19 645	19 645	19 643	19 643	19 643
Adj.R^2	0.226	0.237	0.343	0.560	0.570	0.573

This table shows time-series regression results based on variations of Eq. (6). The dependent variable is the CSAD. A significantly negative coefficient for the squared market return indicates herding. Panels A and B only include observations during positive or negative market returns, respectively. The variables are as defined in Table 1, except CSAD which is here given in basis points. Newey and West (1987) standard errors are reported in parentheses, except for in the fixed effects model, where the standard errors are clustered by date. ***, **, * denotes significance at the 1%, 5%, 10%–level, respectively.

power ARCH model of Ding et al. (1993). The results are presented in Table A.2 in the Appendix and show that herding is more prominent during low volatility periods, agreeing with the result of Kallinterakis and Wang (2019), although contrary to the finding by Raimundo Júnior et al. (2022), Youssef (2022b) and Youssef and Waked (2022). Nonetheless, we find significant herding in some specifications during high volatility periods as well.

Finally, Table A.3 in the Appendix shows that there are some differences in herding between weekdays and weekends. In particular, herding behavior appears to be much stronger during the weekend. Assuming that the fraction of small retail traders is larger during the weekend, this result is consistent with the notion that these investors are particularly prone to exhibit herd behavior.[10]

[10] Untabulated t-tests show that average trade sizes are smaller during the weekend, which is consistent with the assumption of a larger fraction of retail traders. See also Scharnowski (2021).

4.5. Intraday patterns in herding and attention

So far, the higher granularity of our dataset has allowed us to document significant market return herding behavior while controlling for general trends in the data. In this part, we analyze how investor attention and herding behavior fluctuate throughout the day.

All timestamps used in this study are in Coordinated Universal Time (UTC), though this is simply a convention. Cryptocurrencies trade around the clock in a mostly anonymous, decentralized way, which makes it difficult to know where traders are located geographically. While we only consider trading against the USD, this does not necessarily imply that those traders are located in the United States. Even if they were, it is ex ante unclear when during the day traders would trade: Professional investors likely trade during regular business hours, retail investors might exhibit different patterns of daily trading activity, whereas algorithms trade throughout the day. When visualizing the intraday patterns, we hence provide the times of two additional time zones. Disregarding daylight-saving time, these roughly correspond to the time in New York City and Beijing, respectively.

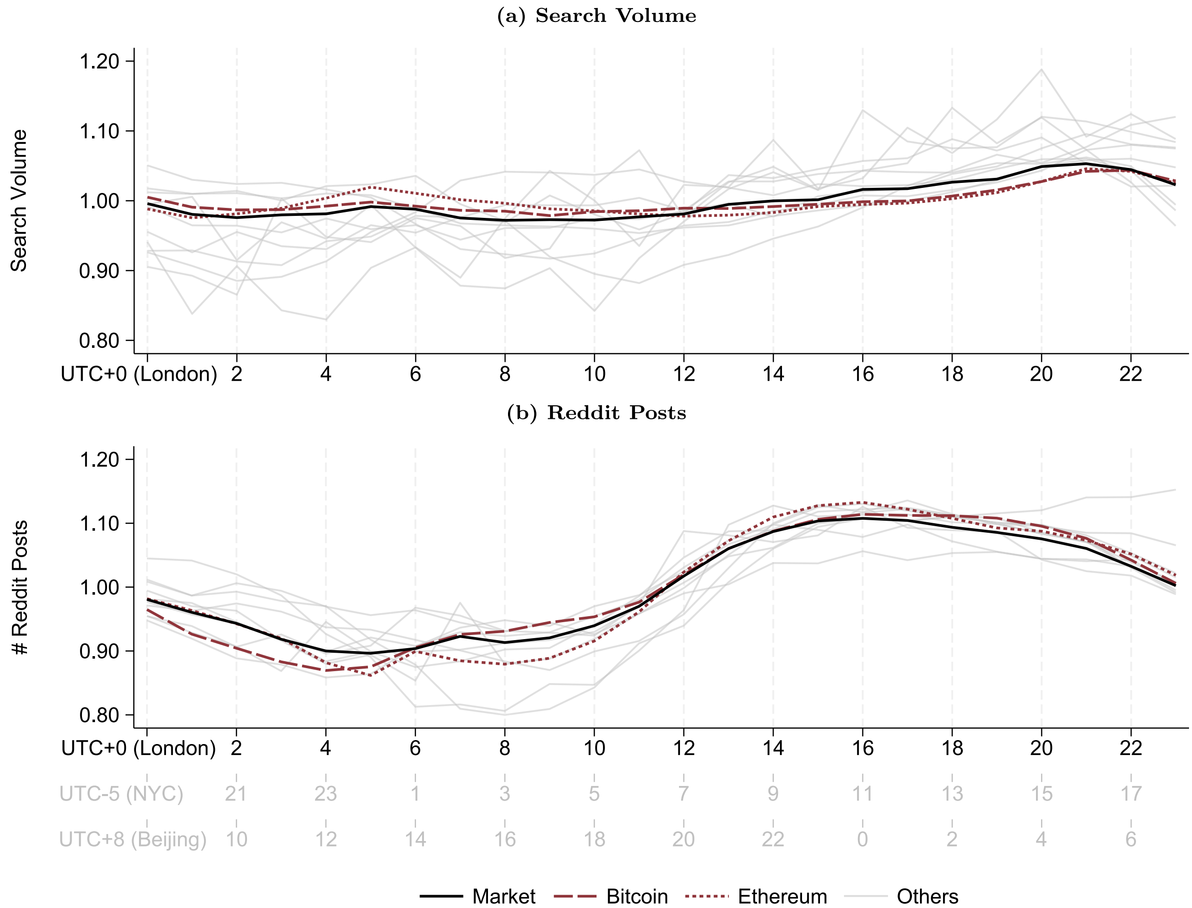

Fig. 1. Intraday patterns in investor attention. These graphs show intraday variations in investor attention. The first graph shows intraday variations in investor attention as measured by Google search volume. The bottom graph shows intraday variations in information supply as measured by Reddit submissions and comments. The data is normalized and averaged for every one hour windows of the day. Bitcoin and Ethereum have been highlighted. *Market* is the equally weighted average across all currencies. For the purpose of this graph, all time series have been standardized by dividing by their respective averages.

To provide a ballpark approximation of how the potential non-algorithmic investor base fluctuates throughout the day, we estimate the worldwide population with internet access that is awake at a given point in time from the perspective of an investor in UTC+0. We combine data from the International Telecommunication Union and the United Nations World Population Prospects and further assume that for a given time zone, half the population is awake between 6:00 h and 8:00 h, the full population is awake between 8:00 h and 23:00 h, and again half the population is awake between 23:00 h and 01:00 h (in local time). For countries spanning multiple time zones, the geographical distribution of internet users is assumed to be identical to that of the overall population. Under these assumptions, we find that the potential investor base is largest from 11:00 h to 14:00 h UTC+0, which would be the morning in eastern North and all of South America, mid-day in Europe and Africa and the evening in large parts of Asia. The finding coincides with the one of Brauneis et al. (2023) who find that trading activity is lowest in the early morning UTC hours and highest around 15:00 and 16:00 UTC. The intraday variation of the online population can be found in Fig. A.1 in the Appendix.

Before analyzing intraday herding in detail, we turn to the intraday patterns in investor attention. Fig. 1(a) shows how attention as measured by the level of search volume evolves throughout the day. We make several observations: First, each individual currency exhibits intraday variation in search volume. The largest currencies show less variation than the smaller ones. Second, there is some co-movement of attention. For example, search volume is generally higher at 21:00 UTC than at 08:00 UTC. The average attention level across the currencies is bimodal with peaks at 05:00 UTC and 21:00 UTC. Third, the co-movement is less than perfect, leading to fluctuations in intraday attention dispersion.[11]

Similarly, Fig. 1(b) shows the intraday development of the scaled number of Reddit posts which measures the information supply aspect of investor attention. Again, all individual currencies exhibit some form of intraday variation. The number of posts is generally higher during the second half of the (UTC+0) day, when investors in Europe and the Americas are likely awake. This probably reflects the geographic distribution of the user base, as Reddit is relatively more popular in the United States than in other parts of the world. The number of new posts for larger cryptocurrencies tends to fluctuate less than for the smaller ones, again leading to differences in the intraday dispersion of attention throughout the day.

We then estimate intraday return herding patterns by Eq. (7). The results in Fig. 2 show the coefficients of squared market returns for every hour of the day, where significantly negative coefficients indicate market return herding. We find a distinct pattern in intraday herding activity: From 00:00 to about 08:00 (all in UTC+0), which corresponds to nighttime in Europe and large parts of the Americas, the herding coefficient is mostly insignificant. Roughly from 10:00 to 17:00, we observe the largest absolute values for the herding coefficient, which

[11] Note that for this graph, the individual time series are scaled by their means to visualize the co-movement. The downside is that attention dispersion is not directly visible in the graph because it depends on the level of differences. The corresponding graph of search volume attention dispersion can be found in Fig. A.2 in the Appendix.

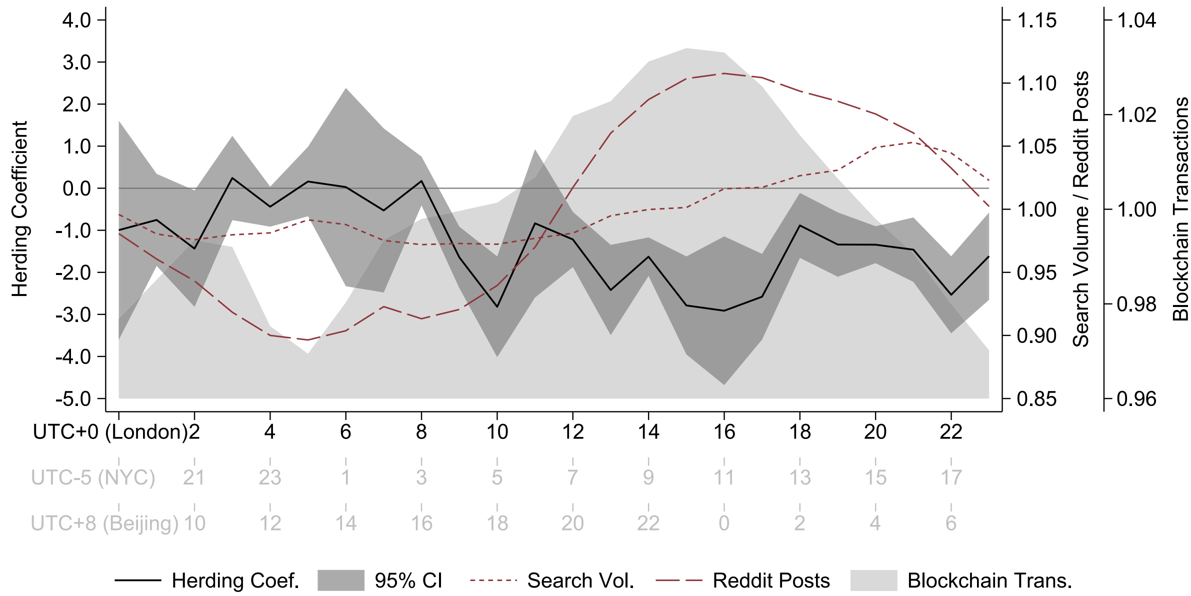

Fig. 2. Intraday market return herding patterns. This graph shows the regression coefficients $\beta_{2,h}$ from estimating Eq. (7). The dark gray area indicate the 95% confidence interval for the coefficient estimate based on Newey and West (1987) standard errors. Significantly negative coefficients indicate herding. The dotted line shows the average level of search volume across the sample currencies. The long-dashed line shows the average number of posts on Reddit. Additionally, the light gray area shows the average number of transactions on the blockchains of the sample currencies. Search volume, Reddit posts, and blockchain transactions have been standardized by dividing by the respective overall means of the two time series.

except for the value at 11:00 are all statistically significant. These times also contain the largest overlap of potential investors likely being awake and the overlap of conventional exchange trading hours in Europe and North America. Herding then decreases for the rest of the day but stays significant at the 5% level. Overall, these results are consistent with Hypothesis 5.

The figure also shows the normalized aggregate measures of attention and the normalized aggregate number of transactions recorded on the blockchain. There are striking similarities between the graphs: Intraday periods of high herding activity closely coincide with periods where many transactions are recorded on the blockchains. Furthermore, there is a positive relation between attention and intraday herding around the market consensus.

There is an important difference between this analysis and the previous regressions. In the preceding section, we relate the cross-sectional dispersion of returns to investor attention and activity in the spirit of Bernales et al. (2020). The results indicate that attention and investor activity are associated with higher return dispersion and hence less "conditional herding". This contrasts with the analysis presented here, where we relate the market return herding coefficient, obtained from regressing CSAD on squared market returns, to attention and trading activity. We here thus explicitly capture how the non-linear reaction of return dispersion to more extreme market returns is affected by these other variables. In other words, while previously we found that higher levels of attention and activity are associated with less herding across the entire return distribution, here we find that these variables are positively associated with herding during times of large market movements.[12]

Furthermore, the documented intraday patterns suggest that trading in cryptocurrencies is not fully automated but instead are consistent with a material role of deliberate trading decisions by retail and possibly institutional investors. Our findings thus agree with and supplement those found in Petukhina et al. (2021) and Baur et al. (2019).

[12] For reference, Fig. A.3 shows the development of CSAD throughout the day. Note that while there are some similarities, clearly the herding coefficient exhibits different intraday variations than return dispersion.

4.6. Robustness

We perform several robustness tests. We first confirm in untabulated estimations that additionally including the signed market return in the regressions does not meaningfully impact our results. The same holds for including a market volatility proxy which we estimate for every hour using the asymmetric power ARCH model.

Moreover, untabulated results show that our findings are generally robust to using different market indices. Firstly, we construct a value weighted market index using the square root of market capitalization, thus putting more weight on larger cryptocurrencies. We then employ the extreme case of only using Bitcoin returns as the market index, acknowledging that Bitcoin is often used as a transfer currency (Kaiser and Stöckl, 2020). While these other weighting schemes generally lead to lower estimates of return herding behavior, we still find similar intraday patterns, which are shown in Fig. A.4 in the Appendix.

Since we document strong intraday patterns in herding and attention, a natural question might be whether our results are driven by some other, omitted factor with similar intraday patterns. First note that in another robustness test above we already control for volatility and thus its known intraday patterns (Petukhina et al., 2021). Still, we address this concern by including fixed effects for every hour of the day. Table A.4 in the Appendix shows that our results are indeed robust to including such intraday fixed effects.

5. Conclusion

Using a rich dataset of intraday return dispersion, attention, and transaction activity, we document the presence of substantial market return herding behavior in the cryptocurrency market. Both the level of investor attention, as measured by internet searches and message board posts, and its dispersion increase the cross-sectional dispersion of returns and thus lead to reduced herding behavior. The more investors search for (or are confronted with) coin-specific information, the more idiosyncratic information they incorporate into their trading decisions and thus prices. Likewise, the less investors encounter the same information, the less their individual trading decisions reflect the market consensus. Higher transactional activity on the currencies' blockchains

Table A.1
Correlations.

	CSAD	Market Return	Market Return^2	Trading Volume	Blockchain Trans.	Search Volume$_{Level}$	Search Volume$_{Disp.}$	Reddit Posts$_{Level}$
Market Return	0.01							
Market Return^2	0.35	−0.18						
Trading Volume	0.27	−0.07	0.33					
Blockchain Transactions	0.05	−0.00	0.07	0.51				
Search Volume$_{Level}$	0.38	−0.00	0.15	0.43	0.48			
Search Volume$_{Dispersion}$	−0.15	0.00	−0.03	0.01	0.12	−0.40		
Reddit Posts$_{Level}$	0.37	−0.01	0.13	0.25	0.17	0.73	−0.29	
Reddit Posts$_{Dispersion}$	0.04	0.00	0.02	0.12	0.18	0.08	0.07	0.11

This table shows correlations across the full sample for the variables as defined in Table 1.

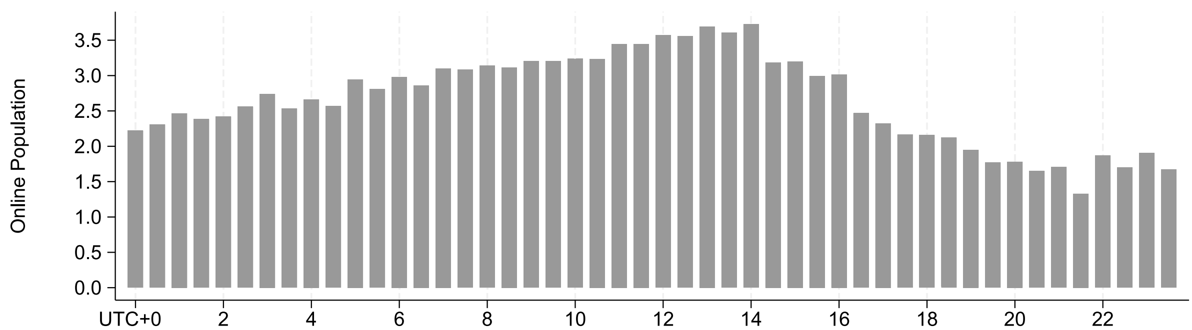

Fig. A.1. Online population throughout the day. This graph shows an estimate of the worldwide population (in 1bn) with internet access that is awake during each 30 min window from the perspective of UTC+0. The values are estimated by combining the percentage of the population with internet access (from the International Telecommunication Union) with the total population (from the United Nations World Population Prospects) for every country. The data is then aggregated to time zones while ignoring daylight saving time. For countries spanning multiple time zones, the geographical distribution of internet users is assumed to be identical to that of the overall population. It is further assumed that for a given time zone, half the population is awake between 6:00 h and 8:00 h, the full population is awake between 8:00 h and 23:00 h, and again half the population is awake between 23:00 h and 01:00 h (in local time).

has mixed effects on herding. In the short run, it is associated with decreased herding behavior. However, in the long run where transactional activity likely correlates with the popularity of the currencies and the breadth of their investor base, the effect turns around so that more transactions are associated with more herding activity. Additionally, we find that investors follow the market more closely during bull markets.

Zooming into potential intraday patterns, we find that herding varies substantially throughout the day. It is strongest during the overlap of hours when traders in major economic centers are likely awake. At the intraday level, investor information demand and supply, blockchain transaction activity, and exchange trading volume are positively correlated with herding behavior. These results are consistent with the presence of retail or unsophisticated institutional investors.

Our results have important implications. Market return herding might deteriorate market quality and lead to inefficient prices as investors disregard the already scarce fundamental information, potentially creating irrational bubbles. Understanding how herding, trading activity, and investor attention are related thus helps traders and regulators to design better trading strategies and more resilient markets, taking into account the particularities of each market. For example, in the case of the cryptocurrency market where little fundamental information is available, educating potential investors about the assets might lead to less herding, since we document that investors are generally willing to search for specific information and incorporate them into prices instead of always blindly following the market. However, they do not consistently choose to gather idiosyncratic information, so there is room for regulatory improvement assuming such information is generally available.

While in this paper we shed light on some of the determinants of intraday herding in cryptocurrency markets, further research may investigate additional potential determinants. Similar to studies on other financial markets, these could include changes in informational supply, regulatory interventions, or spillovers from other markets.

CRediT authorship contribution statement

Stefan Scharnowski: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Yanghua Shi:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing.

Declaration of competing interest

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

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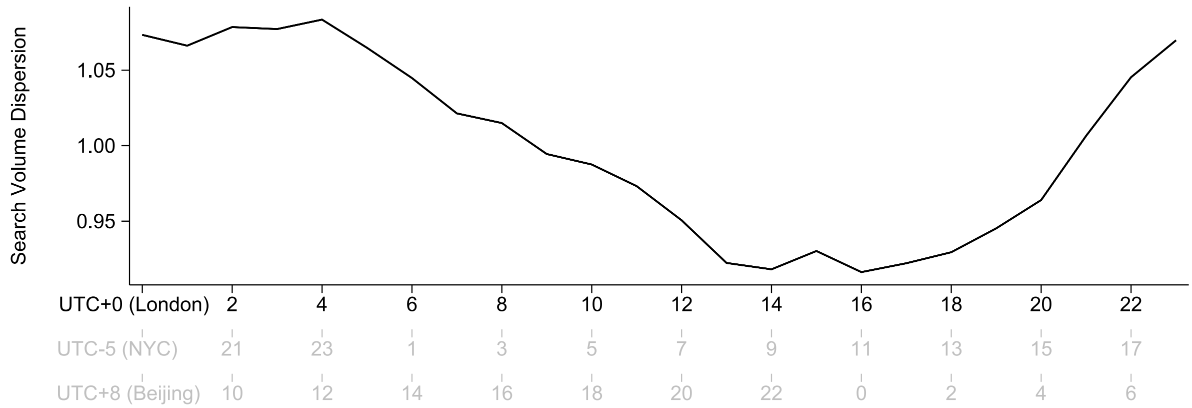

Fig. A.2. Intraday patterns in search volume dispersion. This graph shows hourly averages of investor attention dispersion as measured by the cross-sectional absolute deviation of the log normalized Google search volume from the market average level of attention. For the purpose of this graph, the time series has been standardized by dividing by its mean.

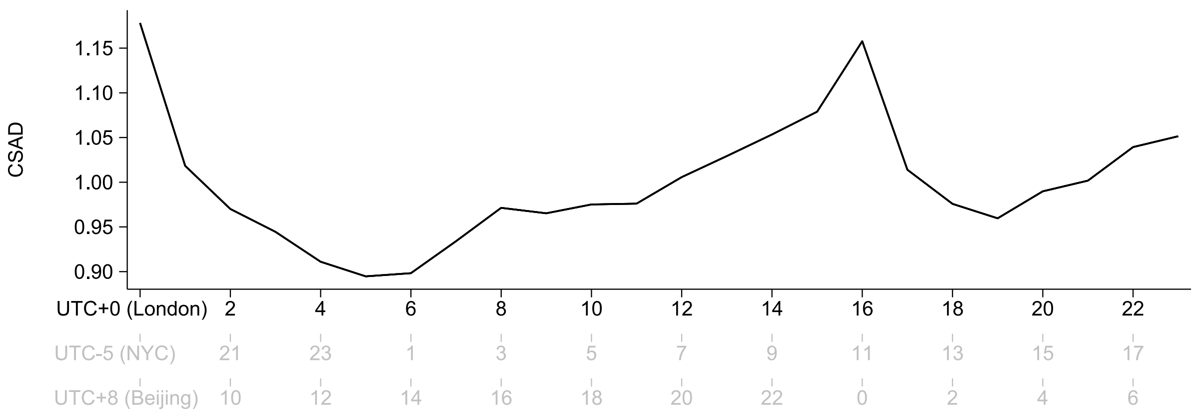

Fig. A.3. Intraday patterns in CSAD. This graph shows hourly averages of the cross-sectional absolute deviation of returns from the market return. For the purpose of this graph, the time series has been standardized by dividing by its mean.

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Appendix

See Tables A.1–A.4 and Figs. A.1–A.4.

Table A.2
Herding during high and low market volatility.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: High market volatility						
|Market Return|	0.218*** (24.34)	0.206*** (23.30)	0.170*** (19.77)	0.144*** (16.91)	0.133*** (16.01)	0.133*** (15.91)
Market Return^2	−0.788*** (−3.39)	−0.906*** (−4.09)	−0.516** (−2.28)	−0.215 (−0.91)	−0.355 (−1.55)	−0.351 (−1.53)
Trading Vol.		0.003*** (7.17)	0.002*** (3.90)		0.004*** (9.00)	0.003*** (8.48)
Blockchain Trans.		−0.091*** (−5.59)	−0.194*** (−12.23)		0.105*** (3.92)	0.085*** (3.15)
Search Vol.$_{Level}$			0.146*** (13.52)			0.063*** (4.72)
Search Vol.$_{Dispersion}$			0.056*** (2.80)			0.078*** (3.86)
Reddit Posts$_{Level}$			0.050*** (4.49)			0.044*** (4.03)
Reddit Posts$_{Dispersion}$			0.045 (1.63)			0.062*** (3.25)

(*continued on next page*)

Table A.2 (*continued*).

	(1)	(2)	(3)	(4)	(5)	(6)
Date FE	–	–	–	✓	✓	✓
Observations	16 365	16 365	16 365	16 296	16 296	16 296
Adj.R^2	0.211	0.227	0.316	0.510	0.524	0.527
Panel B: Low market volatility						
|Market Return|	0.247***	0.230***	0.194***	0.177***	0.166***	0.166***
	(28.38)	(25.48)	(23.33)	(28.27)	(27.06)	(27.41)
Market Return^2	−2.045***	−2.423***	−1.602***	−1.027***	−1.297***	−1.295***
	(−7.07)	(−8.11)	(−5.89)	(−5.36)	(−6.78)	(−6.88)
Trading Vol.		0.004***	0.002***		0.003***	0.003***
		(8.07)	(3.83)		(10.37)	(9.32)
Blockchain Trans.		−0.050***	−0.124***		0.115***	0.089***
		(−4.62)	(−11.81)		(6.61)	(5.03)
Search Vol.$_{Level}$			0.118***			0.033***
			(14.52)			(5.53)
Search Vol.$_{Dispersion}$			0.057***			0.060***
			(4.08)			(5.44)
Reddit Posts$_{Level}$			0.060***			0.045***
			(8.71)			(6.90)
Reddit Posts$_{Dispersion}$			0.019			0.051***
			(1.19)			(4.88)
Date FE	–	–	–	✓	✓	✓
Observations	24 434	24 434	24 434	24 387	24 387	24 387
Adj.R^2	0.165	0.182	0.296	0.520	0.529	0.532

This table shows time-series regression results based on variations of Eq. (6). The dependent variable is the CSAD. A significantly negative coefficient for the squared market return indicates herding. Panels A and B only include observations during high and low market return volatility, respectively. Volatility is estimated by an asymmetric power ARCH model. High market volatility periods are defined as those where the estimated volatility is larger than its moving average of the previous two weeks. The variables are as defined in Table 1, except CSAD which is here given in basis points. Newey and West (1987) standard errors are reported in parentheses, except for in the fixed effects model, where the standard errors are clustered by date. ***, **, * denotes significance at the 1%, 5%, 10%–level, respectively.

Table A.3
Herding during the weekend.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: During the week						
|Market Return|	0.227***	0.212***	0.181***	0.151***	0.136***	0.136***
	(28.38)	(26.13)	(23.24)	(19.76)	(18.11)	(18.09)
Market Return^2	−0.908***	−1.020***	−0.672***	−0.303	−0.387	−0.383
	(−3.77)	(−4.20)	(−2.76)	(−1.18)	(−1.55)	(−1.53)
Trading Vol.		0.003***	0.002***		0.004***	0.003***
		(7.52)	(3.91)		(10.45)	(9.61)
Blockchain Trans.		−0.060***	−0.151***		0.107***	0.081***
		(−4.98)	(−13.60)		(5.98)	(4.43)
Search Vol.$_{Level}$			0.134***			0.047***
			(15.95)			(6.06)
Search Vol.$_{Dispersion}$			0.061***			0.066***
			(4.17)			(5.26)
Reddit Posts$_{Level}$			0.057***			0.044***
			(7.46)			(6.63)
Reddit Posts$_{Dispersion}$			0.040**			0.055***
			(2.19)			(4.51)
Date FE	–	–	–	✓	✓	✓
Observations	29 066	29 066	29 066	29 065	29 065	29 065
Adj.R^2	0.205	0.219	0.317	0.527	0.539	0.542
Panel B: During the weekend						
|Market Return|	0.277***	0.260***	0.211***	0.174***	0.165***	0.165***
	(24.68)	(21.75)	(19.36)	(17.59)	(16.99)	(16.98)
Market Return^2	−1.951***	−2.199***	−1.402***	−0.804***	−1.038***	−1.014***
	(−6.82)	(−7.29)	(−5.17)	(−3.43)	(−4.72)	(−4.63)
Trading Vol.		0.005***	0.002***		0.003***	0.003***
		(8.72)	(4.52)		(5.57)	(5.23)
Blockchain Trans.		−0.062***	−0.149***		0.109***	0.086***
		(−4.41)	(−8.94)		(3.78)	(2.99)
Search Vol.$_{Level}$			0.129***			0.052***
			(11.38)			(5.03)

(*continued on next page*)

Table A.3 (*continued*).

	(1)	(2)	(3)	(4)	(5)	(6)
Search $Vol._{Dispersion}$			0.060***			0.072***
			(2.78)			(4.07)
Reddit $Posts_{Level}$			0.053***			0.044***
			(4.46)			(3.85)
Reddit $Posts_{Dispersion}$			0.013			0.059***
			(0.47)			(3.73)
Date FE	–	–	–	✓	✓	✓
Observations	11 733	11 733	11 733	11 733	11 733	11 733
Adj.R^2	0.229	0.250	0.347	0.546	0.554	0.558

This table shows time-series regression results based on variations of Eq. (6). The dependent variable is the CSAD. A significantly negative coefficient for the squared market return indicates herding. Panels A and B only include observations during the week and the weekend, respectively. The weekend is defined as Saturday and Sunday UTC+0. The variables are as defined in Table 1, except CSAD which is here given in basis points. Newey and West (1987) standard errors are reported in parentheses, except for in the fixed effects model, where the standard errors are clustered by date. ***, **, * denotes significance at the 1%, 5%, 10%–level, respectively.

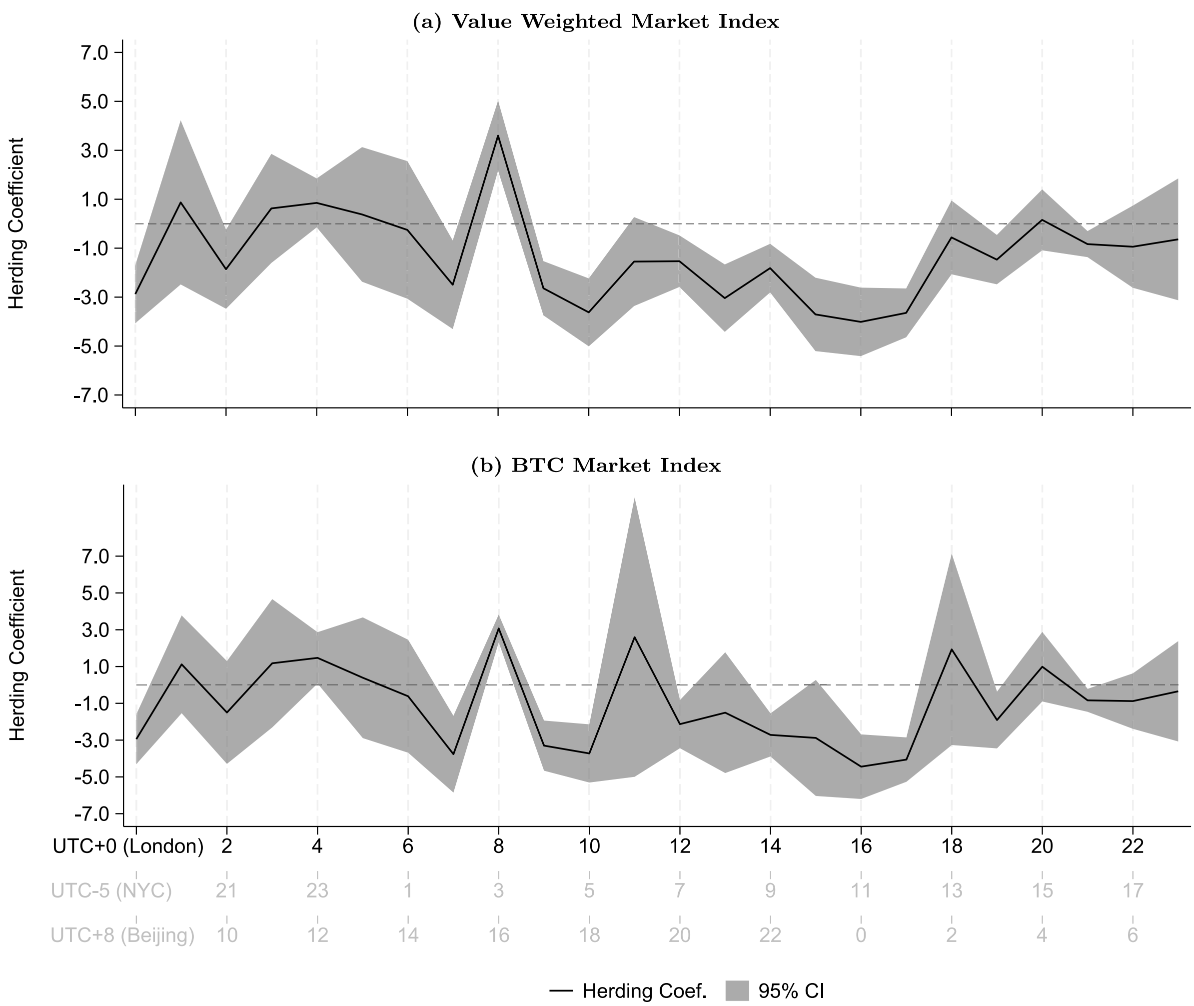

Fig. A.4. Intraday herding patterns using other market indices. These graphs shows the regression coefficients $\beta_{2,h}$ from estimating Eq. (7). In the top graph, the market index is a value weighted index of the currencies in our sample. In the bottom figure, we use Bitcoin returns as the market index. The dashed lines indicate the 95% confidence interval for the coefficient estimate based on Newey and West (1987) standard errors.

Table A.4
Herding during all market states with intraday FE.

	(1)	(2)	(3)	(4)	(5)
Panel A: Intraday fixed effects					
|Market Return|	0.189***	0.187***	0.194***	0.194***	0.186***
	(27.44)	(27.41)	(27.42)	(27.43)	(26.97)
Market Return^2	−0.878***	−0.837***	−0.971***	−0.971***	−0.832***
	(−4.78)	(−4.63)	(−5.26)	(−5.26)	(−4.57)
Trading Vol.	0.002***	0.002***	0.002***	0.002***	0.002***
	(4.76)	(4.33)	(6.31)	(6.29)	(4.50)
Blockchain Trans.	−0.161***	−0.185***	−0.070***	−0.071***	−0.163***
	(−15.92)	(−15.72)	(−6.98)	(−6.93)	(−13.19)
Search Vol.$_{Level}$	0.164***	0.186***			0.147***
	(21.68)	(21.37)			(16.82)
Search Vol.$_{Dispersion}$		0.112***			0.081***
		(7.29)			(5.11)
Reddit Posts$_{Level}$			0.158***	0.158***	0.046***
			(18.05)	(18.03)	(5.46)
Reddit Posts$_{Dispersion}$				0.017	0.027
				(0.89)	(1.55)
Date FE	–	–	–	–	–
Intraday FE	✓	✓	✓	✓	✓
Observations	40 799	40 799	40 799	40 799	40 799
Adj.R^2	0.324	0.328	0.307	0.307	0.331
Panel B: Date and intraday fixed effects					
|Market Return|	0.140***	0.140***	0.140***	0.140***	0.140***
	(23.47)	(23.53)	(23.31)	(23.31)	(23.39)
Market Return^2	−0.527***	−0.527***	−0.527***	−0.526***	−0.525***
	(−2.87)	(−2.89)	(−2.85)	(−2.86)	(−2.87)
Trading Vol.	0.003***	0.003***	0.003***	0.003***	0.003***
	(11.08)	(10.95)	(10.99)	(10.91)	(10.67)
Blockchain Trans.	0.125***	0.123***	0.121***	0.120***	0.114***
	(6.34)	(6.24)	(6.17)	(6.15)	(5.89)
Search Vol.$_{Level}$	0.024***	0.048***			0.045***
	(5.58)	(7.52)			(7.14)
Search Vol.$_{Dispersion}$		0.056***			0.053***
		(5.18)			(4.98)
Reddit Posts$_{Level}$			0.057***	0.062***	0.060***
			(8.29)	(8.81)	(8.61)
Reddit Posts$_{Dispersion}$				0.068***	0.066***
				(6.86)	(6.75)
Date FE	✓	✓	✓	✓	✓
Intraday FE	✓	✓	✓	✓	✓
Observations	40 798	40 798	40 798	40 798	40 798
Adj.R^2	0.549	0.550	0.550	0.551	0.552

This table shows time-series regression results based on variations of Eq. (6). The dependent variable is the CSAD. A significantly negative coefficient for the squared market return indicates herding. In Panel A, intraday fixed effects for every one hour window of the day are included. In Panel B, date fixed effects are included in addition to the intraday fixed effects. The variables are as defined in Table 1, except CSAD which is here given in basis points. The standard errors are clustered by date. ***, **, * denotes significance at the 1%, 5%, 10%–level, respectively.

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