Intraday Herding and Attention Around the Clock†

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Abstract

This paper analyzes return herding at the intraday level in the decentralized cryptocurrency market with its continuous, around the clock trading and dominance of retail investors. We first document substantial herding behavior that is stronger when market returns are positive. Herding is negatively related to both the level and cross-sectional dispersion of investor attention. Moreover, there are pronounced intraday variations: Market return 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.

Keywords: Herding, Investor Attention, Attention Dispersion, Cryptocurrency, Bitcoin
JEL: G10, G12, G15

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1. Introduction

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

In this paper, we analyze return 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 differences of herding behavior throughout the day. Additionally, because there is relatively little fundamental information available, 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, the investor base of cryptocurrencies is different from other, more mature asset classes, making an analysis of how investor attention affects herding especially relevant (Dyhrberg et al., 2018).

While there is already a rich literature on herding in cryptocurrencies, there is no consent about the size or even presence of such behavior. By reconsidering the question of herding, particularly in the market for cryptocurrencies, we make several contributions. Firstly, using intraday data allows us to detect short-term herding by investors, which may not be possible 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 investor attention and its cross-sectional dispersion affect return herding while controlling for general trends in the market.

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 return herding to the overall demand in transactions on the blockchains of the currencies while disentangling long-term and short-term effects.

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 differences in both the time series and cross-section of informational demand are important factors for herd behavior. Moreover, we uncover pronounced intraday variations in investor herding: Market return 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.

The remainder of this paper proceeds as follows: Section 2 discusses the prior literature and 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. Literature and Hypotheses

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 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.

2.1. Herding in Established Financial Markets

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 equity return dispersion around the market return. While both do not find evidence for significant herding in the United States, Chang et al. (2000) observe the behavior in other countries. Regarding other asset classes, investor herding has been analyzed for exchange traded funds (Gleason et al., 2004), foreign exchange (Park, 2011), corporate bonds (Cai et al., 2019), and options (Bernales et al., 2020).

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), but also documented for institutional investors (Sias, 2004; Kremer and Nautz, 2013). In line with theoretical reasoning, it appears to be linked to public news such as macroeconomic announcements (Galariotis et al., 2015). 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).

2.2. Herding and Intraday Patterns in Cryptocurrencies

The literature looking specifically at herding in cryptocurrencies so far does not agree on the prevalence of the behavior. Bouri et al. (2019) notice significant and time-varying herding behavior when accounting for structural breaks in the data, where herding is positively related to economic policy uncertainty. 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. da Gama Silva et al. (2019) find overall weak evidence of herding. Depending on the methodology, herding is detected during down markets. In contrast, Kallinterakis and Wang (2019) and Ballis and Drakos (2020) conclude that herding is more pronounced during up markets. Using the largest cross-section of cryptocurrencies so far, 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 investor. For example, media attention related to Bitcoin increases herding, while high equity returns are associated with reduced herding. Yarovaya et al. (2021) is the only other study we are aware of that uses intraday cryptocurrency data. However, there are substantial differences as they do not study the intraday patterns of herding behavior but instead focus on the effects of the COVID-19 pandemic.

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 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 intraday price clustering in three cryptocurrencies, though the clustering is relatively stable throughout the day. Baur et al. (2019) do not find 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 but instead conclude that much of trading is driven by human traders. Aslan and Sensoy (2020) highlight that conclusions regarding the efficiency of cryptocurrency prices depend on the sampling frequency, which further motivates our study.

2.3. Investor Attention and Price Formation

We link investor herding to their attention, which is not directly observable. Many proxies for investor attention have been proposed in the literature, for example based on extreme returns. However, a more direct proxy for investor attention and deliberate information demand is constituted 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. Furthermore, abnormal search volume 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.

As we do in 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. Since it is also associated with a reduction in order sizes, they posit that the increase in trading activity is driven by retail traders who mistakenly think they are informed. Using intraday Twitter data to measure investor sentiment instead of search volume, Behrendt and Schmidt (2018) find a significant effect on the volatility of stocks mentioned in tweets, though economically the effect is small.

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), though these platforms have also been investigated in the context of conventional assets. Antweiler and Frank (2004) analyze messages posted to two internet stock message boards and find that messages regarding particular stocks lead increases in volatility, although the effect on returns is overall weak. The stronger 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) relate various online and social media factors to cryptocurrency prices. Among their factors are Google search volume and posts and comments on Reddit, a message board popular among cryptocurrency traders. They find strengthening correlations between the factors and prices during periods of bubble-like price increases. Using internet search volume as an attention proxy, Guilherme et al. (2019) show that the sizable speculative bubble for Bitcoin and Ethereum was caused by dramatic price increases attracting the attention of noise traders, mostly uninformed retail investors, which contributed to herding during the bubble. Likewise, 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) investigate how informative signals derived from various exogenous factors impact herding intensity. They find that behavioral patterns of Bitcoin-related tweets and Google search volume amplify return herding.

While most studies focus on the level of investor attention, few look at cross-sectional relationships of attention between individual assets. Drake et al. (2017) introduce the concept of attention comovement, 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 comovements 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 apply 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.

2.4. Hypothesis Development

In this part we develop the hypotheses which are then tested below. There are several reasons to expect investors to herd around the market in cryptocurrencies, which leads us to our first hypothesis. With relatively little fundamental information available, it is likely that investors follow the market more strongly than in conventional financial markets.

[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).

Similarly, because the market for cryptocurrencies is still developing, there might be more 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).

Hypothesis 1: Cryptocurrency investors show herding around market returns.

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., 2020). While it is mostly hypothesized that herding is more pronounced during times of market stress, the same might not always 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. Guilherme et al., 2019). We are hence agnostic on the direction of the effect because it is ultimately an empirical question.

Hypothesis 2: Herding is asymmetric and differs between market states.

Cryptocurrencies trade globally and for various reasons: There is a plethora of different exchanges all around the world to trade cryptocurrencies against each other or against fiat currencies. Additionally, cryptocurrencies can sometimes be used to pay for goods and services or for laundering money. In any case, the demand for transactions in cryptocurrencies is likely to fluctuate over time. 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, which would decrease aggregate investor herding (see e.g. Ajaz and Kumar, 2018).

Hypothesis 3: Transaction activity on the blockchains is related to herding activity.

High levels of investor attention might be associated with lower market herding because investors seek — and find — more idiosyncratic information. This especially holds when attention is measured via internet search volume since it is a direct proxy for informational demand. Likewise, informational supply as measured by posts on internet message boards is positively associated with investor attention, which in itself is not directly observable. 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 of 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 the traders are located.

Hypothesis 5: Herding activity varies throughout the day.

3. Methodology and Data

3.1. Cryptocurrency Data

We obtain hourly intraday data on 13 cryptocurrencies: Bitcoin (BTC), Litecoin (LTC), Ethereum (ETH), Ethereum Classic (ETC), Monero (XMR), Ripple (XRP), Zcash (ZEC), Cardano (ADA), Dash (DASH), NEO, OMG Network (OMG), Waves (WAVES), and Stellar (XLM). For all exchange rates we use USD as the quote currency. As of the end of 2020, these currencies represent about 85% of the total cryptocurrency market capitalization. The sample spans from July 1st, 2017, to November 20th, 2020.

Data quality and reliability is a particular concern when analyzing cryptocurrency markets. For example, Alexander and Dakos (2020) 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 Bittrex, 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. We download the data from cryptodatadownload.com, which in turn obtains the trade data by connecting to the exchanges' application programming interfaces (APIs). Data from this provider has been used in the study by Alexander and Dakos (2020) and suggested for use by Brauneis et al. (2021).

While we mostly take trading data from Bittrex, we fill in some missing prices using data from Bitfinex. The exchanges generally have very similar prices. Across all currencies, the correlation of prices (where available) betweeen the two exchanges is never less than 99.96%. Likewise, differences in returns are minuscule. Nonetheless, due to potential differences in price levels arising from trading fees or other exchange-specific characteristics, we require returns to be based on prices of one exchange only. Reassuringly, we obtain very similar results when using only Bittrex data.

To additionally verify that the Bittrex 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 0.69% (0.43%) 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 price differs by more than 10% from the coinmarketcap.com prices. Alternatively requiring the hourly prices to fall within daily high and low prices from coinmarketcap.com leads to similar results below.[2]

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

[2]However, note that the coinmarketcap.com data is not necessarily better when the datasets disagree.

market portfolio:

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

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. We require the market index to be based on at least five currencies at each point in time, but typically this number is substantially larger. On average, about twelve of the 13 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, except for OMG which runs on a second layer of Ethereum. 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 to the market level:

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

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 typically use the full name of the currency, unless the name does not unambiguously return results related to the currency. In those cases, we either use the ticker or the ticker combined with the word “coin”. The keywords are OMG coin, NEO coin, Waves coin, XLM, Dash coin, Ethereum Classic, Cardano, Monero, Zcash, Litecoin, Ripple, Ethereum, and Bitcoin. 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.

Our measure of market-wide search activity and thus attention is then the average of the logarithms of the appropriately scaled search volume across all currencies that are part of the market portfolio for a given hour:

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

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:

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

We further obtain data on messages posted on Reddit as a proxy for information supply. While the platform fosters discussions on any number of topics, it is especially popular with retail and cryptocurrency investors (Phillips and Gorse, 2018). Using the same keywords as for the search volume above, we use the Pushshift API (Baumgartner et al., 2020) to count the number of new submissions and comments that contain a given keyword during each one hour window of the sample. 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.

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.

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

CSAD itself is not yet a measure of return herding, 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 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 conditional CAPM would predict a linear relationship between return dispersion and market returns. However, if there is herding during periods of market stress, return dispersion will decrease in the market return or at least increase at a decreasing rate.

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

$$\begin{aligned} \text{CSAD}_t = \alpha &+ \beta_1 |R_{m,t}| + \beta_2 R_{m,t}^2 \\ &+ \beta_3 \text{TradingVol}_t + \beta_4 \text{BlockchainTrans}_t \\ &+ \beta_5 \text{SearchVol}_t + \beta_6 \text{RedditPosts}_t \\ &+ \sum\nolimits_d \tau_d D_{(t\in d)} + \varepsilon_t \end{aligned} \tag{1}$$

where $D_{(t\in d)}$ indicates the date d and thus gives day-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 as in the first line. We then include additional variables related to trading volume and blockchain activity. 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. *BlockchainTrans* captures the transaction activity in the currencies of the market portfolio. *TradingVol* is the hourly trading volume at Bittrex 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. Finally, the use of intraday data allows us to add fixed effects for every day in the sample. Importantly, when including date fixed effects, the identification of herding behavior comes from its intraday variation. The fixed effects thus allow us to control for general trends in the data.

Following Chang et al. (2000), we repeat these regressions separately for up and down markets 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 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.

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

$$\mathrm{CSAD}_t = \alpha + \sum_{h=0}^{23} \beta_{1,h} \left| R_{m,t} \right| D_{h,t} + \sum_{h=0}^{23} \beta_{2,h} R_{m,t}^2 D_{h,t} + \varepsilon_t \tag{2}$$

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 54 basis points. For comparison, the time series average absolute deviation of the hourly market return from its mean is about 61 basis points. Market return volatility and cross-sectional dispersion are

Table 1: Descriptive Statistics

	Mean	SD	Min	P5	P50	P95	Max	Skew.	Kurt.	N
***Panel A:** Full Sample*										
CSAD	0.54	0.33	0.07	0.21	0.45	1.15	7.03	2.6	17.9	29,083
Market Return	−0.01	0.98	−11.16	−1.47	0.02	1.33	11.07	−0.6	15.5	29,083
Trading Volume	1.55	3.64	0.00	0.08	0.41	6.69	69.42	6.0	54.6	29,083
Blockchain Transactions	3.10	0.30	1.92	2.58	3.12	3.55	4.55	−0.3	2.9	29,083
Search $\text{Volume}_{\text{Level}}$	2.32	0.53	1.43	1.75	2.19	3.48	4.62	1.7	6.3	29,083
Search $\text{Volume}_{\text{Dispersion}}$	0.42	0.11	0.05	0.24	0.41	0.60	1.03	0.4	4.1	29,083
Reddit $\text{Posts}_{\text{Level}}$	1.94	0.61	0.00	1.13	1.85	3.12	4.40	0.8	4.1	29,083
Reddit $\text{Posts}_{\text{Dispersion}}$	1.12	0.22	0.03	0.70	1.14	1.42	2.01	−0.9	4.7	29,083
***Panel B:** Up Markets*										
CSAD	0.55	0.34	0.07	0.21	0.46	1.17	7.03	2.8	22.2	14,991
Market Return	0.58	0.70	0.00	0.03	0.38	1.84	11.07	3.6	25.4	14,991
Trading Volume	1.52	3.49	0.00	0.08	0.40	6.55	49.18	5.5	43.6	14,991
Blockchain Transactions	3.11	0.30	1.92	2.58	3.13	3.56	4.43	−0.3	2.8	14,991
Search $\text{Volume}_{\text{Level}}$	2.33	0.53	1.43	1.75	2.19	3.49	4.62	1.7	6.2	14,991
Search $\text{Volume}_{\text{Dispersion}}$	0.42	0.11	0.05	0.24	0.41	0.60	1.01	0.4	3.9	14,991
Reddit $\text{Posts}_{\text{Level}}$	1.95	0.61	0.00	1.14	1.86	3.14	4.40	0.8	4.1	14,991
Reddit $\text{Posts}_{\text{Dispersion}}$	1.12	0.22	0.07	0.70	1.14	1.42	1.97	−0.9	4.7	14,991
***Panel C:** Down Markets*										
CSAD	0.52	0.31	0.07	0.21	0.44	1.12	3.75	2.3	11.3	14,092
Market Return	−0.64	0.83	−11.16	−2.18	−0.37	−0.03	−0.00	−3.6	24.5	14,092
Trading Volume	1.58	3.78	0.00	0.08	0.41	6.81	69.42	6.4	62.4	14,092
Blockchain Transactions	3.10	0.30	1.97	2.58	3.12	3.54	4.55	−0.3	2.9	14,092
Search $\text{Volume}_{\text{Level}}$	2.31	0.53	1.50	1.75	2.18	3.46	4.62	1.7	6.4	14,092
Search $\text{Volume}_{\text{Dispersion}}$	0.41	0.11	0.05	0.24	0.41	0.60	1.03	0.5	4.3	14,092
Reddit $\text{Posts}_{\text{Level}}$	1.94	0.60	0.00	1.13	1.85	3.09	4.35	0.8	4.1	14,092
Reddit $\text{Posts}_{\text{Dispersion}}$	1.12	0.22	0.03	0.71	1.14	1.42	2.01	−0.8	4.6	14,092

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. *Blockchain Transactions* is the equally weighted cross-sectional average of the log normalized number of transactions recorded on the blockchain within an hour. $Search\ Volume_{Level}$ is the equally weighted cross-sectional average of the log normalized Google search volume within an hour. Similarly, $Search\ Volume_{Dispersion}$ is its cross-sectional absolute deviation. $Reddit_{Level}$ and $Reddit_{Dispersion}$ 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.

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 value and the higher excess kurtosis. The opposite holds for trading volume which, while still similar on average during up and down markets, exhibits more extreme values for down 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. Herding at high(er) frequency

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. 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 Bittrex and the number of transactions recorded on the blockchains. For the exchange-specific trading volume we find a positive and significant coefficient. This can be interpreted to mean that the higher the aggregate demand to exchange these specific currencies (in particular against the USD), the less investors herd around the market. 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

Table 2: Herding at high(er) frequency

	(1)	(2)	(3)	(4)	(5)	(6)
|Market Return|	0.266***	0.209***	0.206***	0.161***	0.150***	0.148***
	(34.88)	(26.47)	(26.60)	(25.03)	(22.95)	(22.72)
Market Return^2	−1.539***	−1.588***	−1.530***	−0.572***	−0.738***	−0.738***
	(−8.40)	(−7.55)	(−7.30)	(−3.25)	(−4.06)	(−4.03)
Trading Vol.		0.035***	0.036***		0.025***	0.025***
		(20.41)	(21.50)		(11.39)	(11.13)
Blockchain Trans.			−0.155***			0.142***
			(−11.26)			(8.30)
Date FE	–	–	–	✓	✓	✓
Observations	29083	29083	29083	29083	29083	29083
Adj.R^2	0.239	0.374	0.394	0.553	0.572	0.574

This table shows time-series regression results based on variations of Equation 1. 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.

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 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. In a way, 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 before, more transactions were associated with less return dispersion, the opposite is true when considering only intraday variations. 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 the different cryptocurrencies is associated with lower levels of herding around the market, contrary to the results found for stock markets by Hsieh et al. (2020). The magnitude of the return herding coefficient is reduced by about 40% while the adjusted R^2 increases slightly, indicating that investor information demand is indeed an important determinant of investor herding. Similarly, we find a positive effect of search volume dispersion on return dispersion which remains when we also include the level of search volume. In fact, the effects of these attention measures are stronger when both are included in the model simultaneously, which shows that they capture two different dimensions of attention. This is further verified by the untabulated mildly negative time-series correlation of -23% between the level and dispersion of search volume. Interpreting these 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.

We then turn to the investor attention measures capturing the supply of information, where we proceed similarly as with search volume. In models 4–6, we include the level and dispersion of the number of posts on the message board Reddit regarding the different cryptocurrencies. The results generally mimic those found for search volume, though they are

Table 3: **Herding, Attention, and Information Demand and Supply**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: *No Fixed Effects*							
|Market Return|	0.184*** (27.38)	0.203*** (26.93)	0.179*** (27.93)	0.200*** (26.64)	0.207*** (26.62)	0.198*** (26.65)	0.178*** (27.83)
Market Return^2	−1.063*** (−5.92)	−1.542*** (−7.31)	−1.043*** (−5.91)	−1.397*** (−6.91)	−1.536*** (−7.30)	−1.361*** (−6.75)	−1.026*** (−5.80)
Trading Vol.	0.016*** (8.97)	0.040*** (22.53)	0.018*** (10.92)	0.031*** (17.74)	0.037*** (21.37)	0.030*** (17.63)	0.018*** (10.88)
Blockchain Trans.	−0.133*** (−11.20)	−0.135*** (−11.62)	−0.110*** (−10.78)	−0.139*** (−10.17)	−0.154*** (−11.30)	−0.132*** (−9.97)	−0.105*** (−10.28)
Search Vol.$_{\text{Level}}$	0.191*** (19.08)		0.205*** (22.53)				0.195*** (20.69)
Search Vol.$_{\text{Dispersion}}$		0.477*** (14.19)	0.535*** (17.34)				0.526*** (17.17)
Reddit Posts$_{\text{Level}}$				0.059*** (10.65)		0.083*** (12.34)	0.022*** (4.70)
Reddit Posts$_{\text{Dispersion}}$					0.050*** (4.70)	0.130*** (9.82)	0.068*** (6.78)
Date FE	–	–	–	–	–	–	–
Observations	29083	29083	29083	29083	29083	29083	29083
Adj.R^2	0.438	0.418	0.468	0.402	0.395	0.408	0.470
Panel B: *Day Fixed Effects*							
|Market Return|	0.149*** (23.05)	0.148*** (22.78)	0.148*** (23.24)	0.148*** (22.77)	0.148*** (22.71)	0.148*** (22.78)	0.148*** (23.27)
Market Return^2	−0.755*** (−4.18)	−0.735*** (−4.04)	−0.755*** (−4.24)	−0.736*** (−4.03)	−0.735*** (−4.02)	−0.730*** (−4.00)	−0.748*** (−4.21)
Trading Vol.	0.024*** (11.02)	0.025*** (11.13)	0.023*** (10.99)	0.025*** (11.15)	0.025*** (11.11)	0.024*** (11.14)	0.023*** (10.99)
Blockchain Trans.	0.147*** (8.68)	0.141*** (8.30)	0.147*** (8.79)	0.131*** (7.50)	0.141*** (8.29)	0.121*** (6.84)	0.130*** (7.39)
Search Vol.$_{\text{Level}}$	0.223*** (11.28)		0.285*** (12.57)				0.281*** (12.50)
Search Vol.$_{\text{Dispersion}}$		0.144*** (6.19)	0.282*** (10.24)				0.281*** (10.23)
Reddit Posts$_{\text{Level}}$				0.014*** (3.31)		0.025*** (5.38)	0.021*** (4.79)
Reddit Posts$_{\text{Dispersion}}$					0.024*** (2.82)	0.045*** (4.86)	0.040*** (4.49)
Date FE	✓	✓	✓	✓	✓	✓	✓
Observations	29083	29083	29083	29083	29083	29083	29083
Adj.R^2	0.579	0.575	0.581	0.574	0.574	0.575	0.582

This table shows time-series regression results based on variations of Equation 1. The dependent variable is the CSAD. A significantly negative coefficient for the squared market return indicates herding. Panels A does not include fixed effect, whereas Panel B included 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.

smaller in magnitude. Both the level and dispersion of attention are significantly negatively associated with herding around the market return. 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 7, we include both groups of attention measures. While the magnitude of the coefficients for Reddit posts decreases, all coefficients stay significantly positive. 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.

In panel B we repeat the analysis including day fixed effects so that the identification comes from the intraday variation of 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, suggesting that long-term changes in herding behavior are partially explained by long-term changes in aggregate attention. The coefficient for the level of attention stays at a similar level and significance compared to the results without date fixed effects. This means that intraday variations in attention are also strongly related to herding behavior, which will be investigated in more detail below. Similarly, we find a significantly positive effect of intraday attention dispersion on return dispersion.

4.4. Herding across different Market States

Because several prior studies have proposed asymmetries in herding behavior in conventional markets (Chang et al., 2000; Chiang and Zheng, 2010) as well as in cryptocurrency markets (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 herd in both market states, but to different extents. Generally, we find herding in cryptocurrency markets to be stronger as prices increase. For down markets, all herding coefficients are negative, though only insignificantly so when controlling for intraday effects without controlling for trading volume. Our results thus agree with Ballis and Drakos (2020), who also find sig-

Table 4: Herding in Up and Down Markets

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: *Up Markets*						
|Market Return|	0.309***	0.240***	0.211***	0.199***	0.184***	0.183***
	(27.76)	(22.05)	(22.29)	(20.81)	(18.49)	(18.49)
Market Return^2	−2.069***	−1.889***	−1.372***	−0.930***	−1.085***	−1.081***
	(−6.28)	(−5.22)	(−4.12)	(−2.71)	(−2.96)	(−2.97)
Trading Vol.		0.037***	0.020***		0.031***	0.029***
		(17.94)	(8.26)		(10.76)	(10.50)
Blockchain Trans.		−0.135***	−0.092***		0.168***	0.158***
		(−7.57)	(−6.79)		(7.49)	(6.73)
Search Vol.$_{\text{Level}}$			0.189***			0.274***
			(15.06)			(9.66)
Search Vol.$_{\text{Dispersion}}$			0.539***			0.259***
			(13.68)			(7.10)
Reddit Posts$_{\text{Level}}$			0.018***			0.018***
			(3.14)			(2.83)
Reddit Posts$_{\text{Dispersion}}$			0.069***			0.041***
			(5.18)			(3.16)
Date FE	–	–	–	✓	✓	✓
Observations	14991	14991	14991	14989	14989	14989
Adj.R^2	0.244	0.385	0.454	0.529	0.556	0.563
Panel B: *Down Markets*						
|Market Return|	0.229***	0.176***	0.149***	0.130***	0.119***	0.120***
	(24.71)	(18.45)	(18.80)	(15.31)	(14.03)	(14.47)
Market Return^2	−1.044***	−1.129***	−0.662***	−0.259	−0.410*	−0.433**
	(−4.82)	(−4.87)	(−3.48)	(−1.15)	(−1.87)	(−2.05)
Trading Vol.		0.035***	0.017***		0.021***	0.020***
		(18.61)	(10.11)		(7.58)	(7.47)
Blockchain Trans.		−0.177***	−0.122***		0.117***	0.104***
		(−10.48)	(−10.05)		(5.21)	(4.55)
Search Vol.$_{\text{Level}}$			0.196***			0.279***
			(17.70)			(10.60)
Search Vol.$_{\text{Dispersion}}$			0.510***			0.282***
			(13.59)			(8.77)
Reddit Posts$_{\text{Level}}$			0.025***			0.022***
			(4.42)			(4.08)
Reddit Posts$_{\text{Dispersion}}$			0.066***			0.036***
			(5.28)			(3.25)
Date FE	–	–	–	✓	✓	✓
Observations	14092	14092	14092	14091	14091	14091
Adj.R^2	0.244	0.417	0.499	0.589	0.606	0.615

This table shows time-series regression results based on variations of Equation 1. 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.

nificant herding behavior by cryptocurrency investors in both up and down markets that is stronger when prices are increasing. When compared to conventional markets, our results resemble those found for many Asian equity markets in Chiang and Zheng (2010):

Significant herding in both market states, but 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.

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 asymmetric power ARCH model of Ding et al. (1993). The results are presented in Table A1 in the appendix and show that herding is more prominent during low volatility periods, agreeing with the result of Kallinterakis and Wang (2019). Nonetheless, we find significant herding in most specifications during high volatility periods as well. Finally, Table A2 in the appendix shows that differences in herding between weekdays and weekends are generally small.

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.

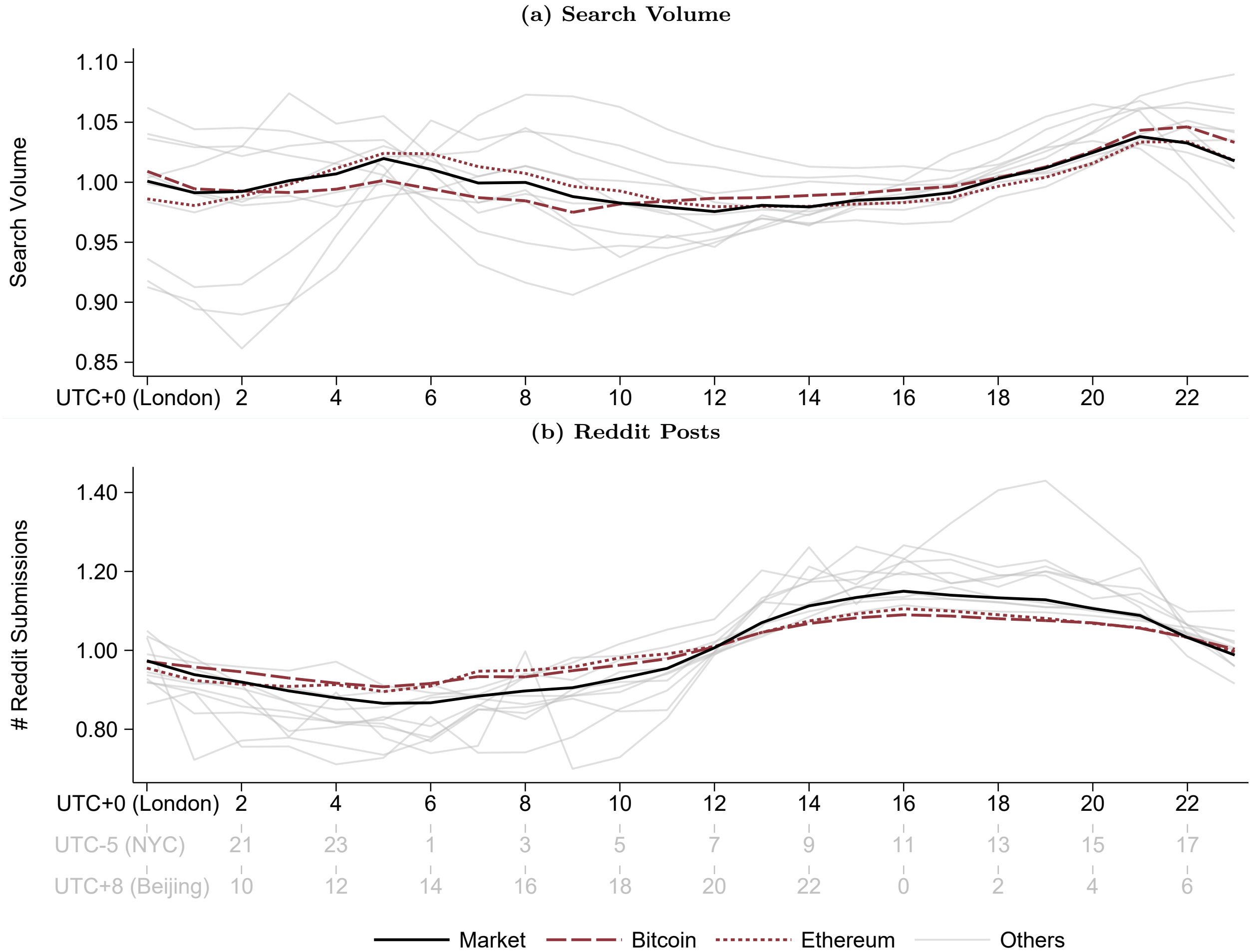
All timestamps used in this study are in Coordinated Universal Time (UTC), though this is simply a convention. Cryptocurrencies trade around the clock in a mostly anonymous, decentralized way, which makes it difficult to know where traders are located geographically. While we only consider trading against the USD, this does not necessarily imply that those traders are located in the United States.[3] 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.

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 6:00h and 8:00h, the full population is awake between 8:00h and 23:00h, and again half the population is awake between 23:00h and 01:00h (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 11:00h to 14:00h 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 intraday variation of the online population can be found in Figure A1 in the appendix.

Before analyzing intraday herding in detail, we turn to the intraday patterns in investor attention. Figure 1a shows how attention as measured by the level of search volume evolves throughout the day. We make several observations: First, each individual currency exhibits

[3] In fact, on April 10th, 2019, the New York State Department of Financial Services (2019) rejected the application of Bittrex to conduct virtual currency business in the state of New York. Before the rejection, Bittrex was operating under the safe harbor policy which allows operations while the license application is pending. After the rejection, Bittrex was required to immediately cease all operations in the state and wind down the business with residents of New York within 60 days, affecting approximately 35,000 clients.

Figure 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.

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 14:00 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.[4]

[4] 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

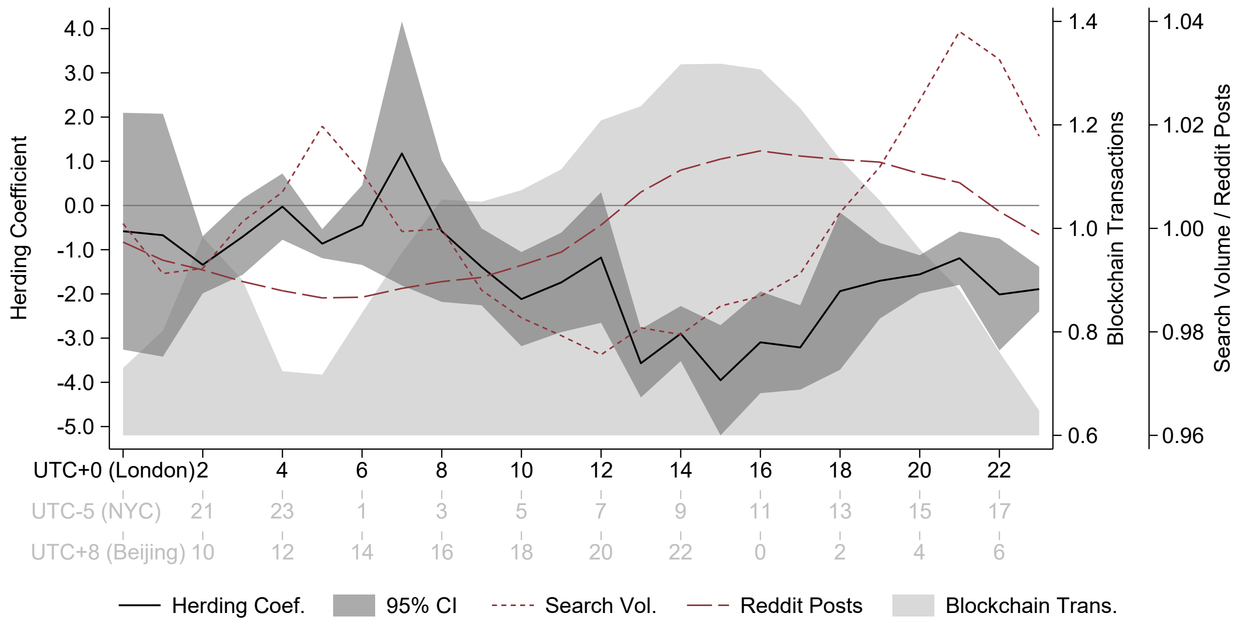
Similarly, Figure 1b shows the intraday development of the scaled number of Reddit posts which measures the information supply aspect of investor attention. Again, all individual currencies exhibit some form of intraday variation. The number of posts is generally higher during the second half of the (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 Equation 2. The results in Figure 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 except for the value at 12:00 are all statistically highly 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.

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 negative relation between search volume and herding, though the reaction of herding seems to slightly lag behind the changes in the attention measure during the second half of the day. Interestingly, at the intraday level, Reddit posts appear to be positively related to market return

of differences. The corresponding graph of search volume attention dispersion can be found in Figure A2 in the appendix.

Figure 2: Intraday Market Return Herding Patterns



This graph shows the regression coefficients $\beta_{2,h}$ from estimating Equation 2. 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 13 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 13 currencies. Search volume, Reddit posts, and blockchain transactions have been standardized by dividing by the respective overall means of the two time series.

herding.

There is a noteworthy difference between this analysis and the previous regressions. In the preceding section, we relate the explanatory variables to the cross-sectional dispersion of returns (as measured by the CSAD). Here we directly relate the market return herding coefficient that we obtain 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 market returns is affected by these other variables.[5] However, because of the resulting low number of observations, we abstain from performing any multivariate regressions to further investigate the interdependencies of these variables.

[5]For reference, Figure A3 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. This is expected since return dispersion can be partially (but not fully) explained by a rational asset pricing model with a market factor such as the CAPM.

Instead, we present simple correlation coefficients in Table 5. We confirm some of our previous conclusions in this alternative analysis that focuses solely on the intraday variation: Investor market return herding behavior is negatively related to both the level and dispersion of search volume as evidenced by the positive correlations with the return herding coefficient. This finding complements the analysis above because it not only shows that investors herd less when they are more attentive, but also that they rely less on market returns as a source of information when their attention is higher, which we could only indirectly show above. The correlations for the lagged values of search volume are slightly stronger for the level and slightly weaker for the dispersion. As seen in the graph, when only considering the average pattern throughout the day, Reddit posts are negatively correlated with the herding coefficient. We find strong correlations with herding for blockchain activity and trading volume, though expectedly these two variables are themselves highly positively correlated. The approximate number of potential investors being awake is positively, but only weakly correlated with herding activity. However, the correlation is substantially stronger for the one hour lagged online population, suggesting that the average herding cryptocurrency investor

Table 5: Intraday Correlations

	Herding Coef.	Search Vol. Level	Search Vol. Level$_{t-1}$	Search Vol. Disp.	Search Vol. Disp.$_{t-1}$	Reddit Level	Reddit Level$_{t-1}$	Reddit Dispersion	Reddit Dispersion$_{t-1}$	Blockchain Trans.	Trading Vol.	Online Pop.
Search Vol. Level	0.33											
Search Vol. Level$_{t-1}$	0.46	0.86										
Search Vol. Disp.	0.25	0.10	0.29									
Search Vol. Disp.$_{t-1}$	0.11	−0.18	0.10	0.79								
Reddit Level	−0.75	−0.02	−0.23	−0.34	−0.26							
Reddit Level$_{t-1}$	−0.66	0.19	−0.02	−0.37	−0.34	0.96						
Reddit Dispersion	−0.67	0.01	−0.10	0.14	0.22	0.83	0.78					
Reddit Dispersion$_{t-1}$	−0.64	0.08	0.01	−0.09	0.14	0.85	0.83	0.88				
Blockchain Trans.	−0.66	−0.69	−0.82	−0.05	0.02	0.59	0.37	0.52	0.35			
Trading Vol.	−0.83	−0.24	−0.26	−0.12	0.06	0.83	0.73	0.79	0.82	0.60		
Online Pop.	−0.13	−0.83	−0.73	0.17	0.29	−0.24	−0.49	−0.17	−0.32	0.56	0.06	
Online Pop.$_{t-1}$	−0.34	−0.83	−0.83	0.11	0.17	0.01	−0.24	0.02	−0.17	0.76	0.25	0.94

This table shows intraday correlations based on 24 hourly observations. *Herding Coef.* are the estimated regression coefficients $\beta_{2,h}$ from estimating Equation 2. The other variables are averages for every hour of the day based on the variables defined in Table 1.

is more likely to live further west or to be awake later during the day than other internet users.

The intraday patterns and correlations 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).

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 Figure A4 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 such an intraday factor could not fully explain the regression results above given that the magnitude of herding decreases substantially — but not fully — when including date fixed effects. Also, 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 A3 in the appendix shows that our results are indeed robust to including such intraday fixed effects. An exception is given by the level of Reddit posts, which is not consistently significantly positive in all specifications. In a similar vein, we verify that the intraday patterns found in Figure 2 persist even when we estimate the herding coefficients while controlling for all the variables included in Equation 1.

In the intraday correlation analysis in Table 5 we include the lagged values of attention and attention dispersion and find substantial correlations with the herding coefficient. For brevity we have not included these lagged values in the regression analyses above. However, untabulated results show that if added to the models in Table 2, the effect of lagged attention is substantially smaller than the concurrent one and mostly insignificant, especially when controlling for date fixed effects.[6]

Finally, we 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 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. Moreover, the bias would affect the level of herding but not the relative differences throughout the day or between different market states.

[6] Future research might investigate the lagged reaction of herding to attention more closely. Documenting the speed of herding adjustments after attention changes could push the analysis further towards claiming causality. However, measuring attention at increasingly shorter intervals proves difficult, especially when using Google search volume.

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 around the market and thus lead to reduced return 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 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 market return herding are negatively related while information supply, blockchain transaction activity and trading volume are positively correlated with the 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 chose to gather idiosyncratic information, so there is room for regulatory improvement assuming such information is principally available.

While in this paper we shed light on some of the determinants of intraday herding in cryptocurrency markets, further research is needed to 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.

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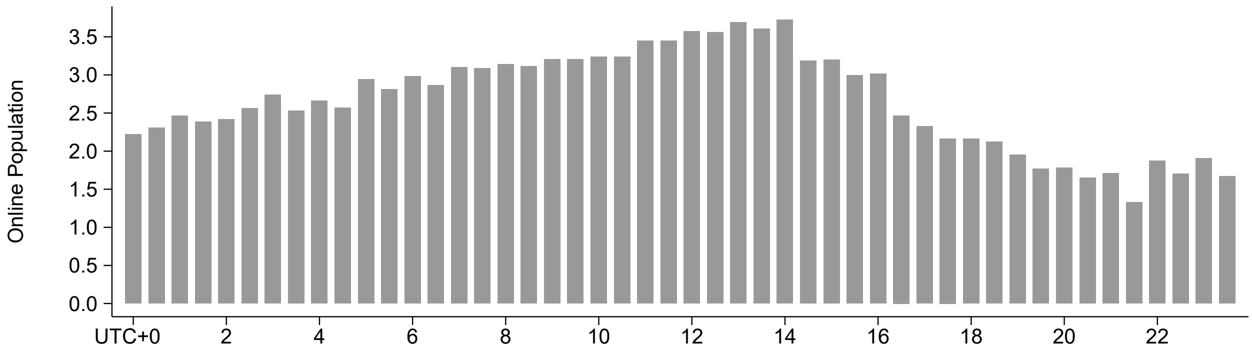
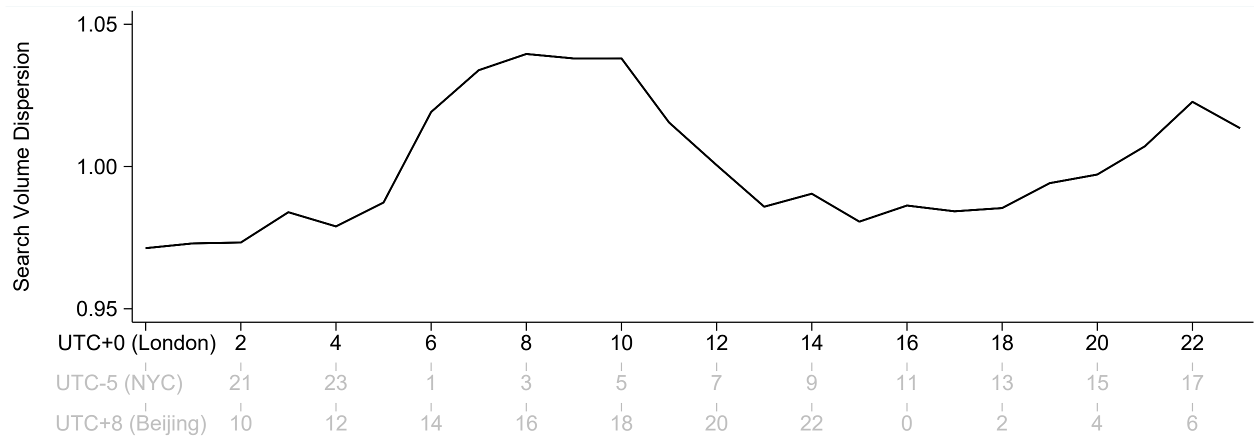
Appendix

Figure A1: Online Population throughout the Day



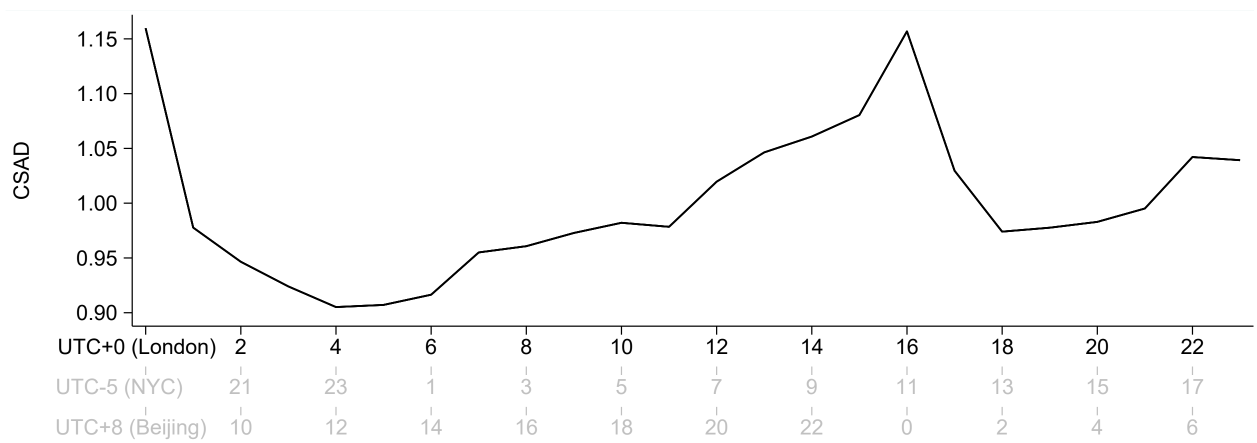
This graph shows an estimate of the worldwide population (in 1bn) with internet access that is awake during each 30 minute window from the perspective of UTC+0. The values are estimated by combining the percentage of the population with internet access (from the International Telecommunication Union) 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 6:00h and 8:00h, the full population is awake between 8:00h and 23:00h, and again half the population is awake between 23:00h and 01:00h (in local time).

Figure A2: 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.

Figure A3: 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.

Table A1: Herding during High and Low Market Volatility

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: *High Market Volatility*						
|Market Return|	0.235***	0.186***	0.160***	0.146***	0.137***	0.137***
	(24.40)	(19.13)	(18.97)	(16.60)	(15.39)	(15.78)
Market Return^2	−1.010***	−1.007***	−0.632***	−0.311	−0.468**	−0.498**
	(−4.77)	(−4.55)	(−3.16)	(−1.40)	(−2.07)	(−2.27)
Trading Vol.		0.029***	0.014***		0.021***	0.020***
		(15.66)	(8.10)		(7.72)	(7.49)
Blockchain Trans.		−0.163***	−0.113***		0.199***	0.187***
		(−7.46)	(−6.89)		(6.43)	(5.95)
Search Vol.$_{\text{Level}}$			0.197***			0.336***
			(13.57)			(7.61)
Search Vol.$_{\text{Dispersion}}$			0.588***			0.369***
			(12.49)			(6.52)
Reddit Posts$_{\text{Level}}$			0.011			0.018**
			(1.50)			(2.22)
Reddit Posts$_{\text{Dispersion}}$			0.045***			0.037**
			(3.11)			(2.42)
Date FE	–	–	–	✓	✓	✓
Observations	11457	11457	11457	11411	11411	11411
Adj.R^2	0.255	0.369	0.438	0.523	0.543	0.552
Panel B: *Low Market Volatility*						
|Market Return|	0.290***	0.214***	0.185***	0.184***	0.170***	0.169***
	(23.81)	(17.04)	(18.71)	(19.17)	(15.96)	(16.37)
Market Return^2	−2.574***	−2.406***	−1.653***	−1.282***	−1.591***	−1.582***
	(−7.09)	(−5.53)	(−4.85)	(−3.81)	(−4.04)	(−4.14)
Trading Vol.		0.043***	0.024***		0.028***	0.027***
		(19.04)	(9.78)		(7.94)	(7.89)
Blockchain Trans.		−0.163***	−0.115***		0.113***	0.105***
		(−10.77)	(−10.01)		(6.31)	(5.68)
Search Vol.$_{\text{Level}}$			0.184***			0.233***
			(16.73)			(9.78)
Search Vol.$_{\text{Dispersion}}$			0.453***			0.213***
			(13.87)			(8.04)
Reddit Posts$_{\text{Level}}$			0.023***			0.019***
			(3.96)			(3.44)
Reddit Posts$_{\text{Dispersion}}$			0.074***			0.034***
			(5.66)			(3.01)
Date FE	–	–	–	✓	✓	✓
Observations	17626	17626	17626	17590	17590	17590
Adj.R^2	0.186	0.404	0.481	0.558	0.583	0.589

This table shows time-series regression results based on variations of Equation 1. 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 A2: Herding during the Weekend

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: *During the Week*						
|Market Return|	0.260***	0.207***	0.181***	0.162***	0.151***	0.150***
	(28.64)	(22.64)	(23.26)	(19.61)	(18.16)	(18.53)
Market Return^2	−1.477***	−1.681***	−1.184***	−0.633***	−0.877***	−0.877***
	(−6.12)	(−6.26)	(−4.97)	(−2.66)	(−3.53)	(−3.61)
Trading Vol.		0.036***	0.019***		0.026***	0.024***
		(19.65)	(9.28)		(10.21)	(10.02)
Blockchain Trans.		−0.150***	−0.099***		0.141***	0.127***
		(−9.82)	(−8.41)		(6.81)	(5.87)
Search Vol.$_{\text{Level}}$			0.195***			0.282***
			(17.81)			(10.49)
Search Vol.$_{\text{Dispersion}}$			0.503***			0.294***
			(14.98)			(8.60)
Reddit Posts$_{\text{Level}}$			0.018***			0.022***
			(3.24)			(4.04)
Reddit Posts$_{\text{Dispersion}}$			0.065***			0.042***
			(5.63)			(4.13)
Date FE	–	–	–	✓	✓	✓
Observations	20718	20718	20718	20718	20718	20718
Adj.R^2	0.235	0.394	0.461	0.538	0.562	0.571
Panel B: *During the Weekend*						
|Market Return|	0.281***	0.205***	0.174***	0.161***	0.146***	0.145***
	(21.22)	(16.10)	(16.52)	(15.56)	(14.35)	(14.88)
Market Return^2	−1.652***	−1.191***	−0.737***	−0.476**	−0.502**	−0.528**
	(−6.28)	(−4.67)	(−3.71)	(−1.98)	(−2.13)	(−2.34)
Trading Vol.		0.036***	0.016***		0.021***	0.020***
		(11.30)	(8.08)		(4.66)	(4.66)
Blockchain Trans.		−0.182***	−0.124***		0.146***	0.141***
		(−7.92)	(−7.53)		(5.06)	(4.83)
Search Vol.$_{\text{Level}}$			0.194***			0.276***
			(13.16)			(6.63)
Search Vol.$_{\text{Dispersion}}$			0.567***			0.251***
			(10.23)			(5.63)
Reddit Posts$_{\text{Level}}$			0.029***			0.019**
			(3.45)			(2.53)
Reddit Posts$_{\text{Dispersion}}$			0.070***			0.034*
			(3.67)			(1.77)
Date FE	–	–	–	✓	✓	✓
Observations	8365	8365	8365	8365	8365	8365
Adj.R^2	0.245	0.396	0.490	0.588	0.601	0.608

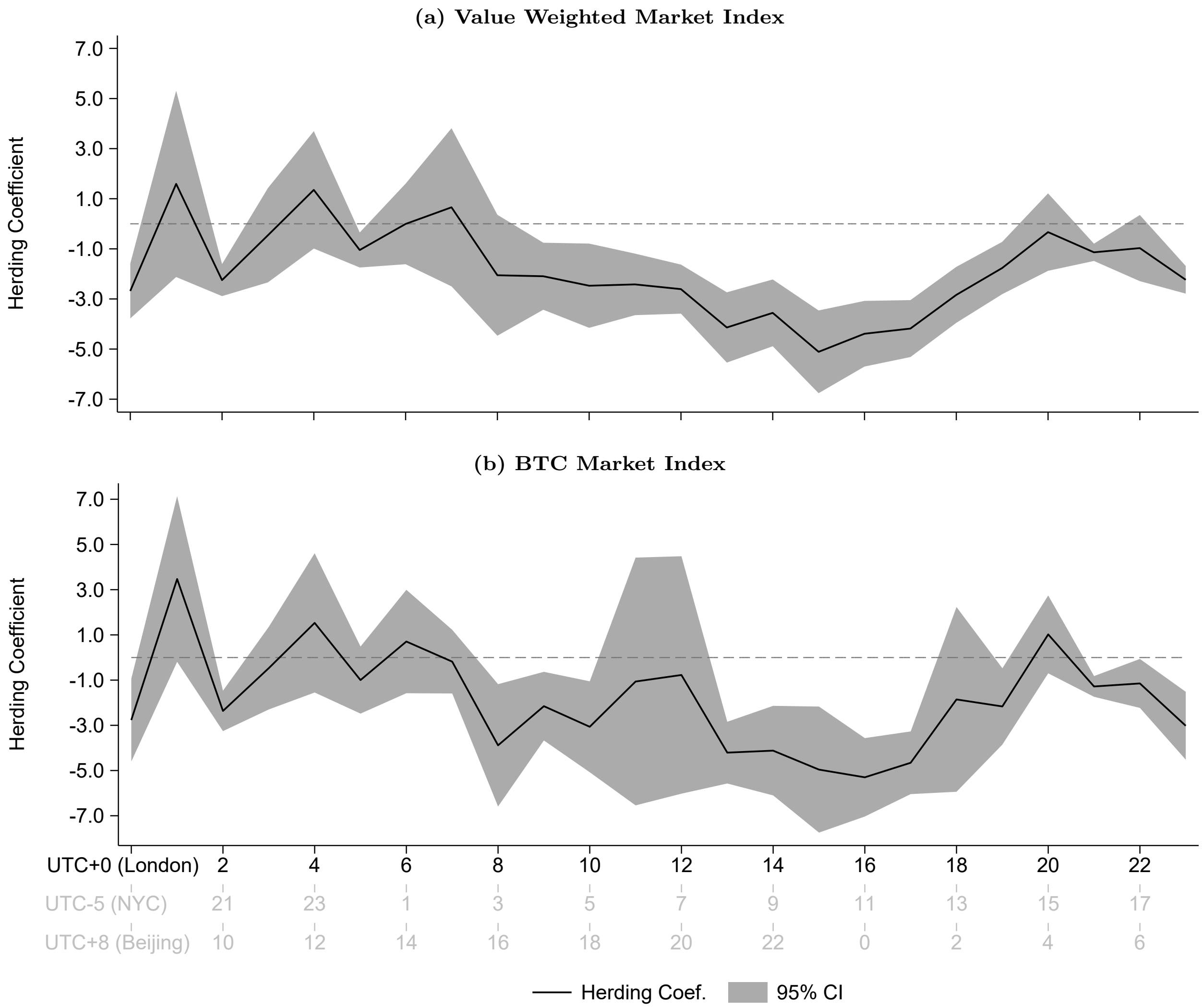
This table shows time-series regression results based on variations of Equation 1. The dependent variable is the CSAD. A significantly negative coefficient for the squared market return indicates herding. Panels A and B only include observations during the week and the weekend, respectively. The weekend 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.

Table A3: Herding during all Market States with Intraday FE

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: *Intraday Fixed Effects*							
|Market Return|	0.177***	0.199***	0.172***	0.197***	0.202***	0.194***	0.172***
	(25.21)	(25.35)	(25.82)	(24.85)	(24.83)	(24.82)	(25.87)
Market Return^2	−0.965***	−1.494***	−0.948***	−1.362***	−1.485***	−1.317***	−0.951***
	(−5.60)	(−7.39)	(−5.65)	(−6.98)	(−7.31)	(−6.81)	(−5.67)
Trading Vol.	0.015***	0.040***	0.017***	0.031***	0.037***	0.030***	0.018***
	(8.18)	(22.61)	(10.39)	(17.56)	(21.44)	(17.06)	(10.59)
Blockchain Trans.	−0.148***	−0.144***	−0.123***	−0.145***	−0.165***	−0.133***	−0.127***
	(−10.43)	(−10.16)	(−10.09)	(−8.58)	(−9.87)	(−8.09)	(−10.03)
Search Vol.$_{\text{Level}}$	0.200***		0.214***				0.225***
	(17.40)		(21.01)				(20.61)
Search Vol.$_{\text{Dispersion}}$		0.482***	0.542***				0.525***
		(12.74)	(15.55)				(15.32)
Reddit Posts$_{\text{Level}}$				0.055***		0.085***	−0.013**
				(7.61)		(9.01)	(−2.09)
Reddit Posts$_{\text{Dispersion}}$					0.044***	0.133***	0.034***
					(3.80)	(8.07)	(3.09)
Date FE	–	–	–	–	–	–	–
Intraday FE	✓	✓	✓	✓	✓	✓	✓
Observations	29083	29083	29083	29083	29083	29083	29083
Adj.R^2	0.447	0.424	0.478	0.405	0.400	0.411	0.479
Panel B: *Day and Intraday Fixed Effects*							
|Market Return|	0.143***	0.143***	0.142***	0.144***	0.143***	0.143***	0.142***
	(22.09)	(22.01)	(22.28)	(21.96)	(21.94)	(21.98)	(22.28)
Market Return^2	−0.687***	−0.689***	−0.678***	−0.692***	−0.690***	−0.690***	−0.676***
	(−3.81)	(−3.81)	(−3.84)	(−3.80)	(−3.79)	(−3.79)	(−3.83)
Trading Vol.	0.023***	0.024***	0.023***	0.024***	0.024***	0.024***	0.023***
	(10.96)	(11.07)	(10.94)	(11.06)	(11.03)	(11.05)	(10.93)
Blockchain Trans.	0.122***	0.165***	0.099***	0.167***	0.169***	0.165***	0.099***
	(5.28)	(7.08)	(4.36)	(7.12)	(7.19)	(7.06)	(4.38)
Search Vol.$_{\text{Level}}$	0.268***		0.366***				0.364***
	(12.92)		(14.72)				(14.69)
Search Vol.$_{\text{Dispersion}}$		0.163***	0.349***				0.345***
		(6.91)	(12.00)				(11.88)
Reddit Posts$_{\text{Level}}$				0.004		0.018***	0.007
				(0.89)		(3.33)	(1.44)
Reddit Posts$_{\text{Dispersion}}$					0.022***	0.039***	0.027***
					(2.63)	(3.83)	(2.73)
Date FE	✓	✓	✓	✓	✓	✓	✓
Intraday FE	✓	✓	✓	✓	✓	✓	✓
Observations	29083	29083	29083	29083	29083	29083	29083
Adj.R^2	0.584	0.580	0.588	0.579	0.579	0.579	0.588

This table shows time-series regression results based on variations of Equation 1. 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.

Figure A4: Intraday Herding Patterns using other Market Indices



These graphs shows the regression coefficients $\beta_{2,h}$ from estimating Equation 2. In the top graph, the market index is a value weighted index of the 13 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.