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Predictability of crypto returns: The impact of trading behavior[☆]

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ABSTRACT

We evaluate the ability of futures market participants' trading behavior decisions to predict cryptocurrency returns. We establish that cryptocurrency returns are driven and predicted by the trading behavior of speculative retail traders. We document that the net-short trading behavior of speculative retail traders is an economically strong and statistically significant determinant of cryptocurrency returns. Further, our findings indicate that changes in the net-short trading behavior remained strong even after controlling for other known predictors such as investor attention, crypto market uncertainty, sentiment, and prior returns.

1. Introduction

The predictability of cryptocurrency returns has recently attracted attention in the finance literature (Liu and Tsyvinski, 2021; Smales, 2022). The predictability of cryptocurrency returns has become a topic of interest in the finance literature due to its high volatility (Al Guindy, 2021) and unique characteristics, such as no discernible cash flow stream (Cheah and Fry, 2015; Smales, 2022). As cryptocurrencies are a relatively new and unregulated market, their returns have been known to exhibit high volatility and are often difficult to predict.[1] Lucey et al. (2022) suggest that the speculative nature of cryptocurrencies makes them particularly appealing to "amateur" retail investors who seem to interpret publicly available information in this market differently. The crypto market dominance by retail traders and a lack of traditional financial fundaments may be a critical reason behind the unexplained price divergence from its fundamental value, often observed during periods of high volatility and price fluctuations.[2] In the context of cryptocurrency markets, herding behavior is often observed during periods of high volatility and price fluctuations, as increased activity by retail traders leads to buying pressure and sizeable price reactions (Barber and Odean, 2008). Prior work by Röthig and Chiarella (2011) documents that retail traders tend to herd with speculators. This tendency makes the need to understand the trading behavior of speculators even more important, given the importance of cryptocurrency trading to retail investors. While significant attention has been paid to behavioral factors influencing the dramatic volatility in the volume and price of cryptocurrencies, there has not been a systematic analysis of the effects of speculative traders' positioning behavior on the direction of crypto returns. In this paper, we attempt to fill this gap.

Despite extensive academic research focusing on factors influencing investor behavior, there remains a gap in the role of trading behavior. We premise that the trading behavior of crypto retail traders picks up on the various factors in its influence on

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[1] The last fifteen years have seen a meteoric rise in cryptocurrency trading, particularly among retail traders. Cryptos are digital currencies operating on various blockchain technologies that allow a decentralized verification of transactions without a centralized custodian. Bitcoin, the most well-known of these digital assets, was the first to be introduced in a paper by Nakamoto (2008) and came into existence in 2009. Since then, the market for cryptocurrencies has evolved dramatically. Today the cryptocurrency market has more than 50 million active investors operating on more than 100 exchanges worldwide (Makarov and Schoar, 2020)

[2] Almeida and Gonçalves (2023) also argue that the crypto market is dominated by irrational traders whose investment decisions are based on market sentiment and whose trading behavior leads to speculative bubbles.

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2214-6350/

cryptocurrency returns. The nascent theoretical literature examining the influence of behavioral factors on the determination of cryptocurrency returns has suggested several potentially important behavioral factors. For instance, behavioral factors have found widespread use in explaining crypto's return dynamics in studies ranging from investor sentiment (Nie et al., 2020; Guégan and Renault, 2021; Drobetz et al., 2019; Akyildirim et al., 2021; Anamika Chakraborty and Subramaniam, 2021; López-Cabarcos et al., 2021), herding behavior (Papadamou et al., 2021; Bouri et al., 2019; Shrotryia and Kalra, 2021; da Gama Silva et al., 2019), news effects (Zhang et al., 2019; Flori, 2019; Domingo et al., 2020), investor attention (Li et al., 2021; Katsiampa, 2019), and momentum effect (Caporale and Plastun, 2020; Li et al. 2021b; Chu et al., 2020).

The motivation for our study is twofold. First, recent research has shown that despite the popularity of cryptos, there needs to be more research on return predictability relative to other traditional asset classes (Liu et al., 2021). Second, Almeida and Gonçalves (2023) argue that the identification of gaps in the investor behavior literature, given the progress of current behavioral finance research, is of extreme significance at this time (Corbet et al., 2019; Angerer et al., 2020).[3] We believe that trading behavior as a predictor can determine the direction of crypto returns. The lack of transparency and the absence of fundamental data in the cryptocurrency market can make it challenging for investors, in general, and retail investors, in particular, to make informed investment decisions. This condition allows behavioral biases to influence investment decisions and returns. Our study focuses on the behavior of speculative retail traders whose positioning in the Bitcoin futures market could potentially provide insights into the price formation process. We examine trading behavior using the weekly Commitment of Traders (COT) report issued by the U.S. Commodity Futures Trading Commission (CFTC). In addition to being widely used among market participants, the COT report has been used to study the behavior of traders in a wide cross-section of futures markets, including currency (Dunbar, 2023), agricultural (Sanders et al., 2009; Wang, 2001), bond (Dunbar and Owusu-Amoako, 2021a,b), metals (Bosch and Pradkhan, 2015; Mutafoglu et al., 2012), energy (Ederington and Lee, 2002; Sanders et al., 2004), domestic U.S. equities (Hong and Yogo, 2012; Dunbar and Jiang, 2020; Schwarz, 2012); Fed Funds (Piazzesi & Schwartz, 2008), and foreign exchange (Röthig and Chiarella, 2011; Tornell and Yuan, 2012) futures. We argue that the predictability of trading behavior could be influenced by aggregating information from behavioral factors such as investor sentiment, attention, and the fear of missing out on potential profits (Ballis and Drakos, 2020; Kaiser and Stöckl, 2020) and information asymmetry. In the cryptocurrency market, trading behavior is especially important because the market is relatively new, unregulated, and highly speculative.

Baur and Smales (2022) find that despite the progress of this literature on crypto return predictability, many empirical issues still need to be solved. For instance, some studies determine that speculators are momentum traders (Mutafoglu et al., 2012; Rouwenhorst and Tang, 2012; Sanders et al., 2004), while others, such as Wang (2003), reports the opposite. Second, there is evidence that speculators' trading positions are positively related to returns (Wang, 2001, 2004). However, Baur and Smales (2022) argue that there is still a need to determine whether the trading behavior of speculators exhibits forecasting ability. Several studies suggest that speculators cannot forecast returns or risk premiums (Gorton et al., 2012; Klitgaard and Weir, 2004; Sanders et al., 2009; Wang, 2003). Nevertheless, others demonstrate that knowledge of speculators' positions is instructive to investors (Piazzesi and Swanson, 2008; Schwarz, 2012), and movements in net positions are helpful predictors (Dunbar, 2023; Dunbar and Jiang, 2020).

Our contribution to the existing literature is twofold: First, our study shows that while the positionings of the speculative market participants have grown significantly over the past few years, the institutional side of the market has been lagging. We also find that changes in speculative retail traders' net short trading behavior are highly pro-cyclical and correlated with crypto market uncertainty, sentiment news, investor attention, and crypto returns. Movements in commodity market interest predict commodity returns. Second, we extend the existing behavioral literature on the importance of behavioral factors in determining cryptocurrency returns. New evidence documents that changes in speculative retail traders' net short positioning behavior predict crypto returns. Our main evidence is from the non-commercial traders in the Bitcoin futures market, which is relatively ideal for testing our hypothesis for two main reasons. First, speculative trading in cryptocurrencies, as evidenced by the strong demand for Bitcoin futures and the limited risk absorption capacity, tends to be more significant among non-commercial traders. Second, given the evidence in Röthig and Chiarella (2011) and Baur and Smales (2022) that retail traders tend to herd with speculators, speculative retail traders' trading behavior should hold important information on the direction of crypto prices among speculative retail investors. We find that, even after controlling for the other well-known behavioral factors, a standard deviation increase in the net trading behavior of speculative retail traders increases named crypto assets (BTC, ETH, XRP) by a weekly 0.62%, 0.93%, and 1.05%, respectively, and the broader crypto market by 1.03%, over our sample period, which is both economically large and statistically significant. The net short trading behavior remains a powerful predictor even after controlling for several other predictors, including investor attention, past crypto prices, sentiment, and crypto market uncertainty.

The remainder of the paper is organized as follows. Section 2 discusses the related literature, while Section 3 discusses the data used in this study. Section 4 presents our empirical results, and, finally, Section 5 concludes the study.

2. Literature review

Baek and Elbeck (2015) show that price changes of crypto assets such as Bitcoin are difficult to reconcile with any economic fundamentals, demonstrating an important role of speculation and sentiment in price formation. In line with this finding, Liu and Tsyvinski (2021) find that cryptocurrencies have very different risk–return tradeoffs compared to stocks, currencies, and precious metals and that their returns are determined by strong time-series momentum and investor attention. Feng et al. (2018) find a sensitivity to regulatory and market events. The speculative nature of the market is confirmed by the evidence of informed trading (Feng et al., 2018) and evidence of price manipulation (Griffin and Shams, 2019). Despite their speculative nature, there is evidence that cryptocurrencies have positive portfolio effects, at least over their short period of existence. Baur et al. (2018) find that returns from Bitcoin are uncorrelated with stock and bond returns—in regimes of both low and high market volatility. Dyhrberg (2016) confirms that Bitcoins allow for hedging against the Financial Times Stock Exchange Index and, to some extent, against exchange rates. Brière et al. (2015) go so far as to conclude that US investors should hold a portion of their wealth in Bitcoin because doing so would substantially improve the risk–return profile of their portfolios. Bouri et al. (2017) document smaller diversification effects, but in summary, the literature suggests that

[3] Almeida and Gonçalves (2023) argue for further research to investigate the herding behavior phenomena in the crypto market. We premise that this herding phenomenon influences speculators' trading behavior.

cryptocurrencies might play an important role in the portfolio selection of individual investors.

Continued growth in cryptocurrency returns in the coming years, particularly in Bitcoin, will undoubtedly continue to attract retail investors to the cryptocurrency market (see, for instance, Hackethal et al., 2022; Chaim and Laurini, 2019; Dyhrberg et al., 2018; Katsiampa, 2017; Kristoufek, 2020; Urquhart, 2018). Since cryptocurrency prices are not subject to the typical economic fundamentals that drive the returns in traditional financial assets, understanding the predictability of crypto return via the behavioral finance literature on the trading behavior of the crypto market's key participants should be highly relevant for the development of the cryptocurrency market and financial innovation.

A thorough review of the broad finance literature on crypto returns predictability reveals three budding strands. The first strand explores the role of general economic measures. Some studies, such as Li and Wang (2017), report predictability by economic measures. However, others, such as Ciaian et al. (2016), find no discernible predictability of crypto returns by these variables. The second strand in the literature explores the role of cryptocurrency-related fundamentals such as trading volume, volatility, and technological measures (e.g., hash rate). The overall results are mixed, with some studies finding predictability (Balcilar et al., 2017; Bouoiyour and Selmi, 2015), while others find unstable relationships that weaken over time (Marthinsen and Gordon, 2022; Kristoufek, 2020).[4] Since much of the more recent literature on cryptocurrencies, finds that prices are generally detached from economic fundamentals (Pieters and Vivanco, 2017; Koutmos, 2018), this has given rise to the third strand in the literature; which focuses on behavioral factors. If cryptocurrency prices cannot be explained using conventional asset pricing factors, they may be irrational (Gandal et al., 2018). Absent real economic fundaments, Almeida and Gonçalves (2023) argue that these behavioral influences on crypto investments lead irrational investors who base their investment decisions on social influence, herding mentality, media attention, and market sentiments, which lead to high trading and speculative bubbles. Evidence of herding behavior in the cryptocurrency market (Almeida and Gonçalves, 2023) supports the premise that "small" retail investors follow the actions of speculators in this market (Baur and Smales, 2022).[5]

Urquhart (2018) shows that investor attention to crypto prices is an important influence on the direction of prices, spurring a literature that explores this influence on cryptocurrency (Al Guindy, 2021; Bouri and Gupta, 2021; Sabah, 2020; Smales, 2022; Liu and Tsyvinski, 2021). However, there is a gap in the literature linking the behavioral literature to retail traders' behavior which could be directed by media attention or herding in financial markets. Building on the third strand of the literature, we argue that since retail traders are irrational in their behavior (noise traders), they will be influenced by a confluence of behavioral factors such as "attention", market sentiment, and herding with speculative traders thereby leading to changes in their net-short positionings in the Bitcoin futures market. Additionally, we further argue that since the Bitcoin futures market is characterized as being mainly driven by the activities of speculative retail traders, the positioning of these participants should be able to predict the direction of crypto prices. Further motivation for this viewpoint is in the theoretical framework of Gong et al. (2021), which illustrates that the trading behavior of market participants in the futures market is an effective channel by which information can be aggregated into the price formation process. They show that traders can adjust their beliefs and trading strategies in subsequent periods, generating updated prices. Notably, Gong et al. (2021) show that behavioral factors such as risk aversion and degree of rationality have a combined effect on the market's ability to aggregate the information needed to form good prices. Thus, speculative retail traders' net short trading behavior may be independent of any previously known behavioral factors or crypto predictors but be a strong determinant of crypto returns since it aggregates information across these other factors.

Our study contributes to this nascent fourth strand in the literature by adding the informativeness of trading behavior to the behavioral literature examining predictability in crypto returns (Chen and Chang, 2015; Park and Shi, 2017; Gong et al., 2021). Along these same lines, Hong and Yogo (2012) have documented that changes in transaction balances in futures markets are more informative than futures prices because information gets transmitted to prices with a lag, unlike changes in futures positions.

3. Data and methodology

For this study, we collected weekly data on our cryptocurrency sample from Coinmarketcap.com, a leading cryptocurrency price and volume data source. In light of the relatively recent introduction of the crypto market and the frequency of developments in the market, high-frequency weekly data has been widely adopted by studies to increase the amount of data (see also Wang et al., 2022; Al-Shboul et al., 2022; Smales, 2022; Liu et al., 2022; Zhang and Li, 2023; Anselmi and Petrella, 2023; Kim, 2022; Hui et al., 2020). Others, such as Long et al. (2021), also report that the enormous volatility in digital currency markets makes many outliers in the extremely short-term data (1-min, 30-min, or daily data). Consequently, Wang et al. (2022) state that weekly data are more suitable for analyzing digital currency variables. In addition, our choice of weekly data is influenced by our novel net short trading behavior predictor, which is only reported weekly. The weekly sample covers April 10th, 2018 (the first week of available data on Bitcoin futures on the CME) to September 1st, 2022, on Bitcoin-*BTC*, Ripple-*XRP*, and Ethereum-*ETH*. We also collected data of aggregate crypto returns from Bloomberg using the Bloomberg BGCI Galaxy crypto index-*Cret*. Market capitalization identifies these three cryptos as three of the major crypto assets. Bitcoin, for instance, has been identified as the most important cryptocurrency market leader (Wang et al., 2022; Corbet et al., 2020). Bitcoin's importance as market-leading crypto is reflected in its extremely high level of attention from the media and the general public (Wu et al., 2021). For each cryptocurrency, we compute time series of returns, as

$$r_t = \ln(P_t) - \ln(P_{t-1}), \tag{1}$$

Where r_t is the weekly change in the crypto asset, P_t is the crypto price. The crypto returns are then adjusted by the one-month T-Bill rate (rf) to get the excess returns. As a proxy for the Federal Reserve's monetary policy stance, we used the one-month T-bill rate (rf) as the risk-free benchmark rate, as is consistent in the finance literature (see Liu et al., 2022; Chen et al., 2022). The 1-month T-bill rate is subtracted from the returns of the study's crypto assets to produce the excess returns. We select the 1-month T-bill rate (rf), although intermediating financial protocols with lending rates are now emerging in the decentralized financing (DeFi) ecosystem.[6] Our choice of the 1-month T-Bill is in

[4] Corbet et al. (2018) document that the introduction of the futures market for Bitcoin futures appears to be associated with an increase in volatility in the Cryptocurrency market. Smales (2022) connects behavioral factors, such as investors' attention, to the increased level of volatility in crypto markets.

[5] Herding behavior is exhibited when a group of investors trade in the same direction for some period of time.

[6] https://www.coindesk.com/learn/aave-understanding-the-crypto-lending-platform/.

keeping with the prior literature and the limited availability of acceptable Defi-rates.

We also collect data on three measures of financial market uncertainty. These include the CBOE's volatility index (vix) as used in Bloom (2009), the economic news sentiment measure (news) of Shapiro et al. (2022), and the cryptocurrency uncertainty index (*Ucry_px*) of Lucey et al. (2022). The vix is popularly used as a forward-looking control measure for market expectations of near-term volatility and is a standard measure of uncertainty in financial markets (Rey, 2015; Akyildirim et al., 2020). A similar relationship has been established for Bitcoin (Griffith and Clancey-Shang, 2023; Bouri et al., 2017) and other cryptocurrencies (Akyildirim et al., 2020) during high financial market uncertainty periods. Interestingly a recent study by Kim et al. (2021) constructed a cryptocurrency volatility index (VCRIX).[7] However, we excluded the VCRIX because the data is currently not publicly available. The Lucey et al. (2022) crypto uncertainty index is designed to focus on price uncertainty in the cryptocurrency market. *Ucry_px* is constructed from the LexisNexis Business database rather than the approach of other uncertainty indexes with a greater focus on major newspapers.[8] This approach uses the index to aggregate information from a wider data source. The Shapiro et al. (2022) sentiment news index focuses on the economic sentiment embodied in the news. Unlike survey-based economic sentiment measures, this index relies on extracting sentiment from newspaper articles using computational text analysis. The news index's positive (negative) values reflect positive (negative) economic news sentiments. Consistent with Smales (2022), we compute the weekly change in each measure of uncertainty.

To control for investor attention, which is well documented in the literature, we collected data on the Google search volume index, which is obtained from Google Trends.[9] The Google Search trend methodology normalizes search queries so that numbers are scaled between 0 and 100 and where a measure between 0 and 100 indicates the level of search activity on a search topic within a given time frame. Since cryptos are traded globally, we use the global search volume option. Consistent with the earlier literature, we search using keywords such as "Bitcoin", "Ethereum", and "Ripple", denoting these as *btc_ai*, *eth_ai*, and *xrp_ai*, respectively (Da et al., 2011; Bijl et al., 2016; Urquhart, 2018; Smales, 2022). For the crypto and the bitcoin futures markets, we consider search volume for the generic search keywords "cryptocurrency" and "bitcoin futures", labeling these as *cret_ai* and *bf_ai*, respectively.

We plot the evolution of crypto prices and the Google search volume indexes for our crypto assets in Figs. 1 and 2, respectively. Fig. 1 shows a strong correlation among crypto prices, whist Fig. 2 shows a similarly strong correlation among the attention indexes. Both Figs. 1 and 2 indicate high crypto prices and attention appears to coincide around 2021.

For instance, surges in investor attention were recorded for April 30th, 2021, when *eth_ai* peaked at 100, 2-weeks later on May 14th, 2021, the attention index for *bf_ai* and BTC peaked at 100, *xrp_ai* also peaked at 100 on July 9th, 2021. These peaks appear to coincide with changes in prices. For our subsequent empirical analysis, we follow the precedent in Smales (2022) and compute the weekly change in each of the uncertainty and investor attention measures as

$$\Delta y_t = \ln(I_t) - \ln(I_{t-1}) \tag{2}$$

where Δy_t is the first difference or weekly change in uncertainty or investor attention measure, and I is the index value.

3.1. Bitcoin futures contracts

Bitcoin futures contracts began trading in late December of 2017 on the Chicago Board of Options Exchange (CBOE). The Chicago Mercantile Exchange (CME) commenced trading Bitcoin futures in early April 2018. Whereas the CME commenced trading Bitcoin futures in April 2018, the CBOE discontinued trading these contracts in May 2019. To ensure we had an appropriate sample to cover our study period, we only used data from the CME through December 2022. The Bitcoin futures contracts traded on the CME are cash settled with an underlying size of five Bitcoins. Contracts are listed to the nearest six months and are traded under the BTC product code 3. At the end of February 2023, the average daily trading volume was 5034 contracts (a notional value of $2.96 billion) with an open interest of 15,161 contracts. In contrast, there is substantial growth in futures market volume, which is well below the BTC spot market, which averages $44.12 billion per day in February 2023.

3.2. Trading positions

We collect weekly data on trader positions from the US Commodity Futures Trading Commission's (CFTC) Commitment of Traders' Report (COT) to construct our net-short positioning factor. This data is freely available from the CFTC's website.[10] CFTC regulation 18.04 requires that reportable futures traders complete "Form 40" detailing their current futures positions on Tuesdays of each week. The COT report provides data on the aggregated "long" and "short" positions held by non-commercial traders (considered to be speculators) and commercial traders (considered hedgers). The aggregated positions by trader group are reported after a 3-day lag in the weekly COT report on the CFTC's website (Piazzesi and Swanson, 2008).

Traders are generally classified as "hedgers" or "speculators" depending on their intended use of the futures contract. The CFTC records those market participants reporting futures positions for hedging purposes as "commercial traders", as defined in CFTC Regulation 1.3, 17 CFR 1.3(z). The determination of the trader classification is derived from information provided by traders on CFTC Form 40: Statement of Reporting Trader.[11] Conversely, participants in the "non-commercial trader" group are considered to be using futures for speculative or market-making purposes. These individuals have no business activities related to the futures market in which they might have a position and are not looking to take delivery of the underlying product or hedge costs. These individuals are taking positions in the market purely to seek a profit from market moves as a speculator. Finally, a third group listed as unreportable includes small individual transactions by groups too small to be tracked by the CFTC.

For our study, we assume that the speculative traders in the Bitcoin futures market are predominantly retail crypto market traders because of two key pieces of evidence. First, given that Lucey et al. (2022) have argued that the speculative nature of cryptocurrencies makes them particularly appealing to retail investors, who generally have a different interpretation of publicly available information relative to institutional investors. Second, given the observation by Röthig and Chiarella (2011) and Baur and Smales (2022) indicating that "small" retail traders tend to herd with speculators, it means that trading behavior in the non-commercial segment of the Bitcoin futures market is attractive to retail investors.

7 https://www.simontrimborn.de/data.

8 https://sites.google.com/view/cryptocurrency-indices/the-indices/crypto-uncertainty.

9 https://trends.google.com/trends/?geo=US.

10 https://www.cftc.gov/MarketReports/CommitmentsofTraders/HistoricalCompressed/index.htm.

11 https://www.cftc.gov/MarketReports/CommitmentsofTraders/ExplanatoryNotes/index.htm.

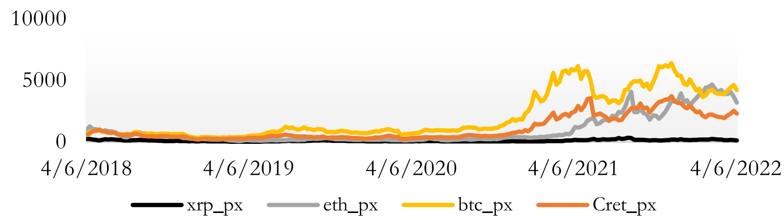

Fig. 1. Crypto prices. **Note:** This figure shows the price evolution of the three largest cryptocurrencies (Bitcoin, BTC; Ethereum, ETH; and Ripple, XRP along with the Bloomberg crypto index). The sample period is 04/10/2018 to 11/08/2022.

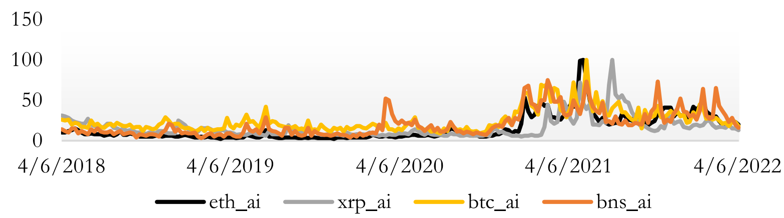

Fig. 2. Google attention index. **Note**: This figure depicts the key measures of investor attention and uncertainty used in this study. The measures are based on Google search volume (GSV) for each specific cryptocurrency together with the general cryptocurrency search term. The sample period is 04/10/2018 to 09/01/2022.

Each week the CFTC staff determines the appropriate trader classification for each trader. The CFTC notes that this determination changes from time to time. The regulator, however, warns that despite their best efforts, it is indeed possible that there may be the occasional misclassification of a trader. However, as discussed in Baur and Smales (2022), while there may be an incentive for some traders to misclassify themselves in some futures products (Ederington and Lee, 2002; Sanders et al., 2004), there are fewer incentives in the financial markets. This is because of the various other regulatory reporting requirements in this sector, which makes it more difficult for these participants to do so (Sanders et al., 2004). This provides confidence that the COT report is reasonably accurate in its trader types and aggregate data. In this study, we assume that retail traders, who are argued to dominate the speculative segment of the Bitcoin futures market, will be net-short in Bitcoin futures since they are using the product for speculative purposes. Since the COT report provides a convenient means to get the long and short positions of speculative traders, we use this data to construct the net-short trading positions (*bc_ns*) for the retail traders in week *t*. The net short positioning between the reported long and short positions in Bitcoin futures for each week is given as

$$bc_{ns,t} = \frac{ns_t}{\sum ln_t + \sum sh_t} \tag{3}$$

where ns_t is the net short Bitcoin futures position at time t of the non-commercial traders, and it is constructed as the total number of short (sh_t) minus long (ln_t) positions of non-commercial market participants at time t, respectively. Dividing by $ln_t + sh_t$ ensures that the measure does not change with a different sample (Baur and Smales, 2022; Dunbar and Owusu-Amoako, 2021a,b).

Figs. 3 and 4 show the total long/short for commercial and non-commercial traders and the net short positions of the non-commercial traders, respectively. Fig. 4 reveals that the speculative traders were net short in every period until about January 2022.

Fig. 4 also reveals the market dominance of speculative traders. The net short positions graphed in Fig. 4 show that noncommercial market participants began taking on huge net long positions ever since the Bitcoin futures market began operating. The graph illustrates that Bitcoin futures are important in providing access for retail traders to speculate in cryptocurrency markets. The graph shows they took on substantial net short positions from 2018 through early 2022, anticipating low or negative excess returns realized when the cryptocurrency market experienced major price declines (Russilillo, 2018; Gerrit and De Vynck, 2022). Hence, consistent with our observations in Figs. 1 and 2, the graph in Fig. 4 illustrates that speculative traders were increasing net short on and around 2020 when crypto prices and attention were high.

3.3. Methodology

The empirical methodology of our study evaluates the contemporaneous relationship between cryptocurrency returns, our measure of trading behavior (bc_{ns}), and the well-known measures of investor attention (*btc_ai*, *eth_ai*, *xrp_ai*, *cret_ai*, and *bf_ai*), uncertainty (*vix*, *Ucry_px*), and news sentiment (*news*). Rapach et al. (2013) state that a predictive Ordinary Least Squares (OLS) regression model in which the excess return of financial asset is evaluated against a set of lagged instruments is the standard framework for analyzing return predictability. We estimate several conventional predictive regression models to validate the statistical significance and economic importance of the trading behavior on cryptocurrency returns. We control for other well-known predictors such as investor attention, measures of uncertainty, past crypto returns and news sentiment. To evaluate the effect of the net positioning behavior on crypto returns our predictive regression model takes the form below

$$r_t = \alpha_t + \beta_1 bc_{ns,t-1} + \beta_2 x_{t-1} + \epsilon_t \tag{4}$$

where the dependent variables are crypto returns for cryptocurrency *i* for week *t* (*BTC*, *ETH*, *XRP*, *Cret*-return on the crypto market index). The right-hand side instruments are our proxy of retail traders' net poisoning trading behavior (bc_{ns}), and where x_t includes the controls for uncertainty (*vix*, *Ucry_px*), economic news sentiment (*news*), and investor attention (*btc_ai*, *eth_ai*, *xrp_ai*, *cret_ai*, and *bf_ai*). The OLS estimates are based on heteroskedasticity-robust standard errors (White, 1980) ε are Huber–White standard errors. Our results provide a greater understanding of the associations that are relevant for investors looking to optimize portfolios, and policymakers seeking to understand indicators of potential financial market instability.

Goyal and Welch (2008) document that, despite significant evidence of in-sample predictive ability, many well-known predictor variables fail to predict the risk premium out-of-sample. Consequently, to examine the robustness of our in-sample results, we next examine the out-of-sample predictive ability of the

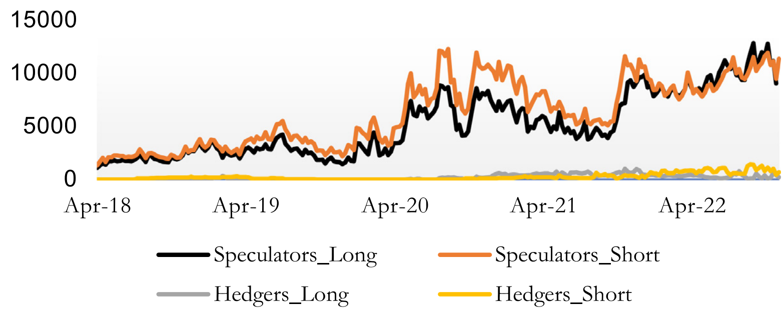

Fig. 3. Bitcoin long and short futures positions. Note: The graph displays the total long and short positions by non-commercial traders. This is the outright long and short BTC futures positions (number of contracts). Data source is the CFT's COT report. The sample period is 04/10/2018 to 09/01/2022.

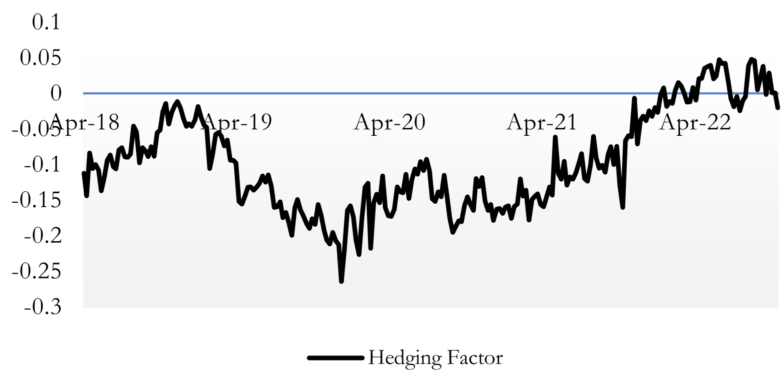

Fig. 4. Bitcoin net-short positions of speculators. **Notes**: The graph shows the net short positions of non-commercial traders normalized by total open interest. Net position is (Long–Short)/Open interest. The sample period is 04/10/2018 to 09/01/2022.
Source: CFTC COT report.

trading behavior innovation. We begin by computing a predictive regression forecast corresponding to each predictor as

$$\hat{r}_{t:t+h} = \hat{\alpha}_t + \hat{\beta}_t x_t \tag{5}$$

where $\hat{\alpha}_t$ and $\hat{\beta}_t$ are the OLS estimates of α and β, respectively in Eq. (4) based on the from the beginning of our sample to week t. The prevailing mean forecast of the average excess crypto return from the beginning of the sample through week t, serves as a natural benchmark. Rapach et al. (2013) claims that this forecast corresponds to the constant expected excess return model, Eq. (4) with $\beta = 0$, and implies that crypto returns are not predictable, as in the canonical random walk with drift model for the log of crypto prices. Following Rapach et al. (2013) we employ the Campbell and Thompson (2008) out-of-sample R^2 statistic (R^2_{OS}), which measures the proportional reduction in mean-squared forecast error (MSFE) for the benchmark forecasting model relative to the predictive model. To determine whether the predictive regression forecast delivers a statistically significant improvement in MSFE, the Clark and West (2007) statistic is used to test the null hypothesis that the prevailing mean MSFE is either less than or equal to the predictive regression MSFE ($R^2_{OS} \geq 0$) against an alternative hypothesis that the prevailing mean MSFE is better than the predictive regression MSFE ($R^2_{OS} > 0$).

4. Results and discussion

Descriptive statistics are presented in Table 1, and correlations of the data are presented in Table 2. A notable result in Table 1 shows that bc_{ns} had a positive skew relative to those of, *BTC*, *ETH*, making it an ideal diversification tool for these two major crypto assets. The corresponding standard deviations of crypto currencies were also quite high, with annualized volatilities of 71.25%, 93.53%, and 96.56% for, *BTC*, *ETH* and *XRP*, respectively.[12] These, along with the negative skews reported in Table 1, make investing in crypto assets extremely risky. Consistent with the earlier findings in Smales (2022), the results show that over the sample period, market participants were on an average net short -0.100 in their net positioning in Bitcoin futures. This level of net short positioning reflects the general direction of speculation in the market. Traders were on average net short given the level of volatility in the market. Another notable observation is the positive skew associated with $bc_{ns}(0.32)$. The positive skew indicates potential portfolio diversification benefits to the negative skew exhibited by $BTC(-0.07)$ and $ETH(-0.11)$.

As can also be seen in Table 1, the average excess returns on cryptocurrencies have been significantly positive over our sample, ranging from about 0.62% to 1.44% per week. For example, holding a net short position in the two-month-ahead bitcoin futures contract and holding it to maturity is a strategy that generated a return of approximately 8.29% per year on average. For a small investment this would explain why retail traders or speculators have amassed very large positions in futures contracts as reported in Fig. 3.

Table 2 presents some noteworthy results. First, the results show a significant connection between the trading behavior of retail traders (bc_{ns}), investors' attention in the Bitcoin futures market (Δbf_ai), financial market and crypto price uncertainty (vix), and news sentiment. The results reveal that the net-short trading behavior of traders (bc_{ns}) has an inverse relationship with the returns on the cryptocurrencies. Second, the correlation analysis shows that the net short trading behavior factor is positively related to Shapiro et al. (2020) economic news sentiment ($news$), cryptocurrency price uncertainty ($Ucry\_px$) and Bitcoin futures

[12] The weekly volatilities are annualized as follows $\sqrt{(52)} \times \sigma_{weekly}$. Two months ahead returns would be $(1 + weekly\,return)^8 - 1$.

Table 1
Summary statistics.

Variables	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis
BTC	1.00	0.97	38.36	−38.96	9.88	−0.07	4.79
bc_{ns}	−0.10	−0.11	0.05	−0.26	0.07	0.32	2.18
ETH	1.44	0.67	42.03	−45.36	12.97	−0.11	4.03
XRP	0.62	0.44	51.94	−44.71	13.38	0.39	4.82
C_{ret}	0.32	0.61	34.51	−55.83	11.23	−0.93	6.61
vix	0.02	−0.33	23.03	−18.74	4.01	0.70	11.04
ΔUcry_px	0.03	−0.03	4.55	−3.52	1.16	0.90	6.93
Δbtc_ai	−0.04	0.00	52.00	−47.00	9.54	0.56	10.63
Δeth_ai	0.00	0.00	56.00	−25.00	6.42	2.67	29.93
Δxrp_ai	−0.05	0.00	47.00	−43.00	7.11	1.51	23.66
Δbf_ai	0.03	−1.00	69.00	−34.00	10.43	1.59	12.84
Δcret_ai	−0.05	0.00	47.00	−30.00	6.62	2.37	24.34
Δnews	−0.10	−0.06	0.19	−0.67	0.19	−1.30	4.46

Note: The table presents the summary statistics that describe the weekly times series used in this study. The variables include the log excess returns over the 1-month T-Bill rate on Bitcoin-*BTC*, Ethereum-*ETH*, Ripple-*XRP*, and the Bloomberg BGCI crypto market index (C_{ret}) of the most liquid cryptocurrencies. The data also include a measure of the net-short positioning trading behavior of speculative retail traders (bc_{ns}) in the Bitcoin futures market; CFTC COT reports are used to construct the net positions of the speculative retail traders (normalized by total open interest). Popular control variables which are also included are the CBOE's implied volatility index (*vix*), cryptocurrency uncertainty index (UCRY), a measure of economic news sentiment (*news*), measures of investor attention in BTC-*bc_ai*, ETH-*eth_ai*, XRP-*xrp_ai*, C_{ret}-*cret_ai*, and Bitcoin futures-*bf_ai*. Sample period: April 10, 2018–September 01, 2022.

Table 2
Correlations between crypto returns, investor attention, uncertainty, and net short trading behavior.

	BTC	bc_{ns}	*ETH*	*XRP*	C_{ret}	*vix*	*Ucry_px*	*Δbtc_ai*	*Δeth_ai*	*Δxrp_ai*	Δbc_{ns}_ai	*Δcret_ai*	*Δnews*
BTC	1.000												
bc_{ns}	**−0.197**	1.000											
ETH	**0.779**	**−0.176**	1.000										
XRP	**0.799**	**−0.137**	**0.786**	1.000									
C_{ret}	**0.875**	**−0.178**	**0.924**	**0.842**	1.000								
vix	**−0.073**	**0.095**	**−0.086**	**−0.113**	**−0.104**	1.000							
Ucry_px	**−0.116**	**0.565**	**−0.095**	**−0.097**	**−0.125**	**0.223**	1.000						
Δbtc_ai	**0.120**	0.040	**0.169**	**0.137**	**0.137**	**−0.059**	**0.389**	1.000					
Δeth_ai	0.010	**0.197**	**0.138**	**0.069**	**0.091**	0.021	**0.541**	**0.743**	1.000				
Δxrp_ai	**0.142**	**−0.089**	**0.236**	**0.231**	**0.207**	**−0.093**	**0.242**	**0.625**	**0.681**	1.000			
Δbf_ai	**−0.040**	**0.263**	−0.015	**−0.050**	−0.039	**0.334**	**0.654**	**0.746**	**0.702**	**0.434**	1.000		
Δcret_ai	**−0.083**	**0.156**	**0.061**	0.006	−0.010	**−0.061**	**0.482**	**0.736**	**0.855**	**0.635**	**0.599**	1.000	
news	**−0.064**	**0.149**	−0.037	0.013	−0.039	**−0.591**	**0.130**	**0.334**	**0.298**	**0.304**	**0.064**	**0.334**	1.000

Note: The table provides the pairwise Pearson correlation estimates for the weekly time series used in the study. The variables include the log excess returns over the 1-month T-Bill rate on Bitcoin-*BTC*, Ethereum-*ETH*, Ripple-*XRP*, and the Bloomberg BGCI Galaxy crypto market index (C_{ret}) of the most liquid cryptocurrencies. The data also include a measure of the net-short positioning trading behavior of speculative retail traders (bc_{ns}) in the Bitcoin futures market; CFTC COT reports are used to construct the net positions of the speculative retail traders (normalized by total open interest). Popular control variables which are also included are the CBOE's implied volatility index (*vix*), cryptocurrency uncertainty index (UCRY), a measure of economic news sentiment (*news*), proxy Google search volume measures of investor attention in BTC-*bc_ai*, ETH-*eth_ai*, XRP-*xrp_ai*, C_{ret}-*cret_ai*, and Bitcoin futures-*bf_*ai. The sample period: April 10th, 2018–September 01st, 2022. Bold indicates statistical significance at the 10% level and above.

market attention (*Δbf_ai*). Recall that the news sentiment index is positive (negative) when economic news sentiment is positive (negative). Hence the procyclical relationships between news sentiment and attention indicate that periods of good economic news and increased investor attention are matched by increasing net positioning by retail investors. These results bolsters a key claim of our study in which we argue that retail traders in the cryptocurrency Bitcoin futures market are irrational in their behavior and react to a confluence of behavioral factors in their positioning decisions in the Bitcoin futures market.

In light of the unit root problem of time series data (Hasbrouck and Seppi, 2001; Arumugam et al., 2023), we next conduct a series of unit root tests before proceeding in our predictive analyses in Section 4.1. Table 3 presents an Augmented Dickey–Fuller (ADF) test for a unit root in our time series data. The results indicate that investors' net short trading behavior exhibited a unit root. These results are further supported by a Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) test,[13] where the *p-values* are greater than the 10% level. This result indicates persistence in this time series which could raise econometric concerns (e.g., Cavanagh et al., 1995; Torous et al., 2004). This persistence can bias predictability, and Welch and Goyal (2008) have argued that persistence can drive predictability, thus leading to biased estimates of the predicted variables by these predictor variables. Persistence can also produce biased estimates of statistical significance. Hence, apart from the series showing no unit root, consistent with the approach in the times series literature we differenced the affected time series in the subsequent analyses to ensure stationarity in the data. Hence going forward net-short positioning trading behavior of retail traders is represented as d_bc_{ns}.

To further assess the importance of changes in the trading behavior (d_bc_{ns}) of retail traders in the cryptocurrency market in predicting cryptocurrency excess returns, we performed Granger causality tests to assess the model specifications of Eq. (4). Pairwise Granger causality tests are the standard tool for studying lead–lag relationships in risk portfolios (e.g., Brennan et al., 1993; Chordia and Swaminathan, 2000; Hou, 2007). We are interested in testing causality between (i) d_bc_{ns} and *bf_ai*, (ii) d_bc_{ns} and *cret*, and (iii) *bf_ai* and *cret*. In the first instance it is important to know if the investor sentiment in the Bitcoin futures market influences net short trading behavior. In our second instance we would like to know if the net short trading behavior factor influences crypto returns in particular but the wider market in general. In the third instance we examine whether investor

13 The KPSS test results are not reported; however, these are available upon request.

Table 3
Unit root test.

Augmented Dickey–Fuller (ADF) test-statistic (The null hypothesis assumes the presence of a unit root)	Adj *t*-Stat	*Prob*[a]
BTC	−13.77306	0.0000
bc_{ns}	−0.731481	0.8290
ETH	−14.02685	0.0000
XRP	−16.54361	0.0000
C_{ret}	−15.20505	0.0000
vix	−3.725733	0.0043
ΔUcry_px	−11.54817	0.0000
Δbc_ai	−2.523678	0.1110
Δeth_ai	−3.540732	0.0077
Δxrp_ai	−3.683067	0.0049
Δbf_ai	−2.954593	0.0407
Δcret_ai	−3.942832	0.0020
Δnews	−11.16633	0.0000
Test critical values	1% level	−3.458104
	5% level	−2.873648
	10% level	−2.573298

[a]MacKinnon (1996) one-sided p-values.

Table 4
Pairwise Granger causality tests between crypto attention and net short trading behavior.

Null	Panel I	
	No Granger Causation from *Δbf_ai* to *Δbc_ai*	No Granger Causation from *Δbc_ai* to *Δbf_ai*
F-Statistic *p-value*	4.731 (0.009)	1.49 (0.227)
Null	Panel II	
	No Granger Causation from C_{ret} to *Δbf_ai*	No Granger Causation from *Δbf_ai* to C_{ret}
F-Statistic *p-value*	2.03 (0.133)	18.39 (0.000)
Null	Panel III	
	No Granger Causation from d_bc_{ns} to *Δbf_ai*	No Granger Causation from *Δbf_ai* to d_bc_{ns}
F-Statistic *p-value*	0.189 (0.828)	2.462 (0.087)
Null	Panel IV	
	No Granger Causation from C_{ret} to Δbc_{ns}	No Granger Causation from Δbc_{ns} to C_{ret}
F-Statistic *p-value*	0.260 (0.771)	6.276 (0.002)

Note. This Table reports the results of the Granger causality analysis using two lags. The null hypotheses are stated in the column headings. For example, column [2] of Panel I tests the null hypothesis that no Granger causation exists from *bf_ai* to *bc_ai*. Likewise, the null hypothesis in column [3] states that no Granger causation exists from *bc_ai* to *bf_ai*. We report the Granger causality tests for four key relationships. Panel I examines the direction of causation between investor attention in the Bitcoin market and Bitcoin, the largest cryptocurrency by market capitalization. Panel II examines Granger causality between the crypto market returns and investor attention in the Bitcoin futures market. Panel III provides information on the direction of causation between the trading behavior of speculative retail traders and investor attention in the Bitcoin futures market. Finally, Panel IV establishes the direction of causation between crypto returns and the trading behavior of speculative retail traders. Corresponding p-values are reported in brackets.

attention in the Bitcoin futures market influences crypto returns. Finally, we examine whether news sentiment has a causal relationship on the net short trading behavior factor.

Table 4 presents the Granger causality results. In Panel I the results show that causality flows from investors' attention in the Bitcoin futures market to investors' attention in Bitcoin. This establishes a leading role for the Bitcoin Futures market. In Panel II the causality results indicate investors' attention in the Bitcoin futures market causes crypto returns. We also receive similar results for the named cryptocurrencies not shown here. Panel III reported weak causality flowing from investors' attention in the Bitcoin futures market to retail traders trading behavior. Finally, Panel IV reveals that causation flows from retail traders trading behavior to cryptocurrency returns and not vice versa.

In summary, consistent with the findings documented in Smales (2022), we find that investor attention in specific crypto assets was positively related to returns in crypto markets. However, our result showing that changes in attention in the Bitcoin futures market are positively related to changes in the returns of the broader crypto market and specific crypto assets is new. Additionally, we show that the net short positioning of speculative traders has a strong positive relationship with the broad Bitcoin futures market, cryptocurrency and financial market uncertainty, and news sentiment. These results are important given that it has previously been reported that asset prices only respond to new information when investors pay attention to it (Huberman and Regev, 2001). Moreover, Barber and Odean (2008) document that increased retail investor attention leads to increased buying and significant price movements or, in our case, net-short speculative positioning in the Bitcoin futures market. Noteworthy, whereas financial market and cryptocurrency uncertainty have a negative contemporaneous relationship with crypto returns, speculative traders' positive relationship positioning would indicate higher volatility as traders irrationally seek greater short futures positions in periods of high uncertainty.

4.1. In-sample predictive analysis of net short trading behavior on crypto returns

Since the net-short trading behavior (d_bc_{ns}) of speculative traders appears to be highly procyclical with investors'' attention in the Bitcoin futures market and changes in investor attention has been documented to predict crypto returns (Liu and Tsyvinski, 2021; Smales, 2022), it is natural to examine the effects of d_bc_{ns} on crypto returns. This viewpoint is important because speculative traders may provide an important explanation of the predictability of cryptocurrency returns, given the difficulty of pricing these financial instruments with no real underlying assets or cash flows. This characteristic suggests that prices will likely be disposed to investor behavioral biases, such as attention, sentiment, and trading behavior.

Despite the progress of the attention literature in explaining cryptocurrency returns, the predictability issue is still unresolved. For instance, on the one hand, while several studies document evidence that investors' attention is a determinant of crypto returns (Bleher and Dimpfl, 2019; Liu and Tsyvinski, 2021; Smales, 2022), on the other hand, the opposite is reported (Aalborg et al., 2019; Ibikunle et al., 2020; Katsiampa, 2019; Shen et al., 2019). Given the evidence in Röthig and Chiarella (2011) and Baur and Smales (2022) that retail traders tend to herd with speculators means that the trading behavior of speculative retail traders should hold important information on the direction of crypto prices given its attractiveness to retail investors.

In this section, we now investigate a key claim of the study in which we argue that the trading behavior of speculative retail traders is a relevant determinant of crypto returns. In Section 4, we document that the net short trading behavior factor is a relevant determinant of cryptocurrency returns because of its correlation and direction of causality on investor attention in Bitcoin futures markets and cryptocurrency returns. Table 5 presents the results of our predictive regression models in Eq. (4) which is the standard framework for analyzing crypto return predictability.

Table 5
OLS results for the predictability of crypto currency excess returns by the net short trading behavior d_bc_{ns} of speculative Bitcoin futures retail traders.

Predictor	Dependent variable - Cryptocurrency returns														
	Bitcoin- *BTC*					Ripple- *XRP*					Ethereum- *ETH*				
	[1]	*[2]*	*[3]*	*[4]*	*[5]*	*[6]*	*[7]*	*[8]*	*[9]*	*[10]*	*[11]*	*[12]*	*[13]*	*[14]*	*[15]*
d_bc_{ns}	0.70***				0.62***	1.03***				0.93***	1.10***				1.05***
	(2.67)				*(2.47)*	*(2.84)*				*(2.94)*	*(2.97)*				*(3.23)*
vix					0.04					−0.09					0.11
					(0.64)					*(−0.76)*					*(1.15)*
Δbtc_ai		0.20***			0.18**										
		(3.46)			*(2.27)*										
Δeth_ai												0.33***			0.24***
												(3.01)			*(2.78)*
Δxrp_ai							0.18			0.15					
							(0.83)			*(0.74)*					
$\Delta news$				0.09	−0.17				−0.02	−0.18				−0.11	−0.09
				(0.56)	*(−0.03)*				*(−0.64)*	*(−0.65)*				*(−0.44)*	*(−0.35)*
Δbf_ai			0.12**		0.03			0.16*		0.16			0.16**		0.09
			(2.12)		*(0.37)*			*(1.83)*		*(1.59)*			*(2.05)*		*(1.01)*
BTC_{t-1}					0.09*										
					(1.63)										
ETH_{t-1}															0.09*
															(1.65)
XRP_{t-1}										−0.04					
										(−1.37)					
$\Delta Ucrp\_px$					−0.18					−0.38					−0.94
					(−0.16)					*(−0.32)*					*(−0.88)*
R^2	2.87	4.04	1.85	0.18	7.79	3.38	1.03	1.79	0.11	6.39	4.29	2.86	1.85	0.13	9.69

Note: This table displays the OLS results of Eq. (4) on the net-short trading behavior of speculative retail traders (d_bc_{ns}) and several well-known behavioral predictors of cryptocurrency excess returns. In Model I, the dependent variable is the weekly change in the named cryptocurrency, while the right-hand side predictor is d_bc_{ns}. Model II's right-hand side variable include measures of investor attention on the named cryptocurrency. The explanatory variable in Model III is the measure of investor attention in the Bitcoin futures market (bf_ai). Model IV's univariate model examines the effect of news sentiment on crypto returns. Model V is a multivariate model which includes bc_{ns} and the other behavioral factor controls. All non-stationary variables are differenced, such as bc_{ns}. The parenthetical numbers below the β estimates report heteroskedastic and autocorrelation robust t-statistics for testing: $\beta = 0$ against HA: $\beta > 0$. The predictor variables are lagged by one week. The sample period: April 10, 2018–September 01, 2022.
*Significance at the 10% level.
**Significance at the 5% level.
***Significance at the 1% level.

The results in Table 5 present several new findings. The results document new evidence indicating that d_bc_{ns} is a robust predictor of changes in cryptocurrency returns. The estimated slope coefficients in the on the trading behavior factor are economically sizeable and statistically significant, with t-statistics ranging from 2.47 to 3.23. Heteroskedastic autocorrelation-robust t-statistics (HAC) were used (Dunbar and Owusu-Amoako, 2022a,b; Rapach et al., 2016) to ensure the robustness of the OLS coefficient estimates used to establish inferences. The coefficient result signs between the net short trading behavior factor and crypto asset returns coefficient are consistent with economic theory. The results show that higher net short-trading behavior leads to higher returns which are matched with the higher short-term gains over the study period, discussed in Section 4.

We begin our empirical analysis by considering the relationship between speculative investors' trading behavior and other documented behavioral determinants (past crypto returns, investor attention, sentiment, uncertainty) on cryptocurrency returns. For the named cryptocurrencies (BTC, ETH, and XRP), we first estimate a set of benchmark univariate models of Eq. (4) including only our trading behavior predictor on cryptocurrency returns in Models [1, 6, and 11] of Table 5. Models [5, 10, and 15] of Table 5 present the multivariate estimates of Eq. (4) in which we control for the known determinants of cryptocurrency returns. Finally, Models [2, 3, 4, 7, 8, 9, 12, 13, and 14] evaluate the univariate performance of the other well-known behavioral factors over the sample period. For the ease of interpretation all coefficients in Table 5 are standardized, so that the coefficients indicate the response to a one standard deviation increase in the independent variable. the percentage point change in weekly expected returns per a 1 percent change in the predictor variable. Interestingly, Models [1, 6, and 11] for *BTC*, *XRP*, and *ETH* show that the net-short trading behavior enters with coefficient estimates of 0.70, 1.03, 1.10 and t-statistics of 2.67, 2.84, and 4.29, respectively. This positive coefficient is consistent with the positive coefficient found for stocks (Dunbar and Owusu-Amoako, 2021a,b). Our results are consistent with that of Baur and Smales (2022), who argue that speculative traders display superb market timing ability by largely adjusting their short positions at the right times, which is matched in subsequent periods by other traders who follow the smart money of the speculative traders.

The baseline estimates in Models [2, 3, 4, 7, 8, 9, 12, 13, and 14], evaluate the influence of investor attention [2, 3, 7, 8, 12, and 13] and news sentiment [4, 9, and 14] on crypto returns. As documented previously in the literature, btc_ai, eth_ai, and xrp_ai demonstrate a positive and significant effect on the returns of the names crypto assets (Liu and Tsyvinski, 2021; Smales, 2022). A finding that is new is the use of bf_ai, our measure of investor attention in the Bitcoin futures market, which was also found to be a significant determinant of the named crypto returns. The variable links attention in the wider crypto futures market to named crypto asset performance.

In our multivariate results of Models [5, 10, and 15] in Table 5, we examine the strength of d_bc_{ns} after controlling for well-known behavioral factors of crypto returns. Models [5, 10, and

15] introduce the popular Bloom (2009) measure of economic uncertainty (vix), Lucey et al. (2022) measure of crypto uncertainty, measures of investor attention based on Google search volume (Da et al., 2011; Liu and Tsyvinski, 2021; Smales, 2022), measures of economic news sentiment (Shapiro et al., 2022), and past crypto returns, and past crypto returns (Liu, 2019; Liu et al., 2020; Liu and Tsyvinski, 2021). The results in Models [5, 10, and 15] confirm a key claim of our study. It shows that the trading behavior of speculative retail traders is an economically important and statistically significant determinant of crypto returns. Even after controlling for the well-known determinants of crypto returns d_bc_{ns} remains statistically strong. It shows that in our named crypto assets (BTC, ETH, and XRP), a one-standard-deviation increase in the net-short trading behavior of speculative traders leads to a 62, 93, and 1.05 basis point increase in BTC, XRP and ETH returns, respectively. The economic impact is far greater than that arising from the attention predictors, past returns, sentiment, and measures of price uncertainty. This finding on the higher net positioning behavior could be used to explain what Smales (2022) refers to as the "fear of missing out – FOMO" rush by retail investors when crypto price increases to hold crypto assets. This is also consistent with the findings of Ballis and Drakos (2020), showing that crypto investors herd more quickly during "up-events", which could be associated with the herding of investors on positive feedback (Kaiser and Stöckl, 2020; Baur and Smales, 2022) on returns or the "smart money".

We extend our analysis to the wider crypto market by evaluating the predictability of the crypto market returns (C_{ret}) by the behavior of speculative retail traders in the Bitcoin futures market. The crypto market return is the Bloomberg BGCI Galaxy crypto index (BGCI). The BGCI is a value-weighted index designed to measure the performance of the largest, most liquid digital assets traded in USD. The index constituents are diversified across different categories of digital assets, including stores of value, mediums of exchange, smart contract protocols, and privacy assets. We assess predictability across four benchmark Models [1, 2, 3, and 4]. We also develop a multivariate Model [5] to assess the predictability of bc_{ns} while controlling for other well-known predictors.

Table 6 presents the results of our evaluation of the ability of d_bc_{ns} to explain the future returns of the value-weighted crypto market index. A notable point in Table 6 is that controlling for the previously known sentiment, investor attention, crypto, and financial market uncertainty factors has almost no influence on the economic significance of the relationship between d_bc_{ns}'s beta and future crypto market returns.

In every model specification, the hypothesis that d_bc_{ns}'s coefficients are zero can be rejected with overwhelming confidence. The clear implication is that the trading behavior of speculative retail traders plays an essential role in determining the predictability of crypto market returns. Moreover, the finding addresses the central question regarding the importance of speculative retail traders' trading behavior on the predictability of crypto market returns. This claim is well described by Table 6, which suggests that speculative retail traders' net short trading behavior has an economically meaningful and statistically significant impact on crypto market returns.

The results in Tables 5 and 6 show that sentiment was not a significant determinant of crypto returns. In other studies, Baur and Smales (2022) received mixed results on the sentiment predictor's effect on changes in the net positioning of speculative traders. Regarding trading behavior, past returns were a poor predictor of crypto returns. This evidence is noteworthy as it shows that speculative retail traders' net short trading behavior contains information about crypto price changes that are not immediately impounded in past returns. Hong and Yogo (2012) document that the economics literature has made longstanding claims on the informativeness of futures prices about asset returns while neglecting to recognize the usefulness of transaction balances.

Table 6
Effect of the net short trading behavior d_bc_{ns} of speculative Bitcoin futures retail traders on Crypto market returns.

Predictor	Dependent variable – Crypto market returns				
	Aggregate Crypto returns - C_{ret}				
	[1]	*[2]*	*[3]*	*[4]*	*[5]*
d_bc_{ns}	1.17*** *(2.91)*				1.03*** *(3.03)*
vix					0.07 *(0.82)*
$\Delta news$			−0.09 *(−0.43)*		−0.08 *(−0.35)*
$\Delta Cret\_ai$		0.18* *(1.70)*			0.21** *(1.93)*
$Cret_{t-1}$					0.06 *(0.78)*
Δbf_ai				0.18*** *(2.94)*	0.12** *(2.04)*
$C_{ret,t-1}$					0.04 *(0.72)*
$\Delta Ucry\_px$					−0.84* *(1.70)*
R^2	6.18	1.23	0.12	2.97	13.03

Note: This table displays the OLS results of Eq. (4) on the net-short trading behavior of speculative retail traders (d_bc_{ns}) and several well-known behavioral predictors of the crypto market's excess returns. The return on the crypto market is proxied by the return on the Bloomberg BGC market index (C_{ret}). In Model I, the dependent variable is the weekly change in the named cryptocurrency, while the right-hand side predictor is bc_{ns}. Model II's right-hand side variable include measures of investor attention on the named cryptocurrency. The explanatory variable in Model III is the measure of investor attention in the Bitcoin futures market (bf_ai). Model IV's univariate model examines the effect of news sentiment on crypto returns. Model V is a multivariate model which includes d_bc_{ns} and the other behavioral factor controls. All non-stationary variables are differenced, such as bc_{ns}. The parenthetical numbers below the β estimates report heteroskedastic and autocorrelation robust t-statistics for testing: $\beta = 0$ against HA: $\beta > 0$. The predictor variables are lagged by one week. The sample period: April 10th, 2018–September 01st, 2022.
*Significance at the 10% level.
**Significance at the 5% level.
***Significance at the 1% level.

We summarize our main findings in Tables 5 and 6 as follows. The fact that speculative retail traders' (d_bc_{ns}) net short positioning trading behavior predicts cryptocurrency returns is consistent with behavioral finance theories. This result, the main contribution of our paper, identifies a new time series predictor of cryptocurrency returns based on the positions of specific Bitcoin futures market participants. These results and findings are timely given that the predictability of cryptocurrency returns has recently attracted attention in the finance literature (see, e.g., Liu and Tsyvinski, 2021; Smales, 2022).

Fig. 5 presents scatterplots of our key results obtained for the main regression models in Table 5 [1, 6, 11] and Table 6 [1]. The graphs show the scatterplots corresponding to the univariate regressions of the net-short positioning behavior of speculative retail traders on BTC, ETH, XRP, and C_{ret}. Fig. 5 is a visual check to see whether a few outlier observations might drive the result since our regressions have relatively low R^2; we also set up binned scatterplots in Fig. 6 using the raw data on cryptocurrency returns and the Bitcoin net positioning trading behavior factor. The binned scatter plot partitions the crypto returns and trading behavior data into rectangular bins that use different colors to display the count of data points in each bin.

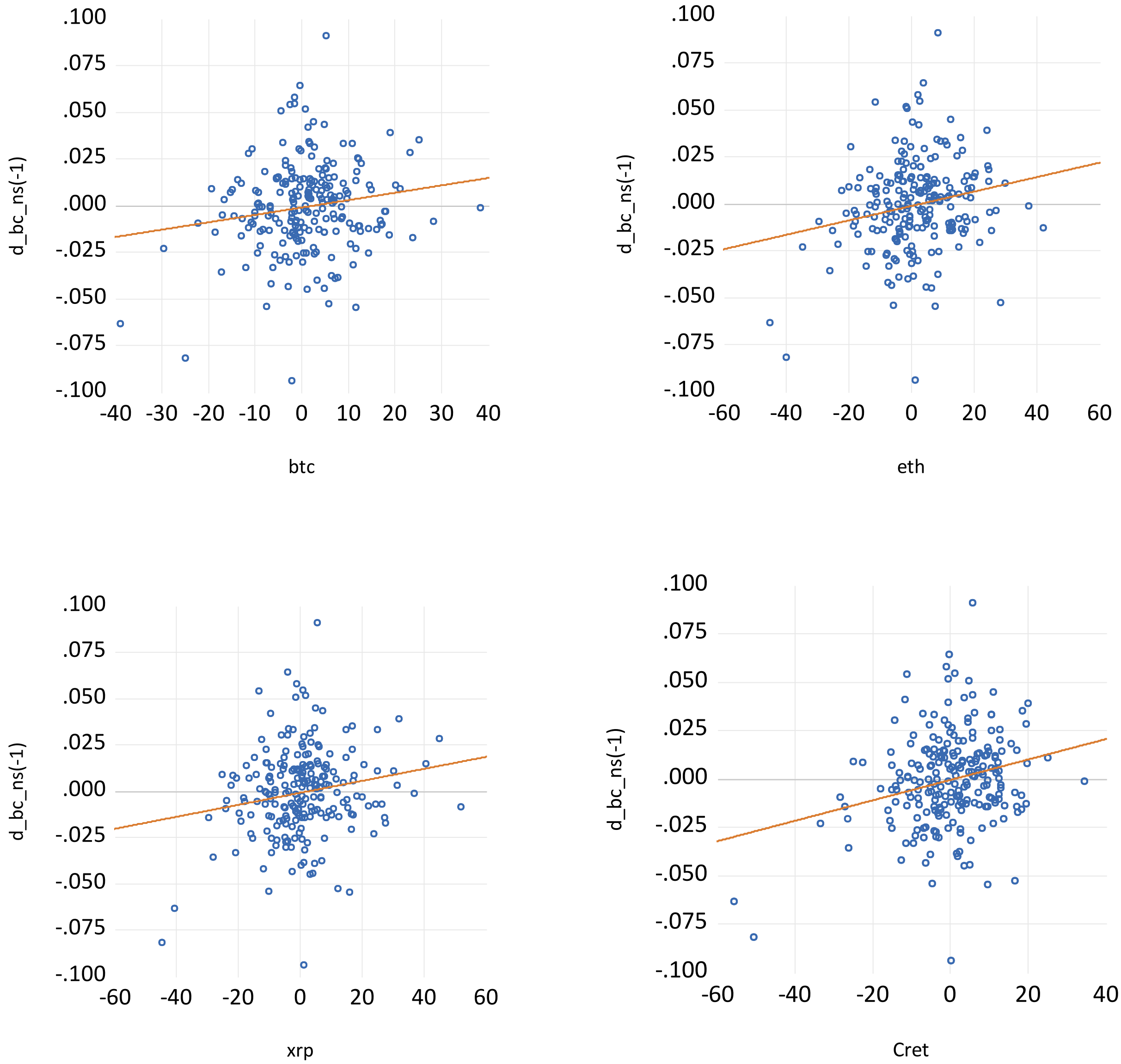

Fig. 5. Scatterplots of the trading behavior predictor (d_bc_{ns}) and crypto returns. **Notes**: Scatterplot of the changes in the net short trading behavior and crypto returns (*BTC*, *ETH*, *XRP* and C_{ret}). *BTC* is the returns on Bitcoin, *XRP* is the returns on Ripple, *ETH* is the returns on Ethereum, and C_{ret} is the returns on the Bloomberg (BGCI) crypto market index.

4.2. Out-of-sample robustness

In light of the vast asset pricing literature on return predictability in general, it is informative to contrast the predictive power of d_bc_{ns} implied premiums against the predictive power of the usual behavioral predictors used in the literature. We conduct out-sample tests that are in line with Welch and Goyal (2008), who show that the in-sample predictive ability of a variety of plausible return predictors does not hold in out-of-sample tests because of in-sample overfitting and large biases due to parameter instability (Koijen and Van Nieuwerburgh, 2011).

We first compute predictive regression forecasts corresponding to each predictor variable (Rapach et al., 2013) based on Eq. (5). Where the dependent variables are the BTC, ETH, XRP, and $C_{ret_{t:t+h}}$ (Bloomberg (BGCI) cryptocurrency index) weekly expected cryptocurrency returns. At the same time, $\hat{\alpha}_t$ and $\hat{\beta}_t$ which are based on data from the start of the sample period to week t, are the OLS estimates of α and β, respectively, in Eq. (5). Based on the framework of Rapach et al. (2016), the prevailing mean forecast of the average cryptocurrency risk premia should serve as a natural benchmark. Where the prevailing mean forecast corresponds to the constant expected excess cryptocurrency return model, Eq. (5) with $\beta = 0$, and implies that returns are not predictable, such as a random walk model with a drift for log crypto risk premia. For the out-of-sample tests, we used an in-sample period of April 10th, 2018, to June 28th, 2019. The remaining data of July 5th, 2019, to September 1st, 2022, are then used for out-of-sample analyses.

The results of the out-sample tests based on the Campbell and Thompson (2008) proportional reduction in the mean squared forecasting errors (MSFE) or out-of-sample (R^2_{OS}) tests are presented in Table 7. This out-of-sample R^2 statistic (R^2_{OS}) is used to evaluate whether our predictive regressions produce significant improvements in the MSFE. To be able to evaluate the significance of the differences between both models we use the canonical (Clark and West, 2007) statistic to test for significance in the differences. The results of the R^2_{OS} statistic indicated that, except for bc_{NS}, the other predictors either underperformed the prevailing mean benchmark in terms of MSFE at all horizons or did not have a significant R^2_{OS} statistic. To the contrary, the R^2_{OS}

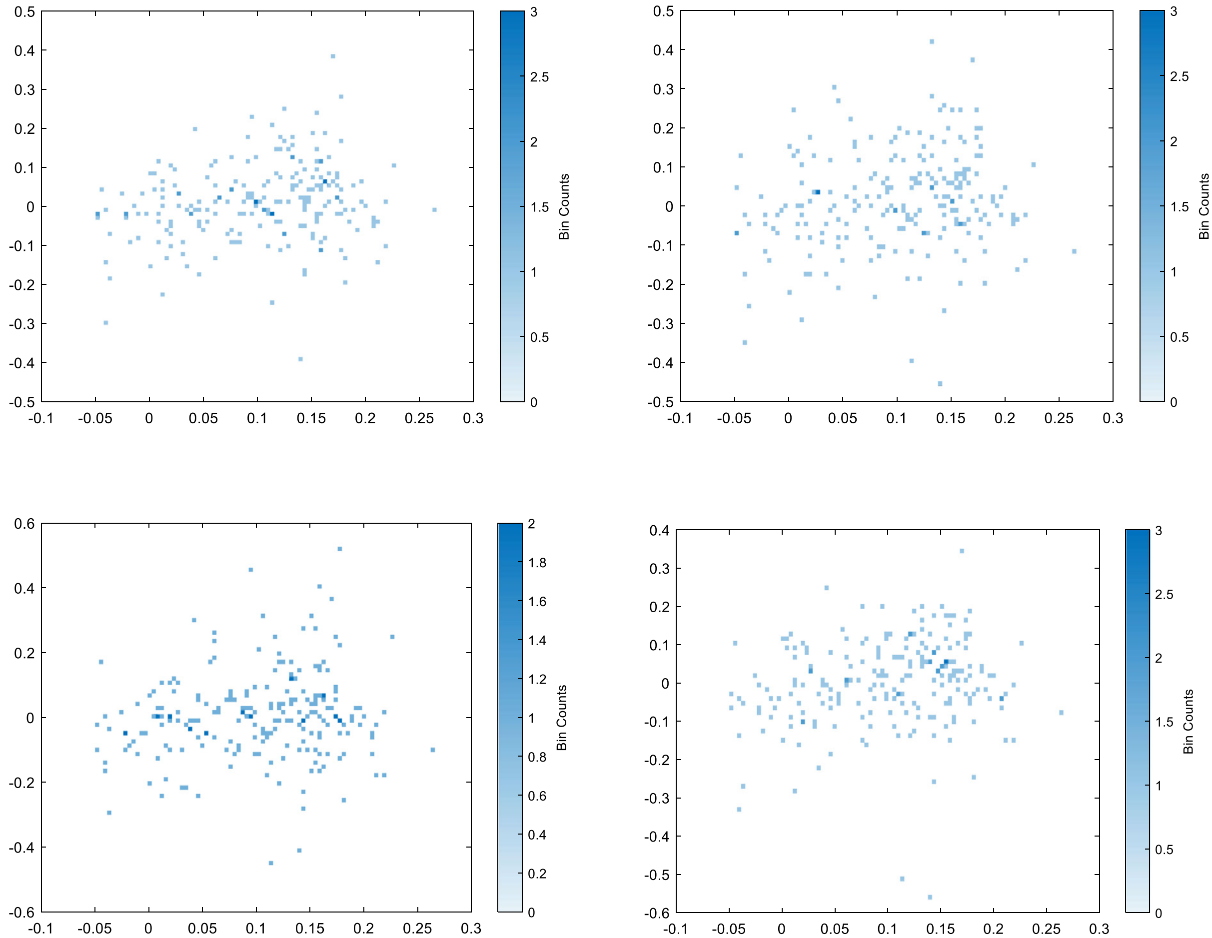

Fig. 6. Binned Scatterplots of trading behavior predictor (d_bc_{ns}) and crypto returns. **Notes**: Binned Scatterplot of the changes in the net short trading behavior and crypto returns (*BTC*, *ETH*, *XRP* and C_{ret}). *BTC* is the returns on Bitcoin, *XRP* is the returns on Ripple, *ETH* is the returns on Ethereum, and C_{ret} is the returns on the Bloomberg (BGCI) crypto market index.

Table 7
Out-of-sample tests Out-of-sample test results, 07/05/2019 – 09/01/2022 . The second through seventh columns report the proportional reduction in mean squared forecast error (MSFE) at the *h*-week horizon for a predictive regression forecast of the crypto currency's log excess return based on the predictor variable in the first column vis-'a-vis the prevailing mean benchmark forecast.

Predictor	Out-Sample R^2_{OS} (%)							
	Bitcoin- *BTC*		Ripple- *XRP*		Ethereum- *ETH*		Crypto Index. - C_{ret}	
	[h = 1]	[h = 2]	[h = 1]	[h = 2]	[h = 1]	[h = 2]	[h = 1]	[h = 2]
d_bc_{ns}	3.71***	5.42**	3.86***	4.75**	4.18***	6.82**	3.61**	5.74**
vix	−0.65	−0.56	0.66	0.74	0.55	1.54	0.49	1.24
Δbc_ai	−2.55	−3.33	–	–	–	–	–	–
Δeth_ai	–	–	–	–	2.09**	8.83**	–	–
Δxrp_ai	–	–	3.26	9.47***	–	–	–	–
ΔC_{ret}_ai	–	–	–	–	–	–	−0.39	1.39*
					–	–		
$\Delta news$	−1.61**	−1.00	−2.48	−0.62	−2.02	0.38	−1.89	−0.46
Δbf_ai	0.47	−1.67	1.16	0.30	1.71*	1.32	2.27**	0.46
BTC_{t-1}	−0.25	−0.26	–	–	–	–	–	–
ETH_{t-1}	–	–	–	–	−2.02	−1.93	–	–
XRP_{t-1}	–	–	−2.97	−1.63	–	–	–	–
$C_{ret,t-1}$	–	–	–	–	–	–	−0.34	0.32
$\Delta Ucrp\_px$	−4.67**	−2.51	−0.47	−0.07	−0.68	1.38	−2.07	−0.52

Note: Statistical significance is based on the Clark and West (2007) statistic for testing the null hypothesis that the prevailing mean MSFE is less than or equal to the predictive regression MSFE against the alternative hypothesis that the prevailing mean MSFE is greater than the predictive regression MSFE.
*Significance at the 10% level.
**Significance at the 5% level.
***Significance at the 1% level.

statistic for d_bc_{NS} is significant and positive across all horizons for all crypto returns, according to the Clark and West (2007) statistic, which indicates that d_bc_{NS} outperforms the prevailing mean benchmark.

In summary, we conclude that the trading behavior innovation (d_bc_{NS}) captures the predictable variation in crypto risk premia better than the fitted values from other well-known behavioral instruments used in the literature. These results also provide economic confirmation of the empirical finding that changes in d_bc_{ns} robustly predicts cryptocurrency returns. This result is not surprising because (Baur and Smales, 2022) have suggested that speculative retail traders whose trading behavior plays a key role in the Bitcoin futures market tend to hold the largest net short trading positions and display a superb market timing ability (see also Piazzesi and Swanson, 2008). They appear to adjust their positions at the right time resulting in other traders following their lead in subsequent periods.

4.3. Economic significance of the net-short trading behavior predictor

From an asset allocation perspective, we measure the economic value of d_bc_{ns}' predictive ability. As in Liu (2019), Campbell and Thompson (2008), and Rapach et al. (2016), we considered a mean–variance investor who allocated between a portfolio of cryptocurrencies (C_{ret}) and risk-free bills using a predictive regression forecast of excess cryptocurrency returns. We assume that the time t optimal allocation of the investor's wealth to the risky C_{ret} at the end of each week is summarized as

$$w_t^* = \left(\frac{1}{\gamma}\right)\left(\frac{\hat{C}_{ret_{t+1}}}{\hat{\sigma}^2_{t+1}}\right), \tag{6}$$

where γ is the investor's coefficient of relative risk aversion, $\gamma = 3$ is commonplace in the literature. $\hat{C}_{ret_{t+1}}$ is the predictive regression's excess return forecast, and $\hat{\sigma}^2_{t+1}$ is the forecast variance of the excess return. The forecast of volatility is generated using an eight-week moving window of past returns (consistent with the approach of Campbell and Thompson, 2008). Finally, given the well-known sensitivity of mean–variance optimal weights to return forecasts, we constrained the portfolio weights for this analysis to be between −0.5 and 1.5, which ensures realistic portfolio constraints and producing better-behaved portfolio weights.[14]

Theoretically, the CER is the return with some level of certainty (returns on the risk-free asset) that an investor would rather accept than risky crypto portfolio returns (C_{ret}), particularly in periods of rising crypto market uncertainty. For evaluation of the potential CER gains, we follow Rapach et al. (2016) and compute the CER for an investor when the prevailing mean excess return forecast is used instead of our predictive regression forecast in Eq. (6). Hence, CER gains is therefore the difference between the CER for the investor using the predictive regression forecast to guide asset allocation and the CER of the prevailing mean benchmark forecast. The CER gains are annualized to facilitate interpretation as the annual portfolio management fee the investor would be willing to pay for the predictive regression's forecast rather than that of the prevailing mean forecast. This allows us to directly measure the economic value of crypto returns predictability.

The investor who allocates using Eq. (6) will realize an average certainty equivalent return CER as follows

$$CER = \bar{C}_{ret} - 0.5\gamma\sigma_p^2, \tag{7}$$

where $\bar{C}_{ret}$ and σ_p^2 are the cryptocurrency return's mean and variance, respectively, over the forecast evaluation period. We assumed a relative risk aversion coefficient of 3.[15] The second through fourth columns of Table 8 shows the CER gains accruing to predictive regression forecasts based on each of our predictor variables (d_bc_{ns}, vix, $\Delta Cret\_ai$, Δbf_ai, $\Delta news$, $C_{ret,t-1}$, and $\Delta Ucry\_px$) over the forecast evaluation period. For the full forecast evaluation period (July 05th, 2019, to September 01st, 2022), reported in columns [2] through [5], the performance of d_bc_{ns} stands out at the one-week forecast horizon. Table 8 reports that at the 1-week horizon, d_bc_{ns} provides a high CER gain of 7.74%. The gains from the other crypto predictors were clearly below that of d_bc_{ns}'s. For additional comparisons, the CER gains of a passive buy-and-hold strategy are also presented in Table 8. The results show that these CER gains were well also below those of d_bc_{ns}.

Table 8 also reports on a subsample period that predates the U.S. COVID-19 shutdown (July 05th, 2019, to December 27th, 2019) in columns [6] – [9] and a subsample that surrounds the COVID-19 crisis period (January 03rd, 2020, to September 01st, 2022) in columns [10] through [13]. Several studies in the cryptocurrency literature document that the COVID-19 period began in January 2020 (Yousaf and Ali, 2020; Haroon and Rizvi, 2020). Hence, we similarly follow the existing literature and list this period as starting January 2020. For the period just prior to the COVID-19 event, the results show that d_bc_{ns} provides sizable CER gains of 7.74%, 7.62%, 5.94%, and 5.01% at the h = 1-, 2-, 3-, and 4-week horizons, respectively. These gains were typically well above those (mostly negative) provided by the other predictors. Quite noteworthy, during the period including the COVID-19 event, the CER gains of d_bc_{ns} were significantly higher than that of the other predictors, thereby illustrating that speculative retail traders are able to earn economically meaningful returns even in periods of economic disruptions.

In summary, the out-sample CER gains analysis showed that speculative retail traders' net-short trading behavior plays a vital role in explaining crypto returns. Our results indicate that speculative interests drive cryptocurrency returns in individual currencies and the wider crypto market. We show that cryptocurrency returns are higher when speculative trading behavior increases. In all cases, the magnitude of the coefficient estimates was economically meaningful and far larger than those of the other known behavioral predictors.

The predictive strength of the trading behavior predictor suggests that speculative retail traders were aware of expected changes in the excess returns of the cryptocurrency market and positioned themselves accordingly, at the expense of the opposite traders. Piazzesi and Swanson (2008) have proposed two primary explanations for why the futures premia in a related (fed funds) futures market are not "competed away" by the market. We believe these explanations are also relevant to the Bitcoin futures market. Piazzesi and Swanson (2008) argue that the assumption that excess returns in these markets would be competed away requires perfectly competitive futures markets and risk-neutral market participants, which in practice may not apply. First, the futures market may not be perfectly competitive, with barriers to entry and small speculative retail traders facing limits on the size of the positions that they can take; thus, hedgers in this market may not face a perfectly elastic supply curve for either the long or short side of these futures contracts. Hence Hong and Yogo (2012) have suggested limited risk absorption in these markets. Second, speculative retail traders may themselves be risk averse. Consequently, Bitcoin futures traders in these markets may be most averse to taking on large bets or risky positions precisely when their financial interests are most in jeopardy, around times of high investor attention.

[14] This precludes short sales and those above 50% financial leverage according to the suggestion of the related literature (e.g., Liu, 2019).

[15] This value is consistent with estimates of relative risk aversion from the literature (e.g., Rapach et al., 2010). The results are similar for other reasonable relative risk aversion coefficient values.

Table 8
Out-of-sample CER gains. The table reports the annualized mean–variance CER gains for a risk-averse investor. It is assumed that this individual allocates between a risky Crypto currencies and risk-free T-bills. The forecast and rebalancing frequency are given by *h*.

Predictors	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]
	07/05/2019–09/01/2022 : *Out-of-sample period*				07/05/2019 – 12/27/2019 : *Out-of-sample period*				01/03/2020 – 09/01/2022 : *Out-of-sample period*			
	$h = 1$	$h = 2$	$h = 3$	$h = 4$	$h = 1$	$h = 2$	$h = 3$	$h = 4$	$h = 1$	$h = 2$	$h = 3$	$h = 4$
d_bc_{ns}	23.19	23.02	5.13	17.97	4.41	4.52	5.91	2.74	7.74	7.62	5.94	5.01
vix	0.07	−2.40	−0.34	0.00	1.06	0.99	−0.84	0.40	0.85	0.33	−0.78	0.23
Δbf_ai	4.79	−7.40	0.34	−2.96	−2.66	0.04	−1.63	0.15	−1.33	−1.32	−1.40	−0.45
ΔC_{ret}_ai	−5.23	−2.20	−1.08	−4.55	2.58	1.33	1.12	1.83	1.12	0.66	0.84	0.64
$\Delta news$	−1.80	10.89	−1.49	6.55	−0.78	−0.37	−0.76	−0.46	−1.00	1.51	−0.86	0.53
$C_{ret,t-1}$	−37.07	4.78	−1.69	−4.59	−10.39	−7.76	−1.23	−4.17	−15.24	−5.65	−1.28	−4.36
$\Delta Ucrp\_px$	2.37	4.28	−0.88	0.56	−2.84	−3.28	3.44	−1.70	−1.93	−2.03	2.90	−1.44
Buy and hold	−68.49	−70.06	−24.23	−81.64	−14.03	−15.46	−25.34	−16.78	−24.06	−25.24	−24.58	−27.10

Notes: The CER displayed in this table is the risk-free rate of return that an investor would be willing to accept in lieu of holding a risky portfolio. The CER gain is computed as the difference between the CER for the investor who uses the predictive regression forecast to guide asset allocation and the CER of the prevailing mean benchmark forecast.

5. Conclusion

In this study, we show that changes in the net-short trading behavior of speculative retail traders has a more significant effect on crypto risk premia than measures of crypto and financial market uncertainty, investor attention, sentiment news, and past crypto returns. Our findings have broader implications for large behavioral finance literature, which documents that crypto returns are affected by investor attention and sentiment. Prior studies have documented the importance of investor attention in predicting cryptocurrencies since they do not possess traditional financial fundamentals (Liu and Tsyvinski, 2021). Investor attention which is itself influenced by past crypto returns (Katsiampa, 2019; Lin, 2021), forecasts future crypto returns (Liu and Tsyvinski, 2021), crypto volatility (Al Guindy, 2021; Sabah, 2020), and the contemporaneous correlation between cryptocurrencies (Chuffart, 2022). The earlier findings assume that investor attention contains timely information about cryptocurrency returns and investor behavior in crypto markets. However, our findings suggest that speculative retail traders' net positioning trading behavior is a much more powerful and economically meaningful predictor of cryptocurrency returns that also performs exceptionally well in out-of-sample tests. Given the renewed attention in the finance literature, our work opens up a new timely approach to predicting crypto returns (Liu and Tsyvinski, 2021).

Our work also opens up a new approach to modeling expected returns in the financial literature. Most empirical models of expected returns are premised on the notion that past returns, sentiment, investor attention, and crypto uncertainty contain all useful information for forecasting future crypto returns, whether such predictability arises from a time-varying risk premium or crypto-specific behavioral factors. Our work shows that trading behavior, particularly among non-commercial traders in the Bitcoin futures market, contains information not fully revealed by other well-known behavioral factors. The idea that trading behavior in the cryptocurrency market could be more informative than these other well-known behavioral factors is entirely new. It offers a richer understanding of movements in crypto returns.

In light of our findings on the importance of the trading behavior of market participants in the Bitcoin futures market and the previously documented evidence of strong time-series effects of investor attention in the cryptocurrency market. We suggest that future directions in this work explore the relationship between trading behavior and investor attention. These two results may capture the same underlying phenomenon. This could cause the trading behavior of speculative retail traders and investor attention to interact with each other. For instance, the cryptocurrency time series on trading behavior effect may be stronger at times of high investor attention because of higher information leakage. This viewpoint is relevant given that the finance literature shows that retail traders tend to herd with speculative traders and follow the behavior of these market participants.

CRediT authorship contribution statement

Kwamie Dunbar: Conceptualization, Methodology, Investigation, Software, Writing – original draft. **Johnson Owusu-Amoako:** Data curation, Writing – reviewing and editing, Literature review.

Declaration of competing interest

None.

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