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Li GUO

Bo SANG

Jun TU
Singapore Management University, tujun@smu.edu.sg

Yu WANG

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Li Guo†

School of Economics, Fudan University

Shanghai Institute of International Finance and Economics

Bo Sang§

Lee Kong Chian School of Business, Singapore Management University

Jun Tuτ

Lee Kong Chian School of Business, Singapore Management University

Yu Wang‡

School of Finance, Shanghai University of Finance and Economics

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† School of Economics, Fudan University. 600 Guoquan Road, Shanghai, 200433. Email: guo_li@fudan.edu.cn.

§ Lee Kong Chian School of Business, Singapore Management University. 50 Stamford Rd, Singapore Management University, Singapore 178899. Email: bo.sang.2017@pbs.smu.edu.sg.

τ Corresponding author. Lee Kong Chian School of Business, Singapore Management University. 50 Stamford Rd, Singapore Management University, Singapore 178899. Email: tujun@smu.edu.sg. Phone: (+65) 68280764. Fax: (+65) 68280427.

‡ School of Finance, Shanghai University of Finance and Economics. 777 Guoding Road, Shanghai, 200433. Email: wang_yu@163.sufe.edu.cn.

Cross-cryptocurrency Return Predictability

Abstract

Using the minute-frequency data on *Binance*, we find strong evidence of cross-cryptocurrency return predictability. The lagged returns of other cryptocurrencies serve as significant predictors of focal cryptocurrencies up to ten minutes, in line with slow information diffusion. The results are robust across various methods, including the adaptive LASSO and principal component analysis. Furthermore, a long-short portfolio formed on the past returns of cryptocurrencies can generate a daily return of 2.16% out-of-sample after accounting for transaction costs, indicating sizable economic value of cross-cryptocurrency return predictability.

JEL classifications: G10, G11, G14, G40

Keywords: Cryptocurrency; return predictability; information spillover; adaptive LASSO

1. Introduction

Since the launch of Bitcoin,[1] investment in cryptocurrencies has increased significantly and attracted trillions of funds over the past decade.[2] Compared to equities or fiat money, cryptocurrencies exhibit a more volatile price movement pattern and are subject to rampant speculation (e.g., Brauneis and Mestel, 2018; Sockin and Xiong, 2021). One challenge is that the fundamentals of cryptocurrencies have few publicly available predictive signals such as analyst coverage and accounting statements, making them hard to value (e.g., Detzel, Liu, Strauss, Zhou, and Zhu, 2020). To gain a better understanding of this new type of asset, recent studies identify some return predictors of cryptocurrencies, including information from initial coin offerings (ICO) and historical coin returns.[3] [4] However, these predictors are based on the information and characteristics of individual cryptocurrencies. There is a lack of study on whether and how the information (e.g., historical returns) of one cryptocurrency can forecast returns of another cryptocurrency, i.e., cross-cryptocurrency return predictability, which is the focus of this study.

Most cryptocurrencies share similar underlying technical details, that is, they function in decentralized networks that are based on blockchain technology.[5] The innovation processes in similar technologies across cryptocurrencies are likely to experience common shocks and knowledge spillovers (Jaffe, Trajtenberg, and Henderson, 1993). The returns of cryptocurrencies can be in turn affected by these common shocks and spillover effects, generating lead-lag effects

[1] First introduced by Nakamoto (2008).
[2] More than 6,000 cryptocurrencies are actively traded nowadays, and their overall market capitalization is above $1.5 trillion U.S. dollars as of February 2021, which is almost 3% of the total U.S. stock market capitalization, according to *CoinMarketCap*.
[3] See, for example, Hou, Li, Liao, and Zhang (2019); Lee, Li, and Shin (2021); Detzel, Liu, Strauss, Zhou, and Zhu (2020); Liu, Sheng, and Wang (2021); Liu and Tsyvinski (2021); Liu, Tsyvinski, and Wu (2021).
[4] The terms cryptocurrencies, crypto, and coins are used interchangeably in this paper.
[5] For example, a lot of cryptocurrencies use the same consensus algorithm as the Bitcoin (Proof of Work) and one common feature of such cryptocurrency platforms is that they involve a group of miners to verify or record transactions on the blockchain (Sockin and Xiong, 2021).

among returns (Lee, Sun, Wang, and Zhang, 2019). For instance, as a leading coin in the cryptocurrency market, BTC may respond to common shocks more promptly than many smaller coins, which are likely to react to the common shock with a delay due to the limited attention or constrained information-processing capabilities of the investors (e.g., Hong, Torous, and Valkanov, 2007; Merton, 1987; Shahrur, Becker, and Rosenfeld, 2010). As a result, the returns of BTC can lead the returns of many other coins with delayed reactions. Overall, we hypothesize that cross-cryptocurrency return predictability is prevalent.

Specifically, we collect the minute-frequency pricing data of cryptocurrencies from a leading cryptocurrency exchange website, *Binance*.[6] [7] To avoid survival bias, we select the top 30 coins with the highest trading volume on *Binance* at the time that we started the project. Our sample spans from 25 March 2019 to 30 April 2021 in the 24/7 cryptocurrency spot market. As of the day we started the project,[8] the dollar trading volume of the 30 coins accounts for more than 86% of the total coin market dollar trading volume, ensuring that our analysis is representative of the cryptocurrency market.

Univariate ordinary least squares (OLS) regressions show that the returns of all 30 cryptocurrencies are significantly influenced by the lagged returns of other cryptocurrencies. Moreover, most coins are found to have positive coefficients on the lagged returns of other coins, consistent with our argument about the lead-lag effect among returns of cryptocurrencies. Particularly, after controlling lagged returns of other coins, a one standard deviation increase in the BTC lagged return will significantly increase the average return of other coins by 1.92 bps,

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[6] *Binance* has been the largest cryptocurrency exchange around the world since 2018 (Source: https://www.bloomberg.com/news/articles/2018-01-11/world-s-top-ranked-crypto-venue-added-240-000-users-in-one-hour).
[7] The minute-level analysis ensures adequate data for us to apply the machine learning method.
[8] The stating day is 9 May 2020.

which is equivalent to 1.15% on an hourly basis. These results provide supporting evidence that cross-cryptocurrency return predictability is prevalent.

To provide further evidence of cross-cryptocurrency return predictability, we also perform multivariate OLS regressions. To reduce statistical concerns associated with correlated regressors, we choose the following two empirical frameworks: 1) pooled estimates with bias-corrected wild bootstrapped confidence intervals (e.g., Rapach, Strauss, and Zhou, 2013); and 2) the adaptive version of least absolute shrinkage and selection operator (LASSO) in the predictor estimation (Tibshirani, 1996; Zou, 2006). In terms of the pooled estimation, returns of about half of the sample coins can be positively and significantly predicted by the pooled lagged returns of other coins. The economic magnitude is large as well. Specifically, a one standard deviation increase in the pooled lagged return of other coins will increase an individual coin's return by 0.40 bps – 4.82 bps on a minute basis, which is equivalent to 24 bps – 289 bps hourly. As for the adaptive LASSO approach, it is a machine learning technique that helps select variables in predictive regressions and improves prediction accuracy. Our observations show that for any one of the 30 coins, the adaptive LASSO identifies lagged returns for at least six other coins as significant return predictors. Particularly, BTC has been selected by the algorithm as a positive and significant return predictor for all other coins except for stablecoins. Other top return predictors are Binance coin (BNB) and Tron (TRX), which also positively predict returns for all other coins excluding stablecoins. Overall, these results strongly corroborate cross-cryptocurrency return predictability.

In addition, we test the robustness of our results by utilizing the principal component analysis (PCA) approach. We extract three main principal components from the 30 cryptocurrency returns. All cryptocurrencies in our sample, except for stablecoins, have positive and relatively uniform loadings on the first principal component, suggesting that the 30 cryptocurrency returns can be affected by some common shocks, as mentioned previously. The varying loadings on the two remaining principal components indicate that these two principal components may capture certain complex coin interdependencies in the cryptocurrency market. According to the distribution of the return variance among the three main principal components, the first principal component represents 36.80% of the total variance, while the other two main principal components represent just 8.26%. These ratios indicate that the common shocks represented by the first principal component may play a much stronger role in cross-cryptocurrency return predictability than the complex coin interdependencies represented by the other two main principal components.

To measure the economic significance of the forecasting power, we implement multiple trading strategies and evaluate the out-of-sample performances of corresponding portfolios. Specifically, we sort cryptocurrencies into equal-weighted quintile portfolios and construct zero-investment long-short portfolios, based on the out-of-sample cryptocurrency return forecasts (minute-level) via the adaptive LASSO, PCA, and the univariate (BTC) regression, respectively. Portfolio returns increase monotonically from the lowest quintile to the highest quintile in all three prediction models, and the minute-level return spread for these three long-short portfolios are 3.55 bps, 1.86 bps, and 1.54 bps, respectively, with all three trading strategies significant at the 1% level. The t-statistics of the returns are larger than three and thus meet the requirement of the multi-hypothesis threshold posed in Harvey (2017), alleviating the p-hacking problem.

We show that the returns of these long-short portfolios cannot be explained by exposures to a variety of risk factors in the cryptocurrency market, including market risk, size, and alternative specifications of momentum. Hence, risk-based explanations are not consistent with our result. In addition, we use size, dollar trading volume, and Google search volume to proxy for investor attention, and our sub-sample tests indicate larger alphas for coins with lower investor attention.

We also investigate nine events (e.g., PayPal's adoption of cryptocurrencies as a payment tool) that have had broad impact on the cryptocurrency market and examine the corresponding long-short portfolio alphas on these event days. Compared with the average alpha for the other days outside those event days with some other potential events sporadically (labelled as normal days hereafter), the alphas on the event days are significantly higher than on the normal days. This is because those market-wide events should affect various coins as common shocks, thereby resulting in abnormally larger common shocks to various coins and a consequential higher level of cross-cryptocurrency return predictability on the event days than on the normal days. Overall, these results are consistent with the spillover-effect mechanism, where common economic linkages among coins coupled with the limited attention of investors cause slow information diffusion.

Moreover, given the relatively high transaction costs in the cryptocurrency spot market,[9] the investment strategies outlined above may yield smaller profits after transaction costs. In order to lower the impact of the transaction costs, we further examine the trading profits in the cryptocurrency futures markets. By investigating the out-of-sample performance using the adaptive LASSO strategy in the futures market, we find that the returns remain economically and statistically significant. For example, a long-short portfolio based on decile sorting and rebalanced every 13 minutes exhibits a minute-level return of 0.15 bps for VIP0 takers (those with the highest trading costs) and 0.19 bps for VIP9 takers (those with the lowest trading costs), equivalent to 2.16% for VIP0 takers and 2.74% for VIP9 takers on a daily basis.

One of the main contributions of our study is that it shows the prevalence of cross-cryptocurrency return predictability, which adds to the growing literature on asset pricing studies

[9] For investors trading on *Binance*, the transaction cost per round-trade is estimated as high as 20 bps. Source: https://www.binance.com/en/fee/trading.

of the cryptocurrency market. For example, Lee, Li, and Shin (2021) find that analyst ratings regarding initial coin offerings (ICO) positively predict long-run cryptocurrency returns. Liu, Tsyvinski, and Wu (2021) document a strong time-series momentum effect and point out that investor attention strongly forecasts future cryptocurrency returns. Studies further show that cryptocurrency market, size and volatility capture cryptocurrency expected returns well (e.g., Li and Yi, 2019; Liu and Tsyvinski, 2021). While there is evidence of several individual cryptocurrency return predictors, cross-cryptocurrency return predictability has seldom been explored. Our paper fills this gap by demonstrating that the lagged returns of other cryptocurrencies can significantly predict returns of the focal cryptocurrencies.

In addition, our work provides some insights on the information spillover effect in the cryptocurrency market. A swathe of earlier studies document the spillover effect in the stock and bond markets (e.g., Lo and MacKinlay, 1990; Brennan, Jegadeesh, and Swaminathan, 1993; Badrinath, Kale, and Noe, 1995; Chordia and Swaminathan, 2000; Cohen and Frazzini, 2008; Menzly and Ozbas, 2010; Shahrur, Becker, and Rosenfeld, 2010; Rapach, Strauss, Tu, and Zhou, 2019; Lee, Sun, Wang, and Zhang, 2019; Ali and Hirshleifer, 2020), pointing out that common economic linkages between firms or industries, coupled with the presence of limited attention or constrained information-processing capabilities, cause investors to underreact to shocks in connected firms or industries (e.g., Hong, Torous, and Valkanov, 2007; Merton, 1987). Our study seems to be the first to investigate cross-cryptocurrency return predictability based on the information spillover effect. A most recent study examines return connectedness among cryptocurrencies. Moratis (2021) conducts a time series in-sample analysis on the risk spillover. However, the risk spillover explanation differs from that of the information spillover: the former is about spillover shocks that could affect returns in either direction while the latter mainly result in a positive lead-lag effect. Furthermore, we use a machine learning method to effectively combine various predictors and form trading strategies to explore the investment value of the information spillover effect. These analyses seem not to have been done by other studies. By shedding light on the information transmission mechanism in the cryptocurrency market, our paper corroborates the gradual information diffusion theory to explain the lead-lag effect (e.g., Hong and Stein, 1999; Hong, Lim, and Stein, 2000; Hou, 2007).

Our study also adds to the existing literature relating to high-frequency trading in the cryptocurrency market. In recent years, the sharp volatility in the cryptocurrency market has attracted many high-frequency traders who use algorithms to conduct rapid bulk trades.[10] [11] Some academic papers have analyzed intra-day cryptocurrency trading data and presented stylized findings about high-frequency trading and return patterns (e.g., Zhang, Chan, Chu, and Nadarajah, 2019; Schnaubelt, Rende, and Krauss, 2019; Krückeberg and Scholz, 2020; Petukhina, Reule, and Härdle, 2021). While prior literature on cryptocurrency high-frequency trading mainly focuses on Bitcoin (a few papers also examine several other major cryptocurrencies, such as Ethereum, Ripple, and Litecoin), this study takes a more comprehensive approach by analyzing the top 30 cryptocurrencies, which account for 86% of the overall cryptocurrency market in terms of dollar trading volume, and exploring cross-cryptocurrency return predictability from a high-frequency perspective.

The rest of this paper is organized as follows. Section II introduces the data. In section III, we present the empirical findings, including various robustness tests. Section IV contains concluding remarks.

[10] Source: https://www.ft.com/content/40a86de6-b5dd-11e7-a398-73d59db9e399.
[11] Exchanges such as *Huobi* and *ErisX* began to offer co-location that allowed investors to execute trades up to a hundred times faster, without additional charges. Source: https://www.coindesk.com/high-frequency-trading-is-new-battleground-in-crypto-exchange-race.

2. Data and summary statistics

We obtain pricing information and trading activities of 30 cryptocurrencies from *Binance*, a leading global cryptocurrency exchange.[12] To avoid the survival bias, we select the coins based on their large trading volume on *Binance* at the time when we started the project, i.e., 9 May 2020. The sample period spans from 25 March 2019 to 30 April 2021, and the data frequency is on a minute basis in the 24/7 cryptocurrency spot market, in order to ensure that the machine learning method avails of an adequate amount of data. For the cryptocurrency futures market, the sample covers from 29 July 2021 to 30 April 2021. The starting date is the first day that all 30 coins were traded on *Binance*. We further standardize coin returns – with means equal to zero and standard deviations equal to one – to make it comparable across different coins. All prices are dominated in Tether (USDT).[13]

<To insert Figure 1 here.>

Figure 1 illustrates the 30 sample coins' dollar trading volume versus that of the remaining coins on the day when we started the project. Indeed, the trading volume of the top 30 coins included in the sample amounts to $1.3 billion U.S. dollars, representing more than 86% of the total cryptocurrency market dollar trading volume. Therefore, our analysis of the 30 top cryptocurrencies is indeed representative of the overall cryptocurrency market.

Table I presents the summary statistics of the 30 cryptocurrencies in our sample, in alphabetical order. It shows that all cryptocurrencies except for stablecoins display a time-series average of the minute-level return larger than 0.01 bps, which is equivalent to an hourly return of 0.60 bps. The average standard deviation of sample coins' minute-level returns is as high as 0.19%,

[12] *Binance* has been ranked the top crypto exchange with the highest trading volume and the largest number of weekly visits. Source: https://coinmarketcap.com/rankings/exchanges/.
[13] Tether is a popular unit symbol used in exchanges, and it is 1:1 pegged to the USD. The results would not change if we use the USD as the unit symbol.

indicating the highly volatile nature of the cryptocurrency market. This rampant price movement of cryptocurrencies is consistent with the literature (e.g., Brauneis and Mestel, 2018; Sockin and Xiong, 2021). Among the sample coins, an ERC token[14] named HoloTokens (HOT) exhibits the highest minute-level return of 0.08 bps, and a utility token named Celer (CELR) has the highest time-series variation of returns, with a standard deviation of 0.31%. In contrast, TUSD, USDC, and PAX, which are the three USD-pegged stablecoins[15] included in our sample, have a zero mean of returns and exhibit the lowest standard deviations. Such zero mean returns and low volatility features are not surprising as the values of these stablecoins are pegged to fiat currency (USD) rather than linked to blockchain protocol, platform utility, or network activities (e.g., Chohan, 2021; Hoang and Baur, 2021). Therefore, they may not share common information with other cryptocurrencies in our sample. From an investment standpoint, we also report the Sharpe ratios for all sample coins. Binance coin (BNB) ranks as the coin with the highest Sharpe ratio (0.29%), followed by Link token (LINK, 0.28%).

<To insert Table I here.>

3. Empirical results

We report our findings of the cross-cryptocurrency return predictability through several sets of predictive regressions. To link this phenomenon to practical investment strategies, we further construct long-short portfolios that go long (short) coins with the highest (lowest) forecasted returns using three predictive models and investigate their out-of-sample performance.

[14] ERC is short for Ethereum Request for Comment. An ERC token is a token that is created based on Ethereum following the ERC application-level standards and conventions.
[15] According to Chohan (2021), stablecoins have emerged in the recent past with an approach to mitigate the high volatility of cryptocurrencies through a sustained peg with traditional instruments such as USD or a basket of currencies.

3.1. Baseline models

We first run a univariate ordinary least squares (OLS) regression model for each sample coin return to examine the explanatory power of other cryptocurrencies' lagged returns and its own lagged return as follows:

$$r_{i,t} = \hat{\alpha}_{i,t} + \hat{\beta} r_{j,t-1} + \epsilon_{i,t} \tag{1}$$

where $r_{i,t}$ is the return of cryptocurrency i at time t (minute-level), $r_{j,t-1}$ is the returns of all cryptocurrencies in the sample at time t-1, $\epsilon_{i,t}$ is the error term, and i, j = 1, …, 30. Note that when j = i, Equation (1) explores the relationship between the coin's own lagged return and its current return.

<To insert Table II here.>

Table II reports the estimated coefficients on $r_{j,t-1}$ in Equation (1). The main finding is that returns of all 30 sample cryptocurrencies are largely influenced by the lagged returns of other cryptocurrencies. Specifically, returns of 24 out of 30 coins can be significantly predicted using the lagged returns of all other coins. As for the remaining seven coins, the returns can be predicted by most of, though not all, other coins' lagged returns. The average number of other coins that significantly predict the returns of these six coins is as high as 26 out of 29, indicating a prevalent spillover effect in the cryptocurrency market. Moreover, most coefficients here are positive, which is consistent with the lead-lag spillover effect documented in the stock market (e.g., Lee, Sun, Wang, and Zhang, 2019). Overall, in the context of the cryptocurrency market, given the limited attention or constrained information-processing capabilities of investors (Subramaniam and Chakraborty, 2020), common information is not homogeneously incorporated into individual coins, so the lagged returns of other coins may contain valuable information that is incorporated into the prices of the focal coins with a delay, thereby engendering positive cross-cryptocurrency return predictability. As the leading coins in the cryptocurrency market, BTC and ETH may respond to new information more promptly than many other coins. As a result, the positive lead-lag effect is weaker for them and their loadings on the lagged returns of the other coins are not always positive. Such negative loadings may capture some complex coin interdependencies in the cryptocurrency market, which may be dominated by the positive lead-lag effect for smaller coins but significantly affect large coins where the positive lead-lag effect is weak.

Another finding is that all cryptocurrencies except for ONT and ZEC have negative coefficients on their own lagged returns. This intraday return reversal pattern is also documented in Petukhina, Reule, and Härdle (2021).[16] To some extent, for each focal coin, if common shock affects its own price gradually with a delay, then the prediction sign of its own lagged return should be positive as well, same as the sign of lagged returns of other coins. We provide some explanation on this as follows.

Given Bitcoin's substantial share in the cryptocurrency market, it should attract a lot of attention from investors. Thus, a positive common shock at time t-1 is likely to cause BTC to have an increase in return at time t-1 without much delay. However, for a smaller cryptocurrency, such as ADA, its return at t-1 may not be affected much by this common shock due to investors' limited attention on small cryptocurrencies. Instead, its return may decrease at t-1 if it faces a large downward price pressure.[17] Such price pressure impact can be treated as independent from that of the common information.[18] Meanwhile, BTC is not likely to face a large downward price pressure same as ADA at t-1 as evidenced by the low correlations among the contemporaneous returns of

[16] Some papers such as Li and Yi (2019) and Liu and Tsyvinski (2021) show price momentum in data with lower frequencies (weekly and monthly).

[17] See, for example, Kraus and Stoll (1972), Duffie (2010), and Hendershott and Menkveld (2014).

[18] Specifically, according to Campbell, Grossman and Wang (1993), the price pressure is caused by selling or buying pressure from the "noninformational" traders, who have not processed the common information reflected in the lagged returns of peer coins, indicating that the common information shocks and the price pressure shocks tend to be uncorrelated.

the cryptocurrencies[19] and is still able to have a positive return increase driven by the positive common shock. In the following time period t, on the one hand, the focal coin, ADA, is likely to experience a return reversal when the downward price pressure starts to taper off from its own lagged return.[20] On the other hand, when the positive common shock starts to be incorporated into the price of ADA, the return of ADA tends to increase. As such common shock also drives the lagged return of BTC at time t-1, we observe the positive cross-crypto return predictability. Meanwhile, given that the common shock effect and the ADA-specific price pressure tend to be uncorrelated (see footnote 19), the return reversal of ADA on its own lagged return due to the ADA-specific price pressure is not likely to be affected by the common shock. Overall, Table II suggests that cross-cryptocurrency return predictability is indeed prevalent, and there is also a wide-spread return reversal pattern for the lagged returns of focal coins.

Moreover, three stablecoins (PAX, TUSD, USDC) have negative loadings on the lagged returns of other coins. As for stablecoins, their values are pegged to fiat currency rather than determined by the blockchain protocol, platform utility or network activities. Hence, stablecoins may not share common information with other cryptocurrencies in our sample except for being positively associated with the fiat currency while negatively associated with or predicted by other cryptocurrencies.

Since BTC has been the largest coin in terms of market capitalization and an essential cryptocurrency market driver,[21] it is expected to react to common information shocks in the

[19] The average correlation is 0.30 among the returns of the top 30 coins, with the first and third quartiles being 0.15 and 0.43, respectively.
[20] Temporary price pressure and the subsequent return reversal in a short horizon are documented in both equity and cryptocurrency literature (e.g., Heston, Korajczyk, and Sadka, 2010; Petukhina, Reule, and Härdle, 2021).
[21] Its market capitalization has been larger than the sum of all other cryptocurrencies for most of the time and its user base far exceeds that of other cryptocurrencies according to *Reuters*. Source: https://fingfx.thomsonreuters.com/gfx/editorcharts/CRYPTO-CURRENCIES-ALTCOINS/0H001PBVN692/index.html.

cryptocurrency market faster than other cryptocurrencies. According to the gradual information diffusion theory, coins with a larger investor base (proxied by market capitalization) are expected to lead returns of smaller coins, in the spirit of Hou (2007). Therefore, we specifically take Bitcoin's influence on the returns of other cryptocurrencies into account. In addition to the univariate regression, we next run another OLS regression model for each sample coin, by including the lagged return of BTC as a regressor and its own lagged return as the control variable, as follows:

$$r_{i,t} = \hat{\alpha}_{i,t} + \hat{\beta}_{i,BTC}\, r_{BTC,t-1} + \hat{\beta}_{i,i}\, r_{i,t-1} + \epsilon_{i,t} \tag{2}$$

where i = 1, …, 29 (excluding BTC).

Table III presents the estimated coefficients in Equation (2). The main finding here is the information spillover effect of BTC on other coins: the coefficients $\hat{\beta}_{i,BTC}$ are all statistically significant at the 1% level. For all cryptocurrencies, except for the three stablecoins (PAX, TUSD, USDC), the lagged BTC return has positive predictability for their returns. As all return variables are standardized, a one standard deviation increase in the BTC lagged return will increase the return of other coins by 1.92 bps, which is equivalent to 1.15% on an hourly basis. By contrast, the lagged BTC return has negative predictability for the returns of the three stablecoins. Overall, Table III indicates that BTC wields a strong information spillover effect upon the returns of other cryptocurrencies, with both statistical and economic significance in the estimated coefficients.

<To insert Table III here.>

We provide further evidence for the cross-cryptocurrency return predictability, by running multivariate OLS regressions with lagged returns of all cryptocurrencies as the independent variables. Specifically, we run the following regression model:

$$\mathrm{r}_{\mathrm{i,t+1}} = \alpha_i + \sum_{j=1}^{N} \beta_{i,j} r_{j,t} + \epsilon_{i,t+1} \tag{3}$$

where $r_{i,t+1}$ is the return of cryptocurrency i at minute t+1 (where i = 1, …, 30), N is the total number of cryptocurrencies, and $\epsilon_{i,t+1}$ is the error term.

However, this multivariate OLS regression model, with a plethora of correlated regressors, potentially suffers from statistical drawbacks such as overfitting and imprecise parameter estimates. Hence, following the approach of Rapach, Strauss, and Zhou (2013), we improve the multi-factor OLS regression model by using pooled estimates to increase estimation efficiency. Table IV reports pooled OLS coefficient estimates with bias-corrected wild bootstrapped 90% confidence intervals (shown in brackets). The results further corroborate our previous findings: for about half of the sample coins (14 out of 30), their returns can be significantly and positively predicted using the pooled lagged returns of other coins. The economic magnitude is large as well, since a one standard deviation increase in the pooled lagged return of other coins will cause the returns of these 14 coins to increase by 0.40 bps – 4.82 bps on a minute basis, which is equivalent to 24 bps – 289 bps hourly. Again, the large and positive coefficients indicate that the common information of the cryptocurrency market is not homogeneously incorporated into individual coins. Accordingly, the lagged returns of other coins contain valuable information that is slowly incorporated into the prices of the focal coins, suggesting the presence of the information spillover effect in the cryptocurrency market.

< To insert Table IV here. >

3.2. Adaptive LASSO method

The aforementioned measure, using pooling estimates and bias-corrected wild bootstrapping, does alleviate, but does not solve, the drawbacks of multivariate OLS regression with an excessive number of regressors. To further circumvent such statistical issues, we follow the statistics literature by employing the adaptive version of least absolute shrinkage and selection operator (LASSO) in the predictor estimation (e.g., Tibshirani, 1996; Zou, 2006; Rapach, Strauss, Tu, and Zhou, 2019). In short, LASSO performs both shrinkage and variable selection while the adaptive LASSO proposed by Zou (2006) further improves the estimation. The adaptive LASSO estimates for the general predictive regression model in Equation (3) are:

$$\widehat{\boldsymbol{\beta}}_i^* = argmin\left\|r_{i,t+1} - \sum_{j=1}^{N} \beta_{i,j}\tilde{r}_{j,t}\right\|^2 + \lambda_i \sum_{j=1}^{N} \widehat{w}_{i,j}\left|\beta_{i,j}\right| \tag{4}$$

where $r_{i,t+1}$ is the return of cryptocurrency i at minute t+1 (i = 1, …, 30), N is the total number of cryptocurrencies, i.e., 30, $\tilde{r}_{j,t}$ is the standardized return for cryptocurrency j, $\widehat{\boldsymbol{\beta}}_i^* = (\widehat{\beta}_{i,1}^*, \ldots, \widehat{\beta}_{i,N}^*)'$ is the N-vector of adaptive LASSO estimates, $\lambda_i$is a non-negative regularization parameter, and $\widehat{w}_{i,j}$ is the weight vector of $\left|\beta_{i,j}\right|$ for j =1,…, N. In particular, $\lambda_i \sum_{j=1}^{N} \widehat{w}_{i,j}\left|\beta_{i,j}\right|$ is the ℓ_1 penalty that allows the coefficient estimates to shrink continuously towards zero as λ_i increases. We also follow Zou (2006) to define the weight vector $\widehat{w}_{i,j}$ as:

$$\widehat{w}_{i,j} = 1/\left|\hat{\beta}_{i,j}\right|^{\gamma_i} \tag{5}$$

where $\hat{\beta}_{i,j}$ is the OLS estimate of $\beta_{i,j}$ and γ_i>0.

Table V presents the adaptive LASSO estimates of the general predictive model for all sample cryptocurrencies. To conserve space, we use bold to denote statistically significant coefficients with bootstrapped 90% confidence intervals or higher. Consistent with the results of univariate OLS regressions, the adaptive LASSO estimates uncover both the information spillover effect and the return reversal pattern in the cryptocurrency market. Indeed, after controlling for lagged return, spillover effects remain strong across all the regression models. Based on machine learning, the adaptive LASSO technique helps select variables in predictive regressions. According to Table V, it identifies at least six other coins' lagged returns as significant return predictors for each sample coin. The average number of other coins selected as informative return predictors for each focal coin is 23, which represents 77% of the sample size. Hence, the results of the adaptive LASSO approach reinforce the findings in OLS regressions that the information spillover effect is indeed prevalent in the cryptocurrency market. Consistent with stock spillover literature (e.g., Cohen and Frazzini, 2008; Menzly and Ozbas, 2010; Lee, Sun, Wang, and Zhang, 2019), we show that in the cryptocurrency market, individual cryptocurrencies do not homogeneously incorporate the common information. Hence, the other coins' lagged returns contain valuable information that is slowly incorporated into the prices of the focal coins, thereby causing cross-cryptocurrency return predictability. Compared to the coefficients generated from the univariate OLS regression, the number of significant predictors in Table V has been largely reduced for many coins in our sample. The variable-dropping phenomenon may be attributed to the improved estimation accuracy by using the adaptive LASSO technique.

Among the return predictors, Bitcoin is selected by the adaptive LASSO technique to positively predict returns for all sample coins except for stablecoins. Its predictability is both statistically and economically significant. Specifically, a one standard deviation increase in BTC lagged returns will increase the returns of other coins (excluding stablecoins, which, due to their special nature of being pegged to fiat currency, exhibit negative coefficients in this case) by 1.25 bps on average, which is equivalent to 75 bps on an hourly basis. This information spillover effect of BTC on other coins is also documented in Table III. A possible explanation is that BTC, as the first widely circulated cryptocurrency and the largest in terms of market capitalization, serves as an essential cryptocurrency market driver and tends to respond to information shocks faster than other coins. As a result, lagged returns of BTC serve as predictors of other coins' returns in the market. Besides BTC, other leading predictors are Binance coin (BNB) and Tron (TRX), which predict returns for all other coins excluding stablecoins. Again, the positive coefficient estimates suggest a faster response of their prices to common information shocks compared with other cryptocurrencies. For the remaining 24 coins in our sample (excluding stablecoins), 7 have lagged returns that positively predict other coins' returns, while the other 17 show estimated coefficients with both positive and negative signs, a finding that is consistent with the complicated interdependencies across assets documented in Rapach, Strauss, Tu, and Zhou (2019). Moreover, the cryptocurrencies that serve as powerful positive predictors, such as BTC, will capture the positive lead-lag effect and the associated positive cross-cryptocurrencies predictability while the less powerful predictors, like those smaller coins, will capture the complicated interdependencies, which may lead to negative cross-cryptocurrencies predictability.

< To insert Table V here. >

3.3. Principal component analysis

To further investigate the information spillover effect, we employ the principal component analysis (PCA), where the number of latent principal components that are common across cryptocurrencies is selected based on the Bai and Ng (2002) criteria. Specifically, we include the lagged estimated factors as regressors as follows:

$$\mathrm{r}_{\mathrm{i,t+1}} = \alpha_i + \sum_{k=1}^{K} \beta_{i,k} \hat{f}_{k,t} + \epsilon_{i,t+1} \tag{6}$$

where the estimated factors $\hat{f}_{k,t}$ is the principal component estimate of a K-vector of latent factors that are common across cryptocurrencies. In our case the number K is set to be 3.

Figure 2 shows the estimated loadings for each cryptocurrency on the three principal components, with estimated factors standardized. All cryptocurrencies in our sample have positive and relatively uniform loadings on the first principal component, suggesting that common links among cryptocurrencies serve as the most important channel that contributes to the cross-cryptocurrency return predictability. Exceptions are again the three stablecoins (PAX, TUSD and USDC), which exhibit much smaller loadings due to designs that differ from other coins. In contrast to the uniform loadings on the first principal component, the loadings on the second and the third principal components fluctuate a lot across sample coins. The magnitude of loadings on the second principal component is close to zero for most coins, except for stablecoins. The fluctuating loadings on these two principal components are consistent with a finding in Table V, namely that some coins have estimated coefficients with mixed signs, which is indicative of the complicated interdependencies between coins.

Overall, the uniform loadings on the first principal component indicate the presence of common shock serves as the most important channel of cross-cryptocurrency return predictability, while the varying loadings on the other two principal components capture some complex coin interdependencies in the cryptocurrency market. According to the return variance's distribution among the three main principal components, the first principal component represents 36.80% of the total variance, whereas the next two principal components together represent just 8.26%, indicating that the common links among cryptocurrencies have the highest explanation power for cross-cryptocurrency return predictability.

< To insert Figure 2 here. >

3.4. Trading strategies

Given the strong cross-cryptocurrency return predictability, we next set about implementing profitable trading strategies and measuring their out-of-sample performance. The goal is to better align the aforementioned cross-cryptocurrency predictability with the utility of investor and to shed light on its economic value. We construct three long-short portfolios for the sample period from March 2019 to April 2021, using out-of-sample minute-level cryptocurrency return forecasts predicted by the adaptive LASSO, PCA, and the univariate (BTC) regression, respectively.

For the portfolios constructed based on the adaptive LASSO technique, we use half-day (720 minutes) data to forecast returns for each sample coin in the next minute, on a rolling basis. To begin with, for each sample coin, i, we use data in the first 720 minutes on 25 March 2019 (referred to as "the first day" subsequently) to estimate $\beta_{i,j}$ via the adaptive LASSO technique in Equation (3). Next, we use the estimated parameters and data in the 720$^{\text{th}}$ minute on the first day to calculate the out-of-sample forecasts. In this way we generate a set of 30 excess return forecasts for the 721$^{\text{st}}$ minute on the first day. We then repeat this calculation for each minute level on a rolling basis (e.g., the 2$^{\text{nd}}$ through the 721$^{\text{st}}$ minute on the first day for the forecasted returns in the 722$^{\text{nd}}$ minute). We sort the sample coins in ascending order based on the excess return forecasts and construct equal-weighted quintile portfolios on a minute frequency, and then form a long-short portfolio that goes long the top quintile portfolio and goes short the bottom quintile portfolio. To further test the robustness of our findings, we also construct portfolios using out-of-sample coin excess return forecasts based on the PCA approach. Again, we follow the aforementioned out-of-sample rolling-window estimation when applying the PCA prediction model shown in Equation (6).

As shown in Table III, BTC serves a market-driving role, where a one standard deviation increase in its lagged return will augment other coins' average return by 1.92bps on a minute basis. Therefore, we construct another long-short portfolio using out-of-sample cryptocurrency return forecasts based on:

$$\mathrm{r}_{\mathrm{i,t+1}} = \hat{\alpha}_{i,t+1} + \hat{\beta}_{i,BTC}\, r_{BTC,t} + \epsilon_{i,t+1} \tag{7}$$

where $r_{i,t+1}$ is the return of cryptocurrency i at minute t+1, $r_{BTC,t}$ is the return of BTC at time t. The portfolio construction method here is the same as that in the adaptive LASSO prediction, except that we now employ the prediction model in Equation (7). Using forecasted returns for each coin during the sample period, we sort coins into five equal-weighted quintiles and construct a zero-investment portfolio that goes long (short) the top (bottom) quintile portfolio.

Table VI reports the out-of-sample returns of all constructed portfolios and the corresponding statistical significance. For all three prediction models, returns increase monotonically from the lowest quintile to the highest quintile. The minute-frequency return based on the adaptive LASSO forecasts is -1.75 bps in the lowest quintile portfolio, increasing markedly to 1.80 bps in the highest quintile. The return spread for the corresponding long-short portfolio is 3.55 bps at the 1% significance level. The portfolio results, shown in the first column, suggest that using information in other coins' lagged returns could help generate sizable out-of-sample returns. Out-of-sample portfolio returns based on the PCA prediction method further corroborate the findings in column (1). Specifically, the portfolio return climbs from -0.91 bps to 0.94 bps from the lowest quintile to the highest quintile according to column (2). The return spread for the long-short portfolio using PCA prediction is 1.86 bps per minute and although its magnitude is only half of the return spread in column (1), it is still significant both statistically and economically. Apart from using the lagged returns of multiple coins as in-sample data, we report out-of-sample portfolio returns in column (3) by using only BTC returns as regressors, according to Equation (7). Consistent with findings contained in Table III, BTC returns still serve as a strong predictor for other coins' returns. Specifically, the return spread for the long-short portfolio is 1.54 bps per minute at the 1% significance level in column (3), indicative of the information spillover effect of BTC on other cryptocurrencies. We also report the portfolio returns predicted via the adaptive

LASSO and PCA by excluding the returns of the focal coins, and the long-short portfolio returns from using these two prediction techniques are 1.79 bps and 1.60 bps per minute, respectively. Both coefficient estimates remain statistically significant. Overall, results from Table VI serve as solid out-of-sample evidence of cross-cryptocurrency return predictability. More importantly, multiple trading strategies based on this spillover effect yield superior out-of-sample performance, indicating potential investment opportunities to crypto traders.

< To insert Table VI here. >

3.5. Economic Channels

As discussed previously, the information spillover effect could explain the cross-cryptocurrency return predictability, in that common technique linkages among cryptocurrencies coupled with investors' limited attention create gradual information diffusion in the market, thereby generating lead-lag relationships among crypto assets. In this section, we conduct several tests to show that risk-based explanations are not likely to drive our results. Moreover, we run additional tests to show that the information spillover mechanism is consistent with our results.

3.5.1. Risk-based explanation

One alternative potential explanation of the cross-cryptocurrency return predictability could be risk-based. We therefore test whether exposures to cryptocurrency risk factors can account for the performance of our trading strategies. Specifically, we further control for multiple factors in the regression to check whether the alpha of the above strategies remain significant:

$$\mathrm{r_t} = \alpha_t + \beta_{MKT}\, MKT_t + \beta_{SMB}\, SMB_t + \beta_{MOM5}\, MOM5_t + \beta_{MOM10}\, MOM10_t + \beta_{MOM30}\, MOM30_t + \epsilon_t \quad (8)$$

where r_t is the portfolio return spread based on the adaptive LASSO prediction, MKT_t is the market factor, SMB_t is the "small-minus-big" size factor, and $MOM5_t$ is the "up-minus-down" momentum factor constructed based on the past 5-minute cumulative returns ($MOM10_t$ based on past 10-minute cumulative returns and $MOM30_t$ based on past 30-minute cumulative returns). Specifically, the risk-adjusted portfolio returns are minute-level, with available cryptocurrency data to construct risk factors. As for the market factor, we use sample cryptocurrencies' market capitalization in the prior day from *CoinMarketCap* as weights to calculate the value-weighted cryptocurrency market return. We sort cryptocurrency returns based on prior day's market capitalization to construct the "small-minus-big" size premium. We further use the minute-frequency cryptocurrency returns from *Binance* to calculate cumulative returns, and construct "up-minus-down" momentum premiums based on the past 5-, 10-, or 30-minute cumulative returns, corresponding to factors $MOM5_t$, $MOM10_t, MOM30_t$, respectively.

Table VII reports risk-adjusted alphas using single- or multiple-factor regressions indicated in Equation (8). The first five columns present alphas controlling for one risk factor (MKT, SMB, MOM5, MOM10, or MOM30). The last column presents alphas controlling for all five factors in the regression. The long-short portfolio returns based on the adaptive LASSO forecasts remain significant and large, even with controlling for all risk factors. The long-short risk-adjusted alpha in the last column is 3.23 bps and is only slightly reduced from 3.55 bps shown in Table VI. The results reveal that the aforementioned return of the long-short portfolio cannot be explained by exposures to a variety of cryptocurrency risk factors.

< To insert Table VII here. >

3.5.2. Investor attention channel

To further verify the information spillover hypothesis that is based on investors' limited attention, we use several proxies for investor attention and conduct sub-sample analysis.

Cryptocurrency size serves as the first proxy. Research works such as Bamber (1987) and Zhang (2006) use firm size to represent information environment or the level of investor attention the firm can attract. They show that larger firms exhibit faster information diffusion compared to smaller firms. In our setting, we use the prior day's coin market capitalization as the proxy for the coin size. For each day, we divide the sample into terciles based on coin size and define coins in the top (bottom) tercile as large (small) coins. We then re-examine the risk-adjusted alphas of the portfolios constructed according to the adaptive LASSO prediction in each sub-sample.

The risk-adjusted alphas calculated from the factor regression in Equation (8) in large and small size groups are presented in the first two panels of Table VIII. Panel A reports alphas for the large-cap coins and Panel B shows results for the small-cap coins. The long-short portfolio alphas in both sub-samples with different regression specifications all remain significant. The risk-adjusted alpha with all risk factors controlled for the long-short portfolio is 3.75 bps for small coins (with low attention) and 1.65 bps for large coins (with high attention). The differences between risk-adjusted alphas from the two panels remain statistically significant, shown in Panel C. Hence, the higher return for coins with smaller size than for coins with larger size is consistent with slow information diffusion among cryptocurrencies due to investors' limited attention.

We also use dollar trading volume and Google search volume to proxy for investor attention.[22] By dividing the sample into terciles based on either dollar trading volume or Google search volume, we report the risk-adjusted alphas calculated from the factor regression in Equation (8) in these sub-samples in Panel D – I of Table VIII. Again, we define coins in the top tercile as coins with high trading volume (high abnormal Google search volume) and those in the bottom

[22] The dollar trading volume is calculated on a daily basis for each coin. To obtain the abnormal Google search volume, we divide each coin's daily search volume by its average search volume in the past week and then subtract one, in accordance with the finance literature (e.g., Da, Engelberg, and Gao, 2011; Liu and Tsyvinski, 2021).

tercile as coins with low trading volume (low abnormal Google search volume). Panel D and E report alphas for the coins with high dollar trading volume and low dollar trading volume, respectively. Although the long-short portfolio alphas in both sub-samples with different regression specifications remain significant, the risk-adjusted alpha with various risk factors controlled for the long-short portfolio is 3.45 bps for coins with low dollar trading volume (with low attention), significantly larger than the 2.12 bps for coins with high dollar trading volume (with high attention).[23]

The sub-sample results based on Google search volume are shown in Panel G and H. Again, the risk-adjusted alpha for the long-short portfolio in the last column is higher for coins with low Google search volume (3.29 bps) than for coins with high Google search volume (2.80 bps). Overall, the results in Table VIII are consistent with slow information diffusion for cryptocurrencies resulting from investors' limited attention. Specifically, information diffuses at a higher speed among coins that attract more investors' attention and thus common information is more promptly reflected in their prices. As a result, the return predictability based on peer coins' past returns becomes weaker for coins with larger investor attention, reinforcing the information spillover channel.

< To insert Table VIII here. >

Moreover, we examine the return spread of the long-short portfolio predicted via the adaptive LASSO approach, constructed in section 3.4, over the subsequent 10-minute horizon. The cumulative excess returns up to the next 10 minutes are presented in Figure 3. The return spread at time t+1 (the first minute) based on the adaptive LASSO prediction is sizable and

[23] The difference between risk-adjusted alphas for the sub-samples divided by either trading volume or abnormal Google search volume is statistically significant, as shown in Panel F and I.

significant[24] at 3.55 bps, as also shown in Table VI. Returns in the subsequent five minutes remain positive and statistically significant though the magnitude decreases over time. Returns after the sixth minute become insignificant, indicating that there is a slow information diffusion as cryptocurrency prices incorporate the information shocks gradually.

< To insert Figure 3 here. >

3.5.3. Market-wide events and information spillover hypothesis

Regarding the information-spillover hypothesis, we investigate nine market-wide events and examine the corresponding long-short portfolio alphas on these event days. These events are selected because of their broad impact on the cryptocurrency market, including President Xi's advocacy of blockchain in China, PayPal's adoption of cryptocurrencies as a payment tool, the IPO of the largest cryptocurrency platform Coinbase, the $3 billion PlusToken Ponzi scheme, and the "Black Thursday" when the cryptocurrency market suddenly collapsed because of the spread of COVID-19.[25] Having had a broad impact on the overall cryptocurrency market, these events should affect various coins as common shocks. The long-short portfolio alphas on event days and normal days are reported in Table IX, where we classify the days other than the nine event days in our sample as normal days. The risk-adjusted alphas are expected to be higher on the event days than on the normal days, as the market-wide events create abnormally larger common shocks to various coins and a consequential higher level of cross-cryptocurrency return predictability on the event days than on the normal days. Indeed, the risk-adjusted alpha with all risk factors controlled for the long-short portfolios on the event days (Panel A) is 4.15 bps, larger than the 3.21 bps on

[24] The t-statistics are not reported here for brevity.
[25] A full list of the market events mentioned in this paper is provided in Table A.I.

normal days (Panel B).[26] The differences between alphas on event days and normal days are shown in Panel C and are statistically significant.

< To insert Table IX here. >

3.6. Transaction costs and the futures market

3.6.1. Trading strategies using futures contracts

The profits documented for the strategies outlined above may subject to relatively high transaction costs in the cryptocurrency spot market. Then, the aforementioned investment strategies with a minute-level turnover rate may no longer yield significant profits. In fact, the transaction cost on *Binance* per round-trade can be as high as 20 bps.[27] Therefore, we further examine the portfolio performance when investors are trading in the futures contracts market, in an effort to avail of lower transaction costs, which range from 1.7 bps (for VIP9) to 4 bps (for VIP0)[28] for market takers.[29]

Such trading strategies are feasible for cryptocurrency investors for multiple reasons. First, we focus on the futures contracts traded on *Binance*, which is widely regarded as the biggest crypto exchange in the world by volume. It is ranked as the top derivative exchange in terms of both the

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[26] There are two potential explanations of why the alphas on normal days remain significantly positive. One is that, on normal days, there could exist sporadic event-based common shocks other than the nine major events. Another is that there may be non-event-based common information shocks, such as an increasing number of digital wallet users or blockchain-related network activities in the market, given the relatively early stage of the cryptocurrency market. On normal days, when these common shocks occur, their impact may not be promptly reflected in prices.

[27] There are various trading fee levels for *Binance* users. The trading fee for 30-day trading volume of less than 50 BTC is 10 bps per trade and thus 20 bps for buying and selling cryptos at a minute frequency. Source: https://www.binance.com/en/fee/trading.

[28] VIP levels are determined by the 30-day trading volume with VIP0 (VIP9) as the one with the lowest (highest) trading volume and highest (lowest) trading fee. Source: https://www.binance.com/en/support/faq/360033544231.

[29] In the contracts market, taker refers to an order that trades at a market price and maker is an order that trades at a limited price.

open interest and trade volume.[30] While trading cryptocurrencies in the spot market that involves recording transactions on the blockchain may take hours, trading futures on the largest cryptocurrency exchange has far lower latency as well as deeper liquidity and is appealing to especially the high-frequency traders.[31] In fact, the trading volume in the derivatives market far exceeds that in the spot market[32] and the average monthly turnover for Bitcoin futures at *Binance* is US$2 trillion, which is far higher than the Bitcoin spot markets' trading volumes.[33] In addition, we focus our study on the top 30 coins, which offer sufficient liquidity to support their futures trading in a timely manner for both long and short positions. We use the real-time market orders and limit orders to execute our trading strategies. Last but not least, we set the portfolio rebalancing intervals up to 15 minutes, providing ample time for investors to enter the next position.

3.6.2. Portfolio performance and transaction costs

We examine the out-of-sample performance using the adaptive LASSO strategy in the futures market, with the portfolio rebalancing frequency ranging from one minute to 15 minutes. According to *Binance*, trading fees of futures contracts for makers are much lower than those for takers at all VIP levels. We report the results for both takers and makers and our portfolio results indeed suggest that the corresponding profits for makers are higher.

Overall, the portfolios indeed yield statistically and economically significant returns and the

[30] According to *Coinmarketcap.com*, the 24-hour volume on *Binance* is US$82.3 billion, over four times of that on the derivative exchange with the second highest volume (US$18.3, *OKEx*). In terms of the spot market, *Binance* is also ranked as the top exchange with a 24-hour trading volume (US$24.4 billion) far higher than other major exchanges (e.g., US$5.5 billion for *Huobi Global* and US$4.0 billion for *Coinbase Exchange*). Source: https://coinmarketcap.com/rankings/exchanges/derivatives/ (accessed on 10 August 2021).

[31] The futures trading platform at *Binance* routinely processes up to 100,000 orders per second with an average latency of 5 milliseconds. Source: https://www.binance.com/en/blog/421499824684900642/Binance-Futures-For-Institutions--Pioneering-Performance--Technology.

[32] Refer to footnote #31.

[33] Source: https://www.binance.com/en/blog/421499824684901983/Crypto-Spot-vs-Crypto-Futures-Trading--Whats-the-difference (accessed on 10 August 2021).

returns are especially higher with a lower rebalancing frequency. In Panel A of Table X, the portfolio returns for takers using decile sorting are positive for VIP7 and above with a 3-minute rebalancing interval, and for all VIP levels with a rebalancing interval of five minutes or longer, after considering transaction costs. When rebalanced at a 13-minute frequency, the corresponding long-short portfolio yields a return of 0.15 bps for VIP0 users and 0.19 bps for VIP9 users, respectively. Both returns are significant at the 1% level and are equivalent to 2.16% and 2.74% on a daily basis, respectively. The results remain consistent when we use the quintile sorting method, as shown in Panel B. The long-short portfolio returns are significantly positive for all VIP levels with a rebalancing interval of eight minutes or longer. For a 13-minute rebalancing frequency, the minute-level return is 0.07 bps for VIP0 and 0.11 bps for VIP9, both significant at the 1% level and are equivalent to 1.01% and 1.58% on a daily basis, respectively. Furthermore, Panel C and D indicate that the portfolio perform better for makers. For a 13-minute rebalancing frequency, the daily return is 2.59% for VIP0 and 3.02% for VIP9 using decile sorting and equals 1.44% for VIP0 and 1.87% for VIP9 using quintile sorting. Hence, the statistically and economically significant long-short portfolio returns validate our prior findings of utilizing cross-cryptocurrency return predictability to achieve sizable profits. Indeed, cryptocurrency investors can attain profits from such investment strategies when trading in the futures market, even after transaction costs are considered.

< To insert Table X here. >

4. Conclusion

In this paper, we find strong cross-cryptocurrency return predictability, where the lagged returns of other cryptocurrencies significantly predict returns of the focal ones. In particular, playing a leading role in the cryptocurrency market, Bitcoin tends to respond to information more promptly and thus its lagged return is a strong predictor for other cryptocurrencies. We also employ the adaptive version of LASSO and the PCA approach to identify and include the lagged returns of other important coins beyond BTC as additional predictors. The results are all significant.

We attribute such findings to common shocks and the information spillover effect in the cryptocurrency market, given that most cryptocurrencies share similar underlying technical details. Due to the limited attention or constrained information-processing capabilities of investors, the information about common shocks is not homogeneously incorporated into individual coins, so the lagged returns of other coins may contain valuable information that is incorporated into the prices of the focal coins with a delay, thereby engendering cross-cryptocurrency return predictability. We run various tests to show that the slow information diffusion mechanism, rather than any risk-based ones, is more consistent with the cross-cryptocurrency return predictability.

In addition, we construct a long-short portfolio based on the past returns of cryptocurrencies in the futures market, which exhibits low latency and deep liquidity, and our portfolio can generate a daily return up to 2.16% out-of-sample after accounting for transaction costs. This result indicates that using cross-cryptocurrency return predictability can achieve sizable economic gains.

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Table I Summary statistics

Table I reports summary statistics for minute-level returns of the top 30 cryptocurrencies, which are selected based on both the large market capitalization and the length of the trading history. The sample period spans from March 2019 to April 2021, and the data frequency is on a minute basis in the 24/7 cryptocurrency market. Returns are standardized with means equal to 0 and standard deviations equal to 1. Sharpe ratio is the average return of each coin in excess of the risk-free rate, divided by the coin's standard deviation. Data are obtained from *Binance*.

Symbol	Name	Mean (bps)	Standard deviation (%)	Minimum (%)	Maximum (%)	Sharpe ratio (%)
ADA	Ada	0.05	0.18	-7.64	8.35	0.25
BAT	Basic Attention Token	0.04	0.21	-12.34	10.20	0.21
BNB	Binance Coin	0.05	0.17	-9.81	10.37	0.29
BTC	Bitcoin	0.03	0.13	-7.24	7.50	0.27
BTT	BitTorrent	0.05	0.22	-13.23	15.71	0.22
CELR	Celer	0.05	0.31	-7.34	12.00	0.17
EOS	EOS coin	0.02	0.17	-6.28	13.90	0.12
ETC	Ethereum Classic	0.04	0.19	-5.73	8.62	0.23
ETH	Ether	0.04	0.15	-5.88	8.17	0.26
FET	Fetch.ai	0.04	0.29	-8.41	13.23	0.15
HOT	HoloTokens	0.08	0.29	-9.96	11.69	0.25
ICX	ICON	0.05	0.24	-10.96	17.35	0.21
IOST	IOStoken	0.05	0.23	-7.88	12.10	0.20
IOTA	IOTA tokens	0.04	0.20	-7.60	10.12	0.19
LINK	Link token	0.07	0.23	-14.51	10.16	0.28
LTC	Litecoin	0.03	0.17	-7.03	10.37	0.17
NEO	Neo token	0.04	0.18	-5.83	9.07	0.22
ONT	Ontology Coin	0.02	0.20	-8.36	6.48	0.12
PAX	Paxos Standard Token	0.00	0.02	-2.96	8.89	-0.01
QTUM	Qtum	0.04	0.19	-5.82	8.80	0.18
TRX	Tronix	0.03	0.17	-7.13	8.50	0.16
TUSD	TrueUSD	0.00	0.02	-1.95	2.34	0.00
USDC	USD Coin	0.00	0.02	-1.70	2.12	0.00
VET	VeChain Token	0.06	0.23	-9.38	22.94	0.25
WAVES	Waves	0.04	0.22	-6.23	17.35	0.16
XLM	Stellar Lumens	0.03	0.18	-9.47	6.53	0.18
XMR	Monero	0.03	0.16	-4.53	6.58	0.17
XRP	XRP coins	0.04	0.20	-15.30	12.45	0.18
ZEC	Zcash	0.03	0.19	-6.75	7.33	0.16
ZIL	Zilliqa	0.04	0.24	-8.08	15.23	0.18

Table II Univariate OLS predictive regression results

Table II reports coefficient estimates (in bps) for each of the 30 cryptocurrencies from the univariate OLS regressions. The minute-level returns are standardized with means equal to 0 and standard deviations equal to 1. Return of each cryptocurrency in the top header serves as the dependent variable in the univariate OLS regression. Lagged return of each cryptocurrency in the left column serves as the independent variable. Each coefficient estimate corresponds to one univariate OLS regression model. For each cryptocurrency, the average value of their coefficient estimates for other coins (estimates for stablecoins are excluded) is reported in an additional column (Avg_Coef). The sample period is from March 2019 to April 2021. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Avg_Coef	ADA	BAT	BNB	BTC	BTT	CELR
ADA	1.09	-0.04*	1.44***	0.47***	0.06***	1.42***	2.41***
BAT	0.64	0.38***	-1.27***	0.15***	-0.06***	0.87***	1.75***
BNB	1.13	0.77***	1.47***	-0.20***	0.07***	1.39***	2.48***
BTC	1.39	0.93***	1.62***	0.63***	-0.02	1.81***	2.83***
BTT	0.56	0.35***	0.67***	0.25***	-0.03*	-0.56***	1.48***
CELR	0.25	0.15***	0.28***	0.05***	-0.03*	0.39***	-2.84***
EOS	1.23	0.89***	1.56***	0.59***	0.02*	1.64***	2.44***
ETC	1.03	0.70***	1.36***	0.49***	0.03**	1.42***	2.24***
ETH	1.36	0.97***	1.75***	0.64***	0.05***	1.71***	2.66***
FET	0.41	0.23***	0.51***	0.10***	-0.03**	0.64***	1.46***
HOT	0.23	0.05**	0.26***	0.03*	-0.09***	0.40***	0.86***
ICX	0.63	0.39***	0.85***	0.25***	0.01	0.84***	1.76***
IOST	0.66	0.43***	0.86***	0.27***	-0.02	1.04***	1.84***
IOTA	0.71	0.42***	0.98***	0.26***	-0.03**	1.03***	1.93***
LINK	0.91	0.63***	1.23***	0.42***	0.04***	1.22***	1.96***
LTC	1.27	0.96***	1.61***	0.59***	0.11***	1.63***	2.52***
NEO	1.05	0.73***	1.35***	0.46***	0.08***	1.46***	2.27***
ONT	0.99	0.63***	1.22***	0.43***	0.03**	1.44***	2.37***
PAX	0.15	0.14***	0.25***	0.02	-0.09***	0.25***	0.23***
QTUM	0.88	0.57***	1.11***	0.37***	0.01	1.28***	2.12***
TRX	1.14	0.86***	1.43***	0.56***	0.09***	1.88***	2.34***
TUSD	0.31	0.19***	0.47***	0.10***	0.06***	0.37***	0.22***
USDC	0.21	0.14***	0.40***	0.04**	-0.03**	0.29***	0.26***
VET	0.77	0.45***	1.02***	0.23***	-0.03**	1.06***	2.04***
WAVES	0.57	0.32***	0.66***	0.20***	-0.01	0.82***	1.51***
XLM	1.02	0.86***	1.33***	0.40***	0.03**	1.27***	2.29***
XMR	0.80	0.52***	1.09***	0.34***	0.01	1.10***	1.97***
XRP	0.97	0.67***	1.17***	0.42***	0.01	1.27***	2.17***
ZEC	0.98	0.74***	1.24***	0.49***	0.12***	1.34***	2.13***
ZIL	0.55	0.29***	0.67***	0.17***	-0.03*	0.84***	1.64***

Table II (Continued) Univariate OLS predictive regression results

	EOS	ETC	ETH	FET	HOT	ICX
ADA	0.32***	0.64***	0.18***	2.53***	2.28***	1.60***
BAT	0.18***	0.33***	0.02	1.69***	1.57***	1.00***
BNB	0.39***	0.64***	0.15***	2.60***	2.48***	1.62***
BTC	0.38***	0.89***	0.23***	2.89***	2.86***	1.78***
BTT	0.18***	0.23***	0.02	1.46***	1.53***	0.79***
CELR	0.08***	0.12***	-0.03*	1.00***	0.79***	0.36***
EOS	-0.06***	0.83***	0.19***	2.69***	2.39***	1.70***
ETC	0.32***	-0.24***	0.13***	2.39***	2.13***	1.49***
ETH	0.30***	0.79***	-0.07***	2.98***	2.78***	1.83***
FET	0.14***	0.23***	0.04**	-2.86***	1.10***	0.62***
HOT	0.05**	0.10***	-0.05***	0.78***	-2.64***	0.33***
ICX	0.17***	0.31***	0.08***	1.76***	1.46***	-1.91***
IOST	0.15***	0.31***	0.04**	1.78***	1.66***	1.03***
IOTA	0.19***	0.36***	0.06***	1.94***	1.75***	1.07***
LINK	0.25***	0.51***	0.14***	2.10***	1.83***	1.31***
LTC	0.34***	0.79***	0.22***	2.74***	2.41***	1.77***
NEO	0.37***	0.62***	0.20***	2.48***	2.15***	1.45***
ONT	0.38***	0.62***	0.14***	2.36***	2.12***	1.43***
PAX	-0.01	0.13***	-0.01	0.17***	0.25***	0.19***
QTUM	0.28***	0.54***	0.13***	2.13***	1.89***	1.28***
TRX	0.36***	0.67***	0.22***	2.53***	2.13***	1.58***
TUSD	0.15***	0.17***	0.04***	0.42***	0.41***	0.48***
USDC	0.06***	0.12***	-0.11***	0.21***	0.27***	0.28***
VET	0.22***	0.43***	0.04**	2.00***	1.84***	1.14***
WAVES	0.14***	0.32***	0.08***	1.51***	1.35***	0.90***
XLM	0.36***	0.62***	0.12***	2.38***	1.99***	1.48***
XMR	0.18***	0.40***	0.12***	1.99***	1.92***	1.17***
XRP	0.30***	0.61***	0.10***	2.30***	1.86***	1.41***
ZEC	0.38***	0.59***	0.25***	2.22***	2.01***	1.39***
ZIL	0.17***	0.35***	0.05***	1.55***	1.33***	0.84***

Table II (Continued) Univariate OLS predictive regression results

	IOST	IOTA	LINK	LTC	NEO	ONT
ADA	1.77***	1.51***	0.76***	0.25***	0.95***	1.27***
BAT	1.08***	0.85***	0.43***	0.12***	0.47***	0.74***
BNB	1.73***	1.51***	0.90***	0.28***	0.99***	1.33***
BTC	2.35***	1.85***	1.07***	0.30***	1.12***	1.60***
BTT	0.92***	0.79***	0.36***	0.08***	0.46***	0.72***
CELR	0.47***	0.30***	0.10***	0.07***	0.18***	0.30***
EOS	1.95***	1.66***	0.96***	0.23***	1.08***	1.52***
ETC	1.62***	1.43***	0.73***	0.17***	0.88***	1.29***
ETH	2.22***	1.84***	1.06***	0.24***	1.18***	1.59***
FET	0.67***	0.53***	0.25***	0.09***	0.31***	0.45***
HOT	0.39***	0.33***	0.09***	-0.02	0.19***	0.28***
ICX	1.08***	0.86***	0.38***	0.15***	0.44***	0.73***
IOST	-0.13***	0.95***	0.36***	0.10***	0.56***	0.86***
IOTA	1.16***	-1.23***	0.44***	0.13***	0.53***	0.87***
LINK	1.48***	1.31***	-1.06***	0.20***	0.73***	1.09***
LTC	2.00***	1.66***	1.11***	-0.21***	1.13***	1.53***
NEO	1.70***	1.45***	0.70***	0.27***	-0.32***	1.37***
ONT	1.75***	1.33***	0.63***	0.23***	0.87***	0.21***
PAX	0.29***	0.17***	0.20***	0.01	0.15***	0.20***
QTUM	1.47***	1.19***	0.61***	0.20***	0.83***	1.21***
TRX	1.78***	1.49***	0.91***	0.24***	0.98***	1.36***
TUSD	0.61***	0.40***	0.28***	0.06***	0.31***	0.36***
USDC	0.44***	0.33***	0.27***	-0.01	0.25***	0.32***
VET	1.30***	1.09***	0.41***	0.12***	0.64***	0.94***
WAVES	0.96***	0.79***	0.33***	0.10***	0.44***	0.65***
XLM	1.62***	1.40***	0.64***	0.24***	0.91***	1.18***
XMR	1.37***	1.10***	0.52***	0.12***	0.58***	0.89***
XRP	1.47***	1.35***	0.69***	0.18***	0.90***	1.17***
ZEC	1.57***	1.35***	0.69***	0.31***	0.86***	1.25***
ZIL	0.93***	0.72***	0.30***	0.14***	0.44***	0.66***

Table II (Continued) Univariate OLS predictive regression results

	PAX	QTUM	TRX	TUSD	USDC	VET
ADA	-0.10***	1.24***	0.72***	-0.16***	-0.15***	1.18***
BAT	-0.06***	0.66***	0.38***	-0.08***	-0.09***	0.76***
BNB	-0.09***	1.21***	0.69***	-0.12***	-0.14***	1.22***
BTC	-0.16***	1.62***	0.74***	-0.23***	-0.24***	1.59***
BTT	-0.06***	0.62***	0.54***	-0.09***	-0.08***	0.60***
CELR	-0.03***	0.28***	0.16***	-0.05***	-0.05***	0.26***
EOS	-0.12***	1.44***	0.78***	-0.18***	-0.18***	1.29***
ETC	-0.09***	1.19***	0.62***	-0.14***	-0.14***	1.09***
ETH	-0.14***	1.55***	0.78***	-0.19***	-0.20***	1.46***
FET	-0.05***	0.48***	0.23***	-0.06***	-0.06***	0.45***
HOT	-0.04***	0.31***	0.13***	-0.05***	-0.04***	0.28***
ICX	-0.06***	0.70***	0.40***	-0.09***	-0.08***	0.71***
IOST	-0.07***	0.75***	0.43***	-0.10***	-0.10***	0.73***
IOTA	-0.08***	0.82***	0.43***	-0.11***	-0.12***	0.76***
LINK	-0.07***	0.96***	0.54***	-0.12***	-0.12***	1.05***
LTC	-0.12***	1.47***	0.79***	-0.18***	-0.18***	1.39***
NEO	-0.11***	1.29***	0.64***	-0.16***	-0.15***	1.22***
ONT	-0.10***	1.21***	0.61***	-0.13***	-0.14***	1.10***
PAX	-0.57***	0.28***	0.04**	0.00*	-0.04***	0.09***
QTUM	-0.09***	-0.34***	0.51***	-0.13***	-0.13***	0.98***
TRX	-0.11***	1.32***	-0.04**	-0.17***	-0.16***	1.23***
TUSD	-0.02***	0.44***	0.19***	-0.61***	-0.07***	0.32***
USDC	-0.02***	0.40***	0.12***	-0.05***	-0.76***	0.16***
VET	-0.06***	0.89***	0.46***	-0.10***	-0.09***	-0.89***
WAVES	-0.06***	0.60***	0.33***	-0.09***	-0.09***	0.62***
XLM	-0.09***	1.20***	0.64***	-0.13***	-0.13***	1.10***
XMR	-0.10***	0.91***	0.40***	-0.14***	-0.14***	0.88***
XRP	-0.09***	1.10***	0.55***	-0.13***	-0.12***	0.99***
ZEC	-0.09***	1.07***	0.56***	-0.13***	-0.12***	1.07***
ZIL	-0.05***	0.63***	0.38***	-0.07***	-0.08***	0.59***

Table II (Continued) Univariate OLS predictive regression results

	WAVES	XLM	XMR	XRP	ZEC	ZIL
ADA	1.31***	0.76***	1.08***	0.33***	1.11***	1.81***
BAT	0.89***	0.39***	0.60***	0.19***	0.63***	1.16***
BNB	1.45***	0.77***	1.03***	0.43***	1.06***	1.93***
BTC	1.79***	0.91***	1.55***	0.45***	1.53***	2.33***
BTT	0.67***	0.32***	0.47***	0.18***	0.57***	0.95***
CELR	0.32***	0.13***	0.20***	0.05**	0.25***	0.42***
EOS	1.53***	0.89***	1.24***	0.41***	1.37***	1.93***
ETC	1.28***	0.67***	1.06***	0.27***	1.19***	1.65***
ETH	1.72***	0.97***	1.43***	0.44***	1.51***	2.17***
FET	0.54***	0.25***	0.32***	0.12***	0.41***	0.83***
HOT	0.31***	0.13***	0.23***	0.04*	0.21***	0.52***
ICX	0.82***	0.37***	0.59***	0.17***	0.64***	1.16***
IOST	0.82***	0.43***	0.57***	0.18***	0.66***	1.16***
IOTA	0.88***	0.44***	0.66***	0.18***	0.74***	1.29***
LINK	1.19***	0.61***	0.87***	0.35***	0.94***	1.54***
LTC	1.54***	0.94***	1.31***	0.40***	1.40***	2.04***
NEO	1.24***	0.71***	1.05***	0.33***	1.17***	1.69***
ONT	1.26***	0.62***	0.94***	0.37***	1.09***	1.64***
PAX	0.26***	0.10***	0.20***	-0.01	0.28***	0.24***
QTUM	1.07***	0.53***	0.87***	0.27***	0.97***	1.43***
TRX	1.40***	0.82***	1.14***	0.36***	1.25***	1.79***
TUSD	0.56***	0.22***	0.39***	0.11***	0.52***	0.46***
USDC	0.38***	0.19***	0.31***	0.02	0.35***	0.32***
VET	0.98***	0.47***	0.70***	0.24***	0.76***	1.27***
WAVES	-1.72***	0.36***	0.53***	0.17***	0.57***	1.04***
XLM	1.24***	-0.04**	0.97***	0.43***	1.07***	1.67***
XMR	0.97***	0.50***	-0.43***	0.23***	0.85***	1.44***
XRP	1.18***	0.93***	0.95***	-0.05**	1.03***	1.54***
ZEC	1.16***	0.68***	1.01***	0.35***	0.14***	1.58***
ZIL	0.66***	0.34***	0.47***	0.18***	0.53***	-1.62***

Table III OLS predictive regression results: lagged BTC returns

Table III reports coefficient estimates for each of the 30 cryptocurrencies, with the lagged return of Bitcoin as the independent variable and its own lagged return as control variable. Return of each cryptocurrency shown in the table serves as the dependent variable in the OLS regression. Each value in the row *btc_lag* is the coefficient estimate of the lagged return of Bitcoin. Returns are on a minute basis and are standardized. Estimates are presented in bps. The sample period is from March 2019 to April 2021. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	ADA	BAT	BNB	BTC	BTT	CELR
btc_lag	1.47***	2.58***	1.12***	–	2.24***	3.44***
	EOS	ETC	ETH	FET	HOT	ICX
btc_lag	0.73***	1.49***	0.76***	3.99***	3.50***	2.99***
	IOST	IOTA	LINK	LTC	NEO	ONT
btc_lag	2.93***	3.11***	2.08***	0.89***	1.95***	2.07***
	PAX	QTUM	TRX	TUSD	USDC	VET
btc_lag	-0.10***	2.39***	1.14***	-0.14***	-0.13***	2.58***
	WAVES	XLM	XMR	XRP	ZEC	ZIL
btc_lag	2.81***	1.33***	2.53***	0.67***	1.99***	3.29***

Table IV Pooled OLS predictive regression results

Table IV reports the pooled OLS coefficient estimates. For each cryptocurrency, the pooled OLS coefficient estimates of lagged returns of the other 29 cryptocurrencies are reported with the bias-corrected wild bootstrapped 90% confidence intervals shown in brackets. Estimates are presented in bps and those with bootstrapped p-values at the 10% level or better are in bold. The sample period is from March 2019 to April 2021.

ADA	BAT	BNB	BTC	BTT
0.91	-0.13	**2.27**	**4.82**	0.05
[0.0049,0.0133]	[-0.0041,0.0016]	[0.0147,0.0306]	[0.0342,0.0621]	[-0.002,0.003]
CELR	EOS	ETC	ETH	FET
-0.05	**1.45**	**0.65**	**2.27**	0.01
[-0.0021,0.0012]	[0.0075,0.0215]	[0.0016,0.0113]	[0.0116,0.0339]	[-0.0017,0.0019]
HOT	ICX	IOST	IOTA	LINK
-0.26	0.10	-0.08	-0.29	**0.63**
[-0.0047,-0.0004]	[-0.0012,0.0032]	[-0.0044,0.0028]	[-0.0065,0.0006]	[0.0039,0.0087]
LTC	NEO	ONT	PAX	QTUM
1.38	**1.04**	**0.80**	-1.56	**0.40**
[0.006,0.0216]	[0.0062,0.0146]	[0.0037,0.0123]	[-0.0547,0.0234]	[0.001,0.007]
TRX	TUSD	USDC	VET	WAVES
1.85	2.93	-0.38	0.07	-0.02
[0.0134,0.0236]	[-0.0236,0.0822]	[-0.0442,0.0366]	[-0.0015,0.0029]	[-0.0032,0.0027]
XLM	XMR	XRP	ZEC	ZIL
1.04	**-0.41**	0.30	**1.05**	-0.02
[0.0059,0.0148]	[-0.0079,-0.0003]	[-0.0015,0.0076]	[0.0061,0.0149]	[-0.0026,0.0022]

Table V Adaptive LASSO predictive regression results

Table V reports coefficient estimates for each of the 30 cryptocurrencies from the adaptive LASSO predictive model. Return of each cryptocurrency in the top header serves as the dependent variable in the adaptive LASSO model. Lagged return of each cryptocurrency in the left column serves as the independent variable. − indicates that the corresponding cryptocurrency in the left column was not selected as a return predictor by the adaptive LASSO. Estimates are presented in bps and those in bold are statistically significant based on their bootstrapped 90% confidence intervals. The sample period is from March 2019 to April 2021.

	ADA	BAT	BNB	BTC	BTT	CELR
ADA	**-8.79**	**1.83**	**0.68**	0.25	**0.23**	**1.15**
BAT	**-0.43**	**-14.35**	**-0.69**	**-0.49**	**-0.49**	**0.74**
BNB	**1.79**	**3.87**	**-6.59**	**0.55**	**1.59**	**4.53**
BTC	**2.08**	**1.20**	**3.55**	**-1.89**	**5.56**	**8.19**
BTT	**-0.21**	−	0.20	-0.22	**-8.36**	**0.85**
CELR	-0.01	−	-0.07	−	**0.05**	**-12.35**
EOS	**1.44**	**1.56**	**1.23**	-0.41	**1.40**	**0.16**
ETC	−	**0.95**	**0.55**	−	**0.85**	**1.06**
ETH	**3.22**	**4.70**	**2.11**	**0.32**	**-0.30**	**-1.38**
FET	-0.07	−	-0.15	-0.01	**0.28**	**2.17**
HOT	**-0.60**	-0.33	**-0.26**	**-0.33**	**-0.08**	**0.49**
ICX	−	**0.58**	−	−	**-0.15**	**1.58**
IOST	−	−	−	-0.15	**0.49**	**1.03**
IOTA	**-0.59**	**0.34**	**-0.34**	-0.32	**-0.30**	**0.69**
LINK	**0.63**	**1.51**	**0.53**	−	**0.80**	**0.96**
LTC	**2.42**	**1.39**	**0.82**	**1.20**	**0.58**	**0.42**
NEO	**0.94**	**1.52**	**0.52**	**0.53**	**1.22**	**0.58**
ONT	**0.21**	**0.76**	**0.51**	−	**1.48**	**2.20**
PAX	−	−	**-2.49**	**-4.47**	−	**-2.36**
QTUM	−	0.36	−	−	**0.77**	**1.02**
TRX	**2.31**	**2.09**	**1.51**	**0.62**	**8.02**	**2.00**
TUSD	−	**3.21**	−	**2.70**	**1.24**	**-9.23**
USDC	**-0.04**	**1.79**	**-2.18**	-1.15	**-0.56**	**-2.80**
VET	**-0.19**	0.50	**-0.46**	-0.34	**-0.02**	**1.39**
WAVES	**-0.31**	−	-0.15	−	**0.02**	**0.49**
XLM	**3.38**	**2.03**	−	−	**-0.06**	**1.43**
XMR	**-0.62**	0.15	-0.21	−	**-0.80**	−
XRP	−	-0.31	−	-0.17	**-0.29**	**0.83**
ZEC	**1.48**	**1.50**	**1.17**	**0.85**	**1.27**	**0.90**
ZIL	**-0.36**	−	-0.23	-0.15	**0.28**	**1.28**

Table V (Continued) Adaptive LASSO predictive regression results

	EOS	ETC	ETH	FET	HOT	ICX
ADA	**0.17**	**0.51**	**0.70**	**1.55**	**1.39**	**2.12**
BAT	**-0.19**	**-0.43**	**-0.49**	**0.45**	**0.51**	**0.71**
BNB	**1.36**	**1.02**	**0.38**	**5.27**	**5.69**	**3.96**
BTC	**2.09**	**4.55**	**4.02**	**6.50**	**8.72**	**3.54**
BTT	–	**-0.55**	**-0.42**	**0.62**	**2.02**	–
CELR	-0.01	**-0.08**	**-0.23**	**1.62**	**0.76**	–
EOS	**-6.06**	**3.53**	**0.74**	**1.16**	**1.36**	**1.40**
ETC	**0.96**	**-8.65**	–	**1.12**	**1.03**	**1.04**
ETH	**-0.81**	**0.93**	**-7.04**	**3.98**	**5.27**	**2.66**
FET	–	**-0.02**	**-0.03**	**-15.23**	**0.77**	**0.33**
HOT	**-0.17**	**-0.25**	**-0.28**	**0.20**	**-12.42**	**-0.27**
ICX	-0.11	**-0.27**	–	**1.57**	**0.31**	**-15.75**
IOST	**-0.43**	**-0.49**	**-0.36**	**0.67**	**0.85**	**0.50**
IOTA	**-0.37**	**-0.61**	**-0.27**	**0.73**	**0.34**	**0.22**
LINK	0.04	**0.30**	**0.38**	**1.47**	**0.53**	**1.22**
LTC	**1.40**	**2.01**	**1.71**	**1.02**	**-0.59**	**1.89**
NEO	**0.97**	**0.66**	**0.91**	**2.03**	**0.76**	**1.27**
ONT	**1.24**	**1.08**	–	**1.27**	**1.34**	**1.50**
PAX	**-2.55**	–	**-0.69**	**-7.47**	**-2.18**	**-3.24**
QTUM	**0.23**	**0.49**	0.11	**0.39**	**0.22**	**0.77**
TRX	**1.33**	**1.42**	**1.17**	**2.69**	**0.48**	**2.20**
TUSD	**4.64**	–	**1.56**	–	**-1.37**	**5.43**
USDC	–	**-1.06**	**-5.79**	**-9.32**	**-7.23**	**-0.05**
VET	-0.09	–	**-0.41**	**0.90**	**0.97**	**0.47**
WAVES	**-0.24**	**-0.11**	–	**0.76**	**0.23**	**0.77**
XLM	**0.92**	**0.76**	–	**1.59**	–	**1.89**
XMR	**-0.81**	**-0.99**	–	–	**0.44**	–
XRP	**0.59**	**0.51**	**-0.21**	**0.81**	**-0.54**	**0.33**
ZEC	**1.25**	**1.13**	**1.24**	**1.14**	**0.97**	**1.51**
ZIL	–	**0.11**	**-0.07**	**0.82**	**0.37**	**0.47**

Table V (Continued) Adaptive LASSO predictive regression results

	IOST	IOTA	LINK	LTC	NEO	ONT
ADA	**1.37**	**2.09**	**0.93**	**0.65**	**1.39**	**0.82**
BAT	**-0.13**	0.05	–	**-0.12**	**-0.48**	**-0.38**
BNB	**2.07**	**3.17**	**3.12**	**1.15**	**2.49**	**2.42**
BTC	**10.12**	**6.23**	**4.80**	**3.59**	**3.17**	**3.39**
BTT	–	**0.31**	**-0.17**	**-0.23**	**-0.09**	**0.20**
CELR	**0.02**	-0.08	**-0.23**	–	**-0.13**	**-0.09**
EOS	**1.56**	**1.97**	**1.40**	**1.45**	**1.85**	**2.85**
ETC	**0.30**	**1.23**	–	**0.15**	**0.59**	**1.21**
ETH	**2.89**	**3.33**	**4.11**	**1.20**	**3.38**	**1.84**
FET	**-0.04**	–	–	–	**-0.14**	**-0.19**
HOT	**-0.41**	-0.17	**-0.44**	**-0.32**	**-0.24**	**-0.36**
ICX	**0.20**	**0.44**	-0.06	–	**-0.32**	**-0.06**
IOST	**-8.24**	**0.42**	**-0.55**	**-0.25**	**0.04**	**0.38**
IOTA	**-0.80**	**-17.83**	**-0.56**	**-0.28**	**-0.61**	**-0.31**
LINK	**0.94**	**1.45**	**-10.48**	**0.17**	**0.29**	**0.90**
LTC	**0.73**	**0.48**	**3.62**	**-7.23**	**2.01**	**1.70**
NEO	**1.13**	**2.19**	**0.26**	**0.90**	**-12.72**	**3.20**
ONT	**2.82**	**1.39**	–	**0.30**	**2.22**	**-9.54**
PAX	**-1.71**	**-4.61**	**0.93**	–	**-1.60**	**-0.99**
QTUM	**0.69**	**0.69**	**0.52**	**0.04**	**1.97**	**2.33**
TRX	**2.03**	**1.97**	**2.43**	**0.81**	**1.94**	**2.30**
TUSD	**7.23**	–	**1.41**	**0.50**	**4.22**	**2.37**
USDC	–	–	**2.12**	**-1.52**	**2.52**	**2.11**
VET	**0.36**	**0.70**	**-0.54**	**-0.28**	**0.07**	**0.20**
WAVES	–	0.23	**-0.14**	**-0.12**	**-0.16**	**-0.31**
XLM	**1.16**	**1.85**	**0.26**	**0.58**	**1.41**	**0.75**
XMR	**-0.41**	–	**-0.54**	**-0.63**	**-1.14**	**-1.50**
XRP	**-0.65**	**0.75**	–	–	**0.71**	–
ZEC	**1.42**	**1.88**	**1.23**	**1.39**	**1.56**	**2.11**
ZIL	–	–	**-0.22**	**0.01**	**-0.07**	**-0.04**

Table V (Continued) Adaptive LASSO predictive regression results

	PAX	QTUM	TRX	TUSD	USDC	VET
ADA	–	**1.01**	**1.46**	**-0.08**	–	**1.34**
BAT	0.01	**-0.51**	**-0.24**	**0.06**	**0.02**	**0.40**
BNB	0.09	**1.36**	**1.47**	**0.24**	**0.12**	**2.52**
BTC	**-0.77**	**5.90**	**1.35**	**-1.00**	**-1.06**	**8.03**
BTT	–	**-0.05**	**1.81**	**-0.04**	**-0.05**	–
CELR	–	**-0.08**	–	**-0.05**	**-0.03**	-0.08
EOS	–	**2.29**	**2.50**	**-0.14**	**-0.22**	**0.64**
ETC	–	**0.95**	**0.63**	**0.04**	–	**0.38**
ETH	**-0.21**	**1.98**	**1.39**	**0.10**	**0.12**	**1.53**
FET	–	–	**-0.11**	**0.02**	–	–
HOT	-0.01	**-0.13**	**-0.24**	**-0.04**	**-0.01**	**-0.13**
ICX	–	–	**0.07**	0.01	**0.07**	**0.29**
IOST	–	–	**0.03**	**-0.05**	**-0.05**	**0.26**
IOTA	–	**-0.26**	**-0.27**	–	**-0.10**	**-0.33**
LINK	0.06	**0.33**	**0.42**	**0.00**	**0.01**	**1.30**
LTC	0.08	**1.41**	**1.82**	**0.07**	**0.11**	**1.58**
NEO	**-0.10**	**3.03**	**0.82**	**-0.10**	**0.03**	**2.15**
ONT	-0.01	**2.72**	**0.67**	**0.02**	**-0.07**	**1.42**
PAX	**-26.95**	**0.33**	**-2.61**	**5.18**	**4.85**	**-5.52**
QTUM	–	**-12.04**	–	**-0.08**	**-0.10**	**0.70**
TRX	-0.01	**2.38**	**-7.48**	**-0.20**	**-0.10**	**1.85**
TUSD	**4.02**	**3.89**	**3.38**	**-26.48**	**4.97**	**1.38**
USDC	**3.72**	**3.20**	–	**3.91**	**-32.23**	**-4.73**
VET	0.07	**0.27**	**-0.11**	**0.04**	**0.09**	**-11.96**
WAVES	–	**-0.27**	**-0.19**	**-0.02**	**-0.03**	–
XLM	–	**1.81**	**0.90**	–	0.02	**1.39**
XMR	**-0.16**	**-0.55**	**-1.13**	**-0.19**	**-0.21**	**-0.64**
XRP	–	–	**0.05**	**0.09**	**0.17**	**-0.24**
ZEC	-0.05	**1.00**	**0.33**	**-0.08**	**-0.07**	**1.31**
ZIL	–	–	**0.07**	–	**-0.02**	**0.20**

Table V (Continued) Adaptive LASSO predictive regression results

	WAVES	XLM	XMR	XRP	ZEC	ZIL
ADA	**0.62**	**1.62**	**0.88**	–	**0.28**	**1.81**
BAT	**0.68**	-0.19	**-0.25**	-0.15	**-0.51**	**0.39**
BNB	**3.00**	**1.51**	**1.05**	**1.40**	**0.56**	**4.14**
BTC	**8.02**	**1.84**	**10.93**	**1.48**	**5.48**	**8.48**
BTT	-0.08	**-0.39**	**-0.37**	–	**-0.12**	0.03
CELR	–	-0.12	**-0.17**	-0.09	**-0.07**	-0.06
EOS	**1.55**	**1.17**	**1.17**	**1.14**	**1.99**	**0.84**
ETC	**0.66**	–	**0.95**	**-0.32**	**1.58**	**0.59**
ETH	**3.08**	**2.33**	**2.44**	**0.52**	**3.08**	**1.58**
FET	**0.26**	–	**-0.30**	–	**-0.08**	**0.57**
HOT	**-0.17**	**-0.33**	**-0.22**	**-0.19**	**-0.46**	0.00
ICX	**0.55**	-0.15	**-0.02**	-0.14	**-0.09**	**0.90**
IOST	–	–	**-0.43**	**-0.26**	**-0.30**	**0.24**
IOTA	**-0.18**	**-0.45**	**-0.48**	**-0.57**	**-0.49**	**0.38**
LINK	**1.34**	**0.39**	**0.50**	**0.50**	**0.59**	**1.42**
LTC	**0.42**	**1.53**	**1.16**	**0.49**	**1.84**	**1.90**
NEO	**0.55**	**0.71**	**1.22**	–	**1.53**	**1.19**
ONT	**1.46**	–	**0.55**	**0.58**	**1.26**	**1.54**
PAX	**-1.46**	-0.50	**-1.57**	**-2.24**	**0.69**	**-3.38**
QTUM	**0.40**	-0.21	**0.56**	–	**0.61**	**0.38**
TRX	**1.95**	**1.47**	**1.77**	**0.69**	**2.01**	**1.79**
TUSD	**8.63**	–	**2.54**	**0.66**	**9.09**	–
USDC	–	–	–	**-0.94**	–	**-3.64**
VET	**0.46**	-0.11	**-0.30**	–	**-0.26**	**0.36**
WAVES	**-14.07**	–	**-0.11**	–	**-0.19**	**0.71**
XLM	**1.16**	**-7.68**	**0.65**	**2.12**	**0.97**	**1.84**
XMR	**-0.64**	**-0.67**	**-13.34**	**-0.51**	–	0.05
XRP	–	**3.87**	**-0.01**	**-3.44**	–	–
ZEC	**1.01**	**0.92**	**2.17**	**0.51**	**-7.44**	**1.26**
ZIL	**0.16**	–	**-0.26**	–	**-0.30**	**-13.98**

Table VI Out-of-sample portfolio performance

Table VI reports the out-of-sample performance of portfolios constructed using minute-level cryptocurrency return forecasts (in bps) predicted by the adaptive LASSO, PCA, and univariate (BTC) regression, respectively. For each minute, we sort the 30 sample coins in ascending order based on the excess return forecasts generated from each of the approaches using a half-day (720 minutes) rolling window and group them into equal-weighted quintile portfolios. We subsequently construct a long-short portfolio that goes long the top quintile portfolio and goes short the bottom quintile portfolio, for each regression model. Minute-level portfolio returns are reported with the Newey-West adjusted t-statistics shown in the parentheses. The t-statistics of the minute-level portfolio returns are larger than three, thus meeting the requirement of the multi-hypothesis threshold posed in Harvey (2017). We also report the portfolio returns predicted via the adaptive LASSO and PCA by excluding the returns of the focal coins. The sample period is from March 2019 to April 2021. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Adaptive LASSO	PCA	Bitcoin	Adaptive LASSO (ExFocal)	PCA (ExFocal)
Short	-1.75***	-0.91***	-0.77***	-0.87***	-0.79***
2	-0.37***	-0.41***	-0.35***	-0.16***	-0.41***
3	0.00	0.00	0.02	0.00	0.00
4	0.36***	0.42***	0.37***	0.17***	0.43***
Long	1.80***	0.94***	0.78***	0.92***	0.81***
Long - Short	3.55***	1.86***	1.54***	1.79***	1.60***
T-stats	*(64.21)*	*(51.86)*	*(42.70)*	*(27.20)*	*(43.89)*

Table VII Risk-adjusted portfolio alphas

Table VII reports risk-adjusted alphas (in bps) based on single- or multiple-factor regressions using minute-level cryptocurrency return forecasts generated by the adaptive LASSO method. Column (1) – (5) present alphas by controlling for one risk factor (MKT, SMB, MOM5, MOM10, or MOM30). Column (6) presents alphas by controlling for all five factors in the regression. Newey-West adjusted t-statistics are shown in the parentheses and are larger than three, thus meeting the requirement of the multi-hypothesis threshold posed in Harvey (2017). The sample period is from March 2019 to April 2021. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	MKT	SMB	MOM5	MOM10	MOM30	ALL
Short	-1.64***	-1.62***	-1.74***	-1.79***	-1.82***	-1.62***
2	-0.31***	-0.29***	-0.58***	-0.58***	-0.55***	-0.46***
3	-0.01	0.01	-0.25***	-0.25***	-0.22***	-0.12***
4	0.29***	0.31***	0.06	0.07*	0.12***	0.20***
Long	1.71***	1.73***	1.43***	1.50***	1.62***	1.61***
Long - Short	3.35***	3.35***	3.17***	3.29***	3.44***	3.23***
T-stats	*(84.59)*	*(87.05)*	*(82.03)*	*(92.30)*	*(93.29)*	*(81.24)*

Table VIII Sub-sample analysis

Table VIII reports risk-adjusted alphas (in bps) for various sub-samples based on single- or multiple-factor regressions using minute-level cryptocurrency return forecasts generated by the adaptive LASSO method. Column (1) shows the excess returns. Column (2) – (6) present alphas controlling for one risk factor (MKT, SMB, MOM5, MOM10, or MOM30). Column (7) presents alphas controlling for all five factors in the regression. For each day, we divide the sample into terciles based on market capitalization (Panel A – B), dollar trading volume (Panel D – E) and abnormal Google search volume (Panel G – H), respectively. The differences between risk-adjusted alphas for the sub-samples divided by each attention proxy are reported in Panel C, F, and I. Newey-West adjusted t-statistics are shown in the parentheses. The sample period is from March 2019 to April 2021. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A Large cap

	Excess Return	MKT	SMB	MOM5	MOM10	MOM30	ALL
Short	-0.72***	-0.75***	-0.73***	-1.05***	-1.05***	-1.02***	-0.88***
2	-0.14***	-0.18***	-0.16***	-0.47***	-0.47***	-0.43***	-0.31***
3	0.02	-0.01	0.01	-0.27***	-0.26***	-0.21***	-0.09***
4	0.20***	0.17***	0.18***	-0.09*	-0.07	-0.03	0.11***
Long	0.83***	0.80***	0.82***	0.53***	0.57***	0.65***	0.77***
Long - Short	1.55***	1.55***	1.55***	1.59***	1.62***	1.67***	1.65***
T-stats	*(63.23)*	*(56.92)*	*(55.80)*	*(57.40)*	*(57.44)*	*(54.27)*	*(48.23)*

Panel B Small cap

	Excess Return	MKT	SMB	MOM5	MOM10	MOM30	ALL
Short	-1.92***	-1.94***	-1.92***	-1.97***	-2.03***	-2.08***	-1.86***
2	-0.37***	-0.40***	-0.38***	-0.65***	-0.65***	-0.63***	-0.56***
3	0.02	0.00	0.01	-0.24***	-0.24***	-0.21***	-0.14***
4	0.40***	0.37***	0.39***	0.17***	0.18***	0.23***	0.29***
Long	2.05***	2.02***	2.04***	1.74***	1.82***	1.95***	1.89***
Long - Short	3.96***	3.96***	3.96***	3.70***	3.85***	4.04***	3.75***
T-stats	*(72.08)*	*(111.02)*	*(114.20)*	*(74.10)*	*(81.48)*	*(87.48)*	*(72.01)*

Table VIII (continued) Sub-sample analysis

Panel C Difference between large and small size

	Excess Return	MKT	SMB	MOM5	MOM10	MOM30	ALL
Short	1.20***	1.19***	1.19***	0.91***	0.98***	1.07***	0.98***
2	0.23***	0.22***	0.22***	0.17***	0.18***	0.21***	0.26***
3	0.00	-0.01	0.00	-0.03**	-0.02	-0.01	0.05***
4	-0.20***	-0.21***	-0.21***	-0.25***	-0.25***	-0.25***	-0.17***
Long	-1.21***	-1.23***	-1.23***	-1.21***	-1.25***	-1.30***	-1.12***
Long - Short	-2.41***	-2.42***	-2.42***	-2.12***	-2.23***	-2.37***	-2.10***
T-stats	*(-51.33)*	*(-50.43)*	*(-47.94)*	*(-42.79)*	*(-45.26)*	*(-45.13)*	*(-36.47)*

Panel D High trading volume

	Excess Return	MKT	SMB	MOM5	MOM10	MOM30	ALL
Short	-0.59***	-0.63***	-0.61***	-0.87***	-0.87***	-0.85***	-0.70***
2	-0.03	-0.06***	-0.04***	-0.38***	-0.37***	-0.32***	-0.22***
3	0.11***	0.08***	0.10***	-0.17***	-0.15***	-0.11***	0.02
4	0.35***	0.31***	0.33***	0.14***	0.15***	0.20***	0.36***
Long	1.20***	1.16***	1.18***	1.09***	1.18***	1.31***	1.43***
Long - Short	1.79***	1.79***	1.79***	1.96***	2.05***	2.16***	2.12***
T-stats	*(64.95)*	*(58.99)*	*(56.47)*	*(50.48)*	*(51.79)*	*(51.76)*	*(44.65)*

Panel E Low trading volume

	Excess Return	MKT	SMB	MOM5	MOM10	MOM30	ALL
Short	-1.91***	-1.93***	-1.91***	-2.00***	-2.06***	-2.10***	-1.90***
2	-0.40***	-0.43***	-0.41***	-0.67***	-0.67***	-0.66***	-0.58***
3	-0.05***	-0.08***	-0.06***	-0.32***	-0.33***	-0.29***	-0.22***
4	0.29***	0.27***	0.29***	0.02	0.03	0.08**	0.13***
Long	1.83***	1.80***	1.82***	1.44***	1.50***	1.60***	1.55***
Long - Short	3.73***	3.73***	3.73***	3.44***	3.56***	3.70***	3.45***
T-stats	*(65.67)*	*(88.25)*	*(123.33)*	*(68.07)*	*(73.16)*	*(100.98)*	*(74.93)*

Panel F Difference between high and low trading volume

	Excess Return	MKT	SMB	MOM5	MOM10	MOM30	ALL
Short	1.31***	1.30***	1.30***	1.13***	1.19***	1.25***	1.21***
2	0.38***	0.37***	0.37***	0.29***	0.31***	0.34***	0.36***
3	0.16***	0.16***	0.16***	0.15***	0.17***	0.18***	0.24***
4	0.05***	0.04***	0.04***	0.12***	0.12***	0.13***	0.23***
Long	-0.63***	-0.64***	-0.64***	-0.35***	-0.32***	-0.29***	-0.12**
Long - Short	-1.94***	-1.94***	-1.94***	-1.48***	-1.51***	-1.55***	-1.33***
T-stats	*(-38.19)*	*(-39.32)*	*(-35.22)*	*(-34.62)*	*(-28.28)*	*(-25.34)*	*(-21.31)*

Table VIII (continued) Sub-sample analysis

Panel G High abnormal Google search volume

	Excess Return	MKT	SMB	MOM5	MOM10	MOM30	ALL
Short	-1.33***	-1.36***	-1.34***	-1.56***	-1.59***	-1.61***	-1.44***
2	-0.28***	-0.30***	-0.29***	-0.61***	-0.60***	-0.57***	-0.49***
3	0.00	-0.03***	-0.02	-0.30***	-0.30***	-0.26***	-0.16***
4	0.35***	0.32***	0.33***	0.06	0.08*	0.13***	0.22***
Long	1.45***	1.42***	1.44***	1.16***	1.21***	1.33***	1.36***
Long - Short	2.79***	2.79***	2.79***	2.72***	2.80***	2.94***	2.80***
T-stats	*(69.60)*	*(69.81)*	*(67.75)*	*(64.63)*	*(67.28)*	*(61.93)*	*(57.38)*

Panel H Low abnormal Google search volume

	Excess Return	MKT	SMB	MOM5	MOM10	MOM30	ALL
Short	-1.68***	-1.71***	-1.69***	-1.77***	-1.82***	-1.86***	-1.65***
2	-0.30***	-0.33***	-0.31***	-0.57***	-0.58***	-0.56***	-0.46***
3	0.03*	0.00	0.02	-0.24***	-0.23***	-0.20***	-0.11***
4	0.35***	0.32***	0.34***	0.10**	0.11***	0.16***	0.24***
Long	1.79***	1.77***	1.79***	1.48***	1.55***	1.67***	1.64***
Long - Short	3.47***	3.47***	3.47***	3.24***	3.38***	3.53***	3.29***
T-stats	*(69.58)*	*(121.06)*	*(92.49)*	*(76.11)*	*(89.32)*	*(91.02)*	*(78.60)*

Panel I Difference between high and low abnormal Google search volume

	Excess Return	MKT	SMB	MOM5	MOM10	MOM30	ALL
Short	0.34***	0.34***	0.34***	0.21***	0.23***	0.25***	0.21***
2	0.03**	0.03*	0.03**	-0.03*	-0.02	0.00	-0.02
3	-0.03**	-0.03**	-0.03**	-0.06***	-0.07***	-0.05***	-0.05**
4	0.00	0.00	0.00	-0.03	-0.03	-0.02	-0.02
Long	-0.33***	-0.33***	-0.34***	-0.31***	-0.33***	-0.32***	-0.28***
Long - Short	-0.67***	-0.67***	-0.67***	-0.52***	-0.56***	-0.58***	-0.48***
T-stats	*(-16.85)*	*(-16.02)*	*(-14.87)*	*(-12.63)*	*(-13.68)*	*(-11.49)*	*(-9.68)*

Table IX Long-short portfolio performance on event day and normal days

Table IX reports the long-short portfolio alphas with different regression specifications on the event and normal days. We identify a total of nine major events and classify the remaining days in our sample as normal days. The alphas on event days and normal days are reported in Panel A and B, respectively. The differences between alphas on event days and normal days are reported in Panel C. Column (1) shows the excess returns. Column (2) – (6) present alphas controlling for one risk factor (MKT, SMB, MOM5, MOM10, or MOM30). Column (7) presents alphas controlling for all five factors in the regression. Newey-West adjusted t-statistics are shown in the parentheses. The sample period is from March 2019 to April 2021. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A Event days

	Excess Return	MKT	SMB	MOM5	MOM10	MOM30	ALL
Short	-2.67***	-2.31***	-2.52***	-3.28***	-3.34***	-3.39***	-2.27***
2	-0.99***	-0.60***	-0.82***	-1.81***	-1.79***	-1.81***	-0.71***
3	-0.44**	-0.08	-0.28*	-1.23**	-1.26***	-1.23***	-0.27*
4	0.03	0.42***	0.21	-0.95*	-0.97*	-0.88**	0.08
Long	1.80***	2.14***	1.95***	0.94**	0.99**	1.07***	1.87***
Long - Short	4.47***	4.45***	4.47***	4.22***	4.33***	4.46***	4.15***
T-stats	*(13.57)*	*(9.84)*	*(10.51)*	*(14.42)*	*(15.14)*	*(12.67)*	*(16.93)*

Panel B Normal days

	Excess Return	MKT	SMB	MOM5	MOM10	MOM30	ALL
Short	-1.59***	-1.63***	-1.61***	-1.72***	-1.77***	-1.80***	-1.61***
2	-0.27***	-0.30***	-0.28***	-0.57***	-0.56***	-0.54***	-0.46***
3	0.02*	-0.01	0.01	-0.25***	-0.24***	-0.21***	-0.12***
4	0.33***	0.29***	0.31***	0.06	0.08**	0.13***	0.20***
Long	1.74***	1.70***	1.72***	1.43***	1.50***	1.62***	1.60***
Long - Short	3.33***	3.33***	3.33***	3.15***	3.27***	3.42***	3.21***
T-stats	*(72.15)*	*(86.13)*	*(81.73)*	*(79.71)*	*(88.74)*	*(91.15)*	*(81.51)*

Table IX (continued) Long-short portfolio performance on event day and normal days

Panel C Difference between event days and normal days	Excess Return	MKT	SMB	MOM5	MOM10	MOM30	ALL
Short	-1.07**	-0.66**	-0.95**	-1.08**	-1.09**	-1.06**	-0.63**
2	-0.73**	-0.30	-0.59*	-0.74**	-0.75**	-0.71*	-0.30
3	-0.46**	-0.03	-0.32*	-0.48**	-0.48**	-0.44*	-0.03
4	-0.29*	0.14	-0.15	-0.31	-0.32	-0.28	0.14
Long	0.07	0.50**	0.19	0.05	0.05	0.08	0.49**
Long - Short	1.14*	1.15**	1.15**	1.13**	1.14**	1.14**	1.12**
T-stats	*(1.93)*	*(2.22)*	*(2.12)*	*(2.37)*	*(2.37)*	*(2.17)*	*(2.37)*

Table X Portfolio performance with different trading costs and rebalance frequencies

Table X presents the portfolio performance with different trading costs and rebalance frequencies (from 1 minute to 15 minutes) in the futures market. For each minute, we sort the 30 sample coins in ascending order based on the excess return forecasts generated from the adaptive LASSO technique using a half-day (720 minutes) rolling window and group them into five or ten equal-weighted portfolios with different rebalance frequencies. We subsequently construct a long-short portfolio that goes long the top quintile or decile portfolio and goes short the bottom quintile or decile portfolio in each specification. VIP0 to VIP9 in Panel A and B (Panel C and D) suggest the corresponding trading fee levels of takers (makers), i.e., the ones with market (limit) orders according to *Binance*. Trading fees of makers (orders with limit orders) are lower and their performances are better. Each column reports the portfolio rebalanced every 1, 2, …, 15 minutes, respectively. Panel A and C (Panel B and D) shows the performance of long-short portfolios when dividing the sample cryptocurrencies into ten groups (five groups), buying futures contracts of the ones in the highest decile (quantile), and selling the ones in the lowest decile (quantile). Returns are minute-level returns in bps. The t-statistics are Newey-West adjusted. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Table X (continued) Portfolio performance with different trading costs and rebalance frequencies

Panel A: Long-short portfolio performance for takers (10 groups)

	1min	2min	3min	4min	5min
VIP0	-9.30***	-1.58***	-0.47***	-0.12***	0.04
VIP1	-9.30***	-1.58***	-0.47***	-0.12***	0.04
VIP2	-7.90***	-1.24***	-0.32***	-0.03	0.10***
VIP3	-7.05***	-1.04***	-0.23***	0.02	0.13***
VIP4	-6.49***	-0.90***	-0.17***	0.06*	0.15***
VIP5	-5.65***	-0.70***	-0.08**	0.11***	0.19***
VIP6	-5.09***	-0.56***	-0.01	0.14***	0.21***
VIP7	-4.24***	-0.36***	0.08**	0.19***	0.24***
VIP8	-3.68***	-0.22***	0.14***	0.23***	0.26***
VIP9	-2.84***	-0.02	0.23***	0.28***	0.29***

	6min	7min	8min	9min	10min
VIP0	0.06**	0.10***	0.11***	0.12***	0.10***
VIP1	0.06**	0.10***	0.11***	0.12***	0.10***
VIP2	0.10***	0.12***	0.14***	0.13***	0.12***
VIP3	0.12***	0.14***	0.15***	0.14***	0.13***
VIP4	0.13***	0.15***	0.16***	0.15***	0.13***
VIP5	0.16***	0.17***	0.17***	0.16***	0.14***
VIP6	0.17***	0.18***	0.18***	0.17***	0.15***
VIP7	0.20***	0.20***	0.19***	0.18***	0.15***
VIP8	0.21***	0.21***	0.20***	0.18***	0.16***
VIP9	0.23***	0.23***	0.21***	0.19***	0.17***

	11min	12min	13min	14min	15min
VIP0	0.14***	0.11***	0.15***	0.15***	0.08***
VIP1	0.14***	0.11***	0.15***	0.15***	0.08***
VIP2	0.15***	0.12***	0.16***	0.15***	0.09***
VIP3	0.16***	0.13***	0.16***	0.16***	0.09***
VIP4	0.16***	0.13***	0.17***	0.16***	0.09***
VIP5	0.17***	0.14***	0.17***	0.17***	0.10***
VIP6	0.18***	0.14***	0.17***	0.17***	0.10***
VIP7	0.18***	0.15***	0.18***	0.17***	0.10***
VIP8	0.19***	0.15***	0.18***	0.18***	0.11***
VIP9	0.19***	0.16***	0.19***	0.18***	0.11***

Table X (continued) Portfolio performance with different trading costs and rebalance frequencies

Panel B: Long-short portfolio performance for takers (5 groups)

	1min	2min	3min	4min	5min
VIP0	-7.95***	-1.47***	-0.49***	-0.18***	-0.06***
VIP1	-7.95***	-1.47***	-0.49***	-0.18***	-0.06***
VIP2	-6.79***	-1.19***	-0.36***	-0.11***	-0.01
VIP3	-6.09***	-1.02***	-0.29***	-0.07***	0.01
VIP4	-5.63***	-0.91***	-0.24***	-0.04**	0.03*
VIP5	-4.93***	-0.74***	-0.16***	0.00	0.06***
VIP6	-4.47***	-0.63***	-0.11***	0.03*	0.08***
VIP7	-3.78***	-0.46***	-0.04**	0.07***	0.10***
VIP8	-3.31***	-0.35***	0.01	0.10***	0.12***
VIP9	-2.62***	-0.18***	0.08***	0.14***	0.15***

	6min	7min	8min	9min	10min
VIP0	0.00	0.01	0.05***	0.05***	0.05***
VIP1	0.00	0.01	0.05***	0.05***	0.05***
VIP2	0.03	0.04**	0.07***	0.07***	0.06***
VIP3	0.05**	0.05***	0.08***	0.07***	0.07***
VIP4	0.06***	0.06***	0.09***	0.08***	0.07***
VIP5	0.08***	0.08***	0.10***	0.09***	0.08***
VIP6	0.09***	0.08***	0.11***	0.09***	0.08***
VIP7	0.11***	0.10***	0.12***	0.10***	0.09***
VIP8	0.12***	0.11***	0.13***	0.11***	0.09***
VIP9	0.14***	0.12***	0.14***	0.12***	0.10***

	11min	12min	13min	14min	15min
VIP0	0.06***	0.06***	0.07***	0.07***	0.04**
VIP1	0.06***	0.06***	0.07***	0.07***	0.04**
VIP2	0.07***	0.07***	0.08***	0.08***	0.04**
VIP3	0.08***	0.07***	0.08***	0.08***	0.04**
VIP4	0.08***	0.07***	0.09***	0.08***	0.05**
VIP5	0.08***	0.08***	0.09***	0.09***	0.05***
VIP6	0.09***	0.08***	0.09***	0.09***	0.05***
VIP7	0.09***	0.09***	0.10***	0.09***	0.05***
VIP8	0.10***	0.09***	0.10***	0.09***	0.06***
VIP9	0.10***	0.09***	0.11***	0.10***	0.06***

Table X (continued) Portfolio performance with different trading costs and rebalance frequencies

Panel C: Long-short portfolio performance for makers (10 groups)

	1min	2min	3min	4min	5min
VIP0	-3.68***	-0.22***	0.14***	0.23***	0.26***
VIP1	-2.55***	0.05*	0.26***	0.29***	0.31***
VIP2	-1.99***	0.19***	0.32***	0.33***	0.33***
VIP3	-1.43***	0.32***	0.38***	0.36***	0.35***
VIP4	-0.87***	0.46***	0.44***	0.40***	0.37***
VIP5	-0.31***	0.60***	0.50***	0.43***	0.39***
VIP6	0.26***	0.73***	0.56***	0.46***	0.42***
VIP7	0.82***	0.87***	0.62***	0.50***	0.44***
VIP8	1.38***	1.00***	0.68***	0.53***	0.46***
VIP9	1.94***	1.14***	0.74***	0.57***	0.48***
	6min	**7min**	**8min**	**9min**	**10min**
VIP0	0.21***	0.21***	0.20***	0.18***	0.16***
VIP1	0.24***	0.23***	0.22***	0.20***	0.17***
VIP2	0.26***	0.24***	0.23***	0.20***	0.18***
VIP3	0.27***	0.25***	0.23***	0.21***	0.18***
VIP4	0.29***	0.27***	0.24***	0.22***	0.19***
VIP5	0.30***	0.28***	0.25***	0.22***	0.19***
VIP6	0.32***	0.29***	0.26***	0.23***	0.20***
VIP7	0.33***	0.30***	0.27***	0.24***	0.20***
VIP8	0.35***	0.31***	0.28***	0.25***	0.21***
VIP9	0.36***	0.32***	0.29***	0.25***	0.22***
	11min	**12min**	**13min**	**14min**	**15min**
VIP0	0.19***	0.15***	0.18***	0.18***	0.11***
VIP1	0.20***	0.16***	0.19***	0.18***	0.11***
VIP2	0.20***	0.16***	0.19***	0.18***	0.11***
VIP3	0.21***	0.17***	0.20***	0.19***	0.12***
VIP4	0.21***	0.17***	0.20***	0.19***	0.12***
VIP5	0.21***	0.17***	0.20***	0.19***	0.12***
VIP6	0.22***	0.18***	0.20***	0.20***	0.12***
VIP7	0.22***	0.18***	0.21***	0.20***	0.13***
VIP8	0.23***	0.19***	0.21***	0.20***	0.13***
VIP9	0.23***	0.19***	0.21***	0.20***	0.13***

Table X (continued) Portfolio performance with different trading costs and rebalance frequencies

Panel D: Long-short portfolio performance for makers (5 groups)

	1min	2min	3min	4min	5min
VIP0	-3.31***	-0.35***	0.01	0.10***	0.12***
VIP1	-2.38***	-0.13***	0.11***	0.16***	0.16***
VIP2	-1.92***	-0.01	0.16***	0.19***	0.18***
VIP3	-1.46***	0.10***	0.21***	0.21***	0.19***
VIP4	-0.99***	0.21***	0.26***	0.24***	0.21***
VIP5	-0.53***	0.32***	0.31***	0.27***	0.23***
VIP6	-0.06***	0.43***	0.36***	0.30***	0.25***
VIP7	0.40***	0.55***	0.41***	0.33***	0.27***
VIP8	0.86***	0.66***	0.46***	0.36***	0.28***
VIP9	1.33***	0.77***	0.51***	0.38***	0.30***

	6min	7min	8min	9min	10min
VIP0	0.12***	0.11***	0.13***	0.11***	0.09***
VIP1	0.15***	0.13***	0.14***	0.12***	0.10***
VIP2	0.16***	0.14***	0.15***	0.12***	0.11***
VIP3	0.17***	0.15***	0.15***	0.13***	0.11***
VIP4	0.18***	0.15***	0.16***	0.14***	0.12***
VIP5	0.20***	0.16***	0.17***	0.14***	0.12***
VIP6	0.21***	0.17***	0.18***	0.15***	0.13***
VIP7	0.22***	0.18***	0.18***	0.15***	0.13***
VIP8	0.23***	0.19***	0.19***	0.16***	0.13***
VIP9	0.25***	0.20***	0.20***	0.16***	0.14***

	11min	12min	13min	14min	15min
VIP0	0.10***	0.09***	0.10***	0.09***	0.06***
VIP1	0.11***	0.10***	0.11***	0.10***	0.06***
VIP2	0.11***	0.10***	0.11***	0.10***	0.06***
VIP3	0.11***	0.10***	0.11***	0.10***	0.06***
VIP4	0.12***	0.11***	0.12***	0.11***	0.07***
VIP5	0.12***	0.11***	0.12***	0.11***	0.07***
VIP6	0.12***	0.11***	0.12***	0.11***	0.07***
VIP7	0.13***	0.12***	0.12***	0.11***	0.07***
VIP8	0.13***	0.12***	0.13***	0.12***	0.08***
VIP9	0.14***	0.12***	0.13***	0.12***	0.08***

Figure 1 Dollar trading volume in the cryptocurrency market

Figure 1 illustrates the dollar trading volume of the 30 sample cryptocurrencies and all other cryptocurrencies in the spot market, on the day that we started the project, i.e., 9 May 2020, based on data obtained from *Binance*. A total of 107 cryptocurrencies were traded on that day.

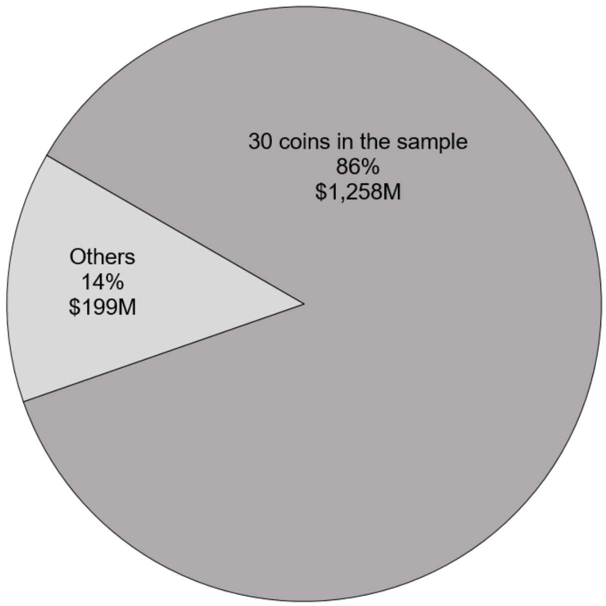


Figure 2 Loadings on the first three principal components

Figure 2 plots the loadings on the first three components extracted from the cross-cryptocurrency portfolio excess returns. Factor loadings of the first three principal components, which are extracted from the minute-level standardized returns of all 30 cryptocurrencies, are shown in the figure. The sample period is from March 2019 to April 2021.

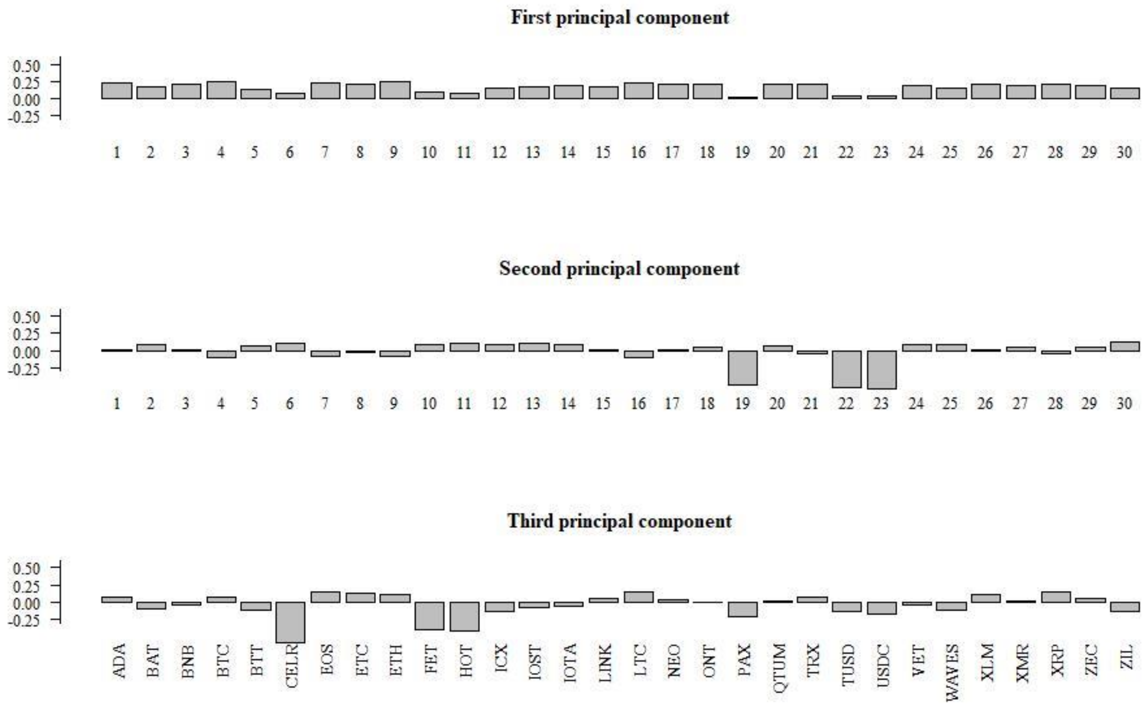
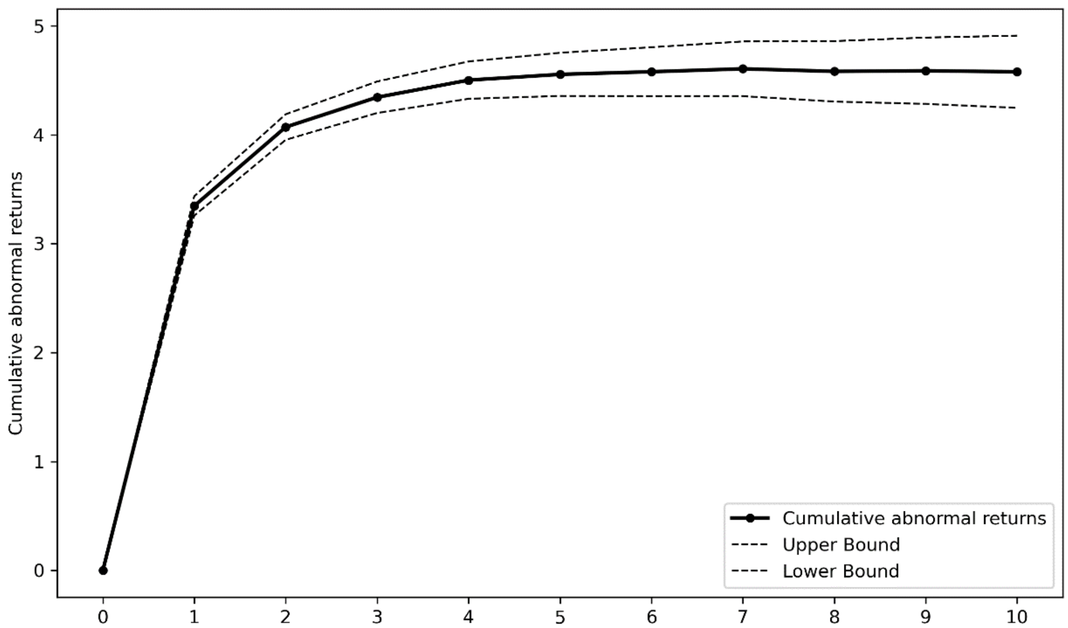


Figure 3 Cumulative excess return over the time horizon

Figure 3 shows the cumulative excess returns of the long-short portfolio predicted by the adaptive LASSO up to the next ten minutes (x-axis) with the corresponding 95% confidence intervals (shown as the upper and lower bounds). Returns are minute-level returns in bps. The sample period is from March 2019 to April 2021.



Appendix

Table A.I Summary of major market-wide events

Table A.I lists the nine major events included in our sample, based on their broad impact on the cryptocurrency market.

No	Event	Date
1	PlusToken Ponzi Scheme	2019/06/29
2	Donald Trump lambasted cryptos on Twitter	2019/07/11
3	President Xi Jinping's advocacy on blockchain	2019/10/24
4	Black Thursday	2020/03/12
5	Elon Musk tweeted doge	2020/12/20
6	Rumor on Bitcoin double spending	2021/01/21
7	Elon Musk added a bitcoin tag on his Twitter bio	2021/01/29
8	PayPal launched "Checkout with Crypto"	2021/03/30
9	Coinbase's IPO	2021/04/14