What Drives Cryptocurrency Prices?

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May 31, 2022

Abstract

The driver of cryptocurrency prices is still unclear in the literature. To investigate the driver of cryptocurrency prices, this paper introduces a new present value model based on the framework of the Campbell-Shiller variance decomposition. By utilizing the model, we decompose the variation of transaction-to-market ratios into return predictability and transaction growth predictability. This paper finds that, at the infinite horizon, both of the two kinds of predictability exist, and that the share of transaction growth predictability is larger than the share of return predictability. The results are corroborated in bootstrap simulations and are robust to a panel VAR analysis, a multivariate VAR analysis, and different frequencies of data. A cross-sectional analysis indicates that return predictability tends to emerge in cryptocurrencies that have large sizes.

JEL Classifications: G12, G17

Keywords: Cryptocurrency, Predictability, Variance Decomposition, Present Value Model

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1 Introduction

Since the introduction of Bitcoin (Nakamoto 2008), popularity of investment in cryptocurrencies is skyrocketed.[1] Coinbase Global Inc., the largest U.S. cryptocurrency exchange, reported net income of $3.62 billion in 2021 up from net income of $322 million in 2020 and noted that its trading volume grew more than 8.5 times from the previous year. Both earnings and transactions reflect that the cryptocurrency market has recently experienced a surge of interest and trading.[2] As the investment mania of cryptocurrencies prevails, valuation and price prediction in the cryptocurrency market become critical issues not only to investors but also to financial economists.

The pricing of cryptocurrency, nevertheless, is still challenging. Fundamental values of traditional financial assets stem from cash flows generated by the assets. For example, fundamental values of stocks are dividends paid from profits, so fundamental-to-market ratios (e.g., dividend-to-price or earnings-to-price) can predict future returns (Cochrane 2008; Cohen, Polk, and Vuolteenaho 2003; Vuolteenaho 2002). Fundamental values of stocks can be also represented by book equity, so book-to-market ratios can predict future returns (Cohen et al. 2003). However, such relationships between fundamentals and returns do not hold in the case of cryptocurrencies. Most cryptocurrencies, such as Bitcoin and Ethereum, have no corresponding cash flows or book values. The lack of cash flows or book values makes it hard to determine fundamental values of cryptocurrencies. It is no wonder that, without concrete fundamentals, seeking the driver of cryptocurrency prices is still a hot issue both in the financial industry and in the literature.

Recently, couples of theoretical articles start to discuss fundamental values of cryptocurrency based on network effects (Biais, Bisiere, Bouvard, Casamatta, and Menkveld 2020;

[1]The overall market value of cryptocurrencies grew by nearly $1.5 trillion in 2021, compared with the S&P 500's rise of nearly $9 trillion in market value, according to FactSet.

[2]Attention on cryptocurrencies becomes much larger especially after the introduction of NFT and metaverses (see Figure 1). Since circulations of NFT and operations of metaverses rely on flows of cryptocurrencies, the role of cryptocurrencies becomes progressively more important over time.

Cong, Li, and Wang 2021a, 2021b; Pagnotta and Buraschi 2018; Sockin and Xiong 2020). These models treat cryptocurrencies as transaction mediums. As more people use a cryptocurrency to conduct transactions, the payment platform of the cryptocurrency grows, and the carry cost is reduced, making the cryptocurrency more valuable. Furthermore, Cong, Li, et al. (2021a, 2021b) and Sockin and Xiong (2020) show that, in equilibrium, cryptocurrency prices should incorporate transaction-to-market ratios and active address-to-market ratios. While most of research on cryptocurrency pricing is still theoretical, some attentions are paid on empirical evidence for theoretical implications on cryptocurrency pricing. Both Cong, Karolyi, Tang, and Zhao (2021) and Liu and Tsyvinski (2021) empirically test whether the cryptocurrency valuation ratios can predict future coin returns and fail to find statistically significant evidence supporting the theoretical implication. Since the role of network as fundamentals is not robustly supported, the driver of cryptocurrency prices remains unclear. This paper aims to investigate the driver of the prices by analyzing predictability of cryptocurrency returns and transaction growth, a proxy for changes in fundamentals.

To analyze predictability of cryptocurrency returns and transaction growth, this paper introduces and utilizes a new present value model based on the framework of the Campbell-Shiller variance decomposition (Campbell and Shiller 1988).[3] The new model shows that the transaction-to-market ratio, a proxy for the fundamental-to-market ratio of cryptocurrencies, equals to an infinite sum of future returns minus an infinite sum of future transaction growth. The concept behind the method is consistent with the theoretical implication of Cong, Li, et al. (2021a, 2021b) that transaction-to-market ratios can predict returns. By running time-series vector autoregressions (hereafter, VARs) on a market portfolio, this paper decomposes the variation of the ratios into one component related to future returns and the other related to future transaction growth. The decomposition can distinguish between

[3]Campbell and Shiller (1988) is the first study to introduce the framework. In particular, they show that dividend-to-price ratios can be expressed as an identity of an infinite sum of future dividend growth minus an infinite sum of future returns. An interpretation of the identity is that changes in unexpected divided-to-price ratios must be attributed to changes in investors' expectations of either future dividend growth or future returns. Another interpretation is that current dividend-to-price ratios must predict either future dividend growth or future returns.

return predictability and transaction growth predictability.[4] This paper also runs bootstrap simulations to corroborate the results. Furthermore, this paper conducts a panel VAR analysis, runs multivariate VARs, and uses different frequencies of data to evaluate the robustness of the results.

The results suggest that both the two kinds of predictability exist, and that the share of transaction growth predictability is larger than the share of return predictability. The time-series VAR results of variables on one-week lagged transaction-to-market ratios indicate that 5% of the variance of the ratios is driven by the covariance attributed to returns. On the other hand, 11% of the variance is driven by the covariance attributed to transaction growth. Both of the two kinds of predictability are statistically different from zero under the 5% significance level. As the horizon approaches to infinity, the evidence is reinforced. The estimates at the infinite horizon that are implied from the one-horizon VARs show that 32% of the variance of the ratios is driven by the covariance attributed to returns. In comparison, 74% of the variance is driven by the covariance attributed to transaction growth. Both of the two kinds of predictability are also statistically significant under the 5% level. The results are somehow different from those in previous studies. Specifically, Cochrane (2008) shows unpredictability of dividend growth and thus predictability of returns in stocks. Cochrane (2011) summarizes that the discount rate effect rather than the fundamental effect dominates in most research of empirical asset pricing. In the case of cryptocurrencies, Liu and Tsyvinski (2021) show that the ability of transaction-to-market ratios to predict future returns is statistically indifferent from zero under the 5% significance level. Our results, in contrast, indicate that both return predictability and transaction growth predictability exist statistically, and that the share of transaction growth predictability is larger than the share of return predictability. In brief, our results indicate that the fundamental effect exceeds the discount rate effect in the case of cryptocurrencies, even though the discount rate effect still plays a role. In the cross-

[4] In our new present value model, return predictability means the extent to which the variance of transaction-to-market ratios is driven by the covariance attributed to returns. Similarly, transaction growth predictability means the extent to which the variance of transaction-to-market ratios is driven by the covariance attributed to returns.

sectional analysis, we also find that return predictability is statistically different from zero only in big cryptocurrencies. The results may imply that returns are predictable only if cryptocurrencies' sizes are large enough.

This paper provides three contributions to the literature. First, the paper contributes to the research on cryptocurrency forecasts. Some studies conduct reduced-form regressions based on theoretical motivations to predict cryptocurrency returns (Cong, Karolyi, et al. 2021; Liu and Tsyvinski 2021), whereas others exploit various machine learning techniques (Jaquart, Dann, and Weinhardt 2021; Khedr et al. 2021). This paper addresses the predictability of cryptocurrency returns by utilizing the present value model, an approach based on the classical framework in asset pricing and different from the empirical studies'.

Second, the paper provides some clues on the gap between the theoretical research and the empirical research in cryptocurrency pricing. Liu and Tsyvinski (2021) find lack of evidence that transaction-to-market ratios proposed in the theoretical research predict future returns, but why the ratios can hardly predict returns still remains unknown. By employing identities of transaction-to-market ratios based on the new present value model, this study shows that the ratios hardly predict returns perhaps because they predict transaction growth instead.

Third, the paper contributes to the literature of variance decomposition. Since the seminal work of Campbell and Shiller (1988), some studies decompose various key ratios in finance and macroeconomics.[5] Others apply the framework of variance decomposition to analyze assets other than stocks. To the best of our knowledge, this paper is the first study to introduce a new present value model for cryptocurrency based on the decomposition

[5]The framework of the variance decomposition is widely exploited since Campbell and Shiller (1988). Specifically, the framework is employed to decompose unexpected returns (Callen and Segal 2004; Campbell 1991; Vuolteenaho 2002), market betas (Campbell and Vuolteenaho 2004), debt-to-output ratios (Jiang, Lustig, Van Nieuwerburgh, and Xiaolan 2021), and book-to-market ratios (Cohen et al. 2003; Vuolteenaho 1999) to figure out what drives variation of the variables. The framework is introduced to analyze the stock market and later applied in other asset markets, such as the bond market (Campbell and Ammer 1993), the REIT market (Campbell, Davis, Gallin, and Martin 2009; Chiang 2020; Plazzi, Torous, and Valkanov 2010) and the foreign currency market (Froot and Ramadorai 2005). Moreover, the framework is used to analyze predictability of asset returns. One notable study is Cochrane (2008). Cochrane's results suggest unpredictability of dividend growth according to the identity of Campbell and Shiller (1988). He argues that, since the identity indicates that either stock returns or dividend growth should be predictable, returns must be predictable.

framework to analyze transaction-to-market ratios in the cryptocurrency market.

2 Construction of the New Present Value Model

Investigating predictability of cryptocurrency returns is equivalent to testing two competing null hypotheses: the null hypothesis of unpredictable returns versus the null hypothesis of unpredictable transaction growth. Under the null hypothesis of unpredictable returns, expected cryptocurrency returns are constant; i.e.,

$$E_t\left(\sum_{h=1}^{\infty} r_{t+h}\right) = E\left(\sum_{h=1}^{\infty} r_{t+h}\right), \tag{1}$$

where r_t is log returns. Under the null hypothesis of unpredictable transaction growth, expected transaction growth is constant; i.e.,

$$E_t\left(\sum_{h=1}^{\infty} \Delta q_{t+h}\right) = E\left(\sum_{h=1}^{\infty} \Delta q_{t+h}\right), \tag{2}$$

where Δq_t is log transaction growth.

To decompose transaction-to-market ratios and analyze predictability, we constructs a new present value model by deriving the identity of the ratios and thus the identity of the variance of the ratios. First of all, transaction-to-market ratios are defined as transactions divided by market values; i.e.,

$$\theta_t \equiv \ln\left(\frac{Q_t}{MV_t}\right), \tag{3}$$

where Q_t is transactions at week t, and MV_t is market values at week t. Following Cohen et al. (2003), we define log returns as changes in log market values of cryptocurrency; i.e., [6]

$$r_t \equiv \ln\left(\frac{MV_t}{MV_{t-1}}\right). \tag{4}$$

Log transaction growth, similarly, are defined as changes in log transactions of cryptocurrency; i.e.,

$$\Delta q_t \equiv \ln\left(\frac{Q_t}{Q_{t-1}}\right). \tag{5}$$

Thus, the following identities of transaction-to-market ratios can be derived based on the definitions (3), (4), and (5):

$$\Delta q_t - r_t = \ln\left(\frac{Q_t}{Q_{t-1}}\right) - \ln\left(\frac{MV_t}{MV_{t-1}}\right) = \theta_t - \theta_{t-1}; \tag{6}$$

$$\theta_t = r_{t+1} - \Delta q_{t+1} + \theta_{t+1}. \tag{7}$$

Iterated forward to week H, (7) becomes the desired identity:

$$\theta_t = \sum_{h=1}^{H} r_{t+h} - \sum_{h=1}^{H} \Delta q_{t+h} + \theta_{t+H}. \tag{8}$$

This identity indicates that current transaction-to-market ratios predict future returns positively and future transaction growth negatively. Based on the identity (8), the decomposition of the variance of transaction-to-market ratios is

$$\mathbf{Var}(\theta_t) = \mathbf{Cov}\Bigg(\sum_{h=1}^{H} r_{t+h}, \theta_t\Bigg) - \mathbf{Cov}\Bigg(\sum_{h=1}^{H} \Delta q_{t+h}, \theta_t\Bigg) + \mathbf{Cov}\Bigg(\theta_{t+H}, \theta_t\Bigg). \tag{9}$$

Intuitively, the decomposition (9) indicates that unconditional variation of transaction-to-market ratios can be decomposed into components attributed to future returns, transaction

[6] Like Cohen et al. (2003), we use log returns rather than changes in log market values when running VAR analyses. The results are robust if changes in log market values are used instead.

growth, and transaction-to-market ratios. Another interpretation is that changes in the current ratios reflect transitory changes in expected returns, transitory changes in transaction growth, and persistent changes in transaction-to-market ratios (Cohen et al. 2003). Divided by $\mathbf{Var}(\theta_t)$ on both sides, (9) becomes

$$1 = \frac{\mathbf{Cov}\Big(\sum_{h=1}^{H} r_{t+h}, \theta_t\Big)}{\mathbf{Var}(\theta_t)} - \frac{\mathbf{Cov}\Big(\sum_{h=1}^{H} \Delta q_{t+h}, \theta_t\Big)}{\mathbf{Var}(\theta_t)} + \frac{\mathbf{Cov}\Big(\theta_{t+H}, \theta_t\Big)}{\mathbf{Var}(\theta_t)}. \tag{10}$$

The intuition behind (10) is more straightforward than (9). This identity depicts the composition of variance shares of current transaction-to-market ratios that can be attributed to changes in future returns, transaction growth, and transaction-to-market ratios. Furthermore, since the variance shares are summed to one, (10) implies that there are no drivers of unconditional variance of transaction-to-market ratios outside the three sources on the right hand side of (10).

The identities (8), (9), and (10) also hold as $H \to \infty$, provided that θ_t, r_t, and Δq_t are all stationary. These three identities, respectively, become

$$\theta_t = \sum_{j=1}^{\infty} r_{t+j} - \sum_{j=1}^{\infty} \Delta q_{t+j}; \tag{11}$$

$$1 = \frac{\mathbf{Cov}\Big(\sum_{j=1}^{\infty} r_{t+j}, \theta_t\Big)}{\mathbf{Var}(\theta_t)} - \frac{\mathbf{Cov}\Big(\sum_{j=1}^{\infty} \Delta q_{t+j}, \theta_t\Big)}{\mathbf{Var}(\theta_t)}. \tag{12}$$

3 Research Design

3.1 Construction of the VAR Model

After constructing the new present value model, this paper runs time-series VARs on a market portfolio to examine predictability. Following previous studies (Chen 2009; Chen, Da, and Priestley 2012; Cochrane 2008; Rangvid, Schmeling, and Schrimpf 2014), this paper forms a one-horizon VAR model in the following way:[7]

$$\begin{aligned}
r_{t+1} &= a_{r,1} + b_{r,1}\theta_t + \varepsilon_t^{r,1} \\
q_{t+1} &= a_{q,1} + b_{q,1}\theta_t + \varepsilon_t^{q,1} \\
\theta_{t+1} &= a_{\theta,1} + b_{\theta,1}\theta_t + \varepsilon_t^{\theta,1}, \qquad (13)
\end{aligned}$$

where t is the time variable in weeks, and ε is the noise term. The estimates of the predictability and the transaction-to-market ratio persistence are denoted by $\hat{b}_{r,1}, \hat{b}_{q,1}$, and $\hat{b}_{\theta,1}$. By (10),

$$b_{r,1} - b_{q,1} + b_{\theta,1} = 1; \qquad (14)$$

$$\hat{b}_{r,1} - \hat{b}_{q,1} + \hat{b}_{\theta,1} = 1. \qquad (15)$$

Estimates of predictability at horizon $H > 1$ that are implied from the VAR model (13) are also calculated:

$$\tilde{b}_{r,H} = \hat{b}_{r,1} \cdot \frac{1 - \hat{b}_{\theta,1}^H}{1 - \hat{b}_{\theta,1}} \qquad (16)$$

$$\tilde{b}_{q,H} = \hat{b}_{q,1} \cdot \frac{1 - \hat{b}_{\theta,1}^H}{1 - \hat{b}_{\theta,1}}; \qquad (17)$$

$$\tilde{b}_{\theta,H} = \hat{b}_{\theta,1}^H, \qquad (18)$$

where $\tilde{b}_{r,H}$, $\tilde{b}_{q,H}$, and $\tilde{b}_{\theta,H}$ are the implied estimates of the coefficients in (13). Iterated forward to infinity, the implied estimates become

$$\tilde{b}_r \equiv \tilde{b}_{r,\infty} = \hat{b}_{r,1} \cdot \frac{1}{1 - \hat{b}_{\theta,1}}; \qquad (19)$$

$$\tilde{b}_q \equiv \tilde{b}_{v,\infty} = \hat{b}_{q,1} \cdot \frac{1}{1 - \hat{b}_{\theta,1}}. \qquad (20)$$

[7] Like Cohen et al. (2003), this study uses log returns rather than changes in log market values when conducting the VAR analysis.

By the identity that $\hat{b}_{r,1} - \hat{b}_{q,1} + \hat{b}_{\theta,1} = 1$, $\tilde{b}_r - \tilde{b}_q = 1$.

3.2 Data Processing and Descriptive Statistics

Data are collected and processed according to the following steps and criteria. First, daily data of prices, market capitalizations, trading volumes, and transactions are retrieved from CoinMarketCap and Coin Metrics. Only cryptocurrencies that have non-missing close prices, market capitalizations, trading volumes, and transactions are kept. After the collection, weekly returns, transaction-to-market ratios, and transaction growth are calculated. The market portfolio is constructed as a value-weighted portfolio of the kept cryptocurrencies, and the value-weighted returns are calculated. The time period of the final sample ranges from 01/01/2014 to 12/31/2021. The period begins from 01/01/2014 because data of trading volumes are inaccessible before the last week in 2013 (Liu, Tsyvinski, and Wu 2022). The period ends at 12/31/2021 because data after 12/31/2021 are unavailable during the collection. At the beginning of the sample period, there are only 4 coins in the portfolio. At the end of the sample period, there are 86 coins in the portfolio.

Table 1 reports descriptive statistics of the variables. On average, the market portfolio generates 2% of weekly returns during the sample period. The large standard deviation of the portfolio returns indicates high volatility of the returns. The cryptocurrency market portfolio actually provides quite decent risk-adjusted returns. The Sharpe ratio of the portfolio is 0.15. During the same sample period, the Sharpe ratio of the stock market portfolio is 0.11, calculated by utilizing the datasets in Fama-French Data Library. Both the transaction growth and the transaction-to-market ratios are even more volatile than the returns. The mean of transaction growth is half of the mean of returns, but the standard deviation of transaction growth is twice as large as that of returns. The autocorrelations of returns are quite small, indicating that returns are not persistent among weeks. Moreover, the autocorrelations of transaction growth are negative, indicating that transaction growth tends to reverse after one week. The Pearson autocorrelation of log transaction-to-market ratios is

0.84. The magnitude of the autocorrelation implies that the ratios are quite persistent, but that the persistence is still tolerable. [8]

[Table 1 here]

4 Main Results

4.1 VAR Results

Panel A of Table 2 reports the VAR results of the market portfolio. At the 1-week horizon, a 1% increase in log transaction-to-market ratios predicts a 0.05% increase in future returns and a 0.11% decrease in future transaction growth. As the horizon increases, so does the magnitude of return predictability. At the infinite horizon, a 1% increase in log transaction-to-market ratios predicts a 0.32% increase in future cumulative returns and a 0.74% decrease in future cumulative transaction growth. From the perspective of variance decomposition, 74% of the variance of log transaction-to-market ratios is driven by the covariance attributed to future transaction growth, whereas 32% of the variance of the ratios is driven by the covariance attributed to future returns. All of the estimates are statistically significant under the 5% level. Overall, the results support the presence of both return predictability and transaction growth predictability, and that the share of transaction growth predictability is larger than the share of return predictability.

[Table 2 here]

[8] Table 2 of Cochrane (2008) shows that persistence in log dividend-to-price ratios is 0.94. Table I of Cohen et al. (2003) shows that persistence in log book-to-market ratios is 0.83. Our VAR results show that persistence in log transaction-to-market ratios is 0.85 (unreported).

4.2 Bootstrap Simulations

Like Cochrane (2008), we conduct simulations to corroborate the results in the VAR analysis. Specifically, we repeat for 5,000 times the following procedures of bootstrap simulations:[9]

1. Decide to adopt the null hypothesis of either unpredictable returns or unpredictable transaction growth.

2. Simulate according to either one of the null hypotheses.

   - Under the null hypothesis of unpredictable returns, $b_{r,1} = 0$ and $b_{q,1} = b_{\theta,1} - 1$ according to the identity (14). Randomly draw an initial value of transaction-to-market ratios θ_0 and an initial value of transaction growth Δq_0 from the joint empirical distribution. Simulate the time-series of transaction-to-market ratios according to the equation $\theta_{t+1} = \hat{a}_{\theta,1} + \hat{b}_{\theta,1}\theta_t + \varepsilon_t^{\theta,1}$, where $\hat{b}_{\theta,1}$ is the estimate in the VAR analysis. Utilize the identity (14) and simulate the time-series of transaction growth according to the equation $\Delta q_{t+1} = (\hat{b}_{\theta,1} - 1)\theta_t + \varepsilon_t^{q,1}$. Both $\varepsilon_t^{\theta,1}$ and $\varepsilon_t^{q,1}$ are drawn with replacement from the joint empirical distribution of estimates $\hat{\varepsilon}_t^{\theta,1}$ and $\hat{\varepsilon}_t^{q,1}$. Generate the time-series of returns according to the identity $r_{t,1} = \varepsilon_t^{q,1} - \varepsilon_t^{\theta,1}$, implied form the VAR system (13) and the null hypothesis of unpredictable returns.

   - Under the null hypothesis of unpredictable transaction growth, $b_{q,1} = 0$ and $b_{r,1} = 1 - b_{\theta,1}$ according to the identity (14). Randomly draw an initial value of transaction-to-market ratios θ_0 and an initial value of returns r_0 from the joint empirical distribution. Simulate the time-series of transaction-to-market ratios according to the equation $\theta_{t+1} = \hat{a}_{\theta,1} + \hat{b}_{\theta,1}\theta_t + \varepsilon_t^{\theta,1}$, where $\hat{b}_{\theta,1}$ is the estimate in the VAR analysis. Utilize the identity (14) and simulate the time-series of returns according to the equation $r_{t+1} = (1 - \hat{b}_{\theta,1})\theta_t + \varepsilon_t^{r,1}$. Both $\varepsilon_t^{\theta,1}$ and $\varepsilon_t^{r,1}$

[9] We conduct the bootstrap rather than Monte Carlo simulations because normality of returns, transaction growth, and transaction-to-market ratios is questionable.

are drawn with replacement from the joint empirical distribution of estimates $\hat{\varepsilon}_t^{\theta,1}$ and $\hat{\varepsilon}_t^{r,1}$. Generate the time-series of transaction growth according to the identity $\Delta q_{t,1} = \varepsilon_t^{r,1} + \varepsilon_t^{\theta,1}$, implied form the VAR system (13) and the null hypothesis of unpredictable transaction growth.

3. Estimate one-horizon predictability according to the VAR system (13). Estimate predictability at longer horizons using (16), (17), (19), and (20).

Table 2 reports the bootstrap p-values of estimates and t-statistics under different null hypotheses.[10] The p-values of the estimates and t-statistics of return predictability never exceed 3% under the null hypothesis of unpredictable either returns or transaction growth. Under the 5% significance level, both of the null hypotheses can be rejected. On the other hand, the p-values of the estimates and t-statistics of transaction growth are always more than 5% under the null hypothesis of unpredictable returns and less than 5% under the null hypothesis of unpredictable transaction growth in finite horizons. Thus, in the case of finite horizons, it is easy to reject the hypothesis of unpredictable transaction growth and favor the hypothesis of unpredictable returns. At the infinite horizon, the p-values are less than 5% under both of the hypotheses, rejecting unpredictability of both returns and transaction growth.Overall, the simulation results suggest that both return predictability and transaction growth predictability exist, a suggestion consistent with the VAR estimation results.

[10]Following Cochrane (2008), we define the p-values as percentages of simulated $\hat{b}_{r,h}$, $\hat{b}_{q,h}$, and their t-statistics larger than sample estimates under the null hypothesis of unpredictable returns or smaller than the sample estimates under the null hypothesis of unpredictable transaction growth.

5 Robustness Analyses

5.1 Panel VAR Analysis

This paper also runs a panel VAR analysis in addition to the time-series one. The following is the one-horizon panel VAR model.

$$\begin{aligned} r_{k,t+1} &= a_{r,1} + b_{r,1}\theta_{k,t} + a_k + \varepsilon_{k,t}^{r,1} \\ \Delta q_{k,t+1} &= a_{q,1} + b_{q,1}\theta_{k,t} + a_k + \varepsilon_{k,t}^{q,1} \\ \theta_{k,t+1} &= a_{\theta,1} + b_{\theta,1}\theta_{k,t} + a_k + \varepsilon_{k,t}^{\theta,1}, \end{aligned} \tag{21}$$

where k represents different cryptocurrencies, and a_k is the fixed effects of different cryptocurrencies.

Panel B of Table 2 reports the panel VAR results. The results are more favorable to transaction growth predictability in the panel VAR estimation than in the time-series one. At the infinite horizon, a 1% increase in transaction-to-market ratios predicts a 0.95% decrease in transaction growth. Equivalently, 95% of the variance of transaction-to-market ratios is driven by the covariance attributed to transaction growth. On the other hand, a 1% increase in transaction-to-market ratios predicts only a 0.01% increase in returns. Furthermore, the t-statistic of return predictability at the infinite horizon is smaller than 1.96, suggesting that the return predictability is statistically indifferent from zero under the 5% significance level. Overall, the results are qualitatively similar in the panel VAR estimation.

5.2 Multivariate VAR Analysis and Variance Decomposition of Return Innovations

Besides the single variate VAR in the main analysis, a multivariate VAR analysis is also conducted. The state variables of the multivariate VARs include returns, transaction growth, transaction-to-market ratios, and Google searches. Google searches are included because Liu and Tsyvinski (2021) show that attention can predict future returns.[11] In short, we run the following multivariate VAR model.

$$\mathbf{z_{t+1}} = \mathbf{A} + \mathbf{B}\mathbf{z_t} + \varepsilon_{\mathbf{t+1}}, \tag{22}$$

where $\mathbf{z_t}$ is a vector that includes r_t, Δq_t, θ_t, and $Google_t$, the Google searches. $\mathbf{A}$ is the constant vector, and $\mathbf{B}$ is the coefficient matrix. $\varepsilon_{\mathbf{t+1}}$ is the noise vector.

Panel A of Table 3 reports the estimation results of the multivariate VARs. The results show that one standard deviation increase in $Google_t$ induces a nearly 0.1 standard deviation increase in r_{t+1}. The coefficient of r_{t+1} on $Google_t$ is statistically different from zero under the 10% significance level. The results imply that investors' attention can predict future cryptocurrency returns, an implication consistent with the findings in Liu and Tsyvinski (2021). Moreover, the results show that one standard deviation increase in r_t induces a 0.2 standard deviation increase in $Google_{t+1}$. The coefficient of $Google_{t+1}$ on r_t is statistically different from zero under the 1% significance level. The results imply that investors' attention tend to increase after superior performance in cryptocurrency returns, an implication consistent with the findings in Liu and Tsyvinski (2021). Note that the coefficients of r_{t+1}, Δq_{t+1}, and θ_{t+1} on θ_t are summed to one as a result of the identity (15). The signs of r_{t+1} and Δq_{t+1} on θ_t are also consistent with those implied from (10).

Panel B of Table 3 reports the estimates and their t-statistics of log returns and log transaction growth on log transaction-to-market ratios at different horizons. The estimates are implied from the estimation results of the one-horizon multivariate VARs in panel A. Like those in the single variate case, the results in the multivariate case also indicate that both returns and transaction growth are predictable, and that the share of transaction growth predictability is larger than that of return predictability. At the infinite horizon, a 1%

[11] Following Liu, Tsyvinski, and Wu (2022), we utilize the Google search volumes of te keyword "blockchain" to measure attention.

increase in transaction-to-market ratios induces a 0.45% increase in returns. The magnitude of the increase is statistically significant under the 5% level. On the other hand, a 1% increase in the ratios induces a 0.64% increase in transaction growth. The magnitude of the increase is statistically different from zero under the 5% level. Overall, the results in the univariate analysis are robust to the multivariate VARs.

To decompose return innovations, we derive an identity of returns. Specifically, inserting (11) into (7) generates the following equations.

$$
\begin{aligned}
r_{t+1} &= \theta_t + \Delta q_{t+1} - \theta_{t+1} \\
&= E_t\left[\sum_{j=1}^{\infty} r_{t+j} - \sum_{j=1}^{\infty} \Delta q_{t+j}\right] + \Delta q_{t+1} - E_{t+1}\left[\sum_{j=1}^{\infty} r_{t+j+1} - \sum_{j=1}^{\infty} \Delta q_{t+j+1}\right] \\
&= -E_t\left[\sum_{j=0}^{\infty} \Delta q_{t+j+1}\right] + E_t(r_{t+1}) + E_t\left[\sum_{j=1}^{\infty} r_{t+j+1}\right] \\
&+ \Delta q_{t+1} + E_{t+1}\left[\sum_{j=1}^{\infty} \Delta q_{t+j+1}\right] - E_{t+1}\left[\sum_{j=1}^{\infty} r_{t+j+1}\right].
\end{aligned} \tag{23}
$$

Rearranging (23), we derive the desired identity.

$$
\begin{aligned}
r_{t+1} = E_t(r_{t+1}) &+ \left[E_{t+1}\left(\sum_{j=0}^{\infty} \Delta q_{t+j+1}\right) - E_t\left(\sum_{j=0}^{\infty} \Delta q_{t+j+1}\right)\right] \\
&- \left[E_{t+1}\left(\sum_{j=1}^{\infty} r_{t+j+1}\right) - E_t\left(\sum_{j=1}^{\infty} r_{t+j+1}\right)\right] \\
&\equiv E_t(r_{t+1}) + \eta_{q,t+1} - \eta_{r,t+1}.
\end{aligned} \tag{24}
$$

Note that $\eta_{q,t+1}$ represents fundamental news, changes in expectations of future transaction growth, and that $\eta_{r,t+1}$ represents discount rate news, changes in expectations of future returns. (24) indicates that returns must equal to expected returns plus fundamental news minus discount rate news. Rearranging (24) and taking variance on both of the sides, we derive the identity of variance of returns.[12]

$$\mathbf{Var}\Big[r_{+1} - E_t(r_{t+1})\Big] = \mathbf{Cov}\Big[r_{+1} - E_t(r_{t+1}), \eta_{q,t+1}\Big] - \mathbf{Cov}\Big[r_{+1} - E_t(r_{t+1}), \eta_{r,t+1}\Big]. \tag{25}$$

(25) indicates that variation of unexpected returns must be driven by covariance attributed to fundamental news and covariance attributed to discount rate news.

To get the variance decomposition results, we run the multivariate VARs in (22) and calculate discount rate news and fundamental news. Specifically, the VARs generate expected returns as

$$E_t(r_{t+j+1}) = \mathbf{e1}'\mathbf{A}^{j+1}\mathbf{z_t}, \tag{26}$$

where **e1** is a column vector whose first row equals to one and the others equals to zero. Thus, the discount rate news in (24) can be re-written as

$$\begin{aligned}\eta_{r,t+1} &= E_{t+1}\left(\sum_{j=1}^{\infty} r_{t+j+1}\right) - E_t\left(\sum_{j=1}^{\infty} r_{t+j+1}\right)\\ &= \mathbf{e1}'\sum_{j=1}^{\infty}\mathbf{A}^j\varepsilon_{\mathbf{t+1}} = \mathbf{e1}'\mathbf{A}(\mathbf{I}-\mathbf{A})^{-1}\varepsilon_{\mathbf{t+1}}\\ &\equiv \lambda'\varepsilon_{\mathbf{t+1}}.\end{aligned} \tag{27}$$

It follows that

$$\eta_{q,t+1} = (\mathbf{e1}' + \lambda')\varepsilon_{\mathbf{t+1}}. \tag{28}$$

Since the discount rate news and fundamental news can be calculated from the VARs, the variance of unexpected returns, the covariance attributed to discount rate news, and the covariance attributed to fundamental news can be also calculated.

[12]This identity is Cochrane's variance decomposition.

Panel C of Table 3 reports the variance decomposition results of unexpected returns. The ratio of covariance attributed to fundamental news to variance of unexpected returns exceeds 100%. In comparison, the ratio of covariance attributed to discount news is only 26%. The difference in magnitude implies that investors change their expectations of future returns more because of changes in expectations of fundamentals than because of changes in expectations of discount rates. This is consistent with the finding in the predictability analysis that the share of transaction growth predictability is larger than the share of return predictability.

5.3 Monthly Data

Table 4 reports the time-series VAR results of the monthly data. The magnitudes of the estimated coefficients also suggest that the share of transaction growth predictability is larger than that of returns. At the infinite horizon, a 1% increase in log transaction-to-market ratios predicts a 0.48% increase in future cumulative returns and a 0.58% decrease in future cumulative transaction growth. From the perspective of variance decomposition, 58% of the variance of log transaction-to-market ratios is driven by the covariance attributed to future transaction growth, whereas 48% of the variance of the ratios is driven by the covariance attributed to future returns. Both of the two kinds of predictability at the infinite horizon are statistically different from zero under the 5% significance level, suggesting that both returns and transaction growth are predictable. The evidence in the panel VAR results is more favorable to predictability of transaction growth. At the infinite horizon, a 1% increase in log transaction-to-market ratios predicts a 0.01% increase in future cumulative returns and a 0.86% decrease in future transaction growth. Furthermore, the t-statistics indicate that return predictability is statistically indifferent from zero under the 5% significance level at each horizon. In contrast, transaction growth predictability is statistically different from zero under the same significance level at each horizon. In short, the results obtained from the analysis of weekly data are robust to the usage of monthly data.

[Table 4 here]

6 Cross-Sectional Analysis

We also follow Liu, Tsyvinski, and Wu (2022) and Maio and Santa-Clara (2015) to examine heterogeneous differences in predictability among cross-sectional portfolios. In each week, cryptocurrencies are sorted into 30-40-30 portfolios according to the values of a given characteristic in the previous week (Liu, Tsyvinski, and Wu 2022, p. 10).[13] The characteristics include the size and the momentum. The size is measured by utilizing market capitalizations. The momentum is measured by calculating cumulative returns in the past three weeks. Following Maio and Santa-Clara (2015), we run the time-series VARs in the portfolio of the smallest value and in the portfolio of the largest value of a given characteristic.

Panel A of Table 5 summarizes log returns among different portfolios. On average, the small size portfolio yields 5% of returns, and the big size portfolio yields 1%. It is consistent with the size premium proposed by Liu, Tsyvinski, and Wu (2022) that small coins yield larger returns than big ones. Moreover, big coins tend to have smaller standard deviations of returns than small ones. Since the trading history and volume of big coins tends to be longer and larger than those of small ones, it is unsurprising that big coins have lower volatility of returns than small ones. Furthermore, the portfolio of high momentum coins yields an average of 3% of returns, and that of low momentum coins yields an average of nearly 0% of returns. It is consistent with the momentum premium proposed by Liu, Tsyvinski, and Wu (2022) that high momentum coins yield higher returns than low ones.

Panel B of Table 5 summarizes log transaction growth among different portfolios. On average, the big size portfolio's transaction growth is twice as large as the small one's. This is unsurprising, since big size coins tend to be regarded as transaction mediums and widely used in daily transactions (e.g., bitcoins and ethereums). Panel C of Table 5 summarizes log transaction-to-market ratios. Overall, the big size portfolio's and the low momentum

[13] Cryptocurrencies are sorted according to 30 and 70 percentiles of the given characteristic.

portfolio's transaction-to-market ratios tend to be smaller than the others'.

Table 6 reports the VAR results of size portfolios. In the case of the small cryptocurrencies, transaction growth predictability dominates return predictability. At no horizon does a 1% increase in transaction-to-market ratios predict a more than 0.02% increase in future cumulative returns. Moreover, the coefficients of return predictability are statistically insignificant under the 5% level. In contrast, a 1% increase in transaction-to-market ratios predicts a more than 0.3% increase in future cumulative transaction growth. The coefficients of transaction growth predictability are statistically different from zero under the 5% level. The results are quite different in the case of the big cryptocurrencies. Specifically, return predictability increases as the horizon increases. At the infinite horizon, a 1% increase in transaction-to-market ratios predicts a 0.3% increase in future cumulative returns. Furthermore, the coefficients of return predictability are statistically significant under the 5% level. The patterns in Table 6 indicate that transaction growth predictability is mainly driven by the presence of small cryptocurrencies, and that return predictability is mainly driven by the presence of big ones. This finding is consistent with that in Maio and Santa-Clara (2015), who find that dividend growth predictability is mainly driven by small stocks, and that return predictability is mainly driven by large stocks. Since the value-weighted market portfolio tends to tilt toward large cryptocurrencies, it is unsurprising that the predictability results in large coins are similar to those in the market portfolio. (Maio and Santa-Clara 2015, p. 41)

Table 7 presents the results of momentum portfolios. In the cases of both the low momentum cryptocurrencies and the high ones, transaction growth predictability doubtlessly dominates return predictability. Take the portfolio of the low momentum cryptocurrencies as an example. At the infinite horizon, a 1% increase in transaction-to-market ratios predicts a nearly 0.01% increase in future cumulative returns. On the other hand, a 1% increase in transaction-to-market ratios predicts a nearly 1% increase in future cumulative transaction growth. Moreover, the coefficients of return predictability are all statistically insignificant under the 5% level. Overall, differences in momentum seem not to drive cross-sectional differences in predictability.

7 Conclusion

This paper shows that transaction-to-market ratios in the literature of cryptocurrency pricing predicts both returns and transaction growth, and that the share of transaction growth predictability is larger than that of return predictability. The results indicate that the variation of transaction-to-market ratios is driven by the variation of both returns and future transaction growth, and that the main force is the variation of transaction growth. In brief, both returns and transaction growth are predictable, and transaction growth is more predictable than returns in the sense of economic significance. The predictability patterns hold both in the time-series VAR analysis and in the bootstrap simulations. The results are robust to the panel VAR analysis, the multivariate analysis, and the usage of different frequencies of data. In the cross-sectional analysis, we also find that transaction growth predictability is mainly driven by the presence of small cryptocurrencies, and that return predictability is mainly driven by the presence of big ones. Our results are different from those in Liu and Tsyvinski (2021) and Cong, Karolyi, et al. (2021), who find little evidence supporting the transaction-to-market ratios' ability to predict future returns. The theoretical linkage between cryptocurrency returns and transaction-to-market ratios seems unclear in the previous studies perhaps because transaction-to-market ratios' ability to predict transaction growth hinders the ratios' ability to predict returns. This paper is the first one to introduce and utilize the new present value model based on the Campbell-Shiller decomposition and to address predictability of cryptocurrency returns under the new model. Utilizing the new model, this paper provides more clues on the driver of cryptocurrency prices.

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Tables

Table 1: Descriptive Statistics

Panel A: Summary Statistics
This table reports means (Mean), standard deviations (S.D.), minima (Min.), percentiles (P), and maxima (Max.) of the variables of the time-series data. The definitions of variables are in Appendix A. The sample period spans from 01/01/2014 to 12/31/2021. The number of time-series observations is 416 weeks. The number of panel observations is 16,307 coin-weeks. The data sources are coinmarketcap.com and coinmetrics.io.

Var.	Mean	S.D.	Min.	$P_{25\%}$	Med.	$P_{75\%}$	Max.
r_t	0.02	0.11	-0.48	-0.04	0.01	0.07	0.42
q_t	0.01	0.22	-0.67	-0.12	-0.00	0.15	0.82
θ_t	-1.92	0.40	-2.68	-2.24	-1.92	-1.64	-0.16
$Google_t$	-0.00	1.00	-4.79	-0.26	-0.02	0.25	7.69

Panel B: Pearson-Spearman Correlations
This table reports Pearson and Spearman correlations of the variables of the time-series data. The Pearson correlations are reported in the lower triangle, and the Spearman correlations are reported in the upper triangle. The definitions of variables are in Appendix A. The sample period spans from 01/01/2014 to 12/31/2021. The number of time-series observations is 416 weeks. The number of panel observations is 16,307 coin-weeks. The data sources are coinmarketcap.com and coinmetrics.io.

	r_t	r_{t+1}	q_t	q_{t+1}	θ_t	θ_{t+1}	$Google_t$	$Google_{t+1}$
r_t	1.00	0.09	0.29	0.30	0.10	0.22	0.20	0.32
r_{t+1}	0.08	1.00	0.09	0.29	0.20	0.10	0.08	0.221
q_t	0.28	0.08	1.00	-0.07	0.27	0.20	0.27	0.27
q_{t+1}	0.31	0.27	-0.07	1.00	-0.17	0.28	0.07	0.27
θ_t	0.05	0.17	0.28	-0.20	1.00	0.85	0.16	0.09
θ_{t+1}	0.21	0.04	0.22	0.29	0.84	1.00	0.19	0.15
$Google_t$	0.25	0.14	0.20	0.04	0.14	0.14	1.00	0.66
$Google_{t+1}$	0.37	0.25	0.22	0.19	0.09	0.14	0.67	1.00

Table 2: VAR Results

Panel A: Time-Series VARs

This table reports the time-series VAR estimates and their t-statistics and bootstrap p-values under the null hypothesis of unpredictable either returns or transaction growth. The standard errors of the t-statistics are based on the delta method. The definitions of variables are in Appendix A. The sample period spans from 01/01/2014 to 12/31/2021. The number of time-series observations is 416 weeks. The number of panel observations is 16,307 coin-weeks. The data sources are coinmarketcap.com and coinmetrics.io.

Horizon	b_r	t_r	$P_{b_r}^{b_r,1=0}$	$P_{t_r}^{b_r,1=0}$	$P_{b_r}^{b_q,1=0}$	$P_{t_r}^{b_q,1=0}$	b_q	t_q	$P_{b_q}^{b_r,1=0}$	$P_{t_q}^{b_r,1=0}$	$P_{b_q}^{b_q,1=0}$	$P_{t_q}^{b_q,1=0}$
1	0.05	2.77	0.00	0.01	0.00	0.00	-0.11	-3.53	0.23	0.34	0.00	0.00
2	0.09	2.77	0.00	0.01	0.00	0.00	-0.21	-3.52	0.12	0.21	0.00	0.00
3	0.12	2.76	0.00	0.02	0.00	0.00	-0.29	-3.51	0.09	0.16	0.00	0.01
4	0.15	2.75	0.01	0.02	0.00	0.00	-0.36	-3.49	0.07	0.14	0.00	0.01
5	0.18	2.74	0.01	0.02	0.00	0.00	-0.41	-3.46	0.07	0.14	0.00	0.01
6	0.20	2.72	0.01	0.03	0.00	0.00	-0.46	-3.43	0.06	0.14	0.01	0.01
7	0.22	2.70	0.01	0.03	0.00	0.00	-0.50	-3.40	0.06	0.14	0.01	0.02
8	0.23	2.69	0.02	0.03	0.00	0.00	-0.54	-3.36	0.06	0.14	0.01	0.02
∞	0.32	2.46	0.00	0.01	0.00	0.00	-0.74	-2.94	0.01	0.01	0.00	0.00

Panel B: Panel VARs

This table reports the panel VAR estimates and their t-statistics. The standard errors of the t-statistics are based on the delta method. The definitions of variables are in Appendix A. The sample period spans from 01/01/2014 to 12/31/2021. The number of time-series observations is 416 weeks. The number of panel observations is 16,307 coin-weeks. The data sources are coinmarketcap.com and coinmetrics.io.

Horizon	b_r	t_r	b_q	t_q
1	0.00	1.60	-0.13	-18.10
2	0.00	1.60	-0.24	-18.06
3	0.00	1.60	-0.33	-17.95
4	0.01	1.60	-0.41	-17.78
5	0.01	1.60	-0.48	-17.56
6	0.01	1.60	-0.55	-17.32
7	0.01	1.60	-0.60	-17.06
8	0.01	1.60	-0.65	-16.79
∞	0.01	1.59	-0.95	-13.15

Table 3: Multivariate Analysis

Panel A: VAR Results
This table reports one-horizon multivariate VAR results. The definitions of variables are in Appendix A. The sample period spans from 01/01/2014 to 12/31/2021. The number of time-series observations is 416 weeks. The number of panel observations is 16,307 coin-weeks. The data sources are coinmarketcap.com and coinmetrics.io.

	r_{t+1}	q_{t+1}	θ_{t+1}	$Google_{t+1}$
r_t	0.04	0.69***	0.69***	1.83***
	(0.06)	(0.10)	(0.10)	(0.67)
q_t	0.00	−0.12**	−0.13**	0.18
	(0.03)	(0.05)	(0.05)	(0.17)
θ_t	0.04***	−0.10***	0.86***	−0.05
	(0.01)	(0.03)	(0.03)	(0.10)
$Google_t$	0.01*	0.00	−0.01	0.61***
	(0.01)	(0.01)	(0.01)	(0.10)
Intercept	0.10***	−0.19***	−0.27***	−0.12
	(0.03)	(0.06)	(0.05)	(0.22)
Obs.	415	415	415	415

Notes: standard errors are in parentheses. *** p<.01, ** p<.05, * p<.1

Panel B: Predictability Estimates
This table reports the multivariate VAR implied estimates and their t-statistics. The standard errors of the t-statistics are based on the delta method. The definitions of variables are in Appendix A. The sample period spans from 01/01/2014 to 12/31/2021. The number of time-series observations is 416 weeks. The number of panel observations is 16,307 coin-weeks. The data sources are coinmarketcap.com and coinmetrics.io.

Horizon	b_r	t_r	b_q	t_q
1	0.04	2.88	-0.10	-3.73
2	0.08	2.87	-0.15	-2.83
3	0.11	2.88	-0.20	-2.64
4	0.15	2.89	-0.24	-2.53
5	0.17	2.90	-0.28	-2.46
6	0.20	2.91	-0.32	-2.42
7	0.22	2.91	-0.35	-2.39
8	0.24	2.91	-0.38	-2.36
∞	0.45	2.94	-0.64	-2.25

Panel C: Decomposition of Unexpected Returns
This table reports the decomposition results of variance of unexpected returns from the multivariate VAR. Cov. is the covariance between $r_{t+1} - E_t(r_{t+1})$ and the variable in the column, and Share is the covariance divided by the variance of $r_{t+1} - E_t(r_{t+1})$. The standard errors of the VAR are Newey-West standard errors with the maximum lag allowed to be 8 weeks. The definitions of variables are in Appendix A. The sample period spans from 01/01/2014 to 12/31/2021. The number of time-series observations is 416 weeks. The number of panel observations is 16,307 coin-weeks. The data sources are coinmarketcap.com and coinmetrics.io.

Stat.	$r_{t+1} - E_t(r_{t+1})$	N_q	N_r
Cov.	0.01	0.02	0.00
Share	1	1.26	0.26

Table 4: Monthly VAR Results

Panel A: Time-Series VAR Results

This table reports the time-series VAR estimates and their t-statistics. The standard errors of the t-statistics are based on the delta method. The definitions of variables are in Appendix A. The sample period spans from 01/01/2014 to 12/31/2021. The number of time-series observations is 96 months. The number of panel observations is 3,789 coin-months. The data sources are coinmarketcap.com and coinmetrics.io.

Horizon	b_r	t_r	b_q	t_q
1	0.16	3.33	-0.19	-2.39
2	0.26	3.30	-0.32	-2.39
3	0.34	3.24	-0.40	-2.36
4	0.38	3.18	-0.46	-2.34
5	0.42	3.11	-0.50	-2.31
6	0.44	3.05	-0.53	-2.28
7	0.45	3.00	-0.54	-2.26
8	0.46	2.95	-0.56	-2.24
∞	0.48	2.82	-0.58	-2.18

Panel B: Panel VAR Results

This table reports the panel VAR estimates and their t-statistics. The standard errors of the t-statistics are based on the delta method. The definitions of variables are in Appendix A. The sample period spans from 01/01/2014 to 12/31/2021. The number of time-series observations is 96 months. The number of panel observations is 3,789 coin-months. The data sources are coinmarketcap.com and coinmetrics.io.

Horizon	b_r	t_r	b_q	t_q
1	0.00	0.28	-0.12	-7.75
2	0.00	0.28	-0.23	-7.74
3	0.00	0.28	-0.32	-7.70
4	0.00	0.28	-0.40	-7.64
5	0.00	0.28	-0.47	-7.57
6	0.00	0.28	-0.52	-7.49
7	0.01	0.28	-0.57	-7.40
8	0.01	0.28	-0.61	-7.31
∞	0.01	0.28	-0.86	-6.12

Table 5: Summary Statistics among Portfolios

Panel A: r_t

This table reports means (Mean), standard deviations (S.D.), minima (Min.), percentiles (P), and maxima (Max.) of r_t among different portfolios. Size1 is the small size portfolio. Size3 is the big size portfolio. Mom1 is the low momentum portfolio. Mom3 is the high momentum portfolio. The definitions of variables are in Appendix A. The sample period spans from 01/01/2014 to 12/31/2021. The number of time-series observations is 416 weeks. The number of panel observations is 16,307 coin-weeks. The data sources are coinmarketcap.com and coinmetrics.io.

Port.	Mean	S.D.	Min.	$P_{25\%}$	Med.	$P_{75\%}$	Max.
VW	0.02	0.11	-0.48	-0.04	0.01	0.07	0.42
Size1	0.05	0.20	-0.46	-0.05	0.02	0.11	1.19
Size3	0.01	0.11	-0.48	-0.04	0.01	0.07	0.40
Mom1	0.00	0.14	-0.51	-0.06	-0.00	0.06	0.77
Mom3	0.03	0.18	-0.89	-0.05	0.02	0.10	0.91

Panel B: q_t

This table reports means (Mean), standard deviations (S.D.), minima (Min.), percentiles (P), and maxima (Max.) of q_t among different portfolios. Size1 is the small size portfolio. Size3 is the big size portfolio. Mom1 is the low momentum portfolio. Mom3 is the high momentum portfolio. The definitions of variables are in Appendix A. The sample period spans from 01/01/2014 to 12/31/2021. The number of time-series observations is 416 weeks. The number of panel observations is 16,307 coin-weeks. The data sources are coinmarketcap.com and coinmetrics.io.

Port.	Mean	S.D.	Min.	$P_{25\%}$	Med.	$P_{75\%}$	Max.
VW	0.01	0.22	-0.67	-0.12	-0.00	0.15	0.82
Size1	0.01	0.87	-4.99	-0.37	-0.01	0.41	4.99
Size3	0.02	0.22	-0.69	-0.12	0.00	0.14	0.90
Mom1	0.00	1.87	-8.00	-0.80	-0.01	0.72	5.60
Mom3	-0.01	2.08	-8.23	-0.61	-0.02	0.66	9.05

Panel C: θ_t

This table reports means (Mean), standard deviations (S.D.), minima (Min.), percentiles (P), and maxima (Max.) of θ_t among different portfolios. Size1 is the small size portfolio. Size3 is the big size portfolio. Mom1 is the low momentum portfolio. Mom3 is the high momentum portfolio. The definitions of variables are in Appendix A. The sample period spans from 01/01/2014 to 12/31/2021. The number of time-series observations is 416 weeks. The number of panel observations is 16,307 coin-weeks. The data sources are coinmarketcap.com and coinmetrics.io.

Port.	Mean	S.D.	Min.	$P_{25\%}$	Med.	$P_{75\%}$	Max.
VW	-1.92	0.40	-2.68	-2.24	-1.92	-1.64	-0.16
Size1	-1.77	1.12	-4.83	-2.56	-1.83	-1.16	1.94
Size3	-1.94	0.40	-2.77	-2.27	-1.94	-1.65	-0.14
Mom1	-1.92	0.94	-5.28	-2.40	-1.92	-1.40	3.36
Mom3	-1.88	0.97	-6.65	-2.31	-1.88	-1.41	2.94

Table 6: VAR Results of Size Portfolios

Panel A: Small

This table reports the time-series VAR estimates and their t-statistics of the small size portfolio. The standard errors of the t-statistics are based on the delta method. The definitions of variables are in Appendix A. The sample period spans from 01/01/2014 to 12/31/2021. The number of time-series observations is 416 weeks. The number of panel observations is 16,307 coin-weeks. The data sources are coinmarketcap.com and coinmetrics.io.

Horizon	b_r	t_r	b_q	t_q
1	0.00	0.55	-0.28	-3.39
2	0.01	0.54	-0.48	-3.35
3	0.01	0.54	-0.62	-3.24
4	0.01	0.54	-0.72	-3.12
5	0.01	0.54	-0.80	-3.00
6	0.02	0.54	-0.85	-2.89
7	0.02	0.54	-0.89	-2.79
8	0.02	0.54	-0.91	-2.71
∞	0.02	0.54	-0.98	-2.41

Panel B: Big

This table reports the time-series VAR estimates and their t-statistics of the big size portfolio. The standard errors of the t-statistics are based on the delta method. The definitions of variables are in Appendix A. The sample period spans from 01/01/2014 to 12/31/2021. The number of time-series observations is 416 weeks. The number of panel observations is 16,307 coin-weeks. The data sources are coinmarketcap.com and coinmetrics.io.

Horizon	b_r	t_r	b_q	t_q
1	0.04	2.74	-0.11	-3.54
2	0.08	2.73	-0.20	-3.54
3	0.11	2.73	-0.28	-3.53
4	0.14	2.72	-0.35	-3.50
5	0.17	2.71	-0.41	-3.48
6	0.19	2.69	-0.46	-3.45
7	0.20	2.68	-0.50	-3.42
8	0.22	2.66	-0.54	-3.38
∞	0.30	2.44	-0.74	-2.95

Table 7: VAR Results of Momentum Portfolios

Panel A: Low

This table reports the time-series VAR estimates and their t-statistics of the low momentum portfolio. The standard errors of the t-statistics are based on the delta method. The definitions of variables are in Appendix A. The sample period spans from 01/01/2014 to 12/31/2021. The number of time-series observations is 416 weeks. The number of panel observations is 16,307 coin-weeks. The data sources are coinmarketcap.com and coinmetrics.io.

Horizon	b_r	t_r	b_q	t_q
1	0.00	0.50	-0.56	-5.56
2	0.01	0.50	-0.82	-5.43
3	0.01	0.50	-0.94	-5.22
4	0.01	0.50	-0.99	-5.05
5	0.01	0.50	-1.01	-4.93
6	0.01	0.50	-1.03	-4.86
7	0.01	0.50	-1.03	-4.82
8	0.01	0.50	-1.03	-4.80
∞	0.01	0.50	-1.04	-4.78

Panel B: High

This table reports the time-series VAR estimates and their t-statistics of the high momentum portfolio. The standard errors of the t-statistics are based on the delta method. The definitions of variables are in Appendix A. The sample period spans from 01/01/2014 to 12/31/2021. The number of time-series observations is 416 weeks. The number of panel observations is 16,307 coin-weeks. The data sources are coinmarketcap.com and coinmetrics.io.

Horizon	b_r	t_r	b_q	t_q
1	-0.01	-0.61	-0.37	-2.15
2	-0.01	-0.61	-0.60	-2.14
3	-0.01	-0.61	-0.76	-2.12
4	-0.01	-0.61	-0.85	-2.10
5	-0.02	-0.61	-0.92	-2.08
6	-0.02	-0.60	-0.96	-2.06
7	-0.02	-0.60	-0.98	-2.04
8	-0.02	-0.60	-1.00	-2.03
∞	-0.02	-0.60	-1.03	-1.99

Figures

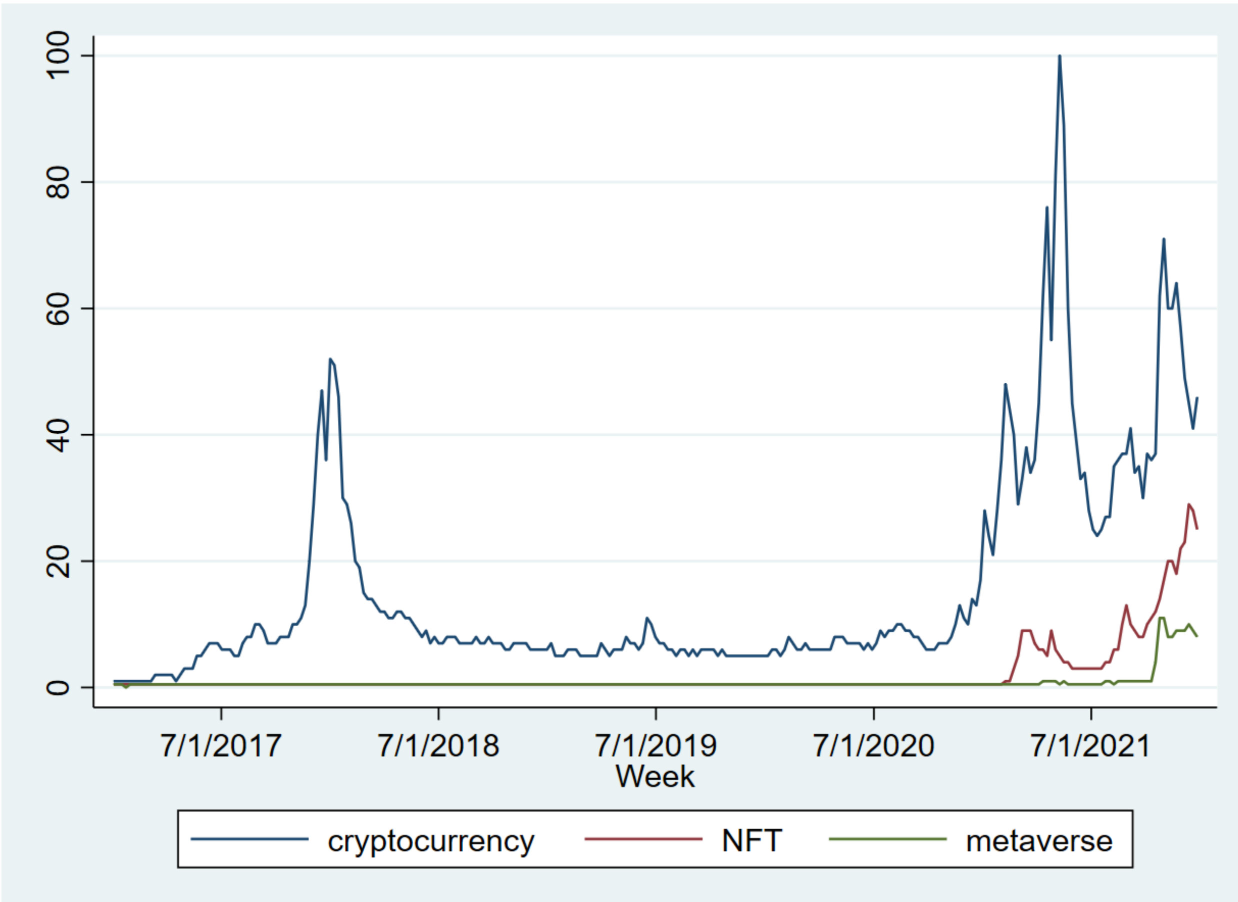

Figure 1: Google Trends of cryptocurrency, NFT, and metaverse
This figure illustrates the weekly time-series of worldwide Google trend indices of “cryptocurrency”, “NFT”, and “metaverse”. The time period spans from 01/01/2017 to 12/31/2021.

Appendix A Definitions of Variables

Variable	Name	Definition	Source
r_t	Return	Log value-weighted return of the market portfolio or return of cryptocurrency	CoinMarketCap
Δq_t	Transaction Growth	Changes in log transactions, defined as the USD value of the sum of native units transferred that interval removing noise and certain artifacts	Coin Metrics
θ_t	Transaction-to-Market Ratio	Log of transactions divided by market values, defined as close prices multiplied by the outstanding number of cryptocurrency	CoinMarketCap, Coin Metrics
$Google_t$	Google Searches	The Google searches of the keyword "blockchain", defined as standardized differences between current week's Google search volumes and the previous four-week moving average of search volumes	Google Trends