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# Economic Evaluation of Cryptocurrency Investment

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## Abstract

This study proposes a method to enhance cryptocurrency portfolios constructed by forecast models. This study forecasts returns on four liquid cryptocurrencies (Bitcoin, Litecoin, Ripple, and Dash) and determines the weights on the cryptocurrencies based upon a dynamic allocation framework. We assess the performances of the portfolios using the performance fee measure. Our results present that the proposed portfolios outperform the benchmark portfolio with the conventional level of the risk aversion parameter. The economic gain for an investor is equivalent to 12% per week. The economic gain is sensitive to a change in the risk aversion parameter, which contrasts with the studies of exchange rates which is due to the high volatility on the cryptocurrencies. Our predictors are related to the price momentum effects and they outperform widely used network factors.

*Keywords:* Cryptocurrency, Bitcoin, Portfolio evaluation, Forecast model, Risk aversion

*JEL codes:* G10, G11, G17

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## 1. Introduction

Cryptocurrencies are regarded as a new asset class and attract significant attention from both investors and regulators. They present low correlations with other asset classes such as stocks, bonds, currencies, and commodities (Baur, Dimpfl, and Kuck, 2018; Kajtazi and Moro, 2019; Klein, Thu, and Walther, 2018; Rognone, Hyde, and Zhang; 2020). Fang, Bouri, Gupta, Roubaud (2019) demonstrate that Bitcoin works as a hedge for multi-asset investors during an increase in economic policy uncertainty. One of the reasons that the cryptocurrency market attracts investors is that its high volatility provides opportunities to create higher returns than those of the traditional assets. For instance, Corbet, Lucey, Urquhart, and Yarovaya (2019) reported that the Bitcoin price increased from \$616 to \$4,800 between October 2016 and October 2017. Biais et al. (2020) propose an equilibrium model that valuation of a cryptocurrency depends upon transactional benefits and large volatility is generated without a change in fundamentals.

In this study, we assess investment strategies for cryptocurrencies in a dynamic allocation context, because the correlation between cryptocurrencies is low and investors receive diversification benefits<sup>3</sup> (Ciaian, Rajcaniova, and Kancs, 2018). Platanakis, Sutcliffe, and Urquhart (2018) show that the equal weight cryptocurrency portfolio

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<sup>3</sup> Diversification benefits including cryptocurrencies are explored by Brière, Oosterlinck, and Szafarz (2015), Dyhrberg (2016) and Guesmi, Saadi, Abid, and Ftiti (2019).

generates a high Sharpe ratio. Platanakis, and Urquhart (2019) consider estimation errors and improve their previous results. We employ a different approach based upon predicting a return on each cryptocurrency and determining the weights on the cryptocurrencies. Adopting forecast models is important for investors since the cryptocurrency markets have not matured yet and markets may not satisfy the informational efficiency (Urquhart, 2016; Nadarajah and Chu, 2017; Tran and Leirvik, 2020). For example, Chu, Zhang, and Chan (2019) find that market efficiency of cryptocurrencies varies over time, which is consistent with the adaptive market hypothesis. Cryptocurrencies have network effects since users receive benefits from participating in a platform that grows the number of users (Cong, Li, and Wang, 2020; Liu and Tsyvinsky, 2020; Sockin and Xiong, 2020). The cryptocurrency markets include bubble periods and are traded by speculators<sup>4</sup> (Cheah and Fry, 2015; Baur, Hong, and Lee, 2018; Corbet, Lucey, and Yarovaya, 2018). Negative bubbles in cryptocurrency markets are also observed in certain periods (Fry and Cheah, 2016). These market features imply that considering past price information is beneficial for investors, as reported by Grosby, Ahmed, and Sapkota (2020), and

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<sup>4</sup> Shen, Urquhart, and Wang (2019) and Philippos, Philippos, Tziogkidis, and Rjiba (2020) find that media attention is a driving force a change in cryptocurrency prices. In contrast, some studies present that macro fundamentals such as money supply are important in the long-run (Kristoufek, 2015; Bouoiyour, Selmi, Tiwari, and Olayeni, 2016; Li and Wang, 2017). Schilling and Uhlig (2019) propose a theoretical model that a monetary policy impacts a cryptocurrency price.

employing forecast models in order to construct a cryptocurrency portfolio enhances the performance of the portfolio. To this end, we use the portfolio construction approach proposed by Della Corte, Sarno, and Tsiakas (2009). This allows us to evaluate whether the forecast models improve the portfolio performance in terms of investor's perspective. Moreover, investors adjust total risk on the portfolios with changing the weights on the cryptocurrencies and the risk-free asset. This is also appealing because the risk on cryptocurrency portfolios is higher than that on traditional assets<sup>5</sup>.

The first contribution of this study is that we evaluate our prediction performance based upon a dynamic allocation framework. Della Corte et al. (2009) highlight that return predictability is not directly associated with an economic gain for investors. They propose a new criterion that is linked to the willingness of investors to pay for switching from a dynamic allocation portfolio based upon the random walk model to one that is based upon forecast models. The effectiveness of the criterion is reported in the stock, bond, and currency markets (Rime, Sarno, and Sojli, 2010; Della Corte, Sarno, and Tsiakas, 2011; Thornton and Valente, 2012; Ahmed, Liu, and Valente, 2016; Opie and Riddiough, 2020).

The second contribution of this study is that we explore a relationship between

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<sup>5</sup> For instance, risks on the cryptocurrencies in our dataset are more than 200% per annum. See Table 1.

the risk aversion parameter and the performance measure. The risk aversion parameter has received attention in the equity market literature and plays an important role to determine an equity risk premium (e.g. Mehra and Prescott, 1985; Benartzi and Thaler 1995; Campbell and Cochrane, 1999). The previous studies which employ the performance measure do not explore the effects of the risk aversion parameter since results are not sensitive to a change in the risk aversion parameter (Della Corte et al., 2009). Cryptocurrencies, however, both risk and return are much larger than those of the other assets (e.g. Baur et al. 2018a). This distinct feature of cryptocurrencies may impact the evaluation framework since less risk averse investors and speculators prefer to invest in cryptocurrencies (Baur et al. 2018b). Zimmerman (2020) highlights that speculators play important roles in cryptocurrency valuation. For this reason, the conventional level of risk aversion may not be reasonable, and hence we consider both the standard risk averse and less risk averse investors.

This paper is related to Platanakis et al. (2018) and Platanakis, and Urquhart (2019), while they do not consider prediction models. Moreover, they do not investigate a relationship between portfolio performances and investor's risk aversion. Focusing upon the investor's risk aversion is an important difference from the studies of Della Corte et al. (2009) and Thornton and Valente (2012), since they examine assets which are less

volatile and speculators are not main players in their markets.

To preview our results, we find that the cryptocurrency portfolios constructed by the forecast models outperform the benchmark portfolio constructed by the historical average return model. More importantly, the economic gain for an investor is large—equivalent to 12% per week. We also note that the investor’s risk aversion plays a key role in determining the economic gain. This is the contrast result reported by the previous literature in the exchange rate context, which is due to the high volatility on the cryptocurrencies.

The remainder of the paper is organized as follows: Section 2 introduces the data set we used and the predictive regression model; Section 3 describes statistical and economic measures in assessing forecast performances; Section 4 reports our main empirical results; Section 5 demonstrates additional tests; and Section 6 presents our concludes.

## **2. Data and Predictive Models**

In this section, we introduce cryptocurrency data used in this study. Then, we describe our predictive model that adopts past price information.

## *2.1 Data*

The data set employed in this study is weekly cryptocurrency market prices against the U.S. dollar, obtained from [coinmarketcap.com](http://www.coinmarketcap.com).<sup>6</sup> We follow Platanakis et al. (2018), and Platanakis and Urquhart (2019) and employ the four most liquid cryptocurrencies: Bitcoin, Litecoin, Ripple and Dash. In addition to these four cryptocurrencies, we use Ethereum for the robustness section.

The literature in the exchange rates often use monthly data, while it does not allow us to obtain a long period of monthly data for cryptocurrencies. Following Platanakis et al. (2018), we focus upon weekly data. We collect every Wednesday prices since the other assets are also traded then, and thus there is no weekend effect (e.g. Keim and Stambaugh, 1984). Our data covers the period from 12<sup>th</sup> July 2015, to 29<sup>th</sup> July 2020, and the total observations are 260 weeks. We calculate a return using the weekly close price. A one-month Treasury bill rate is used as the risk-free rate, which is obtained from the Kenneth French web-site (e.g. Fama and French, 1993).

## *2.2 Predictive models*

We consider a predictability of return on each cryptocurrency in a time series context.

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<sup>6</sup> <http://www.coinmarketcap.com>.



Letting  $r_{t+1}$  denote a cryptocurrency return at time  $t+1$  and  $x_t$  denote a vector of predictors at time  $t$ :

$$r_{t+1} = a + bx_t + u_{t+1} \quad (1)$$

where  $a$  is a constant term,  $b$  is the vector of the estimated parameters and  $u_{t+1}$  is an error term. Following Platanakis et al. (2018), and Platanakis and Urquhart (2019), we employ weekly data sets. Cheah and Fry (2015) and Corbet et al. (2018) find that bubble periods in the cryptocurrency markets, which suggests that price momentum is an important determinant of cryptocurrency prices. Motivated by this finding, we adopt lagged returns as predictors and we employ from one to four-week lagged returns, since a one-week lagged return is not sufficient to capture cryptocurrency price fluctuations (Shen et al., 2019; Grobys et al., 2020)<sup>7</sup>. We also employ network factors which are associated with theoretical models and these are effective at a longer frequency in the robustness section (Liu and Tsyvinsky, 2020)<sup>8</sup>.

### 3. Forecast Evaluation

In this section, we first introduce a statistical evaluation criterion to evaluate each

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<sup>7</sup> We do not employ the Bayesian Information criterion since it supports no lagged return.

<sup>8</sup> Bleher and Dimpfl (2019) report that the google search volume does not predict returns on cryptocurrencies, and therefore we do not focus upon the google search volume.

currency investment forecasting return. Second, we describe the construction of a portfolio based upon the predictive models and determine weights on the cryptocurrencies. Third, we explain our approach about transaction costs. Finally, we illustrate forecast evaluations based upon the portfolios.

### 3.1. *Statistical measure*

This section describes the measures used to evaluate the out-of-sample predictive power for our forecast models. We use the out-of-sample  $R_{os}^2$  and compare the mean squared errors (MSE) of the forecast and those of benchmark models (Campbell and Thompson, 2008; Rapach, Strauss, and Zhou, 2013; Risse, 2019). Let  $\hat{r}_{t+1}$  be the forecast cryptocurrency return based upon the predictive regression model and  $\bar{r}_{t+1}$  the benchmark return. Following Campbell and Thompson (2008), we adopt the historical average of realized returns as the benchmark return. Using  $\hat{r}_{t+1}$  and  $\bar{r}_{t+1}$ , the out-of-sample  $R_{os}^2$  statistic is calculated as follows:

$$R_{os}^2 = \left[ 1 - \frac{\sum_{t=0}^{T-1} (r_{t+1} - \hat{r}_{t+1})^2}{\sum_{t=0}^{T-1} (r_{t+1} - \bar{r}_{t+1})^2} \right] \quad (2)$$

where  $r_{t+1}$  is the realized return. When  $R_{os}^2 > 0$ , the forecast return  $\hat{r}_{t+1}$  outperforms the historical average forecast return in terms of MSE. We conduct a statistical test based upon the adjusted mean squared prediction error statistic (*MSPE-adjusted*) proposed by

Clark and West (2007). This test statistic extends the Diebold and Mariano (1995), and West (1996) statistic given its nonstandard distribution when comparing forecasts from nested models. Following Rapach, Strauss, and Zhou (2010), a  $p$ -value for a one-sided (upper-tail) test is adopted. Our predictive regression models are nested models when we use the historical average as the benchmark.

### 3.2. Asset allocation framework

We consider that an investor adopts a dynamic allocation strategy in order to maximize the conditional expected return subjected to target conditional volatility (Della Corte et al., 2009, 2011; Rime et al., 2010; Thornton and Valente, 2012; Ahmed et al., 2016). We consider the following two steps. First, each cryptocurrency one-week-ahead return forecast is generated by the forecast models described in the previous section. Second, the optimal weights on the cryptocurrencies are determined on the mean-variance efficient frontier.

Let  $r_{t+1}$  be the  $K \times 1$  vector of cryptocurrency returns at time  $t + 1$ ,  $\mu_{t+1|t} = E_t[r_{t+1}]$  the conditional expectation of  $r_{t+1}$  and  $\Sigma_{t+1|t} = E_t \left[ (r_{t+1} - \mu_{t+1|t})(r_{t+1} - \mu_{t+1|t})' \right]$  the conditional variance-covariance matrix of  $r_{t+1}$ . An investor determines the weights on the cryptocurrency portfolios  $w_t$  at each time based upon the

following optimization problem:

$$\begin{aligned} \max_{w_t} \{ & (\mu_{p,t+1|t} = w_t' \mu_{t+1|t} + (1 - w_t' \iota) r_{f,t}) \} & (3) \\ \text{s. t.} \quad & (\sigma_p^*)^2 = w_t' \Sigma_{t+1|t} w_t \end{aligned}$$

where  $\mu_{p,t+1|t}$  is the conditional expectation on the portfolio return vector constructed by the risky cryptocurrency currency portfolio and the risk-free asset  $r_{f,t}$ ,  $\iota$  is a  $K \times 1$  vector of one, and  $\sigma_p^*$  is the target conditional volatility on the portfolio returns. The

optimal weights are obtained as the solution to Equation (3) and written as:

$$w_t = \frac{\sigma_p^*}{\sqrt{C_t}} \Sigma_{t+1|t}^{-1} (\mu_{t+1|t} - \iota r_{f,t}) \quad (4)$$

where  $C_t = (\mu_{t+1|t} - \iota r_{f,t})' \Sigma_{t+1|t}^{-1} (\mu_{t+1|t} - \iota r_{f,t})$ . Following Ahmed et al. (2016), we impose a restriction for the optimal weights to avoid extreme values as:  $-\iota \leq w_t \leq 2 \iota$ .

The gross return of an investor's optimal portfolio is calculated as follows:

$$R_{p,t+1} = 1 + r_{p,t+1} = 1 + (1 - w_t' \iota) r_{f,t} + w_t' r_t \quad (5)$$

where  $1 - w_t' \iota$  is the weight of the risk-free asset. After obtaining the portfolio return

$R_{p,t+1}$ , we assess performances of the predictive models.

### 3.3 Transaction costs

Our asset allocation framework needs to change weights on cryptocurrencies every week.

We consider transaction costs when we change the weights, and we follow Lintilhac and

Tourin (2017) and Platanakis et al. (2018) and calculate transaction costs. A transaction cost for cryptocurrency  $j$  is calculated as the proportionate cost  $pc_j$  multiplied by the change in the weight between  $t$  and  $t-1$ . Then we aggregate all transaction costs and obtain the total transaction cost  $TC_t$  for the portfolio at time  $t$  as:

$$TC_t = \sum_{j=1}^N pc_j (|w_{j,t} - w_{j,t-1}|) \quad (6)$$

where  $N$  is the total number of cryptocurrencies.

### 3.4. Performance measures

We employ two measures to evaluate portfolio performances. The first performance measure is the Sharpe ratio, which is widely used in the literature (e.g. Campbell and Thompson, 2008; Barroso and Santa-Clara, 2015). The Sharpe ratio is interpreted as a risk-adjusted return measure and defined as:

$$\frac{\overline{r_p - r_f}}{\sigma_p} \quad (7)$$

where  $\overline{r_p - r_f}$  is the realized average excess return and  $\sigma_p$  is standard deviation of the excess return.

The second measure is the performance fee measure which is based upon mean-variance analysis and used in the exchange rate and bond market studies (Della Corte et al., 2009, 2011; Rime et al., 2010; Thornton and Valente, 2012; Opie and Riddiough, 2020). The average realized utility  $\bar{U}_{MV}(\cdot)$  for an investor with investor's relative risk

aversion (RRA)  $\gamma$  is constructed by a mean-variance utility function<sup>9</sup> (Ahmed et al., 2016):

$$\bar{U}_{MV}(\cdot) = \bar{R}_P - \frac{\gamma}{2T} \sum_{t=0}^{T-1} (R_{p,t+1} - \bar{R}_P)^2 \quad (8)$$

where  $R_{p,t+1}$  is the gross return on the investor's portfolio and  $\bar{R}_P = \frac{1}{T} \sum_{t=0}^{T-1} R_{p,t+1}$ . We consider weekly expenses as the maximum performance fee that an investor is willing to pay to switch from the alternative portfolio to a benchmark portfolio (e.g. Fleming, Kirby, and Ostdiek, 2001). The performance fee  $\Phi$  is obtained as the difference between the average utility from the gross portfolio return constructed by a predictive model,  $R_{p,t+1}^*$  and that from gross benchmark portfolio return,  $R_{p,t+1}^{BM}$ :

$$\Phi = \bar{U}_{MV}(R_{p,t+1}^*) - \bar{U}_{MV}(R_{p,t+1}^{BM}). \quad (9)$$

Note that  $\Phi \leq 0$  means that the model has no predictive power.

#### 4. Empirical results

This section shows our data and empirical results. First, we present summary statistics for our cryptocurrency data. Second, we report out-of-sample return forecasts based upon the statistical measure. Third, we present out-of-sample portfolio return forecasts based upon

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<sup>9</sup> We do not assume a quadratic utility used by Della Corte et al (2009) and Thornton and Valente (2012), since numerical procedures are often not converged.

the performance measures. Fourth, we explore an impact on a short selling constraint. Finally, we demonstrate a relationship between the risk aversion parameter and the performance fee measure.

#### *4.1. Data and summary statistics*

We begin with summary statistics of cryptocurrency returns. Table 1 presents that Ethereum has the highest weekly mean return, 2.15%, and that Litecoin has the lowest weekly mean return, 1.01% in our sample period. Bitcoin has the lowest standard deviation, 10.70% (204% per annum), while this value is much higher than that of the other assets such as stock and currencies. For comparison, the annualized standard deviation on the U.S stock market return is approximately 14% (e.g. Klein et al., 2018). The annualized Sharpe ratio ranges from 0.45 to 0.97, which is higher than that of the U.S. stock market.<sup>10</sup> Correlations across cryptocurrencies are moderate and hence it is worthwhile to consider a combined portfolio.<sup>11</sup>

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<sup>10</sup> The annualized Sharpe ratio of the U.S. stock market is approximately 0.4 (e.g. Barroso and Santa-Clara, 2015).

<sup>11</sup> We show the correlation result in Table A1.

#### 4.2. Results of statistical measures

We move on to the out-of-sample performances of our predictive models. Following Platanakis et al. (2018), and Platanakis and Urquhart (2019), we use 26-, 52- and 110-week rolling window schemes. Platanakis et al. (2018) employ expanding window schemes, but we instead employ rolling window schemes. This is because our evaluation approach needs to reflect a change in market states. Furthermore, Grobys et al. (2020) report that the effectiveness of moving average technical indicators.

Table 2 displays the results for the out-of-sample  $R_{os}^2$  statistic (Campbell and Thompson, 2008). We notice that the 26-week rolling window predictive model improves the forecast accuracy for all five cryptocurrencies and that these results are statistically significant at the 1% level according to the *MSPE-adjusted* statistics (Rapach et al., 2010). This suggests that the lagged return information contains future return information and is consistent with the finding of Grobys et al. (2020). Interestingly, when we extend the rolling window size, the predictive power decreases. Only the predictive models for Bitcoin and Dash are statistically significant using 110-week rolling windows. This implies that the market states of the cryptocurrencies vary over time (Chu, et al., 2019), and hence it is important to update information. Our result is also associated with the finding of Griffin and Shams (2020) who address that a few large investors inflate a



Bitcoin price when it goes down to a certain level.

In summary, our predictive models with 26- and 52-week rolling window schemes outperform the benchmark models.

#### 4.3. Results of economic measures

Given our promising statistical measure results, we turn to the portfolio evaluations for the out-of-sample forecast models. We focus upon one-week-ahead forecasts. Each cryptocurrency return is predicted by the forecast model in Equation (1), and the portfolio is optimized based upon Equation (3). The optimized portfolio is dynamically rebalanced at a weekly frequency. We use 26-, 52- and 110-week rolling window schemes. When we solve the optimization problem in Equation (3), we need to assume the target volatility  $\sigma_p^*$  and the investor's relative risk aversion (RRA)  $\gamma$ . We set  $\sigma_p^*$  to 8, 10 and 12% per annum<sup>12</sup> and  $\gamma$  to 2 as in Della Corte et al. (2009).<sup>13</sup> The historical average of realized returns is employed as the benchmark (e.g. Campbell and Thompson, 2008).

Table 3 reports annualized returns, standard deviation, Sharpe ratio (SR), and

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<sup>12</sup> These values are divided by square root of 52 and we obtain weekly values.

<sup>13</sup> Grandelman and Hernandez-Murillo (2015) report that the risk aversion parameter is around one.

weekly performance fees for the combined cryptocurrency portfolios. Panel A in Table 3 displays the empirical results when the target volatility  $\sigma_P^*$  is 8%. We focus upon the predictive model with a 26-week rolling window estimation and SR is 0.96, which is much higher than that of the benchmark. The difference of SR is statistically significant at the 10% level. The performance fee measure  $\Phi$  is 11.8% per week and this value is larger than that of the exchange rate context (Della Corte et al., 2009). SR for the predictive model decreases as the window size is extended. This suggests that reflecting recent information is substantial in forecasting the cryptocurrency returns. Clearly, predictive models with a 110-week rolling window have weaker predictive power, which is consistent with our finding in Table 2. Panels B and C in Table 3 indicate the results from changing the target volatility, and we observe the same pattern in Panel A.

#### *4.4. Results of economic measures with short constraint*

Having found significant results for our 26-week predictive model, we explore an impact on the short selling constraint (Platanakis et al., 2018; Platanakis and Urquhart, 2019). They may affect the portfolio returns due to high volatility on cryptocurrencies. We repeat the same exercise but adopt the following new restriction:  $0 \leq w_t \leq 2 \iota$ , which means that an investor does not construct short selling positions.

Table 4 presents the impact on the short selling constraint and we see that the SR for the 26-week predictive model is still higher than that for the benchmark in rows (1), (4), and (7), while the performance fee is no longer positive. This is because the SR of the benchmark model increases with the short constraint. Moreover, the performance fee measure depends upon the investor's utility in Equation (8) and hence the risk aversion parameter plays an important role.

#### *4.5. Change in risk aversion*

Given the importance of short positions in the cryptocurrency markets, we investigate whether the risk aversion parameter  $\gamma$  affects our results. High volatility in the cryptocurrencies means that the second term of the right-hand side in Equation (8) has a dominant impact, which implies that our result may have been sensitive to a change in the risk aversion parameter. Figure 1 depicts the result of the performance fee measure as changing the risk aversion parameter from 0.1 to 5. The left panel in Figure 1 illustrates the results for the 26-week rolling window model without the short constraint. We see that the performance fee measure keeps a positive value over the risk aversion parameter interval.

We move on to the result for the 26-week rolling window model with the short

constraint. The right panel in Figure 1 illustrates that the performance fee measure becomes negative as  $\gamma$  reaches around 1.5. This decay speed is faster than the result reported by the exchange rates as in Della Corte et al. (2009), since volatility on the cryptocurrency portfolio is much larger than that on a currency portfolio. The risk aversion parameter assumption is substantial whether cryptocurrency investors obtain an economic gain. Moreover, when the investor's risk aversion is small, adopting predictive models is a reasonable decision for investors. This reflects the fact that cryptocurrencies are speculative assets and that investor's risk aversion is very low or investors are more risk lovers (Cheah and Fry, 2015; Baur et al., 2018b; Corbet et al. 2018). We do not present results for the 52- and 110-week models since they do not outperform the benchmark model, as reported by Tables 3 and 4.

Overall, the change in the risk aversion parameter affects the results. We find that obtaining a positive economic gain depends upon the degree of the risk aversion if investors are not allowed to hold the short selling positions.

## **5. Robustness**

Having found the effectiveness of using predictive models for cryptocurrency investors, we investigate the robustness of our findings. More specifically, we conduct: (i) change

in proportionate cost; (ii) inclusion of Ethereum in our portfolio; (iii) change in the risk aversion parameter for the Ethereum portfolios; (iv) adopting network factors; and (v) using the elastic-net approach.

### *5.1. Change in the proportionate cost*

In this subsection, we investigate an impact on transaction costs in this subsection. We used 50 basis points for all cryptocurrency proportionate costs in the previous section (Lintilhac and Tourin, 2017; Platanakis et al., 2018). Transaction costs depend upon market states and it may have a large impact on returns (e.g. Burnside et al. 2007). Figure 2 depicts the change in weights on cryptocurrencies when we employ the 26-week predictive model. The weights on the four cryptocurrencies vary over time, and therefore the transaction costs are related to the results. We repeat the same exercise using 25 and 100 basis point proportionate costs.

Table 5 presents whether a change in the proportionate cost impacts our empirical results, and we only report the results using the predictive models to save space. Panel A in Table 5 displays that SR increases by about 0.3 with the 25 basis point proportionate cost and decreases by about 0.6 with the 100 basis point proportionate cost. The performance fee decreases monotonically with the proportionate cost when we focus

upon the 26 week rolling results.

Overall, the change in the proportionate cost is related to SR while the impact on the performance fee measure is marginal, which is associated with both the predictive and the benchmark models.

### *5.2. Including Ethereum*

We employed the most liquid four cryptocurrencies in Section 4, which is consistent with Platanakis et al. (2018) and Platanakis and Urquhart (2019). Dash, however, is a relatively smaller market capitalization compared with the other three cryptocurrencies. We replace Dash with Ethereum, which is the second largest market capitalization,<sup>14</sup> and repeat the same exercise.

Table 6 presents that SRs for both 26- and 52-week regression models are slightly smaller than those of Table 3. The performance fee measure result depends upon the target volatility level when we focus upon the 26- week rolling window model. The 52-week model generates the positive performance fee measures since the SR for the benchmark model is negative.

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<sup>14</sup> This value is based upon the market capitalization of August 25, 2020 and obtained by crypto.com.

Next, we also consider an impact on the short selling constraint and, interestingly, SRs for both the predictive and benchmark models are improved, as reported in Table 7. In particular, the benchmark model provides better results than those of Table 6, which causes the declines in the performance fee measures.

In summary, the predictive portfolios generate high SRs compared with the benchmark portfolios, while the results for the performance fee are mixed.

### *5.3. Change in risk aversion for Ethereum portfolios*

Having found the importance of volatility term for the performance fee measure in the previous section, we explore whether a change in the risk aversion parameter also plays an important role for the portfolio that including Ethereum.<sup>15</sup>

Figure 3 illustrates the relationships between the risk aversion and the performance fee. We note that an investor does not obtain an economic gain if the risk aversion parameter is above 2 with the 26-week predictive model. Turning to the 52-week predictive model, the decay of performance fee measure is slower than that of the 26-week model, while the performance fee becomes negative with an increase in the risk aversion parameter. This supports our previous finding that cryptocurrencies are

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<sup>15</sup> Impacts on the transaction costs are explored in the online Appendix.

speculative assets and hence are preferable for less risk averse investors (e.g. Baur et al., 2018b).

#### 5.4. *Network factors*

Valuations of cryptocurrency depend upon transaction demands since users conduct peer-to-peer transactions on a decentralized digital platform (e.g. Cong et al., 2020; Sockin and Xiong, 2020). Cryptocurrencies have strong network effects and Liu and Tsyvinsky (2020) propose the following network factors: the number of active address (*address*), those of transaction count (*transaction*), those of payment count (*volume*), and a principal component of these factors (*PC*).<sup>16</sup> These data are obtained from Blockchain.com.<sup>17</sup>

We also consider these factors in our out-of-sample prediction context and calculate out-of-sample  $R_{OS}^2$  statistics. Table 8 presents that all four factors outperform the benchmark and most results are statistically significant based upon *MSPE-adjusted p-values*. The impacts, however, are moderate in compared with those of Table 2 which use lagged return information.

#### 5.5. *Elastic-net approach*

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<sup>16</sup> We exclude the number of wallet uses since weekly data is not available. We replace the number of payment count with trading volumes for data availability.

<sup>17</sup> <https://www.blockchain.com/charts#currency>



This section considers to combine cryptocurrency price and network factor information. To this end, we employ the elastic-net approach proposed by Zou and Hastie (2005). The elastic-net is a variable selection method and overcomes the drawback of Lasso (Tibshirani, 1996) that selects a single variable from a group of correlated variables. It has been widely used in the asset return and macroeconomic indicator predictions (e.g. Rapach et al., 2013; Li, Tsiakas, and Wang, 2015). Estimators using the elastic-net are obtained by the following system:

$$\begin{aligned} \arg \min b &= \frac{1}{2} \sum_{t=1}^T \left( r_{t+1} - a - \sum_{j=1}^k b_j x_{j,t} \right)^2 \\ \text{s.t. } &\sum_{j=1}^k |b_j| < \lambda_1 \text{ and } \sum_{j=1}^k b_j^2 < \lambda_2 \end{aligned} \quad (10)$$

where  $k$  is the number of predictors,  $\lambda_1$  and  $\lambda_2$  are the tuning parameters. When  $\lambda_1 = \infty$ , Equation (10) reduces to the ridge regression and when  $\lambda_2 = \infty$ , Equation (10) does to the Lasso. We follow Li and Chen (2014) and decide the turning parameters using cross validation for each window throughout the out-of-sample period. Table A3 shows the out-of-sample  $R_{os}^2$  statistic results and we observe that the combination between legged returns and network factors does not lead to prediction accuracy. We conclude that the lagged returns are strong predictors for cryptocurrency returns at weekly frequencies.

## 6. Conclusion

This study evaluates predictability for cryptocurrency returns using the dynamic allocation approach proposed by Della Corte et al. (2009). Cryptocurrency markets are expanding rapidly and many investors are attracted due to the high risk and return profile. The cryptocurrency markets have not yet matured and some studies report that information efficiency is not satisfied (Urquhart, 2016; Tran and Leirvik, 2020). There is no fundamental value for cryptocurrencies and many investors are speculators, causing bubble periods (Cheah and Fry, 2015; Baur et al., 2018b). These features of the cryptocurrency markets imply that investors may obtain profits using past price information (Grosby et al. 2020). Moreover, a cryptocurrency return is not strongly correlated to the returns of other cryptocurrencies (Klein et al. 2018), and hence adopting the portfolio approach provides diversification benefits with investors.

We find the following results. First, the forecast model for each cryptocurrency outperforms the historical average benchmark model in the out of sample context. Second, our cryptocurrency portfolios constructed by the forecast models generate a higher SR than that of the benchmark and the difference between SRs is statistically significant. Third, an investor obtains an economic gain around 12% per week when he or she switches from the benchmark portfolio to the predictive model portfolio. Fourth, a change

in the investor's risk aversion impacts the economic gain. In particular, the result is sensitive to the change in the investor's risk aversion with the short selling constraint. This contrast result to the exchange rate literature reflects high volatility on the cryptocurrencies.

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Table 1 Summary statistics of cryptocurrency returns

	Mean	Std Dev	Skewness	Kurtosis	Max	Min	SR
Bitcoin	1.44	10.70	-0.23	5.34	36.83	-41.23	0.95
Litecoin	1.01	16.07	2.18	15.24	110.37	-36.38	0.44
Ripple	1.31	19.86	2.55	14.32	125.81	-47.15	0.47
Dash	1.27	16.38	1.62	9.25	91.61	-37.98	0.55
Ethereum	2.15	17.50	1.05	6.40	80.45	-52.88	0.88

Notes: This table reports mean, standard deviations, skewness, kurtosis, maximum, minimum, and the annualized Sharpe ratio of cryptocurrency returns. A one-month Treasury bill rate is used as the risk-free rate in order to calculate the Sharpe ratio. We employ weekly returns and the sample period covers from 12<sup>th</sup> July, 2015 to 29<sup>th</sup> July, 2020.

Table 2 Out-of-sample forecasting  $R_{os}^2$  results

	Bitcoin		Litecoin		Ripple		Dash		Ethereum	
(1) 26 weeks	21.26	***	12.82	***	41.30	***	20.06	***	22.02	***
(2) 52 weeks	10.38	***	7.75	**	21.76	**	11.04	**	12.38	***
(3) 110 weeks	1.30	**	0.68		2.04		3.62	**	-0.10	

Notes: This table displays statistical measures of the out-of-sample forecast of predictive models in Equation (1). We conduct the one-week-ahead return forecasts of cryptocurrencies using rolling regressions. Predictors are from one to four-week lagged returns and the window sizes are 26, 52 and 110 weeks. The Campbell and Thompson (2008) out-of-sample  $R_{os}^2$  statistic is reported, and the  $p$ -value based upon the Clark and West (2007) *MSPE-adjusted* statistic is employed: the statistic corresponds to a one-side test of the null hypothesis that the competing model has equal MSPE relative to the historical average benchmark forecasting model against the alternative hypothesis that the competing forecasting model has a lower MSPE than the historical average benchmark forecasting model. \*, \*\*, and \*\*\* indicate significance at the 10%, 5% and 1% levels, respectively.

Table 3 Out-of-sample portfolio return predictability

	Benchmark			Predictive			
	Mean	St.Dev	SR	Mean	St.Dev	SR	$\Phi$
Panel A: $\sigma_p=8$							
(1) 26 weeks	-0.22	7.99	-0.03	7.76	8.08	0.96 *	11.80
(2) 52 weeks	2.77	8.20	0.34	2.15	8.19	0.26	-0.61
(3) 110 weeks	-2.60	8.04	-0.32	-6.01	7.69	-0.78	-119.02
Panel B: $\sigma_p=10$							
(4) 26 weeks	0.04	9.98	0.00	10.02	10.11	0.99 *	13.68
(5) 52 weeks	3.82	10.24	0.37	3.04	10.23	0.30	-0.58
(6) 110 weeks	-2.81	10.05	-0.28	-7.07	9.60	-0.74	-183.57
Panel C: $\sigma_p=12$							
(7) 26 weeks	0.31	11.97	0.03	12.28	12.13	1.01 *	15.14
(8) 52 weeks	4.87	12.29	0.40	3.93	12.27	0.32	-0.47
(9) 110 weeks	-3.02	12.06	-0.25	-8.14	11.52	-0.71	-262.12

Notes: This table presents the out-of-sample economic value of the predictive models for cryptocurrency portfolio returns, including the historical average benchmark model. We conduct the one-week-ahead return forecasts of cryptocurrencies using rolling regressions. The window sizes are 26, 52 and 110 weeks. We employ four cryptocurrencies: Bitcoin, Litecoin, Ripple and Dash. Mean is the annualized returns and St.Dev is the annualized standard deviation on the portfolio. SR indicates the annualized Sharpe ratio (SR) and the SR difference between the benchmark and the predictive models are tested by the method of Ledoit and Wolf (2008). The weekly performance fee measure ( $\Phi$ ) for the predictive model against the benchmark model is calculated by Equation (9). We set the portfolio target volatility ( $\sigma_p^*$ ) to 8%, 10% and 12%, respectively. The relative risk aversion parameter  $\gamma$  is 2 (Della Corte et al., 2009). \*, \*\*, and \*\*\* indicate significance at the 10%, 5% and 1% levels, respectively.

Table 4 Out-of-sample portfolio return predictability with the short constraint

	Benchmark			Predictive			
	Mean	St.Dev	SR	Mean	St.Dev	SR	$\Phi$
Panel A: $\sigma_p=8$							
(1) 26 weeks	1.52	5.69	0.27	5.96	6.17	0.97 *	-2.44
(2) 52 weeks	3.25	6.20	0.52	3.01	6.18	0.49	0.20
(3) 110 weeks	-1.31	6.50	-0.20	-3.67	5.61	-0.66	-64.73
Panel B: $\sigma_p=10$							
(4) 26 weeks	2.22	7.11	0.31	7.77	7.71	1.01 *	-6.46
(5) 52 weeks	4.41	7.74	0.57	4.11	7.72	0.53	0.46
(6) 110 weeks	-1.20	8.13	-0.15	-4.15	7.01	-0.59	-99.36
Panel C: $\sigma_p=12$							
(7) 26 weeks	2.92	8.53	0.34	9.58	9.25	1.04 *	-11.84
(8) 52 weeks	5.58	9.29	0.60	5.22	9.26	0.56	0.79
(9) 110 weeks	-1.09	9.75	-0.11	-4.64	8.41	-0.55	-141.43

Notes: This table presents the out-of-sample economic value of the predictive models for cryptocurrency portfolio returns, including the historical average benchmark model. Portfolios are constructed without short positions. We conduct the one-week-ahead return forecasts of cryptocurrencies using rolling regressions. The window sizes are 26, 52 and 110 weeks. We employ four cryptocurrencies: Bitcoin, Litecoin, Ripple and Dash. Mean is the annualized returns and St.Dev is the annualized standard deviation on the portfolio. SR indicates the annualized Sharpe ratio (SR) and the SR difference between the benchmark and the predictive models are tested by the method of Ledoit and Wolf (2008). The weekly performance fee measure ( $\Phi$ ) for the predictive model against the benchmark model is calculated by Equation (9). We set the portfolio target volatility ( $\sigma_p^*$ ) to 8%, 10% and 12%, respectively. The relative risk aversion parameter  $\gamma$  is 2 (Della Corte et al., 2009). \*, \*\*, and \*\*\* indicate significance at the 10%, 5% and 1% levels, respectively.

Table 5 Impacts on transaction costs

Panel A: without short constraint												
	TC=25				TC=50				TC=100			
Panel A: $\sigma_p=8$	Mean	St.Dev	SR	$\Phi$	Mean	St.Dev	SR	$\Phi$	Mean	St.Dev	SR	$\Phi$
(1) 26 weeks	10.30	8.06	1.28	12.00	7.76	8.08	0.96	11.80	2.66	8.16	0.33	11.68
(2) 52 weeks	4.48	8.19	0.55	0.19	2.15	8.19	0.26	-0.61	-2.52	8.19	-0.31	-2.10
Panel B: $\sigma_p=10$												
(3) 26 weeks	13.20	10.07	1.31	13.91	10.02	10.11	0.99	13.68	3.64	10.21	0.36	13.66
(4) 52 weeks	5.96	10.24	0.58	0.51	3.04	10.23	0.30	-0.58	-2.80	10.23	-0.27	-2.61
Panel C: $\sigma_p=12$												
(5) 26 weeks	16.10	12.09	1.33	15.39	12.28	12.13	1.01	15.14	4.63	12.25	0.38	15.27
(6) 52 weeks	7.44	12.28	0.61	0.94	3.93	12.27	0.32	-0.47	-3.08	12.28	-0.25	-3.11
Panel B: with short constraint												
	TC=25				TC=50				TC=100			
Panel A: $\sigma_p=8$	Mean	St.Dev	SR	$\Phi$	Mean	St.Dev	SR	$\Phi$	Mean	St.Dev	SR	$\Phi$
(7) 26 weeks	7.39	6.17	1.20	-2.21	5.96	6.17	0.97	-2.44	3.11	6.18	0.50	-2.74
(8) 52 weeks	4.12	6.18	0.67	0.83	3.01	6.18	0.49	0.20	0.78	6.17	0.13	-0.93
Panel B: $\sigma_p=10$												
(9) 26 weeks	9.56	7.71	1.24	-6.29	7.77	7.71	1.01	-6.46	4.20	7.72	0.54	-6.67
(10) 52 weeks	5.51	7.73	0.71	1.38	4.11	7.72	0.53	0.46	1.33	7.71	0.17	-1.20
Panel C: $\sigma_p=12$												
(11) 26 weeks	11.73	9.25	1.27	-11.73	9.58	9.25	1.04	-11.84	5.30	9.26	0.57	-11.90
(12) 52 weeks	6.89	9.27	0.74	2.08	5.22	9.26	0.56	0.79	1.88	9.25	0.20	-1.48

Notes: This table presents the out-of-sample economic value of the predictive models for cryptocurrency portfolio returns. We set the proportionate cost to 25, 50 and 100 basis points in order to calculate the transaction costs (TC). TC=50 is employed in Tables 3 and 4. Panel A presents the results without the short constraint and Panel B does the results with the short constraint. The window sizes are 26 and 52 weeks. We employ four cryptocurrencies: Bitcoin, Litecoin, Ripple and Dash. Mean is the annualized returns and St.Dev is the annualized standard deviation on the portfolio. SR indicates the annualized Sharpe ratio (SR) and the SR difference between the benchmark and the predictive models are tested by the method of Ledoit and Wolf (2008). The weekly performance fee measure ( $\Phi$ ) for the predictive model against the benchmark model is calculated by Equation (9). We set the portfolio target volatility ( $\sigma_p^*$ ) to 8%, 10% and 12%, respectively. The relative risk aversion parameter  $\gamma$  is 2 (Della Corte et al., 2009).

Table 6 Out-of-sample portfolio return predictability: Ethereum

	Benchmark			Predictive			
	Mean	St.Dev	SR	Mean	St.Dev	SR	$\Phi$
Panel A: $\sigma_p=8$							
(1) 26 weeks	-0.31	7.92	-0.04	6.50	8.28	0.79	1.59
(2) 52 weeks	-2.48	8.02	-0.31	-0.32	8.09	-0.04	0.75
Panel B: $\sigma_p=10$							
(3) 26 weeks	-0.07	9.90	-0.01	8.45	10.35	0.82	-1.57
(4) 52 weeks	-2.75	10.02	-0.27	-0.04	10.11	0.00	1.66
Panel C: $\sigma_p=12$							
(5) 26 weeks	0.17	11.87	0.01	10.40	12.42	0.84	-6.16
(6) 52 weeks	-3.01	12.02	-0.25	0.23	12.13	0.02	1.16

Notes: This table presents the out-of-sample economic value of the predictive models for cryptocurrency portfolio returns, including the historical average benchmark model. We conduct the one-week-ahead return forecasts of cryptocurrencies using rolling regressions. The window sizes are 26 and 52 weeks. We employ four cryptocurrencies: Bitcoin, Litecoin, Ripple and Ethereum. Mean is the annualized returns and St.Dev is the annualized standard deviation on the portfolio. SR indicates the annualized Sharpe ratio (SR) and the SR difference between the benchmark and the predictive models are tested by the method of Ledoit and Wolf (2008). The weekly performance fee measure ( $\Phi$ ) for the predictive model against the benchmark model is calculated by Equation (9). We set the portfolio target volatility ( $\sigma_p^*$ ) to 8%, 10% and 12%, respectively. The relative risk aversion parameter  $\gamma$  is 2 (Della Corte et al., 2009). \*, \*\*, and \*\*\* indicate significance at the 10%, 5% and 1% levels, respectively.

Table 7 Out-of-sample portfolio return predictability:  
Ethereum and the short constraint

	Benchmark			Predictive			
	Mean	St.Dev	SR	Mean	St.Dev	SR	$\Phi$
Panel A: $\sigma_p=8$							
(1) 26 weeks	2.17	6.00	0.36	5.99	6.39	0.94	-2.17
(2) 52 weeks	1.03	6.12	0.17	2.53	6.21	0.41	0.92
Panel B: $\sigma_p=10$							
(3) 26 weeks	3.04	7.50	0.41	7.80	7.99	0.98	-5.66
(4) 52 weeks	1.65	7.65	0.22	3.51	7.76	0.45	0.55
Panel C: $\sigma_p=12$							
(5) 26 weeks	3.91	8.99	0.43	9.62	9.58	1.00	-10.33
(6) 52 weeks	2.26	9.18	0.25	4.50	9.31	0.48	-0.06

Notes: This table presents the out-of-sample economic value of the predictive models for cryptocurrency portfolio returns, including the historical average benchmark model. Portfolios are constructed without short positions. We conduct the one-week-ahead return forecasts of cryptocurrencies using rolling regressions. The window sizes are 26 and 52 weeks. We employ four cryptocurrencies: Bitcoin, Litecoin, Ripple and Ethereum. Mean is the annualized returns and St.Dev is the annualized standard deviation on the portfolio. SR indicates the annualized Sharpe ratio (SR) and the SR difference between the benchmark and the predictive models are tested by the method of Ledoit and Wolf (2008). The weekly performance fee measure ( $\Phi$ ) for the predictive model against the benchmark model is calculated by Equation (9). We set the portfolio target volatility ( $\sigma_p^*$ ) to 8%, 10% and 12%, respectively. The relative risk aversion parameter  $\gamma$  is 2 (Della Corte et al., 2009).

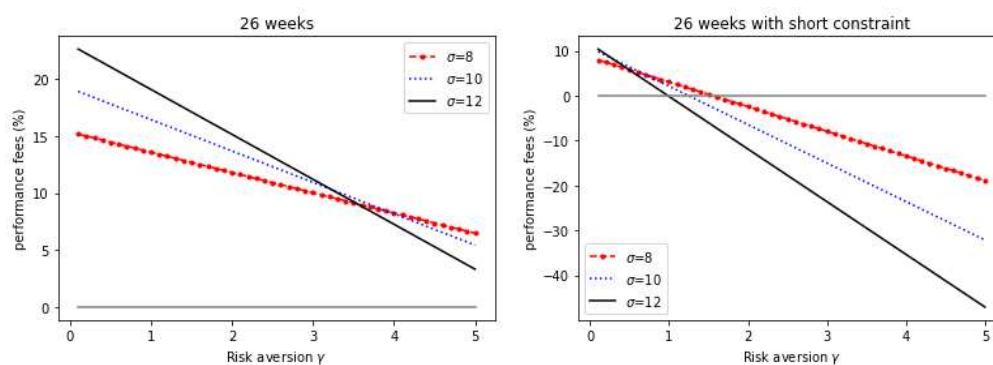
Table 8 Out-of-sample forecasting  $R_{os}^2$  results: network factors

	Bitcoin		Litecoin		Ripple		Dash		Ethereum	
Panel A: address										
(1) 26 weeks	6.88	***	3.48	***	3.78	***	5.42	**	6.15	**
(2) 52 weeks	2.03	*	1.41	*	1.56	*	1.46		1.56	*
Panel B: transaction										
(3) 26 weeks	5.03	**	7.44	***	5.46	**	5.30	***	5.07	***
(4) 52 weeks	1.82	**	2.34	*	3.46		1.82	**	2.78	**
Panel C: volume										
(5) 26 weeks	4.05	***	5.96	***	6.45	***	4.70	***	5.68	***
(6) 52 weeks	3.35	***	4.59	***	4.04	***	2.12	***	3.32	***
Panel D: PC										
(7) 26 weeks	5.83	***	2.67	*	6.87	***	5.48	***	5.84	***
(8) 52 weeks	2.89	**	5.48	*	4.27	**	6.10	***	5.01	***

Notes: This table displays statistical measures of the out-of-sample forecast of predictive models in Equation (1). We consider the following four network factors as predictors (Liu and Tsyvinsky, 2020): the number of active address (*address*), those of transaction count (*transaction*), trading volumes (*volume*), and a principal component of these factors (*PC*). We conduct the one-week-ahead return forecasts of cryptocurrencies using rolling regressions. The window sizes are 26 and 52 weeks. The Campbell and Thompson (2008) out-of-sample  $R_{os}^2$  statistic is reported, and the  $p$ -value based upon the Clark and West (2007) *MSPE-adjusted* statistic is employed: the statistic corresponds to a one-side test of the null hypothesis that the competing model has equal MSPE relative to the historical average benchmark forecasting model against the alternative hypothesis that the competing forecasting model has a lower MSPE than the historical average benchmark forecasting model. \*, \*\*, and \*\*\* indicate significance at the 10%, 5% and 1% levels, respectively.

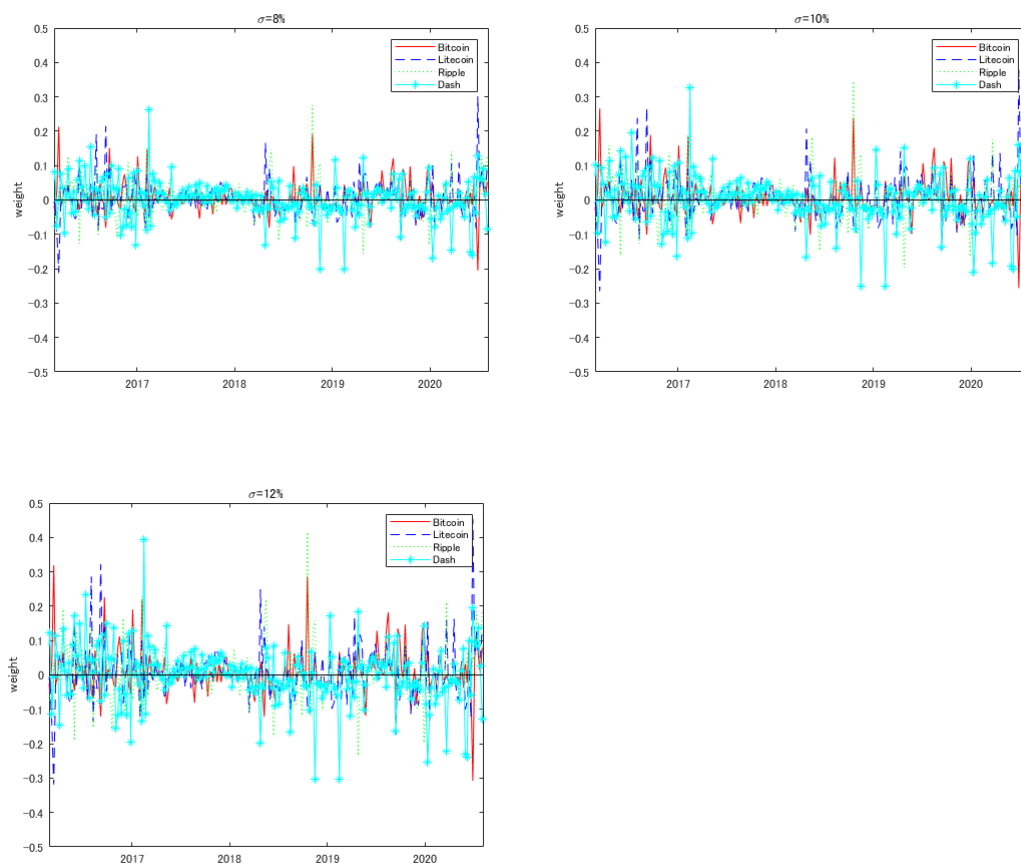


Figure 1. Risk aversion and performance fee measure



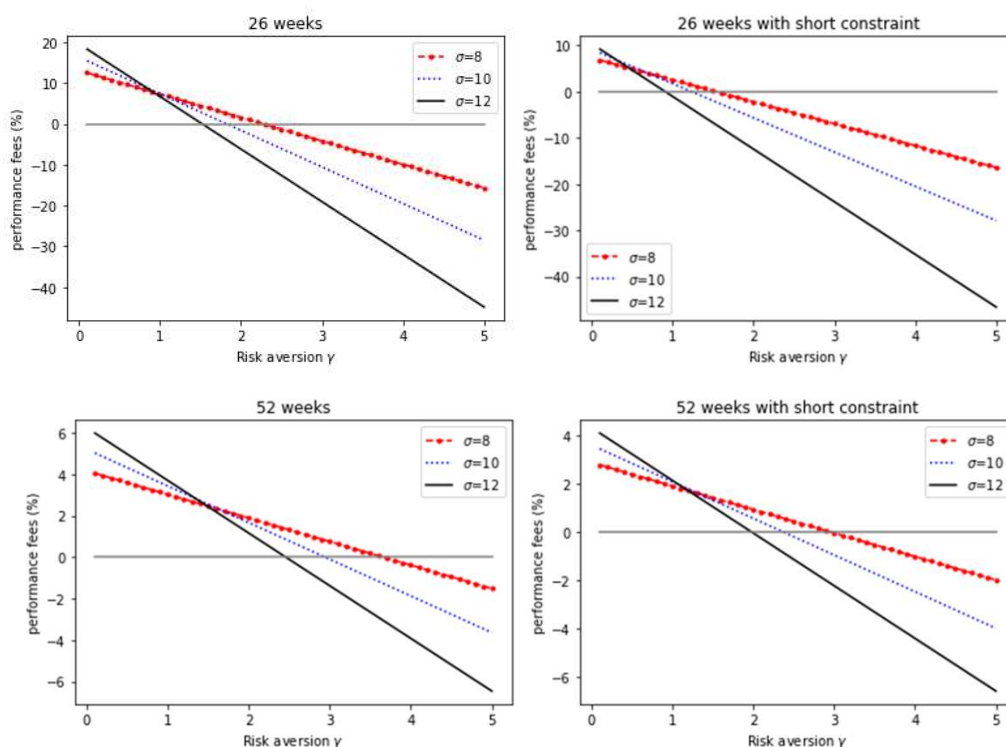
Notes: This figure provides the relationships between the risk aversion parameter ( $\gamma$ ) and the performance fee measure ( $\Phi$ ). The left figure presents the 26-week rolling regression, the right figure does the 26-week rolling regression with the short constraint. We employ four cryptocurrencies: Bitcoin, Litecoin, Ripple and Dash. We set the portfolio target volatility ( $\sigma_p^*$ ) to 8%, 10% and 12%, respectively.

Figure 2. Weights on cryptocurrencies



Notes: This figure provides weights on cryptocurrencies based upon the predictive models. We employ the 26-week rolling regressions and the weights are determined by Equation (4). We use four cryptocurrencies: Bitcoin, Litecoin, Ripple and Dash. The upper left panel sets the target volatility to 8%, the upper right panel does that to 10% and the lower panel does that to 12%. We do not impose the short constraint.

Figure 3. Risk aversion and performance fee measure: Ethereum



Notes: This figure provides the relationships between the risk aversion parameter ( $\gamma$ ) and the performance fee measure ( $\Phi$ ). The upper left figure presents the 26-week rolling regression, the upper right figure does the 26-week rolling regression with the short constraint, the lower left figure does the 52-week rolling regression and the lower right figure does the 52-week rolling regression with the short. We employ four cryptocurrencies: Bitcoin, Litecoin, Ripple and Ethereum. We set the portfolio target volatility ( $\sigma_p^*$ ) to 8%, 10% and 12%, respectively.

## Economic Evaluation of Cryptocurrency Investment

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This material provides additional results which are not reported in the main text. These include Table A1 Correlation matrix of cryptocurrency returns, Table A2 Impacts on transaction costs: Ethereum, Table A3 Out-of-sample forecasting  $R_{OS}^2$  results: elastic-net, Figure A1 Weekly cryptocurrency returns, Figure A2 Cumulative returns on cryptocurrencies, Figure A3 Cumulative returns on combined portfolios, Figure A4 Cumulative returns on combined portfolios: Ethereum, Figure A5 Weights on cryptocurrencies: Ethereum.

Table A1 Correlation matrix cryptocurrency returns

	Bitcoin	Litecoin	Ripple	Dash	Ethereum
Bitcoin	1.00				
Litecoin	0.63	1.00			
Ripple	0.38	0.57	1.00		
Dash	0.55	0.48	0.25	1.00	
Ethereum	0.52	0.44	0.33	0.58	1.00

Notes: This table presents the Pearson correlation matrix between weekly cryptocurrency returns. The sample period covers from 12<sup>th</sup> July, 2015 to 29<sup>th</sup> July, 2020.

Table A2 Impacts on transaction costs: Ethereum

Panel A: without short constraint													
	TC=25				TC=50				TC=100				
Panel A: $\sigma_p=8$	Mean	St.Dev	SR	$\Phi$	Mean	St.Dev	SR	$\Phi$	Mean	St.Dev	SR	$\Phi$	
(1) 26 weeks	9.05	8.26	1.10	1.25	6.50	8.28	0.79	1.59	1.41	8.35	0.17	2.67	
(2) 52 weeks	2.22	8.10	0.27	0.89	-0.32	8.09	-0.04	0.75	-5.39	8.11	-0.67	3.92	
Panel B: $\sigma_p=10$													
(3) 26 weeks	11.63	10.32	1.13	-2.16	8.45	10.35	0.82	-1.57	2.08	10.44	0.20	0.21	
(4) 52 weeks	3.13	10.12	0.31	-0.01	-0.04	10.11	0.00	1.66	-6.38	10.13	-0.63	0.05	
Panel C: $\sigma_p=12$													
(5) 26 weeks	14.22	12.38	1.15	-7.06	10.40	12.42	0.84	-6.16	2.75	12.53	0.22	-3.49	
(6) 52 weeks	4.04	12.14	0.33	-1.34	0.23	12.13	0.02	1.16	-7.38	12.16	-0.61	6.22	
Panel B: with short constraint													
	TC=25				TC=50				TC=100				
Panel A: $\sigma_p=8$	Mean	St.Dev	SR	$\Phi$	Mean	St.Dev	SR	$\Phi$	Mean	St.Dev	SR	$\Phi$	
(7) 26 weeks	7.38	6.38	1.16	-1.62	5.99	6.39	0.94	-2.17	3.20	6.44	0.50	-3.24	
(8) 52 weeks	3.72	6.23	0.60	0.41	2.53	6.21	0.41	0.92	0.15	6.19	0.02	1.91	
Panel B: $\sigma_p=10$													
(9) 26 weeks	4.32	8.05	0.54	-4.86	7.80	7.99	0.98	-5.66	4.32	8.05	0.54	-7.20	
(10) 52 weeks	5.00	7.78	0.64	-0.26	3.51	7.76	0.45	0.55	0.54	7.73	0.07	2.13	
Panel C: $\sigma_p=12$													
(11) 26 weeks	11.71	9.56	1.23	-9.24	9.62	9.58	1.00	-10.33	5.44	9.66	0.56	-12.42	
(12) 52 weeks	6.29	9.33	0.67	-1.25	4.50	9.31	0.48	-0.06	0.93	9.28	0.10	2.25	

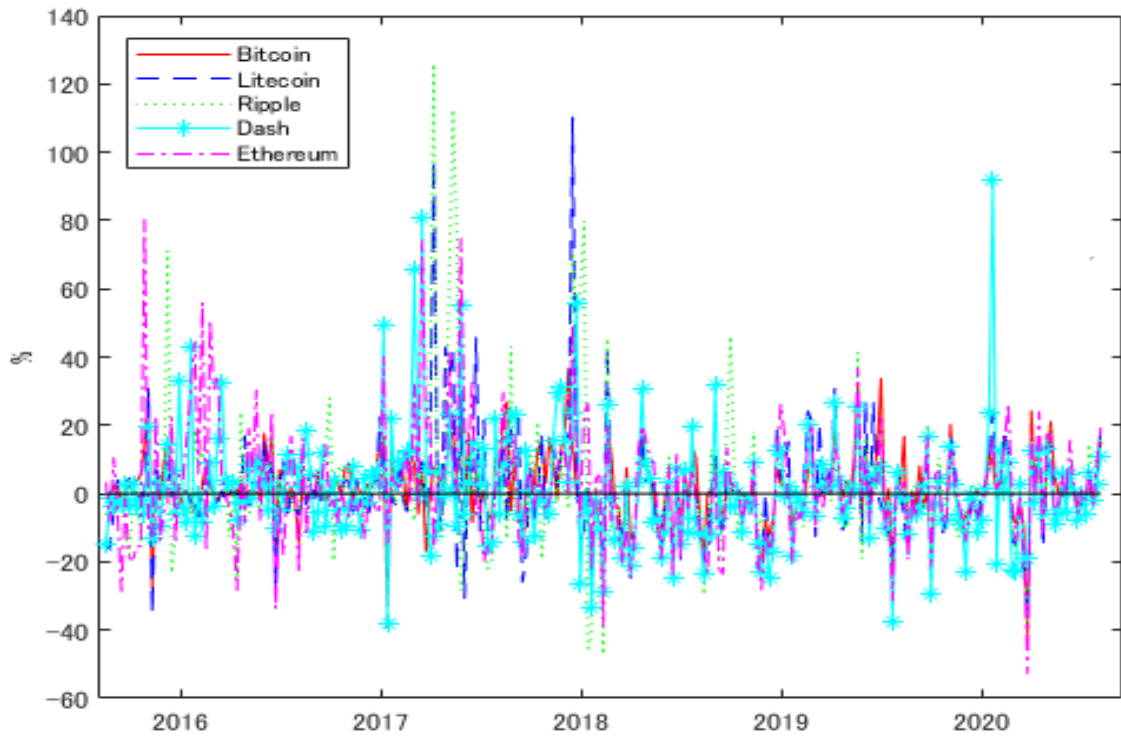
Notes: This table presents the out-of-sample economic value of the predictive models for cryptocurrency portfolio returns. We set the proportionate cost to 25, 50 and 100 basis points in order to calculate the transaction costs (TC). We employ four cryptocurrencies: Bitcoin, Litecoin, Ripple and Ethereum. TC=50 is employed in Tables 6 and 7. Panel A presents the results without the short constraint and Panel B does the results with the short constraint. We conduct the one-week-ahead return forecasts of cryptocurrencies using rolling regressions. The window sizes are 26 and 52 weeks. Mean is the annualized returns and St.Dev is the annualized standard deviation on the portfolio. SR indicates the annualized Sharpe ratio (SR) and the SR difference between the benchmark and the predictive models are tested by the method of Ledoit and Wolf (2008). The weekly performance fee measure ( $\Phi$ ) for the predictive model against the benchmark model is calculated by Equation (9). We set the portfolio target volatility ( $\sigma_p^*$ ) to 8%, 10% and 12%, respectively. The relative risk aversion parameter  $\gamma$  is 2 (Della Corte et al., 2009).

Table A3 Out-of-sample forecasting  $R_{OS}^2$  results: elastic-net

	Bitcoin	Litecoin	Ripple	Dash	Ethereum
(1) 26 weeks	-38.16	-45.35	-101.64	-50.20	-37.68
(2) 52 weeks	-19.35	-16.08	-23.10	-19.85	-9.27

Notes: This table displays statistical measures of the out-of-sample forecast of predictive models in Equation (1). We consider one to four-week lagged returns and the four network factors as predictors. They are selected by the elastic-net approach (Zou and Hastie, 2005). Turning parameters are determined by cross validation for each window throughout the out-of-sample period. We conduct the one-week-ahead return forecasts of cryptocurrencies using rolling regressions. The window sizes are 26 and 52 weeks. The Campbell and Thompson (2008) out-of-sample  $R_{OS}^2$  statistic is reported, and the  $p$ -value based upon the Clark and West (2007) *MSPE-adjusted* statistic is employed: the statistic corresponds to a one-side test of the null hypothesis that the competing model has equal MSPE relative to the historical average benchmark forecasting model against the alternative hypothesis that the competing forecasting model has a lower MSPE than the historical average benchmark forecasting model.

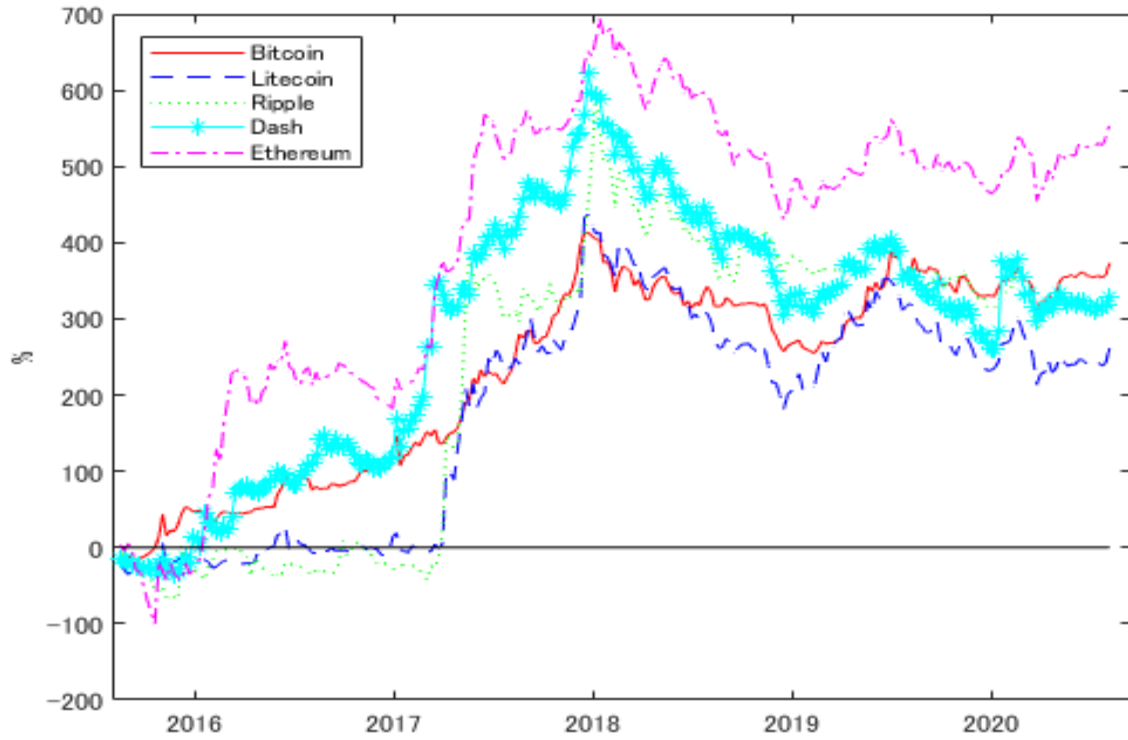
Figure A1. Weekly cryptocurrency returns



Notes: This figure illustrates weekly cryptocurrency returns. We employ five cryptocurrencies: Bitcoin, Litecoin, Ripple, Dash and Ethereum. The sample period covers from 12<sup>th</sup> July, 2015 to 29<sup>th</sup> July, 2020.

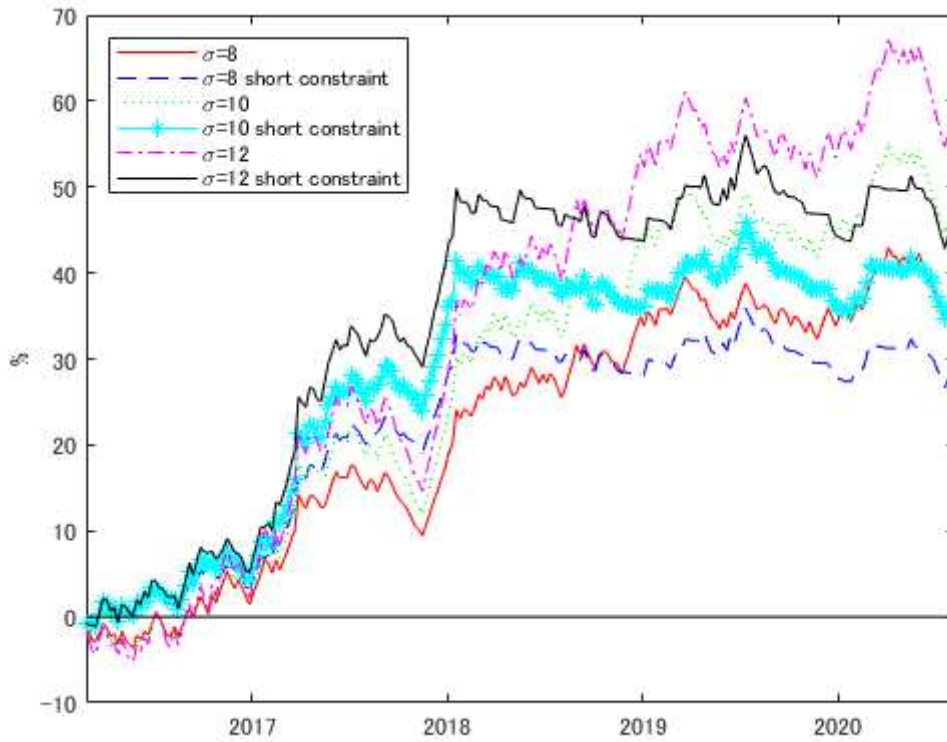


Figure A2. Cumulative returns on cryptocurrencies



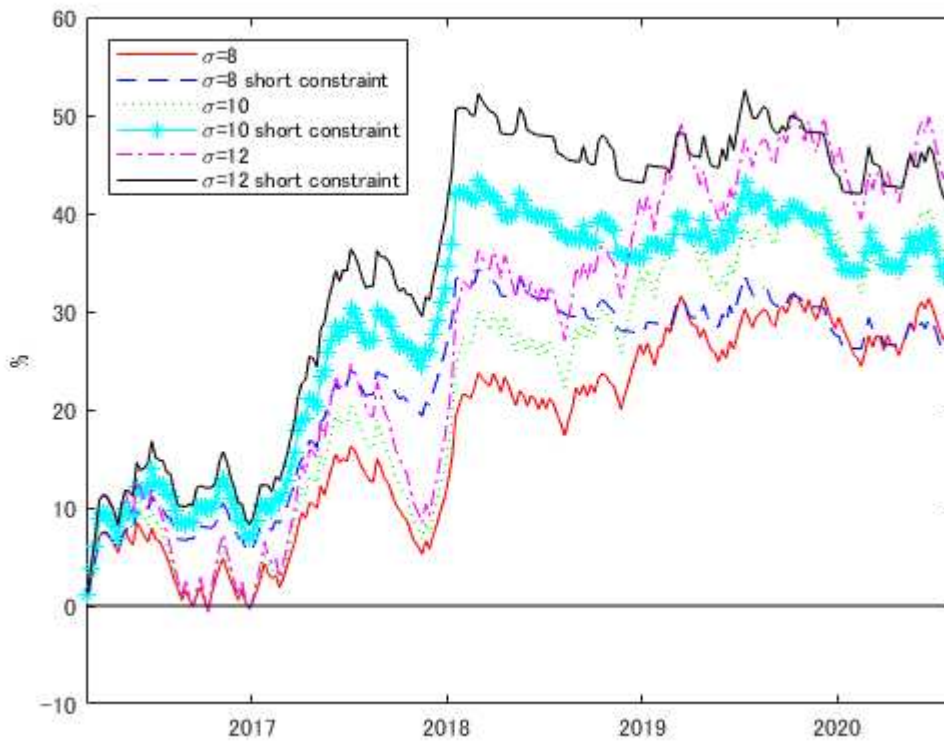
Notes: This figure illustrates cumulative returns on cryptocurrencies. We employ five cryptocurrencies: Bitcoin, Litecoin, Ripple, Dash and Ethereum. The sample period covers from 12<sup>th</sup> July, 2015 to 29<sup>th</sup> July, 2020.

Figure A3. Cumulative returns on combined portfolios



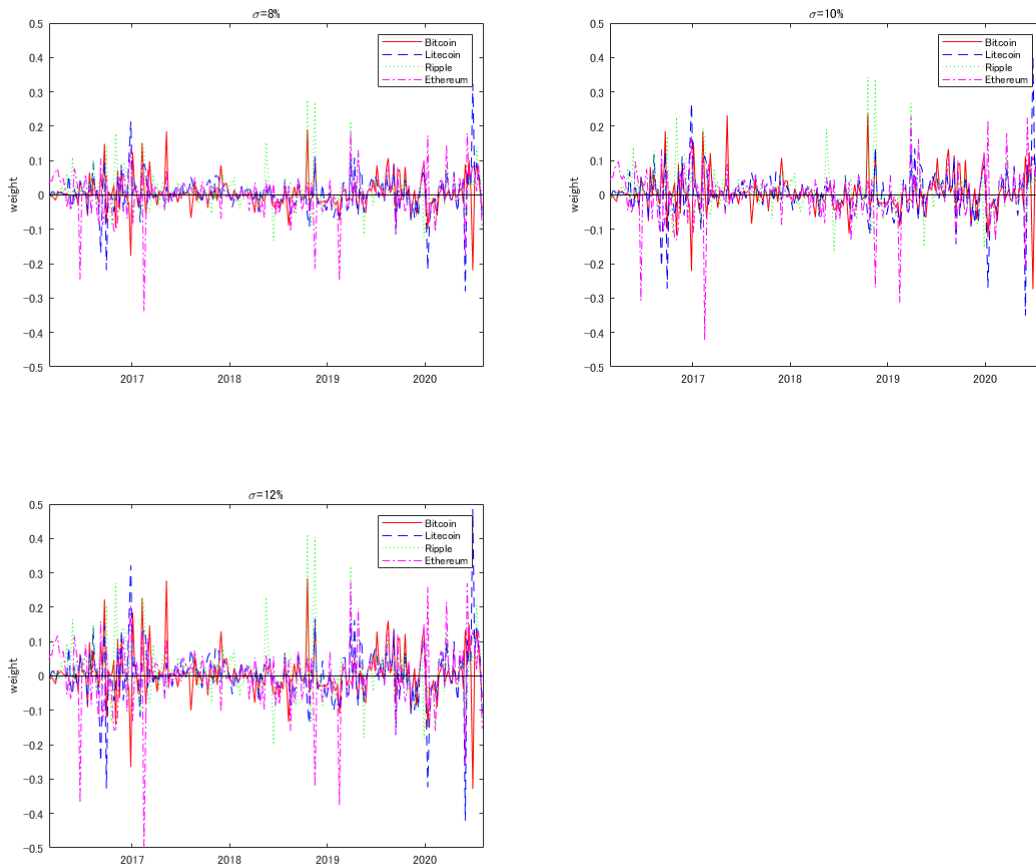
Notes: This figure illustrates cumulative returns on combined cryptocurrency portfolios. We employ four cryptocurrencies: Bitcoin, Litecoin, Ripple and Dash. Portfolio returns are calculated by Equation (5). We use the 26-week rolling regressions and three target volatilities: 8%, 10% and 12%, respectively. We consider both with and without the short constraint.

Figure A4. Cumulative returns on combined portfolios: Ethereum



Notes: This figure illustrates cumulative returns on combined cryptocurrency portfolios. We employ four cryptocurrencies: Bitcoin, Litecoin, Ripple and Ethereum. Portfolio returns are calculated by Equation (5). We use the 26-week rolling regressions and three target volatilities: 8%, 10% and 12%, respectively. We consider both with and without the short constraint.

Figure A5. Weights on cryptocurrencies: Ethereum



Notes: This figure provides weights on cryptocurrencies based upon the predictive models. We employ the 26-week rolling regressions and the weights are determined by Equation (4). We use four cryptocurrencies: Bitcoin, Litecoin, Ripple and Ethereum. The upper left panel sets the target volatility to 8%, the upper right panel does that to 10% and the lower panel does that to 12%. We do not impose the short constraint.