Macro factors in the returns on cryptocurrencies

Kei Nakagawa

Nomura Asset Management Co, ltd.

Ryuta Sakemoto

Okayama University

Abstract

This study investigates the relationship between expected returns on cryptocurrencies and macroeconomic fundamentals. Investors employ a lot of macroeconomic indicators for their investment decision, and hence adopting a few macroeconomic indicators is not sufficient in capturing a change in economic states. Moreover, due to aggregation, macroeconomic indicators are not measured precisely. To overcome these problems, we employ a dynamic factor model and extract common factors from a large number of macroeconomic indicators. We find that the common factors are strongly linked to the cryptocurrency expected returns at a quarterly frequency, while we do not observe this relationship using individual macroeconomic indicators such as inflation and money supply. We uncover that the output common factor negatively affects the expected return on BTC. This impact is the opposite direction predicted by the theoretical model in Schilling and Uhlig (2019). Our common factor approach contains rich information, and therefore our empirical results may capture a channel that is not considered by the theoretical model.

Keywords: Cryptocurrencies, Macroeconomic Factor, Factor Model

*Corresponding author
Email address: kei.nak.0315@gmail.com (Kei Nakagawa)

Preprint submitted to Elsevier *April 22, 2022*

1. Introduction

Cryptocurrencies have received attention from both academic researchers and investors as a new asset class due to their low correlations with other assets (e.g., Bouri et al. (2017); Baur et al. (2018); Klein et al. (2018)). A price on Bitcoin presents higher volatility than prices on other assets, and many cryptocurrency studies seek a driving force for price fluctuations.[1] For instance, Shen et al. (2019) and Philippas et al. (2020) focus on media attention, Bleher & Dimpfl (2019) employ Google search volumes, Kraaijeveld & De Smedt (2020) and Naeem et al. (2021) use the sentiment index, and Grobys et al. (2020) explores whether past prices contain information for the prediction.

In a recent important study, Schilling & Uhlig (2019) proposed a theoretical model for determining cryptocurrency prices. They introduce an endowment economy with two competing currencies namely, Dollar and Bitcoin. The central bank adjusts the supply of Dollar, but it does not affect that of Bitcoin. Consequently, the price of Bitcoin is related to macroeconomic conditions and the monetary policy implemented by the central bank. Motivated by the theoretical model, we investigate whether macroeconomic fundamentals are linked to cryptocurrency returns. In previous studies, the empirical results for the relationships are mixed (Li & Wang (2017) and Liu & Tsyvinski (2020)). One of the reasons for these weak results is that we do not have the best macroeconomic indicators to capture economic states.[2] Investors extract signals from many macroeconomic indicators and make their investment decisions in the financial market; hence, using a few indicators is not sufficient in explaining future asset returns. Moreover, due to aggregation, they are not measured precisely.

To overcome this problem, we adopt a large number of macroeconomic indicators and construct a dynamic factor model to explain the expected returns on

[1] Corbet et al. (2019) survey studies in this research area

[2] Another reason is that the Bitcoin market is not efficient (Urquhart (2016); Nadarajah & Chu (2017);Tran & Leirvik (2020); Shrestha (2021)), and therefore it includes bubble periods (Cheah & Fry (2015) and Fry & Cheah (2016)).

cryptocurrencies. Common factors across indicators provide useful information for economic states (Stock & Watson (2002)). This approach has been successful in the stock, bond, and currency markets (Ludvigson & Ng (2007); Ludvigson & Ng (2009); Filippou & Taylor (2017)). An important difference between this study and those of Li & Wang (2017) and Liu & Tsyvinski (2020) is that we summarize common information of wider macroeconomic indicators and focus on a long- term relationship. Changes in macroeconomic variables are slower than those in financial variables, and hence such fundamentals matter in the long-term context (e.g., Bansal & Yaron (2004); Ortu et al. (2013)).[3]

The remainder of this paper is organized as follows: Section 2 introduces the dataset and describes our econometric method. Section 3 presents our empirical results and concluding remarks are provided in Section 4.

2. Dataset and Methodology

2.1. Dataset

We employ four cryptocurrency prices and a large number of macroeconomic indicators. We focus on the four most liquid cryptocurrencies: BitCoin (BTC), LiteCoin (LTC), Ripple (XRP), and Ethereum (ETH).[4] We obtain the end of month prices for the cryptocurrencies and calculate monthly returns. The price data are obtained from CoinMarketCap (`https://coinmarketcap.com/coins/`).

Moreover, we use macroeconomic indicators to construct a dynamic factor model. Following Ludvigson & Ng (2009), these indicators cover the following eight categories: (1) output, (2) labor market, (3) housing sector, (4) orders and inventories, (5) money and credit, (6) bond and foreign exchange, (7) prices, and (8) stock market. We transform these indicators into stationary series. All datasets and transformations are listed in Appendix A. The data sources are

[3] Liu et al. (2020) and Shen et al. (2020) proposed Fama & French (1993) type factor models that are not linked to macroeconomic fundamentals.

[4] See Grobys et al. (2020) and Tran & Leirvik (2020).

Table 1: Summary statistics of cryptocurrencies and macroeconomic indicators.

Statistic	N	Mean	St. Dev.	Min	Max	ADF	p value
BTC	106	0.054	0.272	-0.453	1.711	-6.669	0.000
LTC	87	0.03	0.382	-0.707	1.705	-5.395	0.000
XRP	101	0.042	0.501	-1.106	2.216	-6.830	0.000
ETH	76	0.106	0.369	-0.769	1.152	-5.060	0.000
Money Supply	106	0.007	0.033	-0.062	0.221	-7.088	0.000
Interest Rate	106	-0.005	0.296	-3.000	1.000	-7.747	0.000
Inflation Rate	106	0.002	0.003	-0.008	0.009	-5.864	0.000

Notes: We employ monthly and quarterly data for four cryptocurrencies: Bitcoin (BTC), Litecoin (LTC), Ripple (XRP), and Ethereum (ETH), and three macroeconomic indicators: money supply, interest rate, and inflation rate. These indicators were transformed based on Table A1 in Appendix A. The full sample is from July 2013 to August 2020 (86 months).

economic data travel from St. Louis Fed's Economic Research Division and Bloomberg terminal. The full sample is from April 2013 to January 2022 (106 months).

2.2. Methodology

This section outlines our estimation methodology. First, we construct a dynamic factor model to explain the expected returns on cryptocurrencies. Following Stock & Watson (2002) and Ludvigson & Ng (2007), common factors are estimated from a large panel of macroeconomic indicators using principal components analysis (PCA). Each variable $X_{i,t}$ can be decomposed into a common factor F_t and an idiosyncratic component $e_{X_{i,t}}$ using PCA:

$$X_{i,t} = \Gamma_i F_t + e_{X_{i,t}} \tag{1}$$

where Γ_i is the factor loading. A factor model allows us to summarize information as a small number of estimated factors. Note that all variables should be stationary and we provide our transformation within Appendix A. In this study, we employ 10 factors that explain approximately 80% of the total variance of all indicators.

Then we consider the following regression model:

$$r_{t+1} = a + b^{\top} Z_t + e_{t+1} \tag{2}$$

where r_{t+1} is the cryptocurrency return at month $t+1$, and Z_t is a set of predictors at month t.

We consider a longer relationship between macroeconomic variables and cryptocurrency returns. To deal with this problem, we follow Maio & Santa-Clara (2012) and Fernandez-Perez et al. (2017) and consider the following long-horizon predictive regressions:

$$r_{t+1:t+3} = a + b^{\top} Z_t + e_{t+1:t+3} \tag{3}$$

where $r_{t+1:t+3}$ is the cryptocurrency return from $t+1$ to $t+3$. We do not employ quarterly data because collecting sufficient observations is difficult due to a short price history of cryptocurrencies. We also construct a regression model without factors as the benchmark model. Following Li & Wang (2017), we select the following three macroeconomic indicators for the benchmark model: money supply (monetary base), interest rate (Federal Fund rate), and inflation rate (consumer price index for all urban consumers: CPI-U All) for Z_t. We follow Ludvigson & Ng (2009) and transform these variables to obtain stationary variables. We employ a log first difference of the Federal Fund rate and log second differences of the money supply and the inflation rate.

3. Empirical Results

3.1. Summary statistics

First, we introduce Table 1, the summary statistics of cryptocurrency returns and macroeconomic indicators. We note that ETH has the highest return, whereas XRP is the most volatile cryptocurrency in our sample.

3.2. Interpretation of factors

Next, we investigate information about the factors. Following Ludvigson & Ng (2009), we regress each data indicator onto the estimated factors and

Table 2: Mean of marginal R^2s.

	Output	Labor	Housing	Money	Bond	Price	Stock
F1	0.611	0.601	0.241	0.380	0.078	0.321	0.217
F2	0.035	0.049	0.218	0.019	0.039	0.205	0.047
F3	0.009	0.038	0.081	0.006	0.139	0.022	0.203
F4	0.021	0.044	0.054	0.214	0.065	0.039	0.103
F5	0.006	0.008	0.040	0.031	0.126	0.030	0.044
F6	0.008	0.019	0.009	0.082	0.065	0.047	0.091
F7	0.011	0.024	0.020	0.015	0.060	0.019	0.010
F8	0.039	0.013	0.030	0.029	0.026	0.021	0.051
F9	0.030	0.011	0.026	0.007	0.051	0.018	0.016
F10	0.027	0.016	0.010	0.008	0.043	0.017	0.016

Notes: This table shows marginal R^2. We regress each data indicator onto the estimated factors and obtain a marginal R^2, then we calculate the mean of marginal R2s for each data category.

obtain marginal R^2. Table 2 shows the mean of marginal R^2s for each data category. We observe that F1 relates to the output and labor market variables and F2 contains information about the housing and price variables. Moreover, we consider F3 as the stock market factor, F4 as the money supply factor, and F5 as the interest rate factor. The other factors are more difficult for interpretation because marginal R2s are not so different across the data categories.

3.3. Regression results: BTC

We move onto the regression results in this section. Table 3 reports the result of regression analysis for BTC. For the monthly model in column (1), the coefficients of F1 and F8 are statistically significant at the 5% level. Factor loadings for the output variables are negative and this indicates that a decline in the output leads to an increase in the BTC return[5]. One standard deviation

[5] The unreported results of factor loadings are available upon requests.

of change in F1 leads to a 13.1% decline in the BTC return[6]. We find that the link between individual macroeconomic indicators and BTC is not observed in column (2). Both results in columns (1) and (2) show low adjusted R^2s, which weakly supports the effectiveness of our factor model.

Having found a weak relationship between macroeconomic fundamentals and the expected return on BTC, we consider the quarterly model in equation (2). The relationship between risk and expected returns depends upon return intervals, and it is stronger at a longer frequency (e.g., Handa et al. (1993)). Moreover, macroeconomic fundamentals change gradually, and the quarterly model may therefore capture a clearer macroeconomic impact on the BTC return.

The result in column (3) of Table 3 indicates that the coefficients of F1, F3, and F7 are statistically significant at the 5% level. Column (3) shows that the coefficient of F1 is positive, which indicates that negative output shocks raise the BTC price at longer time horizons since the factor loadings of F1 for the output variables are negative. The impact of the output factor has the opposite direction predicted by Schilling & Uhlig (2019) model. They predict that a decline in the money supply leads to an increase in the BTC price because the money supply and the BTC price are determined by the output in the model. Our common factors contain rich information, and therefore our empirical results may capture a channel that is not considered by the theoretical model.

We also find that the factor loadings of F3 for the stock price variables are negative in column (3) in Table 3[7]. The result of F3 demonstrates that a decline in the stock prices causes an increase in the BTC return. Bouri et al. (2017) do not find a strong contemporaneous relationship between BTC and stock prices. Our results suggest that the stock market information influences the BTC return at longer time horizons. The economic impact of F1 is greater

[6]The coefficient of F1 in column (1) in Table 3 is 0.02 and the unreported standard deviation of F1 is 6.56, and, hence, the economic impact is calculated as $0.020 \times 6.561 = 0.131$. The standard deviation of the factor is available upon requests.

[7]To define this negative relationship, we focus on the stock market variables and large values indicate increases in the market price.

than that of F3 because one standard deviation of change in F1 leads to a 12.5% change in the BTC return, whereas that in F3 does to a 10.5% change in the BTC return[8]. In column (4), we also find that individual macroeconomic variables do not play an important role in the BTC return, which suggests that the common factor approach is useful in the BTC pricing model. Individual macroeconomic variables are not sufficient in capturing business cycles and this is consistent with other asset results (Ludvigson & Ng (2007, 2009); Filippou & Taylor (2017)).

3.4. Controlling for the COVID19 pandemic

Next, we investigate whether the COVID19 pandemic impacted our results. The previous literature reports that the negative sentiment about COVID19 caused a decline in the BTC return(Hoang & Baur (2021))[9]. We add a pandemic period dummy variable in our regression models of Table 3. Following Xie et al. (2021), the pandemic period is defined from January 2020 to June 2020.

Table 4 provides the results including the pandemic dummy variable. We find that the pandemic had negative impacts on the BTC return for the monthly result in column (1), which is consistent with the results of Hoang & Baur (2021), who report that cryptocurrencies experienced negative returns during the pandemic. In contrast, we confirm that the pandemic did not influence the result for the quarterly model in column (3). This is due to the relatively shorter period of the pandemic period.

3.5. The Other cryptocurrency results

Finally, we focus on other cryptocurrencies (LTC, XRP, and ETH). Table 5 presents the results of the quarterly model. We observe that F1 and F7 are important for LTC in column (1), which is consistent with the results of BTC in Table 3. However, the coefficient of F3 is negative for LTC, which contrasts

[8]The economic impact of F1 is calculated as $0.019 \times 6.561 = 0.125$ and that of F3 is calculated as $0.039 \times 2.69 = 0.105$.

[9]Xie et al. (2021) observe that stable coins were less affected by the pandemic.

Table 3: Regression analysis for Bitcoin (BTC).

	Dependent variable:			
	BTC M	BTC M	BTC Q	BTC Q
	(1)	(2)	(3)	(4)
F1	-0.020^{***}		0.019^{***}	
	(0.004)		(0.003)	
F2			0.029^{*}	
			(0.018)	
F3			0.039^{**}	
			(0.018)	
F4	0.049^{*}			
	(0.028)			
F7			0.047^{**}	
			(0.022)	
F8	-0.108^{**}			
	(0.050)			
Money Supply		3.617		5.374
		(4.764)		(4.230)
Interest Rate		0.441		0.475
		(0.634)		(0.336)
Inflation Rate		−28.637		−15.286
		(34.645)		(36.833)
Lag		0.086	0.722^{***}	0.685^{***}
		(0.073)	(0.080)	(0.120)
Constant	0.020	0.036	0.021	−0.002
	(0.089)	(0.131)	(0.071)	(0.114)
Observations	105	105	104	104
Adjusted R^2	0.007	-0.020	0.480	0.491

Notes: We regress an expected return of BTC on constant, common factors (F1-F10), and macroeconomic indicators (money supply, interest rate, and inflation rate). We use monthly returns (BTC M) and quarterly returns (BTC Q). This table reports the coefficients, standard errors (in parentheses), and the adjusted R2. The standard errors are computed using the method on Newey & West (1987) with 12 lags for monthly data and four for quarterly data. *p<0.1; **p<0.05; ***p<0.01

Table 4: Regression analysis for Bitcoin (BTC) with the COVID19 dummy.

	Dependent variable:			
	BTC M	BTC M	BTC Q	BTC Q
	(1)	(2)	(3)	(4)
F1	-0.026^{***}		0.020^{***}	
	(0.006)		(0.003)	
F2			0.030^{*}	
			(0.018)	
F3			0.041^{**}	
			(0.018)	
F4	0.075^{**}			
	(0.035)			
F7			0.048^{**}	
			(0.022)	
F8	-0.106^{**}			
	(0.051)			
Money Supply		3.961		5.500
		(4.885)		(4.458)
Interest Rate		0.413		0.467
		(0.627)		(0.328)
Inflation Rate		-30.286		-15.903
		(35.797)		(36.361)
COVID-19 Dummy	-0.561^{**}	-0.192	-0.124	-0.064
	(0.256)	(0.202)	(0.091)	(0.226)
Lag		0.084	0.722^{***}	0.684^{***}
		(0.073)	(0.080)	(0.119)
Constant	0.051	0.048	0.027	0.002
	(0.090)	(0.138)	(0.075)	(0.120)
Observations	105	105	104	104
Adjusted R^2	0.007	-0.029	0.476	0.486

Notes:We regress an expected return of BTC on constant, common factors (F1-F10), macroeconomic indicators (money supply, interest rate, and inflation rate) and COVID-19 dummy(January 2020 to June 2020). We use monthly returns (BTC M) and quarterly returns (BTC Q). This table reports the coefficients, standard errors (in parentheses), and the adjusted R2. The standard errors are computed using the method on Newey & West (1987) with 12 lags for monthly data and four for quarterly data. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

with the result of BTC. Therefore, we conclude that an increase in the output variables has negative and that in the stock market prices has positive impacts on the LTC return. We find that the magnitudes of these factors are almost similar, since one standard deviation of changes in the factors lead to around 15% changes in the LTC return[10].

When we focus on the XRP result in column (3) in Table 5, F1 and F7 play an important role, which is similar to the result of BTC. This suggests that the output variables have positive impacts on the XRP return at a quarterly horizon. In addition, F4 and F9 are also statistically significant at the 5% level. F4 is the money supply factor and the difference between LTC and XRP stems from that XRP is used for payment, which is linked to money supply. Finally, in column (5), ETC shows that F1 is not an important determinant for the ETC return because it is statistically significant only at the 10% level. This implies that ETH has different characteristics from the other three cryptocurrencies.

In summary, we find that the common factor across the output variables is important for the LTC and XRP returns at a quarterly horizon, which is consistent with the result of BTC.

4. Conclusion

This study investigated the relationship between expected returns on cryptocurrencies and macroeconomic fundamentals. We employed a dynamic factor model proposed by Stock & Watson (2002) and Ludvigson & Ng (2007), and summarized information as common factors. The common factors were strongly linked to the cryptocurrency expected returns at a longer time horizon, while we did not observe this relationship using macroeconomic indicators such as inflation and money supply. Our results indicate that macroeconomic information was important for the quarterly models, which contrasted with the study of Li

[10]The economic impact of F1 is calculated as $0.024 \times 6.561 = 0.157$ and that of F3 is calculated as $0.058 \times 2.69 = 0.156$.

Table 5: Regression analysis for the other cryptocurrencies (LTC, XRP, and ETH).

	Dependent variable:					
	LTC Q	LTC Q	XRP Q	XRP Q	ETH Q	ETH Q
	(1)	(2)	(3)	(4)	(5)	(6)
F1	0.024***		0.015***		0.005*	
	(0.004)		(0.003)		(0.003)	
F2			−0.037**			
			(0.017)			
F3	−0.058***					
	(0.017)					
F4			0.035**			
			(0.015)			
F7	0.056**		0.048**			
	(0.023)		(0.019)			
F8	0.076*				−0.049	
	(0.039)				(0.031)	
F9			−0.061**			
			(0.029)			
F10	0.088**				−0.075**	
	(0.039)				(0.035)	
Money Supply		−7.006		4.369		2.786
		(5.528)		(3.700)		(2.940)
Interest Rate		−1.081		0.258		0.340
		(0.825)		(0.368)		(0.245)
Inflation Rate		−5.495		26.466		−30.293
		(29.906)		(29.888)		(22.465)
Lag	0.652***	−0.142	0.604***	0.596***	0.743***	0.755***
	(0.081)	(0.258)	(0.103)	(0.095)	(0.069)	(0.071)
Constant	0.043	0.169	−0.030	−0.086	−0.004	0.035
	(0.073)	(0.427)	(0.078)	(0.074)	(0.074)	(0.105)
Observations	85	28	99	99	74	74
Adjusted R^2	0.513	-0.062	0.345	0.354	0.637	0.622

Notes: We regress expected returns of cryptocurrencies on constant, common factors (F1-F10) and macroeconomic indicators (money supply, interest rate, and inflation rate). We use quarterly returns (Q). This table reports the coefficients, standard errors (in parentheses), and adjusted R2. The standard errors are computed using the method in Newey & West (1987) with four for quarterly data. *p<0.1; **p<0.05; ***p<0.01

& Wang (2017), who explored a short-term relationship. In particular, we uncovered that the output common factor negatively affected the expected return on BTC. The impact had the opposite direction predicted by the theoretical model in Schilling & Uhlig (2019). Our common factor approach contained rich information and, hence, our empirical results might capture a channel that was not considered by the theoretical model.

References

Bansal, R., & Yaron, A. (2004). Risks for the long run: A potential resolution of asset pricing puzzles. *Journal of Finance*, *59*, 1481–1509.

Baur, D. G., Dimpfl, T., & Kuck, K. (2018). Bitcoin, gold and the us dollar – a replication and extension. *Finance Research Letters*, *25*, 103–110.

Bleher, J., & Dimpfl, T. (2019). Today i got a million, tomorrow, i don't know: On the predictability of cryptocurrencies by means of google search volume. *International Review of Financial Analysis*, *63*, 147–159.

Bouri, E., Molnár, P., Azzi, G., Roubaud, D., & Hagfors, L. I. (2017). On the hedge and safe haven properties of bitcoin: Is it really more than a diversifier? *Finance Research Letters*, *20*, 192–198.

Cheah, E.-T., & Fry, J. (2015). Speculative bubbles in bitcoin markets? an empirical investigation into the fundamental value of bitcoin. *Economics Letters*, *130*, 32–36.

Corbet, S., Lucey, B., Urquhart, A., & Yarovaya, L. (2019). Cryptocurrencies as a financial asset: A systematic analysis. *International Review of Financial Analysis*, *62*, 182–199.

Fama, E., & French, K. (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, *33*, 3–56.

Fernandez-Perez, A., Fuertes, A.-M., & Miffre, J. (2017). Commodity markets, long-run predictability, and intertemporal pricing. *Review of Finance*, *21*, 1159–1188.

Filippou, I., & Taylor, M. P. (2017). Common macro factors and currency premia. *Journal of Financial and Quantitative Analysis*, *52*, 1731–1763.

Fry, J., & Cheah, J. E. T. (2016). Negative bubbles and shocks in cryptocurrency markets. *International Review of Financial Analysis*, *47*, 343–352.

Grobys, K., Ahmed, S., & Sapkota, N. (2020). Technical trading rules in the cryptocurrency market. *Finance Research Letters*, *32*, 101396.

Handa, P., Kothari, S. P., & Wasley, C. (1993). Sensitivity of multivariate tests of the capital asset-pricing model to the return measurement interval. *Journal of Finance*, *48*, 1543–1551.

Hoang, L. T., & Baur, D. G. (2021). Cryptocurrencies are not immune to coronavirus: evidence from investor fear. *Available at SSRN 3778988*, .

Klein, T., Pham Thu, H., & Walther, T. (2018). Bitcoin is not the new gold – a comparison of volatility, correlation, and portfolio performance. *International Review of Financial Analysis*, *59*, 105–116.

Kraaijeveld, O., & De Smedt, J. (2020). The predictive power of public twitter sentiment for forecasting cryptocurrency prices. *Journal of International Financial Markets, Institutions and Money*, *65*, S104244312030072X.

Li, X., & Wang, C. A. (2017). The technology and economic determinants of cryptocurrency exchange rates: The case of bitcoin. *Decision Support System*, *95*, 49–60.

Liu, W., Liang, X., & Cui, G. (2020). Common risk factors in the returns on cryptocurrencies. *Economic Modelling*, *86*, 299–305.

Liu, Y., & Tsyvinski, A. (2020). Risks and returns of cryptocurrency. *Review of Financial Studies*, *Forthcoming*.

Ludvigson, S. C., & Ng, S. (2007). The empirical risk-return relation: A factor analysis approach. *Journal of Financial Economics*, *83*, 171–222.

Ludvigson, S. C., & Ng, S. (2009). Macro factors in bond risk premia. *Review of Financial Studies*, *22*, 5027–5067.

Maio, P., & Santa-Clara, P. (2012). Multifactor models and their consistency with the icapm. *Journal of Financial Economics*, *106*, 586–613.

Nadarajah, S., & Chu, J. (2017). On the inefficiency of bitcoin. *Economics Letters*, *150*, 6–9.

Naeem, M. A., Mbarki, I., Suleman, M. T., Vo, X. V., & Shahzad, S. J. H. (2021). Does twitter happiness sentiment predict cryptocurrency? *International Review of Finance*, (p. Forthcoming).

Newey, W. K., & West, K. D. (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica*, *55*, 703–708.

Ortu, F., Tamoni, A., & Tebaldi, C. (2013). Long-run risk and the persistence of consumption shocks. *Review of Financial Studies*, *26*, 2876–2915.

Philippas, D., Philippas, N., Tziogkidis, P., & Rjiba, H. (2020). Signal-herding in cryptocurrencies. *Journal of International Financial Markets, Institutions and Money*, *65*, S1042443120300755.

Schilling, L., & Uhlig, H. (2019). Some simple bitcoin economics. *Journal of Monetary Economics*, *106*, 16–26.

Shen, D., Urquhart, A., & Wang, P. (2019). Does twitter predict bitcoin? *Economics Letters*, *174*, 118–122.

Shen, D., Urquhart, A., & Wang, P. (2020). A three-factor pricing model for cryptocurrencies. *Finance Research Letters*, *34*, 101248.

Shrestha, K. (2021). Multifractal detrended fluctuation analysis of return on bitcoin. *International Review of Finance*, *21*, 312–323.

Stock, J., & Watson, M. (2002). Macroeconomic forecasting using diffusion indexes. *Journal of Business & Economic Statistics*, *20*, 147–162.

Tran, V. L., & Leirvik, T. (2020). Efficiency in the markets of crypto-currencies. *Finance Research Letters*, *35*, 101382.

Urquhart, A. (2016). The inefficiency of bitcoin. *Economics Letters*, *148*, 80–82.

Xie, Y., Kang, S. B., & Zhao, J. (2021). Are stablecoins safe havens for traditional cryptocurrencies? an empirical study during the covid-19 pandemic. *Applied Finance Letters*, *10*, 2–9.

Macro factors in the returns on cryptocurrencies

Kei Nakagawa

Nomura Asset Management Co, ltd.

Ryuta Sakemoto

Okayama University

Online Supplement, Not for Publication

This appendix presents macroeconomic indicators and transformation and details of factors used in our factor model.

Appendix A. Macroeconomic Indicators

We followed Ludvigson & Ng (2009) and picked up the data series. This appendix lists the description of each series, its code (the series label used in the source database), and the transformation applied to the series. All series are obtained from Economic Data Time Travel from the St. Louis Fed's Economic Research Division and Bloomberg. In the transformation column, ln denotes logarithm, Δln and Δ^2ln denote the first and second difference of the logarithm, level denotes the level of the series, and Δlevel denotes the first difference of the series.

Table A.1: Description of each series, its code (the series label used in the source database), and the transformation applied to the series.

Description	Code	Tran
Output and Income		
Personal Income	PI	Δln
Industrial Production Index - Total Index	INDPRO	Δln
Industrial Production Index - Final Product	IPFINAL	Δln
Industrial Production Index - Consumer Goods	IPCONGD	Δln
Industrial Production Index - Durable Consumer Goods	IPDCONGD	Δln
Industrial Production Index - NonDurable Consumer Goods	IPNCONGD	Δln
Industrial Production Index - Bussiness Equipment	IPBUSEQ	Δln
Industrial Production Index - Materials	IPMAT	Δln
Industrial Production Index - Durable Goods Materials	IPDMAT	Δln
Industrial Production Index - NonDurable Goods Materials	IPNMAT	Δln
Industrial Production Index - Manufacturing SIC	IPMANSICS	Δln
Industrial Production Index - Residential Utilities	IPB51222S	Δln
Industrial Production Index - Fuels	IPFUELS	Δln
NAPM Production Index	NAPMPMI Index	Level
Capacity Utilization	TCU	ΔLevel
Labor Market		
Civilian Labor Force: Employed, Total	USLFTOT Index	Δln
Civilian Labor Force: Employed, Nonagric.Industries	USNATOTN Index	Δln
Unemployment Rate	USURTOT Index	ΔLevel
Unemployment Rate by duration Average duration	USDUMEAN Index	ΔLevel
Unemployment Rate by duration <5W	USDULSFV Index	Δln

Continued on next page

Table A.1 – continued from previous page

Description	Code	Tran
Unemployment Rate by duration 5-14W	USDUFVFR Index	Δln
Unemployment Rate by duration 15+W	USDUFIFT Index	Δln
Unemployment Rate by duration 15-26W	USDUFITS Index	Δln
Unemployment Rate by duration 27+W	USDUTWSV Index	Δln
Average Weekly Initial Claims, Unemploy. Insurance	INJCJC Index	Δln
Employees on nonfarm payrolls total private	NFP P Index	Δln
Employees on nonfarm payrolls Goods producing	NFP GP Index	Δln
Employees on nonfarm payrolls Mining	USMMMINE Index	Δln
Employees on nonfarm payrolls Construction	USECTOT Index	Δln
Employees on nonfarm payrolls Manufaturing	USMMMANU Index	Δln
Employees on nonfarm payrolls Durable Goods	USEDTOT Index	Δln
Employees on nonfarm payrolls NonDurable Goods	USENTOT Index	Δln
Employees on nonfarm payrolls Service providing	USESPRIV Index	Δln
Employees on nonfarm payrolls Trade Transportation and utilities	NFP TTUT Index	Δln
Employees on nonfarm payrolls Wholesale Trade	USEWTOT Index	Δln
Employees on nonfarm payrolls Retail Trade	USRTTOT Index	Δln
Employees on nonfarm payrolls Financial Activities	USEFTOT Index	Δln
Employees on nonfarm payrolls Government	USEGTOT Index	Δln
Avg Weekly Hrs of Prod and Nonsup Employees, Goods-Producing	CES0600000007	Level
Avg Weekly Overtime Hrs of Prod and Nonsup Employees, Mfg	AWOTMAN	Δln
Average Weekly Hours of All Employees, Manufacturing	AWHAEMAN	Level
AHE goods	AHE GOOD Index	Δ^2ln
AHE construction	AHE CONS Index	Δ^2ln
AHE manufacturing	AHE MANU Index	Δ^2ln
Housing		
Housing Starts Total	NHSPSTOT Index	ln
Housing Starts Northeast	NHSPSNE Index	ln
Housing Starts Midwest	NHSPSMW Index	ln
Housing Starts South	NHSPSSO Index	ln
Housing Starts West	NHSPSWE Index	ln
Housing Authorized Total	NHSPATOT Index	ln
Housing Authorized Northeast	NHSPANE Index	ln
Housing Authorized Midwest	NHSPAMW Index	ln
Housing Authorized South	NHSPASO Index	ln
Housing Authorized West	NHSPAWE Index	ln

Continued on next page

Table A.1 – continued from previous page

Description	Code	Tran
Consumption		
Purchasing Managers' Index	NAPMPMI Index	Level
NAPM new ordrs pmno lv Napm New Orders Index (Percent)	NAPMNEWO Index	Level
Manufacturers New Orders Consumer Goods	ACOGNO	Δln
Manufacturers new orders durable goods	DGORDER	Δln
Manufacturers new orders nondefence capital goods	ANDENO	Δln
Manufacturers' Unfilled Orders: Durable Goods	AMDMUO	Δln
Manufacturing Inventries	MNFCTRIMSA	Δln
Manufacturing Inventries to Sales	MNFCTRIRSA	ΔLevel
Real Personal Consumption Expenditure	PCEC96	Δln
Manufacturing Sales	MNFCTRSMSA	Δln
U. Of Michigan Index Of Consumer Expectation	CONSSENT Index	ΔLevel
Money		
M1	M1SL	Δ^2ln
M2	M2SL	Δ^2ln
M2(Real)	M2REAL	Δ^2ln
Monetery base	BOGMBASE	Δ^2ln
Reserves of Depository Institutions	TOTRESNS	Δ^2ln
Reserves of Depository Institutions, Nonborrowed	NONBORRES	Δ^2ln
CI Loans	BUSLOANS	Δ^2ln
Consumer credit outstanding nonrevolving	NONREVNS	Δ^2ln
Bond		
FF Rate effective	FEDFUNDS	ΔLn
CP Rate	CPF3M	ΔLevel
3M T-Bill	TB3MS	ΔLevel
6M T-Bill	TB6MS	ΔLevel
1 year T-Bond	GS1	ΔLevel
5 year T-Bond	GS5	ΔLevel
10 year T-Bond	GS10	ΔLevel
Baa Bond Yield: Bloomberg Barclays US Aggregate Baa	LUBATRUU Index	ΔLevel
Aaa Bond Yield: Bloomberg Barclays US Aggregate Aaa	LU3ATRUU Index	ΔLevel
Spread Between CP Rate and FF Rate	-	Level
Spread Between 3M T-Bill and FF Rate	-	Level
Spread Between 6M T-Bill and FF Rate	-	Level
Spread Between 1 year T-Bond and FF Rate	-	Level

Continued on next page

Table A.1 – continued from previous page

Description	Code	Tran
Spread Between 5 year T-Bond and FF Rate	-	Level
Spread Between 10 year T-Bond and FF Rate	-	Level
Spread Between Baa Bond Yield and FF Rate	-	Level
Spread Between Aaa Bond Yield and FF Rate	-	Level
CHF/USD	CHF Curncy	Δln
JPY/USD	USD Curncy	Δln
GBP/USD	GBP Curncy	Δln
CAD/USD	CAD Curncy	Δln
Real Broad Effective Exchange Rate for United States	RBUSBIS	Δln
Price		
PPI Finished goods	WPSFD49207	Δ^2ln
PPI Finished consumer goods	WPSFD49502	Δ^2ln
Spot market price	PPIACO	Δ^2ln
PPI Nonferrous materials	PCU4299304299302	Δ^2ln
CPI-U All	CPALTT01USM657N	Δ^2ln
CPI-U apparel	CPIAPPSL	Δ^2ln
CPI-U Transportation	CPITRNSL	Δ^2ln
CPI-U MedicalCare	CPIMEDSL	Δ^2ln
CPI-U Commodities	CUSR0000SAC	Δ^2ln
CPI-U Durables	CUSR0000SAD	Δ^2ln
CPI-U Services	CUSR0000SAS	Δ^2ln
CPI-U All ex Food	CPIULFSL	Δ^2ln
CPI-U All ex Shelter	CUUR0000SA0L2	Δ^2ln
CPI-U All ex Medical Care	CUSR0000SA0L5	Δ^2ln
Personal Consumption Expenditure	PCE	Δ^2ln
Personal Consumption Expenditure:Durable	PCEDG	Δ^2ln
Personal Consumption Expenditure:NonDurable	PCEND	Δ^2ln
Personal Consumption Expenditure:Service	PCES	Δ^2ln
Stock		
S&P 500	SPX Index	Δln
S&P500 Dividend Yield	EQY_DVD_YLD_12M	ΔLevel
S&P500 PE Ratio	PE_RATIO	Δln

Table B.2: Sandard deviation, proportion and cumulative percentage explained variation for the first ten factors.

	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10
Standard deviation	6.575	3.364	2.715	2.660	2.203	2.048	1.759	1.722	1.655	1.579
Proportion of variance	0.370	0.097	0.063	0.060	0.041	0.036	0.026	0.025	0.023	0.021
Cumulative proportion	0.370	0.466	0.529	0.590	0.631	0.667	0.693	0.719	0.742	0.764

Appendix B. Standard deviation, proportion and cumulative percentage explained variation for the first ten factors