Attention to Authority: The behavioural finance of Covid-19

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Abstract

In this paper we investigate the predictability of cryptocurrency returns following increases in Covid-19 cases/deaths. We find that the rate of government intervention moderates the impact that Covid-19 cases/deaths have on cryptocurrency returns. We show that in periods of tightening government intervention, increases in Covid-19 cases positively predict cryptocurrency returns. We argue that this is due to investors imputing their expectations of the pandemic through a 'combined' signal.

Keywords: Covid-19, Asset Pricing, Cryptocurrency
JEL codes: G12, G40, E44

1 Introduction

In this paper we investigate the predictability of cryptocurrency returns following increases in Covid-19 cases/deaths. Recent research documents a 'flight-to-quality' effect observed during the pandemic between Covid-19 cases/deaths and cryptocurrency returns (Conlon and McGee, 2020; Corbet et al., 2020; Goodell and Goutte, 2021). Our findings reveal that the rate of government intervention moderates the impact that Covid-19 cases/deaths have on cryptocurrency returns. We show that in periods of increasing government intervention, increases in Covid-19 prevalence positively predict cryptocurrency returns. We argue that this is due to investors imputing their expectations of the pandemic. Our findings are robust to specifications which control for investor attention, and varying time horizons.

Our paper contributes to a growing literature on the asset pricing of cryptocurrencies in three key ways. Firstly, we demonstrate a deviation from ordinary price dynamics as documented by

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Liu and Tsyvinski (2021) and Liu et al. (2022), as a result of ongoing systematic shocks, namely the Covid-19 pandemic. Secondly, we show how cryptocurrency investors begin to impute their expectations on the value of cryptocurrency assets to the government via policy signals. Thirdly, we contribute the first assessment of this effect in an empirical asset pricing framework.

The asset pricing of cryptocurrency is a live topic of academic research with many aspects relating to market efficiency (López-Martín et al., 2021) and price discovery (Doan et al., 2022) seemingly unresolved. This may in part by due to uncertainty surrounding the source of fundamental value (Cheah and Fry, 2015; Detzel et al., 2021). This notwithstanding, it is likely that markets such as cryptocurrencies that are dominated by relatively unsophisticated individual investors would demonstrate predictable price patterns (De Bondt and Thaler, 1985). However, recent suggestions are that institutional investors are playing an increasingly prominent role in Bitcoin (Alexander and Imeraj, 2021; Doan et al., 2022)

Recent research shows that momentum and investor attention (proxied by Twitter and the Google Search Index) are clear determinants of returns (Liu et al., 2022; Liu and Tsyvinski, 2021). Inter alia, there is growing reference to cryptocurrency as a Covid-19 safe haven (Urquhart and Zhang, 2019; Corbet et al., 2020; Conlon and McGee, 2020; Goodell and Goutte, 2021; Iqbal et al., 2021). However, current empirical evidence is divided on this. In this paper we make use of a benchmark asset pricing framework to test the impact of Covid-19 cases/deaths on subsequent returns for cryptocurrency. We identify a statistically and economically significant relationship between higher rates of Covid-19 cases/deaths and positive return predictability for Ethereum and CCi30. However, we show that this effect is moderated by the contemporaneous rate of government policy stringency against virus prevalence and mortality. That is to say, high Covid-19 cases/deaths are only good predictors of positive returns when there are increasing rates of policy restriction. Furthermore, there is some evidence to suggest that throughout the pandemic when policy restrictions have been decreasing, the effect of increases in cases can even be negative on returns. We show evidence that the rate of change in policy alters the effect between virus prevalence and returns, partially forming investors beliefs of the safe haven qualities.

We find our results to be in support of the self-fulfilling safe haven hypothesis (see Section 4). As investors' future expectations of normal economic conditions deteriorate, returns to cryptocurrency increase. Furthermore, we argue that these expectations are guided by a combination of policy change and Covid-19 cases/deaths. Investors are not typically able to evaluate the longevity of a global pandemic from epidemiological information. Consequently, investors take signals from government policy and tangible measures of Covid-19 development. In this paper we show that the positive return predictability of cryptocurrency returns is marked by both high cases numbers and increasing government stringency.

The rest of this paper is laid out as follows. Section 2 presents the data for our empirical application. Section 3 presents our benchmark findings. Section 4 discusses the notion of a cryptocurrency safe haven. Section 5 presents our robustness checks. Section 6 concludes and discusses the opportunities for further research.

2 Empirical application

Our data focuses on the time period between February, 2020 and November 2021. We collect data on Bitcoin (BTC), Ethereum (ETH), and the CCi30 cryptocurrency index. Our BTC and ETH data is taken directly from Yahoo! Finance* and the CCi30 data is taken from cci30.com. Figure 1 presents a graph of the standardised values of the Bitcoin price and the rolling 7 day sum of global Covid-19 cases.

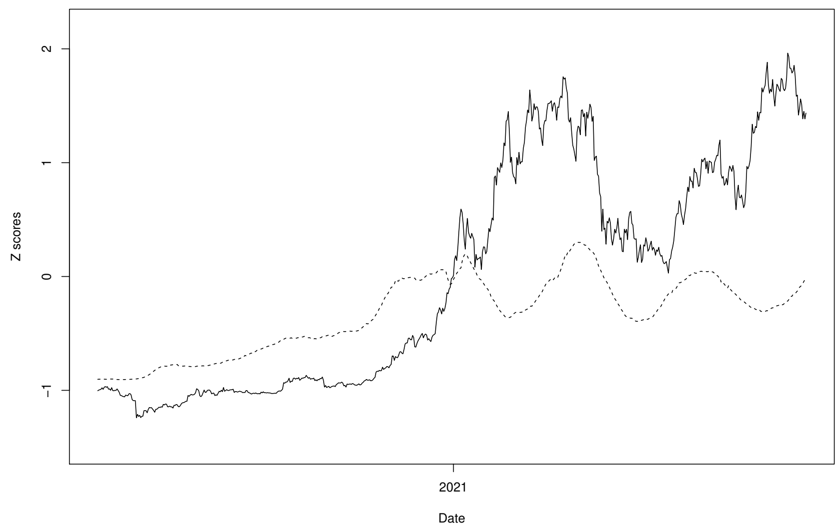

Figure 1: Time series plot of standardized values for Bitcoin (solid line) and Covid-19 cases worldwide (dashed line)

We collect data on Covid-19 from *Our World in Data* (OWID). The OWID dataset provides an extensive range of both time series and cross-sectional information for Covid-19 cases and deaths across numerous countries with additional variables for each country. We focus our empirical analysis on the global case (prevalence) and death (mortality) numbers. This is indeed a global pandemic, and it may be reasonable to conclude that individuals are as influenced by Covid-19 figures in another country as they are in their own. Furthermore, cryptocurrency operates on a multinational level. As such this provides an appropriate test. Summary statistics of our data are provided in Table 1.

We follow recent research by Liu and Tsyvinski (2021), but also benchmark methodology in the field of empirical asset pricing (Ahern and Sosyura, 2015; Tetlock, 2011). Our dependent variable of interest is given by the return of cryptocurrency i over the daily intervals $t = [1, 7]$. Our primary independent variables of interest is given by our measure of cases/deaths. We

*Yahoo Finance! source cryptocurrency data from CoinMarketCap

Table 1: Summary statistics

Statistics	Mean	StDev	Min	Max
$RetEth_{[1,7]}$	3.471	12.563	-53.866	58.056
$RetBtc_{[1,7]}$	2.242	9.874	-45.511	30.093
$RetIndex_{[1,7]}$	2.367	10.612	-49.462	35.850
$Policy_t$	-0.081	0.579	-0.816	1.993
$AbSearch_t$	0.000	1.000	-4.978	3.571
$Cases_{[-7,-1]}$	11,612,352.663	6,411,424.858	21,059.000	23,976,871.000
$Deaths_{[-7,-1]}$	232,460.442	97,218.110	1,865.000	438,330.000

$RetEth_{[1,7]}$, $RetBtc_{[1,7]}$, and $RetIndex_{[1,7]}$ represent the week ahead returns for each cryptocurrency, expressed as percentages. $Policy_t$ and $AbSearch_t$ represent the standardised weekly policy response and Google trends data respectively. Data for $Policy_t$ is standardised prior to merging with financial data. $AbSearch_t$ is collected on a weekly basis. $Cases_{[-7,-1]}$ and $Deaths_{[-7,-1]}$ represent the prior week cases and deaths respectively and are summarised here in their raw format, prior to standardisation.

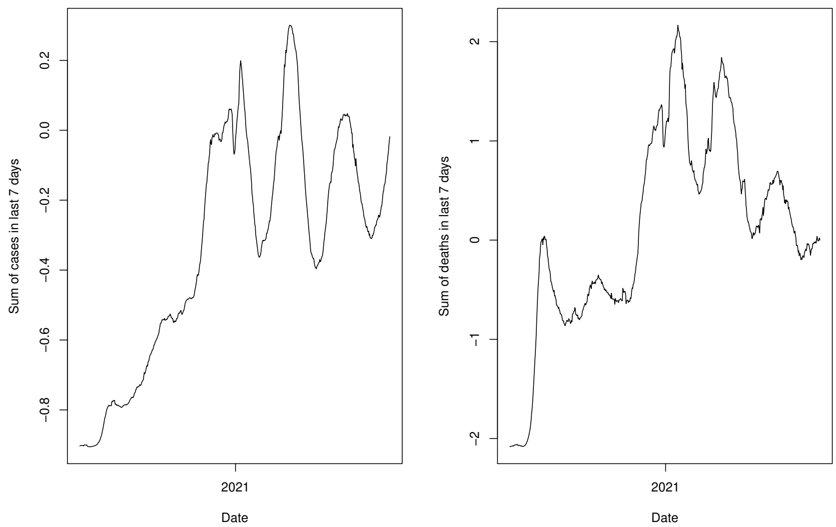

Figure 2: Time series plot of standardized values for the sum of last 7 days cases (left-panel), and last 7 days deaths (right-panel)

consider a cumulative sum of the previous seven day cases/deaths data. Second, we also consider the interaction of cases/deaths with policy intervention, using the *Government Stringency Index* data from the OWID. The stringency index is a composite measure of nine indicators, scaled from 0 to 100, where 100 is the strictest response*. We construct a measure of the rate of change in stringency against Covid-19. We calculate mean global government stringency index of the previous week, against the previous four weeks. Positive values indicate an increasing policy response, representing greater stringency, than that of the previous four weeks. Our cryptocurrency controls are given by the return in the previous week. This controls our results

*The nine metrics used in the stringency index are: school closures; workplace closures; cancellation of public events; restrictions on public gatherings; closures of public transport; stay-at-home requirements; public information campaigns; restrictions on internal movements and international travel controls.

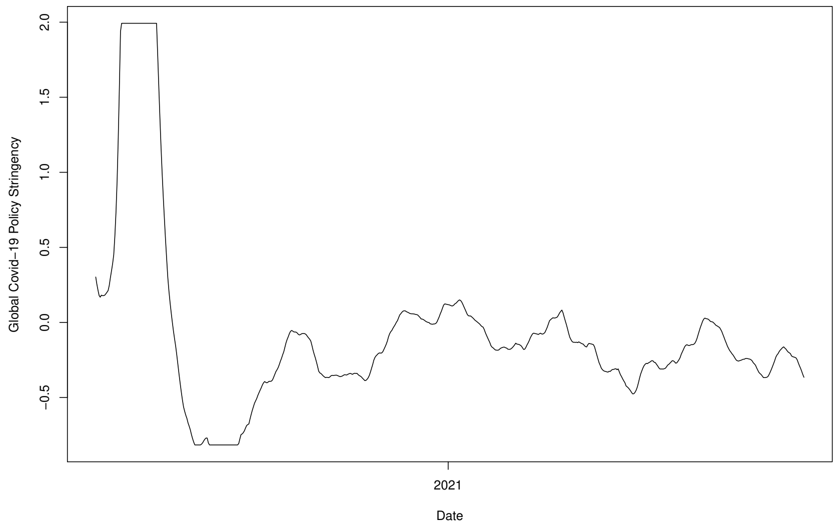

Figure 3: Time series plot of standardized values for Covid-19 policy stringency

for well-known momentum effects in returns (Liu and Tsyvinski, 2021).

Figure 2 depicts the moving sum of the prior 7 days cases (left-panel) and deaths (right-panel). These values are standardized for ease of interpretation and analysis. Figure 3 depicts the time series of standardized values for Covid-19 government intervention measures. It is worth noting that both figures share similar qualitative features.

3 Results

In this section we demonstrate our results for a range of time-series regressions. For each cryptocurrency i in our sample, we perform the following analysis. Our benchmark regression specification is

$$\text{Ret}_{[t+1,t+7]} = \beta_0 + \beta_1\text{Covid19}_t + \beta_2\text{Policy}_t + \beta_3\text{Covid19}_t{\times}\text{Policy}_t + \beta_4\text{Ret}_{[t-7,t-1]} + \epsilon_t \qquad (1)$$

where the dependent variable represents a time-series of cumulative returns over the interval $[t+1, t+7]$. Our Covid-19 data consists of measure of virus prevalence and mortality. This is the sum of cases in the past seven days ($\text{Cases}_{-7,-1}$) and the sum of deaths in the past seven days ($\text{Deaths}_{-7,-1}$). Both sources of information are then assumed to be made publicly available one day later at time 0. The government policy index Policy_t is also included alongside an interaction term between the Covid-19 data and government policy index.

Equation (1) therefore predicts that as the effect of the pandemic subsides the returns will follow an auto-regressive process with

$$\text{Ret}_{[t+1,t+7]} = \beta_0 + \beta_4 \text{Ret}_{[t-7,t-1]} + \epsilon_t \tag{2}$$

Equation (2) therefore predicts that some cryptocurrency market inefficiency and predictability will persist once the pandemic subsides. This is a reasonable expectation given the empirical results of both Katsiampa (2017) and Liu and Tsyvinski (2021). Momentum has also been identified as a factor of significant interest in the prediction of cryptocurrency returns (Liu and Tsyvinski, 2021; Liu et al., 2022). However, equation (2) also reduces to the classical random walk with drift model when that $\beta_4 = 0$.

When estimating equation (1) we standardise each of our independent variables to ease interpretation and enable statistical tractability. Furthermore, we also estimate each of our regressions with Newey and West (1987) standard-errors and control for 7 days of lag. These are the most restrictive standard-errors we could apply (Petersen, 2009).

Table 2: One week return predictability of returns based on Covid-19 data

Dependant Variable	$ETH_{[1,7]}$	$BTC_{[1,7]}$	$Index_{[1,7]}$	$ETH_{[1,7]}$	$BTC_{[1,7]}$	$Index_{[1,7]}$
$Cases_{[-7,-1]} \times Policy_t$	25.500*	3.064	21.955*			
	(14.864)	(12.000)	(12.303)			
$Deaths_{[-7,-1]} \times Policy_t$				3.705*	0.227	1.393
				(2.184)	(1.804)	(2.051)
$Cases_{[-7,-1]}$	8.408**	1.842	5.110			
	(3.824)	(3.186)	(3.240)			
$Deaths_{[-7,-1]}$				2.630	0.979	2.128
				(1.418)	(1.275)	(1.346)
$Policy_t$	22.295*	3.992	19.114**	5.403**	1.825	3.359*
	(11.574)	(9.403)	(9.553)	(2.129)	(1.670)	(1.901)
$Ret_{[-7,-1]}$	-1.754**	-0.238	-0.909	-1.705**	-0.262	-0.750
	(0.737)	(0.694)	(0.748)	(0.710)	(0.689)	(0.733)
$Intercept$	8.337**	3.207*	5.840**	3.838**	2.264**	2.432**
	(1.647)	(1.646)	(1.407)	(0.993)	(0.842)	(0.814)

Table 2 shows the results of estimation equation (1). We estimate the dependent variable, listed in the top row, against the corresponding variables on each row below that. We estimate our regressions using Newey and West (1987) standard errors and control for up to 7 days of lag. Our standard errors are in parentheses. ** and * represent statistical significance at the 5% and 10% level respectively.

Table 2 presents our results. We show that Covid-19 data has an economically and statistically significant impact on cryptocurrency returns. In addition, we also emphasise the importance of government restriction in moderating this effect. We also note the relative loss of predictive power in the momentum effect (Liu and Tsyvinski, 2021). Although we argue this is most easily explained by the sample size, and substantial shift in dynamics of prices following the pandemic. Figure 4 depict the interaction effect of Covid-19 cases/deaths with global policy intervention for Ethereum, Bitcoin and CCi30 respectively. In each case the graphs show the interaction effect of policy intervention ($Policy_t$) with Covid-19 cases (left-panels) and Covid-19 deaths (right-panels). The upper, middle and lower lines on each individual graph depict constant, increasing, and decreasing global policy stringency ($Policy_t$) defined in terms of the

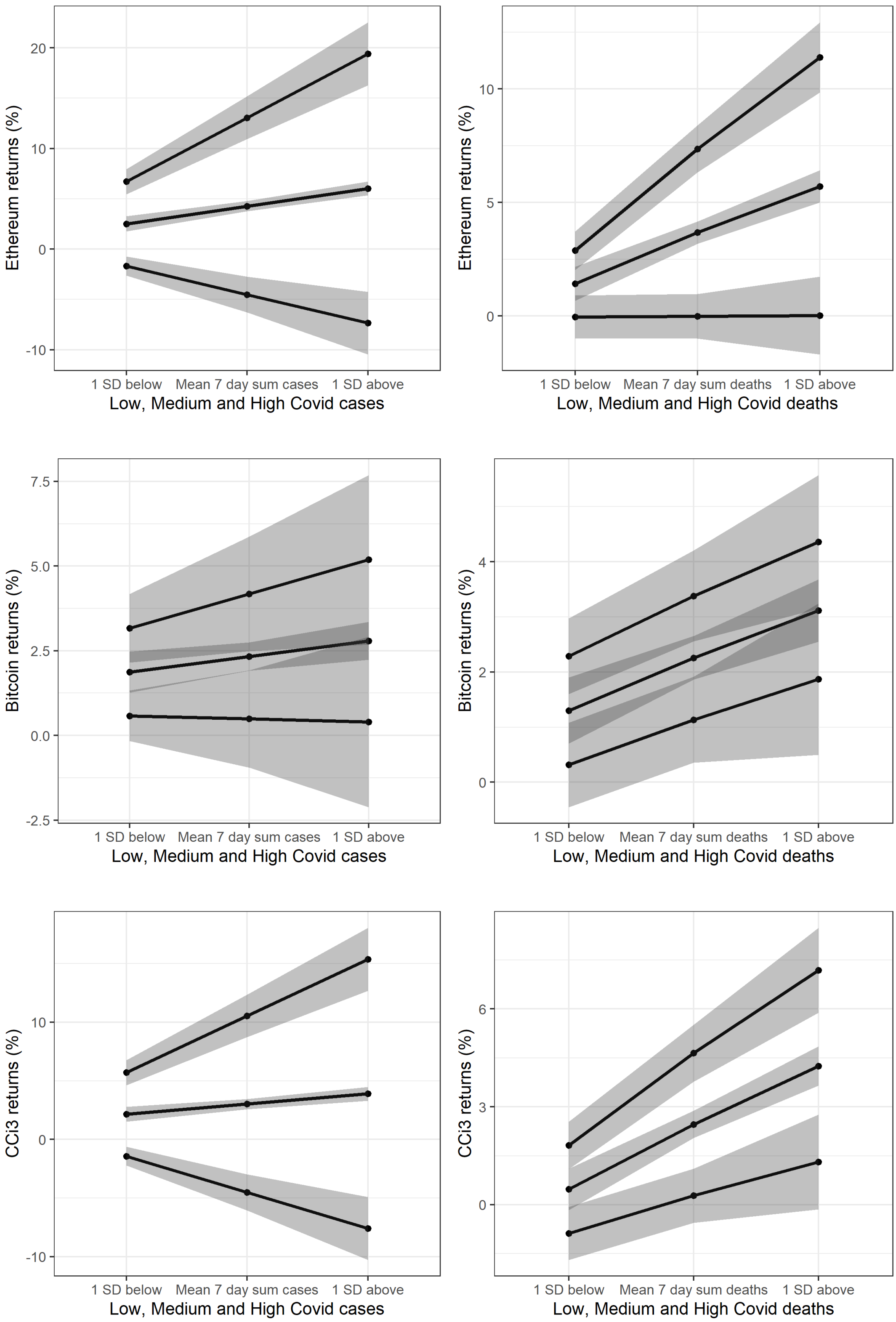

Figure 4: Interaction effect of $Cases_{[-7,-1]} \times Policy_t$ (left-panels) and $Deaths_{[-7,-1]} \times Policy_t$ (right-panels) for Ethereum (top), Bitcoin (middle), and CCi30 (bottom). The upper, middle and lower lines on each graph depict increasing, constant, and decreasing global policy stringency ($Policy_t$) respectively.

mean $\pm$ 1 standard deviation. We show that cryptocurrency returns are at their highest for the interaction with Covid-19 cases, when both $Cases_{[-7,-1]}$ and $Policy_t$ are highest. The pattern is most consistent overall for Covid-19 cases. That is to say, as cases and government restrictions rise contemporaneously, there is a significant positive effect on cryptocurrency returns. This effect reverses when policy is loosening, suggesting that stringency acts as a propagation mechanism through which patterns of virus prevalence yield significant yet varied economic effects on cryptocurrency returns. The results have a lower level of economic significance for Covid-19 death interactions. Although this may be due in part to the lagged relationship between cases and deaths.

These results show how the development of the pandemic has influenced cryptocurrency returns. First, increases in both cases and deaths have a positive impact on returns. However, this effect is amplified in the presence of an increasing rate of government policy stringency. We argue that the reason for this is that it signals a continuation of the pandemic into the next period. In this way, investors are deferring to the government to fulfil their expectations surrounding the development of the pandemic. Policy can therefore act to amplify how investors react to virus prevalence, partially forming their beliefs of the safe haven qualities.

4 Cryptocurrency safe haven

The extent to which Bitcoin and cryptocurrencies serve as a genuine safe haven is open to debate. There is some suggestion that Bitcoin can hedge against short-term inflation (Choi and Shin, 2022; Smales, 2021). However, since Bitcoin offers limited diversification potential during market downturns it is not a genuine safe haven (Alexander and Imeraj, 2021; Zhang et al., 2021). There are even suggestions that including Bitcoin in a portfolio may have actually increased downside risks during the early stages of the pandemic (Conlon and McGee, 2020).

In this paper we take the view that cryptocurrencies constitute a self-fulfilling safe haven. Cryptocurrencies hold a limited number of safe haven properties precisely because investors consider this to be the case. At a time of conventional uncertainty cryptocurrencies may offer a convenient contemporary source of the security historically sought for from gold and other precious metals (Corbet et al., 2020). The pandemic may also have increased demand by highlighting the need for new forms of electronic payment including cryptocurrency (Iqbal et al., 2021).

If Bitcoin and cryptocurrencies operate as above then we would expect that they would regularly be subject to self-fulfilling speculative bubbles. Using the model of Cheah and Fry (2015) evidence of self-fulfilling speculative bubbles during the pandemic is presented in Table 3. In line with Fry and Cheah (2016) the bubble effect may be so powerful as to cause investors to overlook adverse events such as the 2020 market crash.

Table 3: Test of speculative bubbles in cryptocurrencies

Market	$\hat{v}$	e.s.e. $\hat{v}$	t-value	p-value
Bitcoin	0.395	0.102	3.825	0.000
Ethereum	0.507	0.094	5.383	0.000
CCi30 Index	0.383	0.065	5.855	0.000

Table 3: Test of the null hypothesis of no speculative bubble (v=0) against the alternative hypothesis of a speculative bubble (v>0).

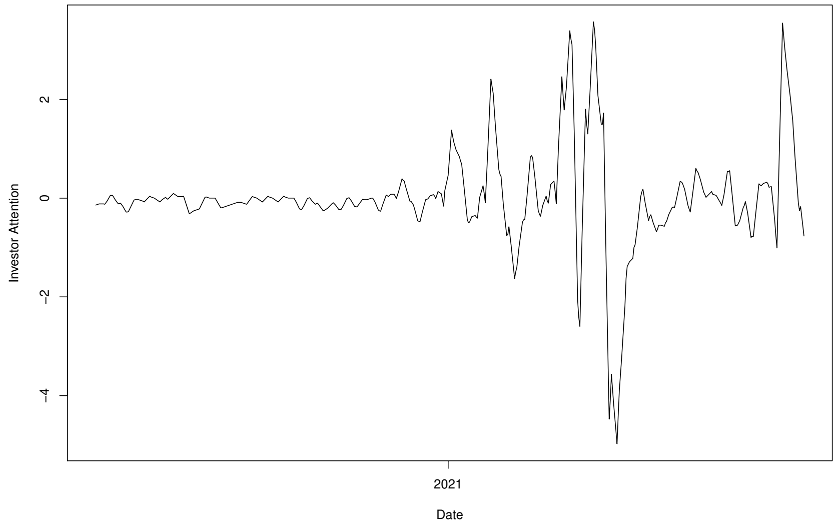

Figure 5: Time series plot of standardized values for investor-attention, proxied by Google searches for the topic 'Cryptocurrency'

5 Robustness checks

In this section we consider an alternative explanation for the effect we observe. People may be treating cryptocurrency as a Covid-19 self-fulfilling safe haven. However it may simply be the case that higher levels of investor attention are ultimately responsible for this activity. In this section we present our results with additional robustness checks which include a well-known proxy for investor-attention, namely Google searches (Liu and Tsyvinski, 2021).

We construct a measure for abnormal investor attention. Using Google trends data, we identify abnormal attention by taking the mean search index of the previous week against that of the previous four weeks. We take search data for the topic 'Cryptocurrency'. This includes all related search terms and represents search intensity in cryptocurrency more broadly. The time-series of our data is given in Figure 5. This is consistent with the variable used in Liu and Tsyvinski (2021). Our results in Table 4 show that our benchmark findings remain robust to the inclusion of this variable.

Non-significant results for Bitcoin have two possible roots. Firstly, this could reflect that Bitcoin is thought to be the most efficient cryptocurrency market (López-Martín et al., 2021).

Table 4: One week return predictability of returns based on Covid-19 data

Dependant Variable	$ETH_{[1,7]}$	$BTC_{[1,7]}$	$Index_{[1,7]}$	$ETH_{[1,7]}$	$BTC_{[1,7]}$	$Index_{[1,7]}$
$Cases_{[-7,-1]} \times Policy_t$	27.338*	5.627	22.855*			
	(15.444)	(12.574)	(13.167)			
$Deaths_{[-7,-1]} \times Policy_t$				3.775*	0.460	1.419
				(2.248)	(1.929)	(2.143)
$Cases_{[-7,-1]}$	8.840**	2.467	5.347*			
	(3.737)	(2.961)	(3.064)			
$Deaths_{[-7,-1]}$				2.656*	1.070	2.136
				(1.398)	(1.226)	(1.318)
$Policy_t$	23.828**	6.116	19.870*	5.507**	2.124	3.396*
	(12.080)	(9.872)	(10.276)	(2.218)	(1.793)	(2.008)
$AbSearch_t$	-0.911	-1.098	-0.497	-0.454	-1.004	-0.163
	(1.082)	(1.032)	(1.061)	(1.117)	(1.053)	(1.168)
$Ret_{[-7,-1]}$	-1.603**	-0.144	-0.805	-1.612**	-0.151	-0.710
	(0.738)	(0.730)	(0.791)	(0.729)	(0.731)	(0.843)
$Intercept$	8.614**	3.602**	5.982**	3.844**	2.284**	2.434**
	(1.688)	(1.587)	(1.388)	(0.996)	(0.836)	(0.813)

Table 4 shows the results of estimation equation (1) with the addition of $AbSearch_t$. $AbSearch_t$ represents abnormal Google search activity for cryptocurrencies. We estimate the dependent variable, listed in the top row, against the corresponding variables on each row below that. We estimate our regressions using Newey and West (1987) standard errors and control for up to 7 days of lag. Our standard errors are in parentheses. ** and * represent statistical significance at the 5% and 10% level respectively.

Table 5: Two week return predictability of returns based on Covid-19 data

Dependant Variable	$ETH_{[1,14]}$	$BTC_{[1,14]}$	$Index_{[1,14]}$	$ETH_{[1,14]}$	$BTC_{[1,14]}$	$Index_{[1,14]}$
$Cases_{[-14,-1]} \times Policy_t$	25.546*	13.903	23.174*			
	(13.091)	(11.193)	(11.809)			
$Deaths_{[-14,-1]} \times Policy_t$				1.384	1.279	0.952
				(1.205)	(0.866)	(0.970)
$Cases_{[-14,-1]}$	6.218	-0.305	2.799			
	(3.819)	(3.236)	(2.778)			
$Deaths_{[-14,-1]}$				1.613	0.358	1.468
				(1.474)	(1.364)	(1.455)
$Policy_t$	21.763**	11.624	19.370**	2.524**	1.842*	1.828*
	(10.461)	(9.024)	(9.401)	(1.095)	(1.037)	(0.977)
$Ret_{[-14,-1]}$	-2.463**	-0.875	-1.586*	1.784	-0.664	-1.054
	(1.181)	(0.760)	(0.927)	(1.094)	(0.747)	(0.870)
$Intercept$	8.219**	3.554*	5.509**	4.047**	2.595**	5.526**
	(2.177)	(1.965)	(1.738)	(0.939)	(0.771)	(0.730)

Table 5 shows the results of equation (1) re-configured to incorporate a two-week estimation period. We adjust the variables to account for a two-week estimation period. We estimate the dependent variable, listed in the top row, against the corresponding variables on each row below that. We estimate our regressions using Newey and West (1987) standard errors and control for up to 14 days of lag. Our standard errors are in parentheses. ** and * represent statistical significance at the 5% and 10% level respectively.

Secondly, an increasingly prominent role played by institutional investors (Alexander and Imeraj, 2021; Doan et al., 2022) which could dilute the impact of unsophisticated investor behaviour, proxied by Google Trends, upon Bitcoin markets.

Finally, we also present in Table 5 a further robustness test where we extend our analysis to a two week horizon. In this setting we expand our backward looking analysis up to 14 days, and our forward looking analysis by the same.

6 Conclusions

Much remains to be learned about the asset pricing of cryptocurrencies. We have documented three key findings. Firstly, the self-fulfilling safe haven effect is heavily moderated by government policy. Secondly, the ordinary asset pricing dynamics of cryptocurrency, as documented by Liu and Tsyvinski (2021), are disrupted during the pandemic. Thirdly, that our results remain robust to key determinants of cryptocurrency returns, namely momentum and investor-attention.

Investor optimism in cryptocurrencies during the pandemic is most plausibly explained by the self-fulfilling safe haven effect. Our results provide support for this. Furthermore, we show that investors impute their expectations surrounding the duration of the pandemic using signals from the government. Higher case numbers alongside increasing government intervention is when optimism in cryptocurrency is at its peak. Policy therefore acts as a mechanism which amplifies how investors respond to virus prevalence.

The results of this study have important theoretical implications for market efficiency. Results contradict the semi-strong form of the efficient market hypothesis since we present evidence that state and government response to the pandemic can be used to predict returns. Results in Section 4 also suggest speculative bubble effects are present in cryptocurrency markets during the pandemic. This tallies with recent suggestions that short-term booms and busts are an intrinsic feature of these markets (Fry, 2018).

We contribute to the growing understanding of asset-pricing dynamics in cryptocurrency. In addition, we highlight the importance of government intervention as a signal of optimism for cryptocurrency investors. Cryptocurrency markets and economic aspects of the pandemic remain subjects of significant interest and importance. Future work will include the factorisation of the various policies and their effects as variables to extend the above framework. Future work will also address novel applications of behavioural finance and speculative-bubble models.

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