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Cryptocurrencies, Technology Stocks, Covid-19 and US Policy Responses: A Fractional Integration Analysis

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CRYPTOCURRENCIES, TECHNOLOGY STOCKS, COVID-19 AND US POLICY RESPONSES: A FRACTIONAL INTEGRATION ANALYSIS

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Abstract

This paper assesses the impact of US policy responses to the Covid-19 pandemic on various cryptocurrencies and also technology stocks using fractional integration techniques. More precisely, it analyses the behaviour of the percentage returns in the case of nine major coins (Bitcoin - BITC, Stella - STEL, Litecoin - LITE, Ethereum - ETHE, XRP (Ripple), Dash, Monero - MONE, NEM, Tether – TETH) and two technology related stock market indices (the KBW NASDAQ Technology Index – KFTX, and the NASDAQ Artificial Intelligence index - AI) over the period 1 January 2020-5 March 2021. The results suggest that fiscal measures such as debt relief and fiscal policy announcements had positive effects on the series examined during the pandemic, when an increased mortality rate tended instead to drive them down; by contrast, monetary measures and announcements appear to have had very little impact and the Covid-19 containment measures none at all.

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1. Introduction

The Covid-19 pandemic is a global shock that has had a significant impact on both the real economy and international financial markets since the initial outbreak in Wuhan, China in December 2019. Baker et al. (2020) concluded that it affected stock markets more than any other infectious disease, including the Spanish Flu. Al-Awadhi et al. (2020) found that both the daily growth in reported cases and the increasing number of deaths caused by Covid-19 resulted in a sharp fall in Chinese stock returns. Corbet et al. (2020) analysed the dynamic linkages between the Chinese stock market and cryptocurrencies and reported that the latter do not act as hedges or safe havens, but instead amplify contagion. Baffes and Nagle (2020) found that the pandemic caused the largest slump in crude oil prices since the Gulf war. Other studies reporting a negative impact of the Covid-19 pandemic on crude oil and conventional asset prices include Sharif et al. (2020), Salisu et al. (2020), Topcu and Gulal (2020), Ashraf (2020), Zhang et al. (2020) , Salisu et al. (2021), Okorie and Lin (2021), Mazur et al. (2021), Tiwari et al. (2021), Le et al. (2021), among others. It is also well known that governments' policy responses have generally helped the global economy and financial markets. For example, in the case of US, the introduction of relief schemes such as the Coronavirus Aid, Relief, and Economic Security (CARES) Act was followed by an increase in US aggregate stock indices, namely the NASDAQ, S&P 500 and DJI, by 7.33%, 7.3% and 7.73% respectively. Caporale et al. (2021) and Abakah et al. (2021) provided evidence of the positive impact of US government Covid-19 policy responses on US aggregate and sectoral indices respectively. Mazey and Richardson (2020) and Bouri et al. (2021) documented a similar impact in the case of New Zealand, and Huynh et al. (2021) in the case of Australia.

Only a few papers, though, have that investigated the effects of the Covid-19 pandemic and of policy responses on the cryptocurrency and technology markets (Le et al., 2021; Tiwari et al., 2021; Corbet et al., 2020; Mnif et al., 2020; Rubbaniy et al., 2021; Umar et al., 2021; Iqbal et al., 2021; Nasreen et al., 2021). The initial impact of the pandemic was clearly very severe. On 8 March 2020 (by which time several European countries had already introduced lockdown measures) a massive sale of cryptocurrencies led to the loss of about $21 billion in the total market capitalisation value within 24 hours; this was followed by Black Monday in the stock market on 9 March 2020. Shortly after, on 11 March 2020, the World Health Organisation declared Covid-19 a global pandemic, and two days later, on 13 March 2020, the cryptocurrency markets lost more than half of their total capitalisation value. However, they had fully recovered by the end of May 2020, and subsequently exceeded the $300 billion dollar threshold at the end of July, the $500 billion one at the end of November, and finally recorded a peak market value of over $760 billion on 31 December 2020.

Since the US is the main country in terms of trading volumes on online exchanges (see Figure 1 for Bitcoin) it is plausible to assume that US policy responses to the Covid-19 pandemic would have had a significant impact on the cryptocurrency markets. The present study aims to investigate this issue in the case of nine major cryptocurrencies (Bitcoin - BITC, Stella - STEL, Litecoin - LITE, Ethereum - ETHE, XRP (Ripple), Dash, Monero - MONE, NEM, Tether – TETH) and also of two indices for technology stocks (the KBW NASDAQ Technology Index – KFTX, and the NASDAQ Artificial Intelligence index – AI). Its contribution to the literature is twofold. First, it provides evidence on both the direct impact of the pandemic and the effects of US policy responses on those markets, such a comprehensive analysis not having been carried out before. Second, it uses a very general and flexible

approach allowing for fractional values of the integration/cointegration parameter d and thus for a much wider range of possible stochastic behaviours of the series under examination. The layout of the paper is as follows: Section 2 describes the data; Section 3 outlines the econometric framework; Section 4 presents the main empirical findings; Section 5 offers some concluding remarks.
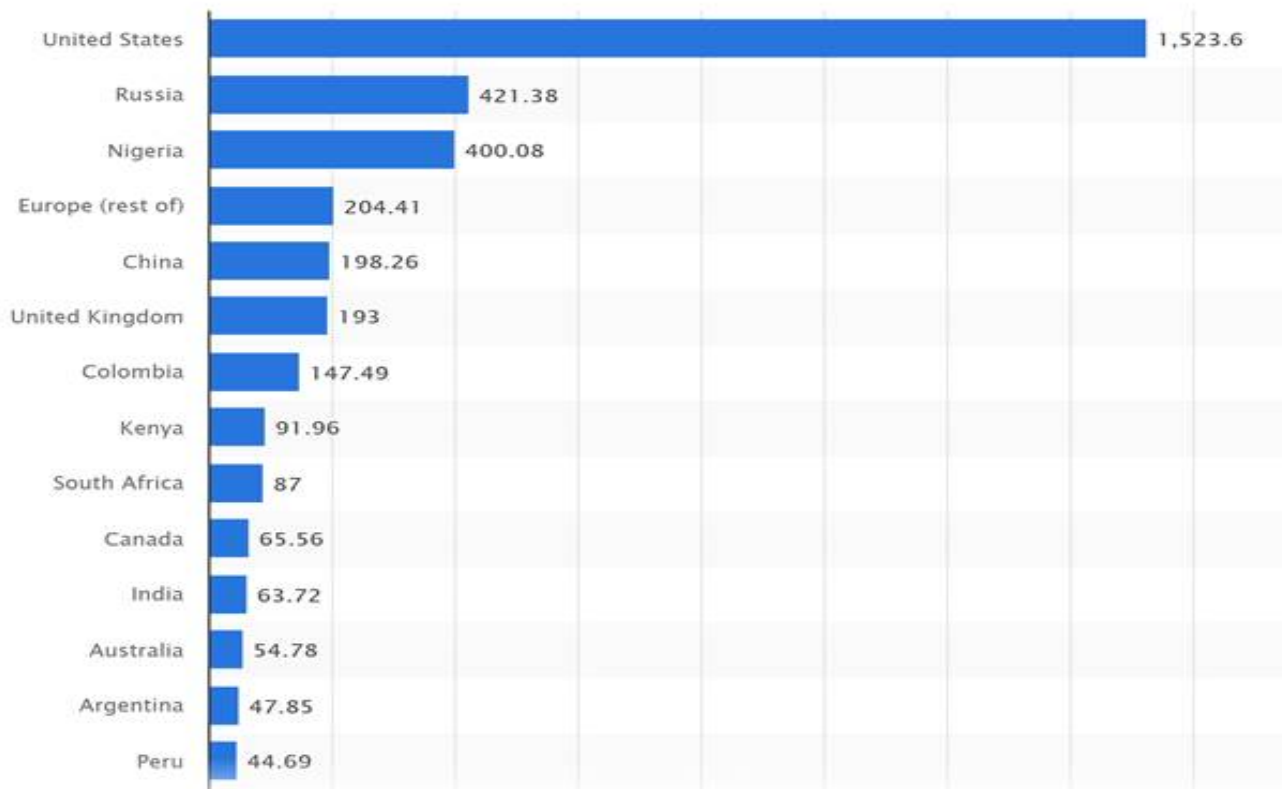

Figure 1 Bitcoin trading volume on online exchanges in various countries worldwide in 2020 *(in million U.S. dollars). Source: Statista[1].*

[1] https://www.statista.com/statistics/1195753/bitcoin-trading-selected-countries/

2.   Data Description

To analyse the cryptocurrency markets, the most representative coins are selected, namely those that have been in existence for more than 3 years with a market capitalization above the average for the market as a whole as of 5 March 2021. Specifically, daily prices are collected for nine major coins (Bitcoin - BITC, Stella - STEL, Litecoin - LITE, Ethereum - ETHE, XRP (Ripple), Dash, Monero - MONE, NEM and Tether – TETH) from https://coinmarketcap.com. Two more series are used for the analysis, namely the KBW NASDAQ Technology Index (KFTX) constructed to track the performance of listed financial technology (Fintech) firms in the US following Le et al. (2021), and the NASDAQ Artificial Intelligence Robotics (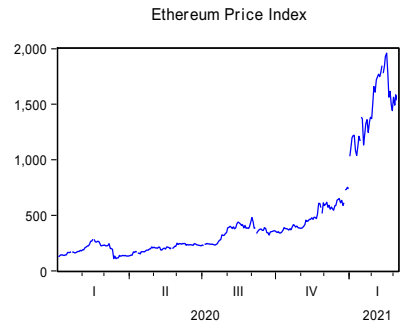AI) index constructed to track the performance of AI firms following Tiwari et al. (2021). The sample period goes from 1st January 2020 to 5th March 2021. Figure 2 displays time series plots of the series examined. It can be seen that in all cases there were sharp falls at the peak of the pandemic followed by a recovery.
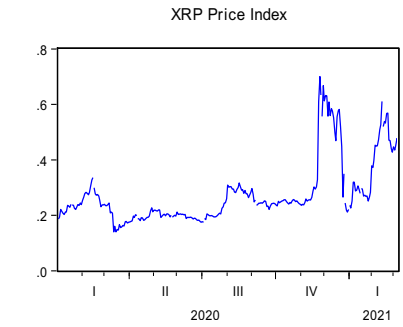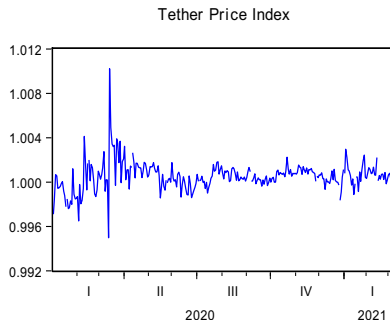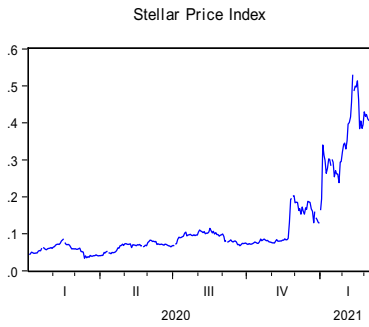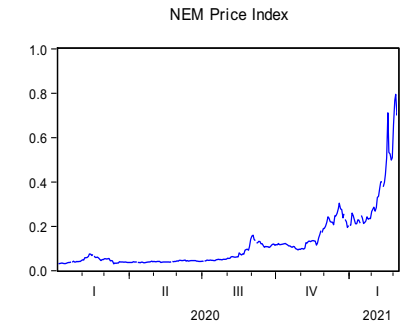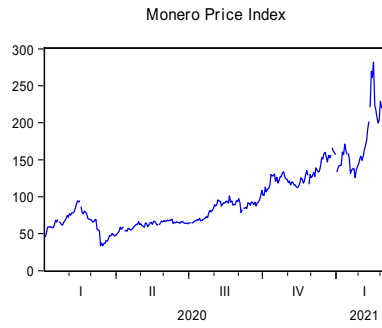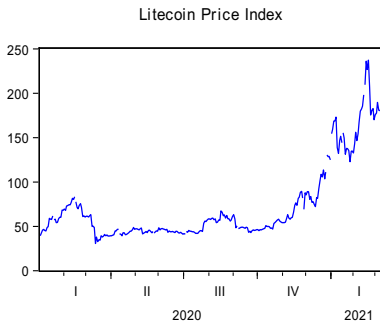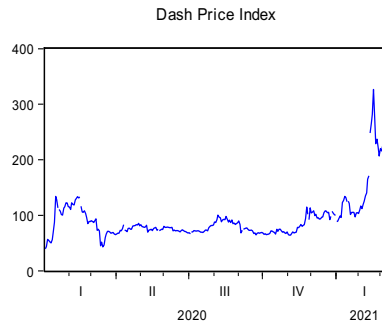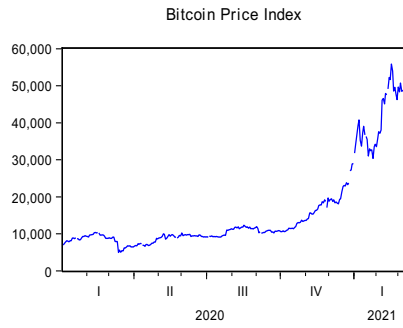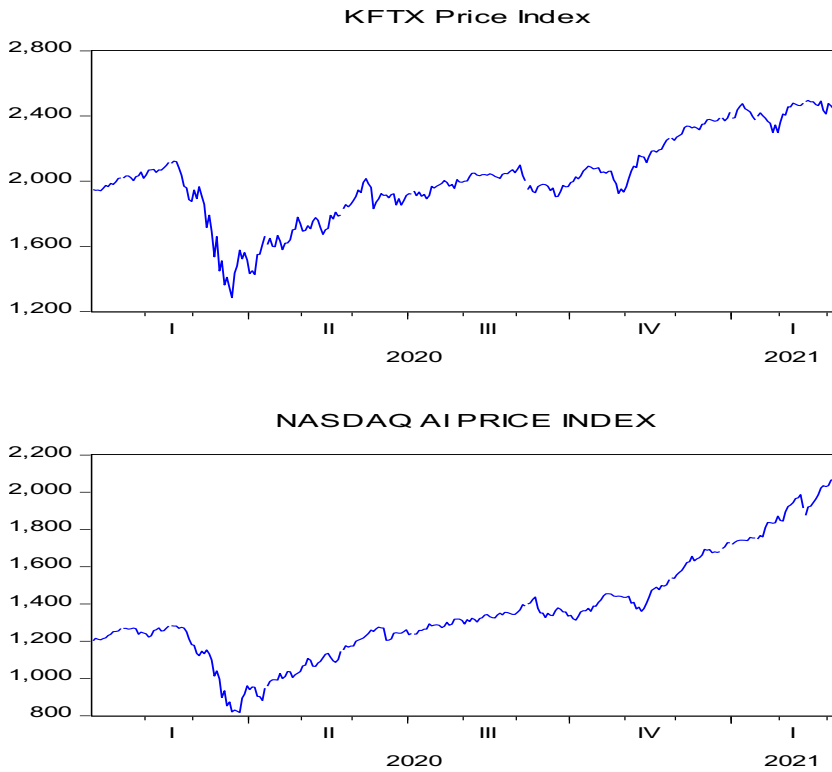
Figure 2 Price indices of cryptocurrencies, FinTech and AI.

The Covid-19 policy response measures have been taken from the Oxford Coronavirus Government Response Tracker (https://ourworldindata.org/policy-responses-covid.com). The Containment and Health Index is a composite measure based on: workplace closures, school closures, public events cancellations, public gatherings restrictions, public transport closures, stay-at-home restrictions, public campaigns restrictions, internal movement restrictions, restrictions on international travels, testing policy, magnitude of contact tracing, covering of face and vaccine policy. The index on any given day is calculated as the mean score of the thirteen metrics, each taking a value between 0 and 100. A higher score indicates a stricter response (i.e. 100 = strictest response).

The fiscal policy response variables include: income support, which provides information about the extent to which the US government has covered salaries or provided universal basic

income, direct cash payments, or similar, to people who lost their jobs or could not work; debt or contract relief, which indicates whether the US government froze loan repayments and other types of utility payments, banned evictions etc. during the pandemic. Finally, the effective Federal Funds rate is included to account for monetary policy responses

We also construct shift dummies corresponding to key dates when the US government made monetary policy and fiscal policy announcements. In the case of the former, the chosen date is 15th March 2020, when the Federal Funds rate was lowered by 150bp to 0-0.25bp. As for fiscal announcements, the following dates were selected: 28th December 2019, when President Trump signed a US $ 868bn (about 4.1 percent of GDP) coronavirus relief and government funding bill as part of the Consolidated Appropriations Act of 2021; 8th August 2020, when he issued executive orders, mostly to address the expiration of certain Coronavirus reliefs provided by previous legislation; 11th March 2021, when the House of Representatives approved the American Rescue Plan, which provides another round of coronavirus relief with an estimated cost of $1,844bn (about 8.8 percent of 2020 GDP).

Finally, following Ozkan et al. (2021), the direct impact of the pandemic is taken into account by using two alternative measures of the Covid-19 mortality rate (DR), namely (i) the ratio of the number of confirmed Covid-19 deaths to the total number of confirmed cases, which is widely referred to as the case-fatality rate (DR1), and (ii) the crude fatality rate (DR2), defined as the number of deaths per 100,000 of the population.

3.   Methodology

We consider the following regression model:

$$y(t) = \beta^T z(t) + x(t); \qquad (1 - L)^d x(t) = u(t). \tag{1}$$

where $y(t)$ denotes the percentage returns of each of the market indices considered (namely Bitcoin - BITC, Stella - STEL, Litecoin - LITE, Ethereum - ETHE, Ripple - XPR, Dash - DASH, Monero - MONE, NEM, Tether – TETH, KFTX and AI) which are calculated as the first differences of the logged series, β is a vector of unknown parameters to be estimated including a constant; $z(t) = (1,$ CHI (t), ISP(t), DRP(t), EFFR(t), MMFPM(t), FP(t), DR(t))^T is a vector including the regressors, where CHI stands for the Containment Health Index, ISP for Income Support Policy, DRP for Debt-Relief Policy, EFFR for the Effective Federal Funds Rate, MMFPM and FP are two dummies corresponding to policy announcements concerning (i) Monetary and Macro-Financial Policy Measures and (ii) Fiscal Policy, and DR for the Mortality Rate per 100,000 people. $x(t)$ is assumed to be an $I(d)$ process with the differencing parameter d to be estimated from the data; finally $u(t)$ is an $I(0)$ process, which is assumed in turn to be a white noise and a weakly autocorrelated process. Note that the second equation in (1) implies that $x(t)$ is integrated of order d (where L is the lag operator, i.e., $L^k x(t) = x(t-k)$), and thus if $d > 0$ the series displays long memory, with higher values of d indicating higher dependence between the observations, even if they are far apart in time.

The estimation is carried out for the d-differenced regression following the approach developed in Robinson (1994); his procedure tests the null hypothesis:

$$H_o : \ d \ = \ d_o,$$

(2)

in (1) for any real value d_o. Thus, under the null hypothesis H$_o$ (2), the two equalities in equation (1) can be expressed as

$$\widetilde{y}(t) \ = \ \beta^T \widetilde{z}(t) \ + \ u(t)$$

(3)

where $\widetilde{y}(t) = (1 - L)^{d_o} y(t)$ and $\widetilde{z}(t) = (1 - L)^{d_o} z(t)$, and noting that $u(t)$ is $I(0)$ by construction, the estimation of β can be carried out using OLS (GLS) (see, e.g. Gil-Alana and Robinson, 1997 for a full description of this procedure).

4. Empirical Results

First we report the results under the assumption of white noise errors using in turn each of the two measures of the mortality rate (see Table 1 and 2), and then the corresponding estimates when allowing for weakly autocorrelated process as in the non-parametric model of Bloomfield (1973; see Table 3 and 4).

Table 1 displays the results when assuming white noise errors and using DR1. It can be seen that the constant is significant in the majority of cases, whilst DRP is significant and positive for eight out of the eleven series examined, EFFR is positive in the case of TETH and negative for KFTX and AI, and insignificant in all other cases. MMFPM is significant and positive for three cryptocurrencies (BITC, ETHE, TETH) and the Fintech index (KFTX), and FP for eight cryptocurrencies as well as the AI index. Finally, DR1 is also significant and negative in nine cases, whilst CHI (the Covid-19 containment measures) and ISP are not significant. Note also that the null of $d = 0$ cannot be rejected in the majority of cases and evidence of anti-persistence ($d < 0$) is obtained only for KFTX.

INSERT TABLE 1 ABOUT HERE

Table 2 presents the estimates for the corresponding model including DR2 instead of DR1. It can be seen that the estimates of d are now smaller than in the previous case. Short memory is detected in most series and anti-persistence in the case of TETH and KFTX. The most significant regressors are the constant, DRP and FP (the latter two having a positive effect) and DR2 (with a negative effect). EFFR is significant only for TETH (with a positive impact) and for KFTX and AI (with a negative effect). Again, CHI and ISP play no role.

INSERT TABLE 2 ABOUT HERE

Table 3 includes the estimated coefficients when using DR1 as the mortality rate and allowing for autocorrelated (Bloomfield) errors. The results are consistent with previous ones. DRP is significant and positive in a number of cases (BITC, STEL, LITE, ETHE, MONE, NEM). There is also is a significant and positive impact of MMFPM on NEM and TETH and of FP on most series. Finally, significant and negative coefficients on EFFR are estimated for TETH and KFTX, and the coefficient on DR1 is also generally negative when significant whilst those on CHI and ISP are insignificant.

INSERT TABLE 3 ABOUT HERE

Finally, Table 4 reports the results for the model including DR2 and under the assumption of autocorrelated disturbances. TETH is the only series showing anti-persistence. In all the other cases, the null of d = 0 (short memory) cannot be rejected. The constant is significant in many cases. Significant and positive coefficients on DRP, FP, EFFR and TETH are estimated for most series, whilst the coefficient on DR2 is significant but negative and those on CHI, ISP and MMFPM are now insignificant.

INSERT TABLE 4 ABOUT HERE

On the whole, these findings suggest that fiscal measures such as debt relief and fiscal policy announcements had a positive impact on the markets examined during the pandemic, when an increased mortality rate tended instead to drive them down; by contrast, there is little evidence of an impact of monetary measures and announcements, and the Covid-19 containment measures appear not to have had any impact.

5.   Conclusions

This paper examines the impact of US policy measures on various cryptocurrencies as well as two technology related stock market indices during the Covid-19 pandemic. This is an interesting issue to address given the fact that the US is the main country in terms of trading volumes on online exchanges for cryptocurrencies and also for technology stocks. Specifically, the analysis is conducted for the percentage returns in the case of nine major cryptocurrencies (Bitcoin - BITC, Stella - STEL, Litecoin - LITE, Ethereum - ETHE, XRP (Ripple), Dash, Monero - MONE, NEM, Tether – TETH) and two technology related market indices (the KBW NASDAQ Technology Index – KFTX, and the NASDAQ Artificial Intelligence index - AI) over the period from 1st January 2020 to 5th March 2021. The adopted framework allows for both the direct impact of the pandemic (through a higher mortality rate) and the effects of US policy actions and announcements on the markets being investigated. Moreover, a very general and flexible approach allowing for fractional values of the integration parameter d is used; this includes a wide range of stochastic behaviours of the series of interest. As a robustness check, two measures of the mortality rate are considered in turn and also two alternative assumptions are made about the disturbances, which are modelled as a white noise and an autocorrelated process (as in Bloomfield, 1973) respectively. The results provide clear evidence that, despite the direct negative impact of the pandemic, US measures and announcements had a positive effect on the markets examined, whilst monetary actions and announcements appear to have had a very limited impact and the Covid-19 containment measures none at all. This represents useful information to be used by policy makers in the event of future pandemics.

Future research could investigate additional issues such as the possible presence of nonlinearities (for instance, using a model with Chebyshev polynomials as in Cuestas and Gil-

Alana, 2016), endogenous structural breaks (applying the tests developed by Bai and Perron, 2003 and, in the specific context of fractional integration, by Gil-Alana, 2008 and Hassler and Meller, 2014) and gradually evolving parameters (by carrying out recursive and/or rolling estimation).

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Table 1: Estimated coefficients for the returns with DR1 and white noise errors

Series	d	Constant	CHI	ISP	DRP	EFFR	MMFPM	FP	DR1
BITC	-0.08 (-0.14, 0.00)	**0.00621** **(2.08)**	0.00001 (0.34)	0.00005 (0.02)	**0.00909** **(3.69)**	-0.00309 (-0.90)	**0.00340** **(1.98)**	**0.01281** **(2.95)**	**-0.1588** **(-3.04)**
STEL	0.00 (-0.08, 0.10)	**0.00756** **(1.97)**	0.00002 (0.26)	0.00001 (0.05)	**0.00935** **(1.90)**	-0.00375 (-0.51)	0.00163 (0.29)	**0.01740** **(1.91)**	**-0.1599** **(-1.75)**
LITE	-0.09 (-0.16, 0.00)	**0.00462** **(1.77)**	0.00006 (0.04)	0.00010 (0.06)	**0.00703** **(2.28)**	-0.00125 (-0.29)	0.00179 (0.59)	**0.01196** **(2.23)**	**-0.1172** **(-1.84)**
ETHE	-0.07 (-0.14, 0.01)	**0.00816** **(1.95)**	0.00008 (0.15)	0.00005 (0.03)	**0.01050** **(2.97)**	-0.00158 (-0.33)	**0.00440** **(1.98)**	**0.01345** **(2.24)**	**-0.1946** **(-2.67)**
XRP	-0.01 (-0.09, 0.08)	0.00310 (0.45)	0.00006 (0.07)	0.00001 (0.06)	0.00415 (0.73)	-0.00196 (-0.27)	0.00156 (0.28)	0.00565 (0.63)	-0.0699 (-0.60)
DASH	0.03 (-0.06, 0.14)	0.00678 (0.84)	-0.00001 (-0.12)	-0.00012 (-0.03)	0.00418 (0.63)	0.00198 (0.25)	-0.00033 (-0.05)	**0.01051** **(1.95)**	-0.0856 (-0.64)
MONE	-0.05 (-0.12, 0.03)	**0.00533** **(1.93)**	0.00006 (0.07)	-0.00006 (0.03)	**0.00676** **(2.00)**	-0.00235 (-0.53)	0.00326 (1.00)	**0.00617** **(1.90)**	**-0.1213** **(-1.75)**
NEM	-0.01 (-0.08, 0.07)	**0.00956** **(1.74)**	0.00006 (0.07)	0.00032 (0.11)	**0.01425** **(2.74)**	-0.00109 (-0.16)	0.00546 (1.09)	**0.01715** **(2.09)**	**-0.23548** **(-2.22)**
TETH	-0.61 (-0.66, 0.14)	**0.00001** **(3.68)**	0.00001 (0.03)	-0.00002 (-0.09)	-0.00001 (-0.29)	**0.00001** **(3.00)**	**0.00007** **(1.94)**	**0.00002** **(2.05)**	**-0.00034** **(-4.22)**
KFTX	-0.11 (-0.17 -0.04)	0.00073 (0.66)	0.00005 (0.32)	0.00003 (0.07)	**0.00228** **(2.41)**	**-0.00240** **(-1.82)**	**0.00107** **(1.96)**	0.00144 (0.85)	**-0.0302** **(-1.74)**
AI	0.02 (-0.05, 0.10)	0.00168 (0.93)	0.00007 (0.32)	0.00023 (0.29)	**0.00368** **(2.48)**	**-0.00319** **(-1.77)**	0.00139 (0.97)	**0.00330** **(1.65)**	**-0.05493** **(-1.83)**

Note: in brackets the 95% confidence interval in the case of d and the t-statistic for the other coefficients; significant coefficients are displayed in bold.

Table 2: Estimated coefficients for the returns with DR2 and white noise errors

Series	d	Constant	CHI	ISP	DRP	EFFR	MMF PM	FP	DR2
BITC	-0.08 (-0.15, 0.00)	**0.00609 (2.04)**	0.00009 (0.24)	0.00005 (0.02)	**0.00920 (3.65)**	-0.00342 (-0.99)	0.00188 (0.77)	**0.01963 (3.95)**	**-19.822 (-3.46)**
STEL	-0.01 (-0.09, 0.10)	**0.00729 (1.90)**	0.00001 (0.21)	0.00005 (0.12)	**0.00944 (1.70)**	-0.00376 (-0.54)	0.00077 (0.14)	**0.02650 (2.63)**	**-23.518 (-1.92)**
LITE	-0.09 (-0.16, 0.01)	**0.00449 (1.94)**	-0.00008 (-0.01)	0.0010 (0.06)	**0.00714 (2.31)**	-0.00152 (-0.36)	0.00088 (0.29)	**0.01788 (2.90)**	**-16.075 (-2.28)**
ETHE	-0.08 (-0.14, 0.00)	**0.00793 (2.01)**	0.00006 (0.06)	0.00007 (0.03)	**0.01065 (3.18)**	-0.00195 (-0.42)	0.00231 (0.71)	**0.02133 (3.23)**	**-23.273 (-3.06)**
XRP	-0.01 (-0.09, 0.08)	0.00300 (0.44)	0.00004 (0.04)	0.00002 (0.06)	0.00416 (0.73)	-0.00199 (-0.28)	0.00098 (0.18)	0.00891 (0.86)	-9.093 (-0.73)
DASH	0.03 (-0.05, 0.12)	0.00663 (0.83)	-0.00001 (-0.15)	-0.00012 (0.03)	0.00416 (0.62)	0.00203 (0.25)	-0.0005 (-0.08)	**0.01590 (1.78)**	-13.585 (-0.94)
MONE	-0.06 (-0.13, 0.03)	**0.00514 (1.96)**	0.00007 (0.01)	-0.00005 (-0.02)	**0.00681 (2.13)**	-0.00250 (-0.58)	0.00179 (0.58)	**0.01034 (1.78)**	**-13.308 (-1.85)**
NEM	-0.02 (-0.09, 0.07)	**0.00920 (1.96)**	0.00006 (0.07)	0.00032 (0.12)	**0.01927 (2.89)**	-0.00126 (-0.20)	0.00339 (0.71)	**0.02808 (3.09)**	**-30.226 (-2.76)**
TETH	-0.61 (-0.65 -0.57)	**0.00001 (3.66)**	-0.000002 (-0.04)	-0.000002 (-0.09)	0.00002 (0.05)	**0.00001 (2.55)**	0.00005 (0.90)	**0.00002 (2.03)**	**-0.0379 (-3.37)**
KFTX	-0.12 (-0.19 -0.05)	0.00070 (0.67)	0.00003 (0.27)	0.00003 (0.07)	**0.00229 (2.56)**	**-0.00244 (-1.93)**	0.00070 (0.88)	**0.00249 (1.94)**	**-3.374 (-1.93)**
AI	0.00 (-0.07, 0.07)	0.00157 (0.98)	0.000005 (0.27)	0.000020 (0.28)	**0.00370 (2.76)**	**-0.00311 (-1.87)**	0.00087 (0.68)	**0.00566 (2.35)**	**-6.647 (-2.26)**

Note: in brackets the 95% confidence interval in the case of d and the t-statistic for the other coefficients; significant coefficients are displayed in bold.

Table 3: Estimated coefficients for the returns with DR1 and Bloomfield errors

Series	d	Constant	CHI	ISP	DRP	EFFR	MMFPM	FP	DR1
BITC	0.03 (0.10, 0.26)	**0.00651** **(1.92)**	0.00002 (0.29)	0.00003 (0.14)	**0.00893** **(2.03)**	-0.00378 (-0.71)	0.00313 (0.81)	**0.00104** **(1.98)**	**-0.1492** **(-1.69)**
STEL	-0.03 (-0.18, 0.19)	**0.00753** **(1.95)**	0.00002 (0.25)	0.00010 (0.03)	**0.00942** **(1.99)**	-0.00370 (-0.56)	0.00176 (0.36)	**0.01764** **(2.18)**	**-0.1649** **(-1.91)**
LITE	-0.01 (-0.16, 0.19)	0.00479 (0.86)	0.00003 (0.04)	0.00017 (0.07)	**0.00689** **(1.94)**	-0.00122 (-0.20)	0.00115 (0.25)	**0.01174** **(1.91)**	**-0.1097** **(-1.96)**
ETHE	0.05 (-0.08, 0.26)	**0.00838** **(1.96)**	0.00001 (0.11)	0.00018 (0.05)	**0.00989** **(1.92)**	-0.00216 (-0.28)	0.00386 (0.62)	**0.01068** **(1.92)**	**-0.1740** **(-1.94)**
XRP	0.06 (-0.09, 0.28)	0.00350 (0.35)	0.00008 (0.06)	0.00006 (0.01)	0.00384 (0.47)	-0.00238 (-0.25)	0.00061 (0.07)	0.00662 (0.56)	-0.0642 (-0.39)
DASH	-0.02 (-0.17 0.21)	0.00599 (0.97)	-0.00001 (0.12)	-0.00002 (0.12)	0.00415 (0.80)	0.00231 (0.35)	-0.00024 (-0.05)	**0.01093** **(1.93)**	-0.0892 (-0.85)
MONE	0.03 (-0.09, 0.27)	0.00581 (0.94)	-0.00002 (0.03)	0.00020 (0.07)	**0.00645** **(1.97)**	-0.00240 (-0.39)	0.00278 (0.57)	0.00549 (0.72)	-0.1159 (-1.14)
NEM	-0.02 (-0.12, 0.11)	**0.00953** **(1.91)**	0.00001 (0.41)	0.00030 (0.11)	**0.01417** **(2.88)**	-0.00102 (-0.16)	**0.00509** **(1.97)**	**0.01745** **(2.22)**	**0.02353** **(-2.34)**
TETH	-0.55 (-0.61 -0.44)	**0.00001** **(2.59)**	-0.00003 (-0.07)	-0.00006 (-0.07)	-0.00004 (-0.34)	**-0.00001** **(-2.41)**	**0.000002** **(1.64)**	**0.00007** **(1.74)**	**-0.00031** **(-2.89)**
KFTX	0.16 (-0.01, 0.44)	0.00126 (0.26)	0.00001 (0.21)	0.00036 (0.17)	0.00232 (0.60)	**-0.00406** **(-1.95)**	0.00088 (0.10)	0.00145 (0.28)	-0.03912 (-0.53)
AI	0.16 (0.03, 0.43)	0.00142 (0.38)	0.00002 (0.41)	0.00002 (0.13)	0.00267 (0.88)	-0.00253 (0.84)	0.00143 (0.50)	0.00342 (0.87)	-0.00432 (-0.75)

Note: in brackets the 95% confidence interval in the case of d and the t-statistic for the other coefficients; significant coefficients are displayed in bold.

Table 4: Estimated coefficients for the returns with DR2 and Bloomfield errors

Series	d	Constant	CHI	ISP	DRP	EFFR	MMFPM	FP	DR2
BITC	0.04 (-0.09, 0.26)	**0.00626** **(1.92)**	0.00001 (0.23)	0.00002 (0.10)	**0.00883** **(1.91)**	-0.00372 (-0.67)	0.00220 (0.49)	**0.01702** **(2.15)**	**19.0966** **(-1.90)**
STEL	-0.05 (-0.21, 0.18)	**0.00725** **(1.95)**	0.00001 (0.19)	0.00010 (0.04)	**0.00958** **(2.12)**	-0.00376 (-0.62)	0.00066 (0.15)	**0.02666** **(3.11)**	**-23.574** **(2.32)**
LITE	-0.01 (-0.15, 0.19)	0.00461 (0.83)	0.00001 (0.01)	0.00018 (0.07)	**0.00691** **(1.99)**	-0.00126 (-0.21)	0.00056 (0.12)	**0.01806** **(2.15)**	**-16.316** **(-1.79)**
ETHE	0.04 (-0.11, 0.23)	**0.00802** **(1.98)**	0.00006 (0.06)	0.00018 (0.05)	**0.00991** **(1.71)**	-0.00202 (-0.27)	0.00231 (0.39)	**0.01845** **(1.76)**	**-21.876** **(-1.93)**
XRP	0.05 (-0.10, 0.28)	0.00331 (0.35)	0.00006 (0.05)	0.00005 (0.01)	0.00387 (0.50)	-0.00228 (-0.25)	0.00040 (0.05)	0.01019 (0.78)	-9.639 (-0.58)
DASH	-0.01 (-0.14 0.21)	0.00596 (0.92)	-0.00001 (-0.15)	-0.00002 (-0.08)	0.00413 (0.76)	-0.00231 (-0.33)	-0.00070 (-0.13)	**0.01607** **(1.64)**	**-13.458** **(-1.92)**
MONE	0.04 (-0.12, 0.28)	**0.00568** **(1.78)**	-0.00006 (-0.07)	0.00022 (0.07)	**0.00638** **(1.90)**	-0.00234 (-0.37)	0.00144 (0.28)	**0.00967** **(1.96)**	**-12.998** **(-1.82)**
NEM	0.03 (-0.14, 0.12)	**0.00917** **(1.74)**	-0.00005 (-0.07)	0.00030 (0.12)	**0.01420** **(3.03)**	-0.00124 (-0.20)	0.00296 (0.64)	**0.02830** **(3.26)**	**-30.225** **(-2.90)**
TETH	-0.54 (-0.61 -0.44)	**0.00001** **(2.41)**	-0.00001 (-0.06)	-0.00001 (-0.07)	-0.00001 (-0.12)	**0.00001** **(2.02)**	0.00002 (0.54)	**0.00005** **(1.81)**	**-0.0321** **(-2.08)**
KFTX	0.15 (-0.01, 0.42)	0.00109 (0.24)	0.00001 (0.20)	0.00033 (0.16)	0.00228 (0.62)	-0.00385 (-1.04)	0.00006 (0.01)	0.00276 (0.49)	-4.1655 (-0.53)
AI	0.15 (-0.01, 0.44)	0.00130 (0.37)	0.00001 (0.38)	0.00022 (0.14)	0.00271 (0.94)	-0.00243 (-0.84)	0.00133 (0.49)	**0.00588** **(1.85))**	**-6.6966** **(-1.90)**

Note: in brackets the 95% confidence interval in the case of d and the t-statistic for the other coefficients; significant coefficients are displayed in bold.