Carbon allowances and Bitcoin: a quantile spillover study

Abstract

The Paris Agreement (COP21) sets out a global framework to limit global warming below 2C°. Therefore the target of carbon neutrality has a key role. In this context countries have implemented cap-and-trade markets of carbon emissions allowances, in order to manage the impact of CO2 released by companies. Over recent years, the introduction of cryptocurrencies has given a new drive to pollution, because of the massive energy consumption, due to mining activity. The paper investigates the tail relationship between the carbon credit market and the price of Bitcoin. For this purpose, we use two novel econometric models: the multivariate-quantile conditional autoregressive (MVMQ-CAViaR) model and the Granger causality across quantiles. The results suggest that there is a downside risk spillover, i.e. tail codependence. We find that Bitcoin spillovers have a stronger impact on the carbon market. On the other hand, we find that Carbon not Granger causes Bitcoin. The results of the Granger analysis confirm the multivariate quantile model's findings, i.e. the Bitcoin influences the carbon market in the lower quantiles. We deem our results useful for policymakers, in order to improve the framework of carbon emissions allowances.

Keywords: Carbon allowances; Bitcoin; Carbon footprint; VAR quantile; Risk spillover

JEL Codes: C22, F64, G1, Q54, Q56

1 Introduction

During Paris Climate Conference, COP21 (UNFCCC, 2015) 195 countries, representing nearly 90% of global greenhouse gas (GHG) emissions, adopted the first universal and legally binding agreement on the global climate. The agreement entered into force in November 2016 and represented the reference framework for global actions to reduce greenhouse gas emissions. The agreement defines a global action plan intended to put the world back on track to avoid dangerous climate change by limiting global warming below 2ºC and preferably to 1.5°C. To this purpose, a parallel target is achieving carbon neutrality by 2050, namely a balance between emitting carbon and absorbing carbon from the atmosphere in carbon sinks. It means that all worldwide greenhouse gas emissions will have to be counterbalanced by carbon sequestration, that is removing carbon dioxide from the atmosphere and then storing it.

In light of this, we want to anticipate another extremely topical issue, such as cryptocurrencies and understand what kinds of relationships can link "the right to pollute" (carbon allowances) to Bitcoin. Indeed, the Paris Agreement established market-based mechanisms as one of the international community's key tools to tackle climate change. More than half of these countries have presented national action plans that include market mechanisms as part of their strategies to promote the cost-effective delivery of their nationally determined contributions to the Paris Agreement's objectives.

Formerly, following the Kyoto Protocol (UNFCCC, 1997), flexible market mechanisms were established through the trade of emissions permits. Specifically, the most adopted market scheme is based on the "cap-and-trade" system, i.e. a market-based environmental policy that places a limit to pollutants (CO2) and establishes a market-based price on emissions. The "allowances" for emissions are issued and priced in the primary market through auction mechanisms; then firms buy and sell at prices determined by supply and demand, in order to hold the permission they need to "pollute" through their production (Schmalensee and Stavins, 2017). In these fields, we recall the EU Emission Trading System (EU ETS), the California's AB-32 cap-and-trade system and the US Regional Greenhouse Gas Initiative.

The EU ETS is the world's largest carbon pricing regime [1]. Adopted in 2003 it became active in 2005. The system covers the CO2 emissions of all 27 EU member states plus Iceland, Liechtenstein, and Norway (Ellerman and Buchner, 2007). More specifically, this new carbon pricing system has more than doubled the share of global emissions covered by emissions trading. The EU ETS was implemented in Phases: a pilot Phase from 2005 to 2007, a Phase II from (Kyoto Phase) from 2008 to 2012, Phase III over the period 2013-2020 and Phase IV from 2021 to 2030. The setting of caps and allowances was

[1]Please see the Emissions Trading System: http://ec.europa.eu/clima/policies/ets/index_en.htm. (Accessed 15 March 2021)

decentralized among states over the first two phases (Kruger et al., 2007) The system is cost-effective as it offers considerable flexibility to companies. It creates incentives to save energy and to innovate in low-carbon technologies, such as renewable energy.The first and second phases of the EU ETS required member states to distribute almost all of the emissions allowances freely to regulated sources, but since 2013, member states were allowed to auction larger shares of their allowances. The cap was tightened for Phase II. Allowance prices increased to over €20/tCO2 in 2008, then fell when economic recession brought decreased demand for allowances, due to reduced output in energy-intensive sectors and lower electricity consumption. Prices were down to €10/tCO2 by the fall of 2011, and have remained in the range of €5/tCO2 to €10/tCO2 since then. The impact of recession and of an unorganized regulatory framework, induced to a significant evolution of the system. During Phase III the chased target was decreasing regulated emissions by at least 21% compared to 2005. But most of all, Phase III was characterized by the definition of a unique cap for all the EU and a single set of rules for the allocation. Moreover, there was a radical change in the allocation method: auctioning for the electricity sector and benchmark free allocation for the others. In 2015, in a context of dropped demand and prices, the Market Stability Reserve (MRS) was introduced in order to give flexibility in the allowance supply. Specifically, the MRS is an instrument that addresses the imbalances caused by unanticipated exogenous shocks in regulated emissions and consequently in permissions demand. Finally, Phase IV aims to reach three main objectives: strengthening the price signal by tightening the cap and by enhancing the MSR, better targeting free allocation, and establishing new funding mechanisms for low-carbon innovation and energy sector modernization in lower-income member states (Schmalensee and Stavins, 2017; Verde et al., 2019, 2021).

In 2006 the California's Assembly Bill 32 (AB-32) was enacted, with the aim to cut the state's GHG to the 1990 level by 2020. The document introduces a cap-and-trade system along with other energy efficiency instruments (California Environmental Protection Agency, 2014) such as energy standards for vehicles, buildings, and appliances; renewable portfolio standards for electricity producers; a low carbon fuel standard that requires refineries to reduce the carbon content of motor vehicle fuels. The Californian carbon dioxide emissions market was enacted in 2013 and establishes an annual decline of the cap; it started covering the electricity sold in the state and large-scale manufacturing, and in 2015 was expanded to include fuels in 2015: overall the system covers 85% of the Californian emissions. This system provides a series of peculiar characteristics that make it a virtuous example of carbon emission market among the other existing. First of all, since 2014 California's system was linked to Quebec's one: this fact testifies the importance of linkage between different regions and jurisdictions in order to reduce abatement costs and price volatility, and to restrain market power (Ranson and Stavins, 2012). Furthermore, the Californian AB-32, provides a price structure analogous to a collar: as a matter of fact, along with the cap pledged through an allowance price containment reserve, there is a price floor ensured by an auction reservation price. In this way, manufacturers are protected from competitiveness effects by an output-based updating allocation system, in order to convey free allowances in proportion to previous production levels.

The US Regional Greenhouse Gas Initiative (RGGI), is the first cap-and-trade system of carbon credits in the United States. Limited to the power sector, the program became effective in 2009 with the aim of limiting emissions over the period 2009-2014. The emissions cap was set to decrease by an annual 2.5% each year, beginning in 2015, until it reached an ultimate level 10% below 2009 emissions in 2019. It was originally anticipated that meeting this goal would require a reduction approximately 35% below business-as-usual emissions. Notwithstanding, the joint effects of economic recession and of the drastic decline of gas price over coal, induced the states to loosen the cap by 45% in 2005 and then by 2.5% per year until a 10% cut would be achieved by 2019. The RGGI requires the states to auction at least 25% of their allowances, but in practice they have auctioned virtually all permissions, because of the proceeds that are thereby generated for government programs. The program is a hybrid combination of a cap-and-trade system and a carbon tax: so in actual fact it works like a price collar. Indeed, a price cap is created through a cost-containment by which additional allowances are released and sold when the auction price hits a specified limit level. Conversely, a price floor is made by an auction reserve price. In more detail, any unsold allowance is retired from the market after 3 years carrying out an automatic mechanism for tightening the cap against any chronic allowance surplus (Schmalensee and Stavins, 2017).

The Paris Agreement (Article 2c) also establishes that "finance flows consistent with a pathway towards low greenhouse gas emissions and climate-resilient development". Notwithstanding, there is strong evidence of an association between economic growth, financial development, foreign direct investment, trade openness, and CO2 emissions (Buhari et al., 2020; Canh et al., 2020; Lv and Li, 2021; Nguyen et al., 2021). In this context, the efficient functioning of the aforementioned carbon markets, has a central role in order not to violate the Agreement. The multifaceted evolution of financial markets has shown the disruptive introduction of cryptocurrencies, specifically of Bitcoin, and their massive environmental impact (Bouri et al., 2017; Truby, 2018; Kristoufek, 2020; Corbet et al., 2020; Rehman and Kang, 2020). The peculiar blockchain networks based on the Proof of Work (POW) protocol and the connected "mining" activity, cause growing carbon footprint, therefore raising concerns about Bitcoin's role in climate change (Mora et al., 2018). To work effectively, the machine hardware used to "mine" Bitcoin consumes electricity at a high rate 24h a day, producing vast amounts of heat and emissions; one of the best models has an energy consumption rate of 0.098 W/Gh[2].

[2]Please see: https://www.bitcoinmining.com/bitcoin-mining-hardware. (Accessed 15 March 2021)

Going into detail, as previously anticipated, Nakamoto (2009) developed the digital currency called "Bitcoin"as an alternative and unconventional money. Bitcoins are based on blockchain technology. It is a method for storing and distributing the data created in any process in which action is performed, such as a transaction or a movement of goods. All this happens more safely without relying on a third party to keep and process data. The Bitcoin miners try to obtain this cryptocurrency through complex mathematical calculations carried out by the computer processor or a video card. They extrapolate Bitcoin (mining) using very powerful computing systems connected to high energy expenditure.

There are several works in the literature on Bitcoin, and most of them refer to the relationship that exists with carbon dioxide emission. For example, Stoll et al. (2019) affirm that participation in the Bitcoin blockchain validation process requires vast electricity, translating into a significant carbon emission level. In this study, the authors estimate the carbon emissions produced by Bitcoin that sit between the levels produced by Jordan and SriLanka. The Bitcoin network is criticized for its energy consumption. Mora et al. (2018) estimated that the 2017 carbon footprint of Bitcoin was 69 Mt of CO2 -equivalent (MtCO2 e). The authors affirm that given the decentralized nature of Bitcoin, its computing verification process is likely to migrate to places where electricity is cheaper. Thus, suggesting that electricity decarbonization could help mitigate Bitcoin's carbon footprint, but only where the electricity cost from renewable sources is more inexpensive than fossil fuels. Kristoufek (2020) study, by cointegration analysis, the relationship between mining costs and Bitcoin price. The author shows how the increase in Bitcoin price implies an increase in the mining costs, i.e. more power consumption. Focusing on Bitcoin's energy consumption and miner's revenue, Das and Dutta (2020) find a negative relationship between these variables. Their findings document how the "energy costs do serve as the Achilles heel to miner's revenue". The same evidence is found by Polemis and Tsionas (2021). Applying a Bayesian quantile cointegration model (CQVAR), Polemis and Tsionas (2021) analyze the casual relationship between blockchain technology and the environment. For this purpose, the authors use a panel of 50 countries over the period 2016-2018. Their results show a negative correlation between miner's revenue and carbon dioxide emissions. Qin et al. (2021) find that Bitcoin's annual electricity consumption to be 0.4 PWh and cumulative CO2 emissions of 2 gigatons by 2100; however, with much faster decarbonization that achieves carbon neutrality around the mid-century. Bitcoin's cumulative CO2 emissions will not be decisive for limiting global warming to below 2°C.

In this context, since cryptocurrency is an ever-growing market, it is important to evaluate and understand the possible impact this market could have on the environment. Therefore, the paper aims to investigate the relationship between Bitcoin (BTC/USD) and the carbon credit market (IHS Global Carbon Market) during the period 1 August 2014 to 11 March 2021. For this purpose, we adopt two novel econometric models: the multivariate-quantile conditional autoregressive (MVMQ-CAViaR) model proposed by

White et al. (2015) and the Granger causality across quantiles of Candelon and Tokpavi (2016). Thanks to these models we are able to analyze the extreme spillovers effect between these two markets. In particular, the methodology proposes the estimation and inference in multivariate, multi-quantile models. These frameworks can simultaneously accommodate models with multiple random variables, multiple confidence levels, and multiple associated quantiles' lags. Our results show an asymmetric effect in terms of downside and upside spillovers. There is a significant downside risk spillover between Bitcoin to Carbon, while there is no upside risk spillover. The Granger causality analysis confirms these relations, which documents the extreme left tail relationship from Bitcoin to Carbon. Moreover, our findings hold after adopting an alternative proxy for the carbon credit markets, the Carbon Emission Futures. Finally, by quantile impulse response function (QIRFs) we show how an extreme negative shock from Bitcoin implies a decrease in Carbon quantile and the impacts are stronger when larger fluctuations happen.

This research offers a fresh evidence of Bitcoin and environmental relationships. Therefore, we contribute to the emerging literature in several ways. First, this research highlights the important role assumed by Bitcoin in influencing the environment. To the best of our knowledge, this is the first paper that uses the MVQM-CAViaR framework, therefore, we are able to capture the extreme risk spillover between the carbon credit market and Bitcoin. Second, by distinguishing the upside and downside quantiles, we observe strong evidence of asymmetric risk spillovers in this context. Third, the results provide new insights into Bitcoin's carbon footprint showing a significant negative spillover from Bitcoin to Carbon, i.e., the tail risk dependence is stronger during bad conditions.

2 Econometric methods

In this paper, we use two fresh econometric models in order to study the tail relationship between carbon credit market and Bitcoin. First, we compute the multivariate-quantile conditional autoregressive (MVMQ-CAViaR) model proposed by White et al. (2015). Second, we apply the Granger causality in quantile of Candelon and Tokpavi (2016), to analyze the direction of causality between these markets. We provide the details of our empirical approach in the following sections.

3 The MVMQ-CAViaR model

To investigate the extreme spillover, we use the multivariate-quantile conditional autoregressive model of White et al. (2015). There are two main reasons for using MVMQ-CAViaR (1,1). First, it is a useful method to understand the extreme spillovers transmission and quantify the carbon credit market's sensitivity to cryptocurrency shocks. Therefore, we can directly investigate the tail interdependence structure between these markets and further study how risk is transmitted from one market to another. Besides, the model permits us to study extreme spillovers and thus shocks in different market scenarios (bearish and bullish market). Given the rapid growth of cryptocurrency markets and growing concerns about climate change, it is essential to capture the feedback effect of Bitcoin on the carbon market in terms of tail spillover. Hence, this methodology seems to be adequate to study these effects. Especially, the model captures the transmission of the quantile-spillover effect on tail interdependence. It is an extension of the CAViaR model, proposed by Engle and Manganelli (2004). In particular, the idea is that the distribution quantile of one-time series variables is given by the lag of own returns and the lags of covariates (quantiles).

The MVMQ-CAViaR (1,1) can be written as follows:

$$q_{1t} = c_1 + a_{11}|r_{1(t-1)}| + a_{12}|r_{2(t-1)}| + b_{11}q_{1(t-1)} + b_{12}q_{2(t-1)} \tag{1}$$

$$q_{2t} = c_2 + a_{21}|r_{1(t-1)}| + a_{22}|r_{2(t-1)}| + b_{21}q_{1(t-1)} + b_{22}q_{2(t-1)} \tag{2}$$

where $|r_{1(t-1)}|$ and $|r_{2(t-1)}|$ stand for absolute values of returns, a_{ij} and b_{ij} are the parameters terms, while c_1 and c_2 are the constant. The model can be rewrite as follows:

$$q_{1,t} = -Q_\theta\left(r_{1,t}|I_{t-1}\right) = -inf\left\{q \in R|Pr\left(r_{1,t} \leq q|I_{t-1}\right) \geq \theta\right\} \tag{3}$$

$$q_{2,t} = -Q_\theta\left(r_{2,t}|I_{t-1}\right) = -inf\left\{q \in R|Pr\left(r_{2,t} \leq q|I_{t-1}\right) \geq \theta\right\} \tag{4}$$

where I_{t-1} is the information set and Q_θ is the quantile function with interval confidence $\theta \in (0,1)$. Therefore, the quantile of the first time series at θ level, depends on the first lag of absolute returns and the first lag of quantiles. The parameters b_{12} and b_{21} are the key elements of the model. In fact, b_{12} and b_{21} capture the extreme spillover effect, i.e., how the quantile in one market influences the quantile in the other ones. The null hypothesis of no tail dependence is given by:

$$H_0 : b_{12} = b_{21} = 0 \tag{5}$$

In the second step, we identify, by pseudo quantile impulse response functions (QIRF), the degree and the reactions of shock across the markets in order to understand the transmission mechanism. In particular, we are able to study carbon credit market responses to the extreme Bitcoin shocks measured by the upside and downside quantiles. Following White et al. (2015), we defined the QIRFs as follows:

$$\Delta_{is}\left(\widetilde{r}_{1,t}\right) = \widetilde{q}_{i,t+s} - q_{i,t+s}, \qquad s = 1, 2, 3.., T \tag{6}$$

where $\widetilde{q}_{i,t+s}$ is the θth conditional quantile of returns $(\widetilde{r}_{1,t})$. Moreover, the QIRF can be expressed as:

$$\Delta_{11}\left(\widetilde{r}_{1,t}\right) = a_{11}(\widetilde{r}_{1,t} - r_{i,t}) + a_{12}(\widetilde{r}_{2,t} - r_{2,t}) \qquad \text{for} \quad s = 1 \tag{7}$$

$$\Delta_{1s}\left(\widetilde{r}_{1,t}\right) = b_{11}\Delta_{1,s-1}(\widetilde{r}_{1,t}) + b_{12}\Delta_{2,s-1}(\widetilde{r}_{1,t}) \qquad \text{for} \quad s > 1$$

QIRFs have two main functions: i) they track how negative or positive cryptocurrency shocks are spreading on the carbon credit market, ii) and how long the market takes to absorb the shocks. The latter is completely absorbed when the pseudo QIRFs converge at zero. The structural shocks are identified by Cholesky factorization.

3.1 Granger causality across quantiles

Hong et al. (2009) introduce the concept of causality of Granger's risk, i.e. the co-movement between the left quantiles of two distributions. The idea is that the ability to predict the future risk of a variable is improved by adding information about the past risk of the other variables. Candelon and Tokpavi (2016) extend the Hong et al. (2009) model, in order study the Granger causality in specific regions on the distribution. In order to analyze the down and upside quantile relationship, in this paper, we following Candelon and Tokpavi (2016), and we consider a set $T^{down} = \left\{\theta_1^{down}, ..., \theta_{m+1}^{down}\right\}$ of $m + 1$ quantiles that covers the left-tail regions on the distribution. The left tail of r_{it} is divided into m disjoint regions, i.e., $Q_{it}(\theta_1^{down}|I_{i,t-1}), ..., Q_{it}(\theta_{m+1}^{down}|I_{i,t-1})$. Following Candelon and Tokpavi (2016), we defined the quantile indicator vector as follows: $H_{it}^{down} = (Z_{it,1}^{down}, ..., Z_{it,m}^{down})$ where

$$Z_{it,k}^{down} = \begin{cases} 1 \ \text{ if } \ \ Q_{it}(\theta_k^{down}) \leq r_{it} \leq Q_{it}(\theta_{k+1}^{down}) \\ 0 \ \text{ else} \end{cases} \tag{8}$$

hence H_{it}^{down} captures the information of downside quantile. For the upside quantile we have: $H_{it}^{down} = (Z_{it,1}^{up}, K, Z_{it,m}^{up})$. According to Candelon and Tokpavi (2016), the null hypothesis of Granger causality in distribution is examined based on non-parametric kernel-based test statistics, i.e.,

$$H_0 : E(H_{i,t}^{down(up)}|I_{i,t-1}^{down(up)}, I_{j,t-1}^{down(up)}) = E(H_{i,t}^{down(up)}|I_{i,t-1}^{down(up)}) \tag{9}$$

where $I_{j,t-1}^{down(up)}$ and $I_{i,t-1}^{down(up)}$ comprise the available information of downside (upside) quantile at time $t-1$. If the null hypothesis is rejected, it indicates the downside (upside) quantile in the Bitcoin market can be used to forecast the downside (upside) quantile of carbon credit market. Therefore, thanks to this method, we are able to verify the direction of tail spillover between these markets. We consider three types of causality, down-to-down ($T^{down} = \{0, 1\%, 5\%, 10\%\}$), center-to-center ($T^{center} = \{20\%, 30\%, ..., 80\%\}$) and the upside-to-upside ($T^{up} = \{90\%, 95\%, 99\%, 100\%\}$).

4 Data source

Our study focuses on the analysis of tail co-movement between carbon and Bitcoin (BTC/USD) price. We use the IHS Markit Global Carbon Index ("Carbon" hereinafter), to represent the global carbon credits markets. This index tracks the most liquid segment of the tradable carbon credit futures markets. Its constituents are contracts on European Union Allowances (EUA), California Carbon Allowances (CCA) and the Regional Greenhouse Gas Initiative (RGGI), so the index describes the European and the U.S. market of carbon emission allowances (see https://indices.ihsmarkit.com/Carbonindex). Bitcoin price is extracted from Datastream. The daily data span from 1 August 2014 to 11 March 2021 (1615 obs.).

To compute the empirical estimation we use the daily returns of prices, calculated as:

$$r_{i,t} = ln(P_{i,t}/P_{i,t-1}) \times 100 \tag{10}$$

where $r_{i,t}$ is the daily return of the indices, P is the price at time t.

Table 1 summarizes the summary statistics of daily returns. Both markets show a positive average return during the sample period. As it is evident, Bitcoin shows the highest standard deviation, highlighting the high uncertainty of the investment in cryptocurrencies. The skewness coefficients are negative, while the kurtosis coefficients are greater than 3 for all return series. Therefore, the probability distribution of the returns has a skewness and a leptokurtic distribution. This is confirmed by the JB test, which rejects the null hypothesis of the normal distribution at the 1% significance level. Finally, the ADF test suggests that the series are stationary.

Table 1. Summary statistics of daily returns

	Carbon	Bitcoin
Mean	0.07	0.28
Median	0.05	0.20
Min	−22.52	−49.72
Max	10.43	24.08
Std.Dev	2.10	4.70
Skewness	−1.11	−0.81
Kurtosis	12.43	12.04
J-B	10723.2***	9923.77***
ADF	−18.52***	−40.44***

Notes: J-B is the Jarque-Bera test of normality. ADF stands for the Dickey and Fuller (1979) test. *** indicates statistical significance at 1% level.

5 Empirical results

5.1 Multivariate quantile model estimation

In Table 2, we report the estimation of the MVQM-CAViaR (1,1) model for downside risk spillover effects ($\theta = 0.05/0.01$) and for upside risk (0.95/0.99). Each VAR structure relates the conditional quantile of the change in Carbon to the quantile of Bitcoin and vice versa. The first equation relates to the quantile of Carbon while the second relates to the quantile of Bitcoin. Focusing on downside risk (θ= 0.05/0.01), we can note that all a_{11} and a_{22} coefficients are significant and negative, suggesting that an increase in its return provokes a decrease in quantile. The coefficients of the quantile lagged are significant for both markets, indicating the existence of a strong persistence on quantile of Carbon and Bitcoin. The table shows the tail risk spillover between the two markets. In fact, as we can see, the Carbon price return is conditioned by the return of bitcoin (a_{12} is significant), and by the quantile of Bitcoin (b_{12} is significant). The significant coefficient indicates that the lagged quantile of Bitcoin has a predictive power on the quantile of Carbon. This testifies to the existence of significant downside risk spillovers between the two markets.

In terms of upside quantile spillovers (0.95/0.99) we can note a different picture of the tail relationship. In this case, the upside quantile of the Carbon depends only on its lagged return and its lagged quantile. In fact, coefficient b_{11} is significant at 1%, exhibiting the persistence on quantiles of Carbon returns. Unlike the estimates of downside

Table 2. Results of the MVQM-CAViaR (1,1)

	Downside quantiles $\theta = 0.01$					**Upside quantiles $\theta = 0.99$**				
Carbon	c_1	a_{11}	a_{12}	b_{11}	b_{12}	c_1	a_{11}	a_{12}	b_{11}	b_{12}
	-0.229	-0.396**	-0.086***	0.865***	-0.030*	-0.326	0.329***	-0.045	0.877***	0.043
	(0.227)	(0.174)	(0.032)	(0.066)	(0.018)	(1.589)	(0.052)	(0.048)	(0.112)	(0.079)
Bitcoin	c_2	a_{21}	a_{22}	b_{21}	b_{22}	$c2$	a_{21}	a_{22}	b_{21}	b_{22}
	-4.145***	0.518	-0.897***	0.075	0.546***	1.739	-0.291	0.224***	0.012	0.852***
	(0.729)	(0.902)	(0.133)	(0.178)	(0.108)	(5.425)	(0.564)	(0.044)	(0.111)	(0.286)
	Downside quantiles $\theta = 0.05$					**Upside quantiles $\theta = 0.95$**				
Carbon	c_1	a_{11}	a_{12}	b_{11}	b_{12}	c_1	a_{11}	a_{12}	b_{11}	b_{12}
	-0.252	-0.163***	-0.037*	0.866***	-0.032***	-0.034	0.051***	-0.013	0.971***	0.014
	(0.134)	(0.061)	(0.019)	(0.052)	(0.013)	(0.035)	(0.012)	(0.013)	(0.011)	(0.009)
Bitcoin	c_2	a_{21}	a_{22}	b_{21}	b_{22}	c_2	a_{21}	a_{22}	b_{21}	b_{22}
	-0.348	-0.081	-0.263***	-0.082	0.852***	0.351	-0.085	0.207	0.08	0.84***
	(0.427)	(0.156)	(0.071)	(0.152)	(0.036)	(0.411)	(0.051)	(0.169)	(0.083)	(0.099)

Notes: Estimated coefficients are in the first row. Numbers in parentheses are standard errors. ***, **, and * indicate statistical significance at 1%, 5%, and 10% level, respectively.

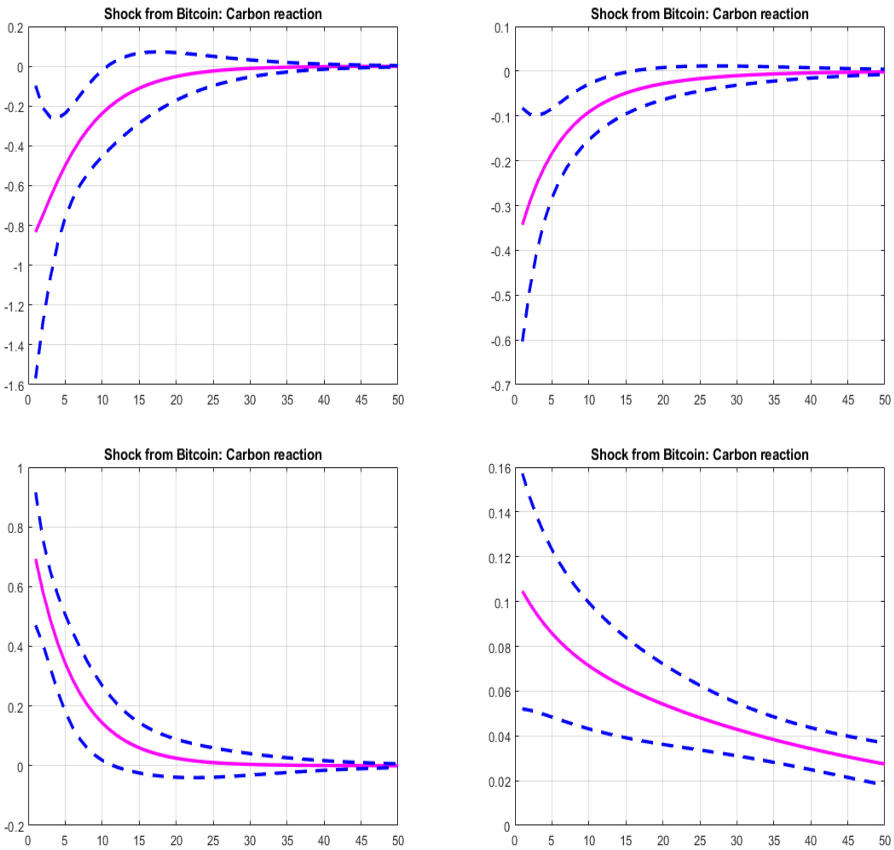
quantile spillovers, in this case the coefficient b_{12} is statistically insignificant. This implies that there is no upside extreme spillover from Bitcoin to Carbon, i.e, the Bitcoin only affects the Carbon in downward quantiles. This evidence shows that upside and downside spillover effects between the Carbon market and Bitcoin market are asymmetric. A downside event occurring in the Bitcoin market would contribute to the downside extreme quantile of Carbon index. However, an extreme (upside/downside) event occurring in the Carbon index would not have an impact on the extreme (upside/downside) risk of Bitcoin price returns.

To further analyze the tail join dynamics between Carbon and Bitcoin, we compute the pseudo impulse response functions (QIRFs). These impulse responses allow us to quantify and distinguish between reactions to negative shocks (left quantiles) and extreme positive shocks (right quantiles). As above, we consider two downside quantiles (0.01/0.05) and two upside quantiles (0.95/0.99). Recall that the horizontal axis measures the time (days), on the other hand the vertical axis quantifies the change in the 1% quantiles of Carbon (percentage returns) as a reaction to Bitcoin shock. Since our goal is to investigate the relationship linking Bitcoin to Carbon, we focus our analysis only on Carbon's responses to Bitcoin shocks[3].

Figure 1 presents the QIRFs of risks in the Carbon market to a one standard-deviation shock to the Bitcoin. The dotted line is the 95% confidence interval, while the horizontal axis reflects the time in days, and the vertical axis measures the change of the Carbon index (percent of returns) as a reaction to the Bitcoin shock. The shock is absorbed when the curve (blue) converges to zero. In the upper part of the figure, Carbon's responses to a negative shock (0.01 left, 0.05 right) of Bitcoin are depicted. At the bottom of the graph, Carbon's responses to a positive shock (0.99 left, 0.95 right) of Bitcoin are plotted.

[3]The pseudo impulse responses for Bitcoin are available on request.

Figure 1. QIRFs - Carbon reaction



Notes: The upper panel shows the responses of Carbon to the shocks of the Bitcoin at downside quantile: $\theta = 0.01$ on left-side, $\theta = 0.05$ on right side. The bottom panel plots the responses of Carbon to the shocks of the Bitcoin at upside quantile: $\theta = 0.01$ on left-side, $\theta = 0.05$ on right side

Table 3. Asymmetric response

Bitcoin shock	1%	99%	Asymmetric	5%	95%	Asymmetric
Carbon response	-0.81	0.71	0.1	-0.33	0.11	0.22

A close inspection of the plot suggests how the two markets move together, i.e, there is a tail codependence. As we can see from Figure 1, if Bitcoin's returns fall, there is a negative response in the Carbon market. The shock is absorbed around day 25. Hence, a downward shock in the cryptocurrency market will induce a negative reaction in Carbon. This result is fully consistent with Polemis and Tsionas (2021) who find how, at downside quantile, the two markets are positively correlated. The authors show that an increase in the Bitcoin returns, increases the carbon releases, and vice versa. The shock is absorbed around day 25, so the equilibrium is restored quite slowly. On the other hand, if a positive upward shock occurs, it will induce a positive reaction, which will be reabsorbed after 25 days for $\theta = 0.99$, after 50 days for $\theta = 0.95$. Furthermore, we find that the magnitude of the shock is greater at quantiles 0.01 and 0.99 (0.81 and 0.71) than at quantiles 0.05 and 0.95 (0.33 and 0.11). This suggests how the impacts of Bitcoin shocks are stronger when larger fluctuations happen (Wen et al., 2019). In fact, during bearish and bullish conditions, investors will decrease (increase) their demand for Bitcoin causing a drop (rise) of its price, which in turn will cause a reduction (growth) in energy consumption then on carbon emission (Krause and Tolaymat, 2018; Das and Dutta, 2020; Gallersdörfer et al., 2020; Kristoufek, 2020).

Finally, in Table 3, we report the asymmetric property of quantile spillover. Following Shen (2018), we compute the asymmetry measure as the absolute difference between losses and gains, namely for $\theta = 1\%$ and 5% and for $\theta = 95\%$ and 99%, respectively.

The results suggest that the downside quantiles have a greater impact with respect to the upside. This suggests that risk in the cryptocurrency market would result in extreme carbon market behavior, making reaction patterns asymmetric with respect to market losses and gains.

5.2 Granger quantile causality

In this subsection, to investigate the tail dependence between these markets, we compute the quantile Granger causality proposed by Candelon and Tokpavi (2016). This method is useful to study the existence of co-movement between two series in the tails. Table 4 reports the Granger causality test for downside and upside quantile.

Table 4. Granger results

	Type of spillover		
Direction of spillover	down-to-down	center-to-center	up-to-up
Carbon does not Granger cause Bitcoin	-1.108	1.11	-0.329
Bitcon does not Granger cause Carbon	2.268***	-1.055	-0.784

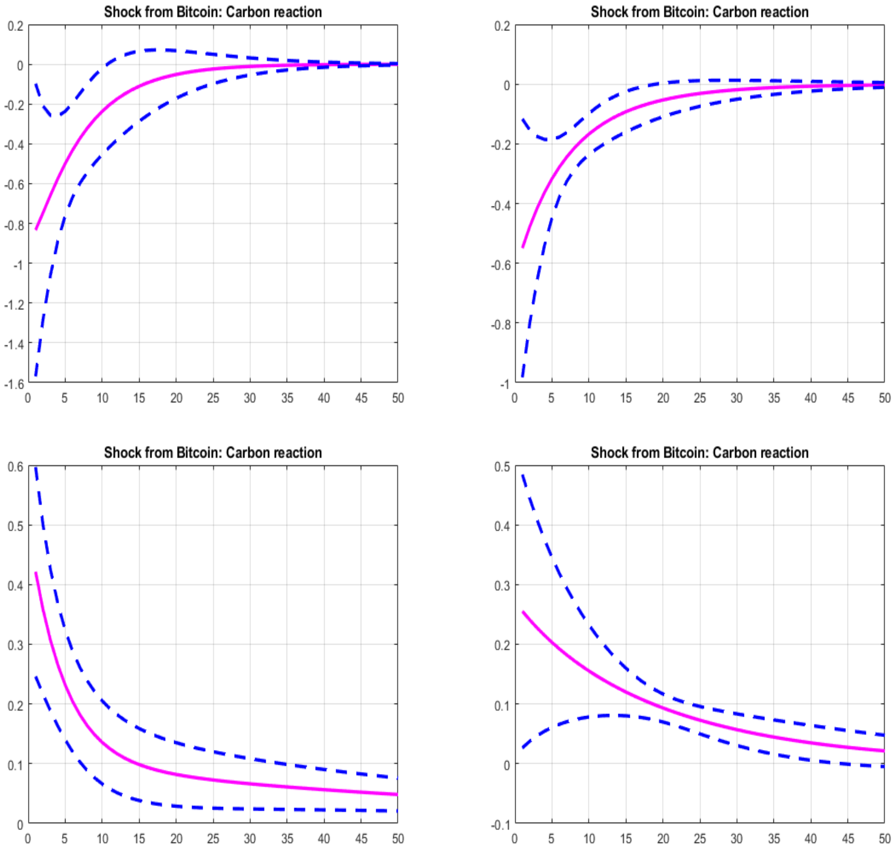
Notes: The table reports the kernel-based test statistics in tails and center of the distribution. *** denotes statistical significance at 1%.

The findings suggest that there is a significant tail spillover from Bitcoin to Carbon at downside quantile distribution. This implies that the downside quantile information from the Bitcoin market has significant predictive power on Carbon returns. On the other hand, we find that Carbon not Granger causes the Bitcoin.The results confirm the findings of the multivariate quantile model, i.e. the Bitcoin influences the Carbon market in the lower quantiles.

5.3 Robustness check

In this section, we check the robustness of the findings adopting an alternative proxy for the carbon credit market. In particular, we use Carbon Emissions Futures (as in Corbet et al., 2019). The results are shown in Figure 2. The dynamics of QIRFs are perfectly in line with the results above. An extreme negative (positive) shock from Bitcoin, implies a decrease (increase) in Carbon quantile.

Figure 2. Robustness QIRFs - Carbon reaction



Notes: The upper panel shows the responses of Carbon to the shocks of the Bitcoin at downside quantile: $\theta = 0.01$ on left-side, $\theta = 0.05$ on right side. The bottom panel plots the responses of Carbon to the shocks of the Bitcoin at upside quantile: $\theta = 0.01$ on left-side, $\theta = 0.05$ on right side

We also provide evidence of the tail downside relationship, computing the Granger causality across quantiles. As we can see from Table 5, also in this case, we find a downside relationship between these markets[4].

Table 5. Robustness Granger results

	Type of spillover		
Direction of spillover	down-to-down	center-to-center	up-to-up
Carbon does not Granger cause Bitcoin	-1.109	0.322	-1.654
Bitcon does not Granger cause Carbon	5.559***	2.00	0.748

Notes: The table reports the kernel-based test statistics in tails and center of the distribution. *** denotes statistical significance at 1%.

[4] In order to verify the robustness of our findings, we also applied the Granger-causality in quantiles proposed by Troster (2018). The results are qualitatively the same, namely that the Bitcoin Granger causes the Carbon, only in the lower quantiles ($\theta = 0.05$). The results are available on request.

We conclude that the tail dependence is significantly related to the between the two markets, indicating the strong driving force of Bitcoin in the credit Carbon market.

6 Discussion

Our main results show asymmetry between the downside and upside analysis of Carbon and Bitcoin quantiles. In particular, the most interesting finding deals with the downside spillovers of Bitcoin quantile on carbon emissions allowances' quantile. This is the only quantile spillover effect that we observe between the two markets. Moreover, our results show a persistence in quantile over the days for both quantiles. The co-movement expressed by the two variables over time, derives from the strict connectedness between cryptocurrency market dynamism and the demand of carbon fossils (e.g. Stoll et al., 2019; Mora et al., 2018; Krause and Tolaymat, 2018).

The Bitcoin quantile spillover effect on carbon credits can be explained under two points of view:

- the cause-effect relation that Bitcoin market has to carbon dioxide production;
- carbon credits' sensitivity to downside risk rather than to the upside one.

Theoretically, we can assume that an abrupt depreciation of BIT/USD return implies a slowdown in the Bitcoin market, with a consequent less need of carbon emission allowances. In this sense, we see that the downside risk of Bitcoin returns might determine a decrease of carbon credit prices. The effect of downside spillover is particularly strong in a market, like the carbon emissions, characterized by a general surplus of supply (e.g. Bel and Joseph, 2015; Chèze et al., 2020). Moreover, previous research (Feng et al., 2012) has demonstrated over both future and spot carbon emissions markets, that downside risk is higher than upside. Consistently, we think that carbon allowances are more sensitive to extreme negative spillovers, than to positive.

Another important point is the response of carbon credits to downside Bitcoin shocks around 25 days. We guess that this is a key point: the renovation of the equilibrium testifies that the "collar" structure of carbon price mechanism allows supporting the market even during bearish times (Schmalensee and Stavins, 2017). Notwithstanding, the absorption of the shock is quite slow: we deem that this aspect might be pointed out to policymakers, in order to improve the functioning of the market in terms of "price floor".

7 Conclusion

The analysis carried out in the paper draws its origin from two fundamental factors that have emerged in recent years, namely the fight against climate change and the introduction of cryptocurrencies, specifically of Bitcoin. The paper investigates the relationship between the price of the latter and the credit carbon market. The relationship arises as large amounts of energy are required to mine Bitcoin. In particular, energy is produced mostly from non-renewable sources, especially from coal (Stoll et al., 2019).

Our analysis shows downside risk spillovers between Bitcoin and IHS Markit Global Carbon Index, i.e. there is a tail codependence. We find that the tail risk of Bitcoin impacts on the carbon credit market. These results are confirmed by Granger causality across quantile, which documents the extreme left tail relationship from Bitcoin to Carbon. Moreover, our findings hold after adopting an alternative proxy for the carbon credit markets, the Carbon Emission Futures. Finally, the QIRFs show how an extreme negative shock from Bitcoin implies a decrease in Carbon quantile and the impacts are stronger when larger fluctuations happen.

Our study provides significant policy implications for cryptocurrency energy management, i.e., reducing the carbon footprint of Bitcoin mining. The strong tail relationship between Bitcoin and the carbon credit market suggests that the higher the Bitcoin market's risk, the more abrupt the negative environmental effect. Therefore, as Polemis and Tsionas (2021) suggested, an environmental strategy focused on incentivising clean energies on miner activities could decrease carbon emissions. Moreover, as the QIRFs suggest, the slow adjustment to equilibrium allows policymakers to quickly intervene and constraining negative lagged risk spillover effects between the two markets. In particular, the "collar" price structure and the MSR are key starting points for new improvements of the market.

All such tools can be designed unilaterally by environmentally conscious governments, but the limitations overwhelmingly point to an international response's need. The purpose would not be to harm the industry overall but to develop sustainable alternatives. This is happening due to electricity costs, but the greater the Bitcoin value, the greater the incentive to participate and the worse the harm caused to the environment. A common theme found with all policy tools available has been the global mobility of the economic actors in question. A strong base can be created for international cooperation to jointly implement measures, as has already happened to regulate digital currencies for financial stability and carbon neutrality.

What must be emphasized is that we need to increase also the culture of climate change, so the policies must also consider factors such as education that seems to play an important role by reducing energy consumption and carbon emissions to achieve carbon neutrality (Shahbaz et al., 2020). Economic prosperity has come at a very high ecological cost. Simultaneously it is recommended that there be strict and selective environmentally friendly economic and financial policies concerning renewable and green energy to achieve sustainable economic development (Nasir et al., 2021).

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