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On the Potential Hedging Instruments Against Central Bank Digital Currency Uncertainty and Attention Indices

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We study dynamic conditional correlations of Central Bank Digital Currency (CBDC) uncertainty and attention indices with US dollar futures, 1-year US government bond, and gold futures. We find that USD futures hedges CBDC uncertainty, while the US bond hedges the CBDC uncertainty index subsequent to 2019. Interestingly, gold does not hedge CBDC uncertainty. The CBDC attention index exerts a negative effect on the other assets. These results are important for portfolio management.

I. Introduction

Central banks from more than 60 countries around the world have been exploring the use of Central Bank Digital Currencies (CBDCs) since 2014 (PWC, 2021).¹ Given the regulatory uncertainty around the cryptocurrencies as well as their rising environmental concerns, CBDCs are gaining momentum in the policy arena. The increased discussions on the prospects of the issuance of CBDCs have received significant media attention. Similarly, increased uncertainty on the potential impacts of CBDC issuance means that investors should be aware of the related portfolio implications and the financial market spillovers.

The cryptocurrency market has received significant investor attention (Smales, 2022). In the literature, cryptocurrencies' popularity has grown around several features, such as (i) as a financial asset, (ii) as a portfolio diversifier, and (iii) as a medium of exchange (Bariviera & Merediz-Solà, 2021; Corbet et al., 2019). Given the role of cryptocurrencies as a safe haven asset (Dyhrberg, 2016), as well as the spillovers from cryptocurrency environmental attention to the conventional and green assets (Kamal & Hassan, 2022), investors may feel motivated to look for assets that hedge CBDC related uncertainty and attention because both CBDCs and cryptocurrencies are considered as competing assets.

Recently, to gauge the potential spillovers of the discussion on the CBDCs to the financial markets, Wang et al. (2022) developed CBDC uncertainty and attention indices using a large number of news articles from LexisNexis database. CBDC related uncertainty and attention indices can have a strong relation with cryptocurrencies, and this could

have spillover effects on other asset classes as well. For example, Wang et al. (2022) find that CBDC uncertainty has a negative relationship with the MSCI World Banks Index, USEPU, and the FTSE All-World Index, and a positive relationship with cryptocurrency market volatility, VIX, and gold. They used a dynamic conditional correlations (DCC) via AR (1)-GJR-GARCH (1,1) model. Motivated by the above discussions, in this paper, we study how CBDC uncertainty and attention indices affect US bond, US dollar futures, and gold using the DCC-GJR-GARCH (1,1) model.

We contribute to the literature in two ways. First, our results have important policy implications for investors since CBDC uncertainty is new to the investors. For example, given a higher CBDC uncertainty, investors are unsure about which asset can hedge such uncertainty. Can digital or fiat currencies play a hedging role? We attempt to answer this question in our paper. Second, we reveal the potential impacts that CBDC uncertainty can have on the conventional monetary policy (Bank for International Settlements, 2018; Williamson, 2021). We attempt to understand how CBDC related uncertainty and attention can affect conventional monetary policy via interest rate channels (for example, through studying US bonds).

We find that US dollar hedges CBDC uncertainty completely, while the US bond hedges against CBDC uncertainty index subsequent to 2019. CBDC attention index exerts a negative impact on the assets in general. Importantly, gold does not hedge CBDC uncertainty.

This paper is organized as follows. Our next sections present data and methodology, results and conclusions.

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¹ <https://www.pwc.com/gx/en/industries/financial-services/assets/pwc-cbdc-global-index-1st-edition-april-2021.pdf>

Table 1. Descriptive statistics

	$\Delta \ln \text{CBDCUI}$	$\Delta \ln \text{CBDCAI}$	$\Delta \ln \text{GOLD}$	$\Delta \ln \text{USBOND}$	$\Delta \ln \text{USDFUTURE}$
Panel A: Descriptive statistics					
Mean	0.0001	0.0001	0.0007	-0.0022	0.0001
Std. Dev.	0.005	0.003	0.019	0.12	0.010
Skewness	0.91	2.61	-0.08	-2.04	0.15
Kurtosis	10.79	23.95	6.74	25.41	5.50
Jarque-Bera	939.60***	6839.23***	205.59***	7615.70***	93.43***
ADF	-20.63***	-17.22***	-20.21***	-11.54***	-15.67***
Obs.	352	352	352	352	352
Panel B: Correlation matrix					
$\Delta \ln \text{CBDCUI}$	1				
$\Delta \ln \text{CBDCAI}$	0.61***	1			
$\Delta \ln \text{GOLD}$	-0.05	-0.08	1		
$\Delta \ln \text{USBOND}$	0.08	-0.02	-0.19***	1	
$\Delta \ln \text{USDFUTURE}$	0.02	0	-0.54***	0.07	1

Notes: This table reports selected descriptive statistics and correlations for the first differenced series of the variables in the estimation. *CBDCUI* is CBDC uncertainty index, *CBDCAI* is CBDC attention index and other variables are self-explanatory. Full data sample are used. *** indicates 1% level significance. $\Delta \ln$ refers to log difference. ADF means Augmented Dicky Fuller test.

II. Data and Methodology

A. Data

We use data on three assets and CBDC uncertainty index (*CBDCUI*), and CBDC attention index (*CBDCAI*). Three assets are USD futures (*USDFUTURE*), gold futures (*GOLD*), and 1-year US bond (*USBOND*). Baur & Dimpfl (2021) suggest that gold, US bonds, and US dollars are well known safe haven assets. We collect the data on CBDC uncertainty and attention indices from Professor Lucey website. The *USD-FUTURE*, *GOLD*, and *USBOND* data are from [investing.com](https://www.investing.com) (<https://www.investing.com>).

Our data include weekly observations of all variables from January 11, 2015, to October 3, 2021. The data availability determines the data frequency. Figure 1 shows that US bond is highly volatile. There is a stable period during 2017-2019.

Table 1 shows the descriptive statistics for the variables used in the estimation. *GOLD* has the highest mean, while *USBOND* has the highest standard deviation. The excess kurtosis statistic shows the variables have fat tails, and the Jarque-Bera statistic shows that variables are non-normally distributed. The variables are stationary based on the ADF test. The correlation matrix shows that *CBDCUI* and *CBDCAI* have insignificant correlation with the chosen assets.

B. Methodology

We applied the GJR-GARCH based model proposed by Glosten et al. (1993) with the DCC approach. In the first stage, we estimate the following equation:

$$Y_t = \mu + \varepsilon_t \quad (1)$$

$$\varepsilon_t / \Omega_{t-1} \sim St_s(0, 1)$$

where Y_t is the $(n \times 1)$ vector of variables in log first difference form; μ represents the vector of constants; and

$\varepsilon_t = [\varepsilon_{i,t}, \dots, \varepsilon_{n,t}]$ is the vector of residuals. Due to the high risk and non-normal asset distribution of the assets, as shown in the descriptive statistics, we applied the skewed student t -distribution for the errors (Nekhili & Sultan, 2020).

The conditional volatility of the GJR-GARCH model is as follows:

$$h_{it}^2 = \omega + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 + \gamma \varepsilon_{t-1}^2 I_{t-1} \quad (2)$$

where if $\varepsilon_{t-1} < 0$, and $I_{t-1} = 1$, otherwise $I_{t-1} = 0$. The asymmetric effects of positive and negative shocks are represented by the leverage term (γ). Meanwhile, when $\omega > 0$, $\alpha, \beta, \gamma \geq 0$, and $\gamma + (\alpha + \beta)/2 < 1$, then volatility is positive and stationary in Equation (2).

In the second stage, according to Engle (2002), H_t is as follows:

$$H_t = D_t^{1/2} R_t D_t^{1/2} \quad (3)$$

$$R_t = \text{diag} (K_t^{-\frac{1}{2}} k_t \text{diag} (k_t)^{-\frac{1}{2}}) \quad (4)$$

$$k_t = (1 - a - b)V + a \text{diag} (k_{t-1})^{\frac{1}{2}} \hat{\varepsilon}_{i,t-1} \hat{\varepsilon}'_{i,t-1} \text{diag} (k_{t-1})^{\frac{1}{2}} + b K_{t-1} \quad (5)$$

where R_t refers to the $n \times n$ conditional correlation matrix; $D_t = \text{diag}(h_{i,t}, \dots, h_{n,t})$ defines the diagonal conditional variances; a and b are non-negative scalars that conform to the condition of $a + b < 1$. R_t has element in the following form:

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t} q_{jj,t}}} \quad i, j = 1, 2, \dots, n, \text{ and } i \neq j \quad (6)$$

For bivariate relationship, Eq. (6) becomes

$$\rho_{12,t} = \frac{q_{12,t}}{\sqrt{q_{11,t} q_{22,t}}} \quad (7)$$

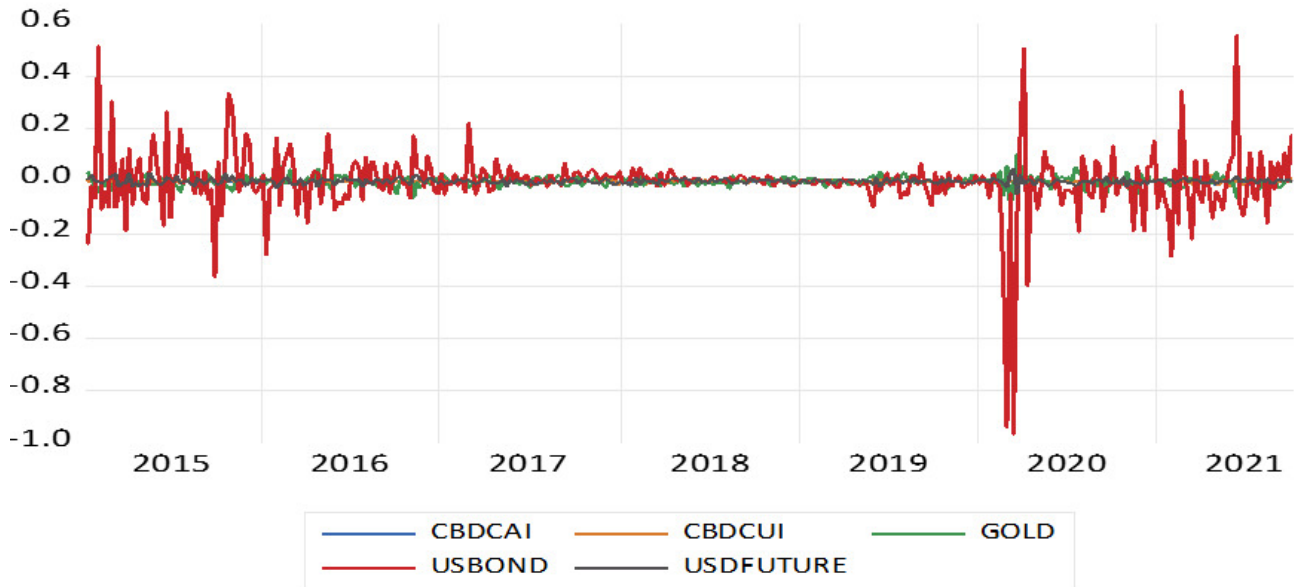


Figure 1. Plot of the first difference of variables

Notes: This figure presents plot for the first differenced series of the variables. *CBDCUI* is CBDC uncertainty index, *CBDCAI* is CBDC attention index, *GOLD* is gold, *USBOND* is 1-year US bond, *USDFUTURE* is US dollar future

III. Results

A. DCC results

[Table 2](#) presents the results of the DCC-GJR-GARCH (1,1) model.² ARCH and GARCH terms are positive and significant for all the variables in the estimation. Positive and significant GARCH term implies volatility persistence and clustering. The leverage term (γ) is negative and significant for *CBDCUI*, *CBDCAI*, and *USDFUTURE*. This suggests that negative news creates less volatility than positive news. The DCC term (α) is insignificant for all the variable pairs, which suggests that there is no short run volatility clustering. Meanwhile, the DCC term (β) is positive and significant for all the variable pairs. This implies that there is long term volatility persistence.

[Figure 2](#) presents the time-varying DCC results. It is seen that *GOLD* has both positive and negative relationships with *CBDCUI* during the whole period. This suggests that *GOLD* is not a hedge against *CBDCUI*, which contrasts prior finding (Baur & Lucey, 2010; Wang et al., 2022). Increase in hedging costs may have led to the loss of safe haven properties for gold (Akhtaruzzaman et al., 2021). The *USBOND* hedges *CBDCUI* subsequent to 2019 and hence the hedging potential of *USBOND* is regime-dependent. Wang et al. (2022) observe few events that arose during 2019-2021, such as cryptocurrency bear markets, China-US trade war, and Cryptocurrency bull markets, which may have driven

the positive shift in the DCCs between *USBOND* and *CBDCUI* during this period. The *USDFUTURE* is a hedge against *CBDCUI* over the full sample period because there is a positive relationship between them. Meanwhile, *CBDCAI* exerts both positive and negative effects on *GOLD* and *USD-FUTURE*. However, *CBDCAI* exerts a negative effect on the *USBOND* over the entire period. Overall, there is a negative relationship between *CBDCAI* and the assets in general.

B. Sub-Sample analysis

Covid-19 has been identified as a black swan event. There were unprecedented policy responses from the governments to control the negative effects of Covid-19 on the financial markets across the world. These may have affected financial markets' response to the policy related uncertainty. For this reason, we perform a sub-sample analysis to see whether our results are not affected by the high economic policy uncertainty period of Covid-19. We use pre-Covid-19 data from 11/2015 to 02/2020 to see how *CBDCUI* and *CBDCAI* affected the variables in the estimation. These results are available upon request. We find that gold is a hedge against *CBDCUI* for the pre-Covid-19 data, which contrasts our full sample analysis. This is consistent with the literature that gold has hedging capability during pre-Covid-19 period (Akhtaruzzaman et al., 2021). Interestingly, with the preCovid-19 data, *USDFUTURE* lost its safe haven properties against *CBDCUI* as compared to the full

² Our GJR-GARCH with skewed student *t*-distribution model is found to have the lowest AIC. For the sake of brevity, we did not present the results of the alternative GARCH models' (i.e., GARCH, EGARCH, and IGARCH) results with skewed student *t*-distribution for error terms. We also test whether student-*t* or skewed student-*t* performs well for GJR-GARCH model and find that skewed student-*t* errors perform well. These results are available upon request.

Table 2. DCC-GJR-GARCH (1,1) results

Univariate GARCH results	$\Delta \ln CBDCUI$	$\Delta \ln GOLD$	$\Delta \ln USBOND$	$\Delta \ln USDFUTURE$	$\Delta \ln CBDCAI$	$\Delta \ln GOLD$	$\Delta \ln USBOND$	$\Delta \ln USDFUTURE$
μ	0.00**	0.00	0.00**	0.00	0.00**	0.00	0.00**	0.00
ω	0.00	0.00**	0.00	0.00***	0.00	0.00**	0.00	0.00***
ARCH	0.67***	0.09*	0.07*	0.15***	0.72***	0.09*	0.07*	0.15***
GARCH	0.73***	0.92***	0.85***	0.77***	0.62***	0.92***	0.85***	0.77***
γ	-0.71***	-0.06	0.15	-0.06***	-0.61***	-0.06	0.15	-0.06***
skew	1.54***	0.96***	1.07***	1.07	1.25***	0.96***	1.07***	1.07
shape	5.89***	6.44***	3.60***	26.88	3.85***	6.44***	3.60***	26.88
DCC results								
α		0.03	0.01	0.00		0.07	0.00	0.04
β		0.63***	0.98***	0.92***		0.80***	0.88***	0.55***
shape		6.38	4.40	8.79		4.98***	4.00***	5.66***
Information Criteria								
Akaike		-13.37	-10.89	-14.65		-15.25	-12.77	-16.52
Bayes		-13.17	-10.69	-14.45		-15.05	-12.57	-16.32
Shibata		-13.38	-10.90	-14.66		-15.25	-12.77	-16.52
Hannan-Quinn		-13.29	-10.81	-14.57		-15.17	-12.69	-16.44

Note: This table reports DCC GARCH results. *CBDCUI* is CBDC uncertainty index, *CBDCAI* is CBDC attention index and other variables are self-explanatory. The results are for full data sample. *** indicates 1% level significance. Variables are in log first difference form.

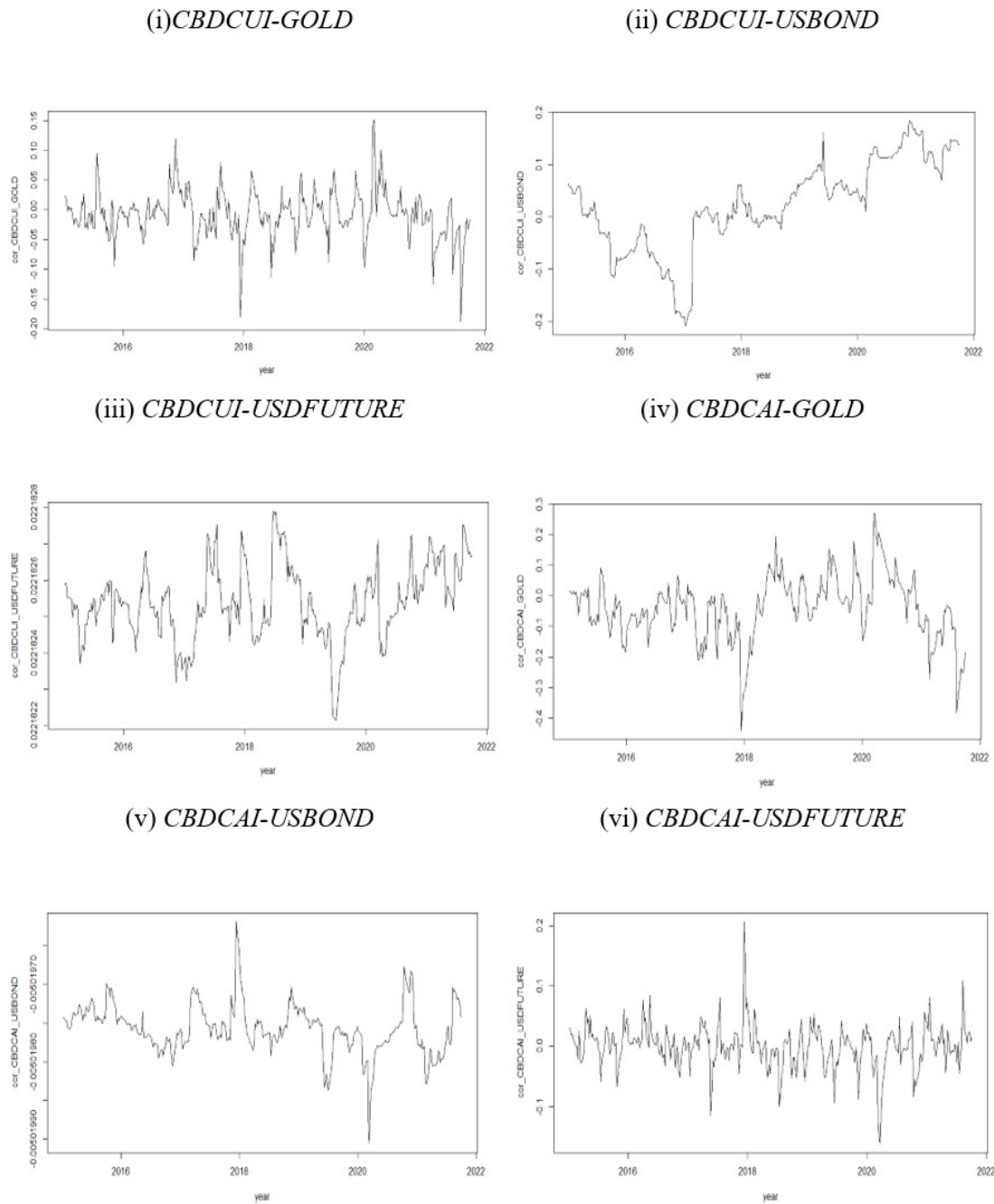


Figure 2. DCC GARCH time-varying coefficients

Notes: This plot contains DCC results. *CBDCUI* is CBDC uncertainty index, *CBDCAI* is CBDC attention index, *GOLD* is gold, *USBOND* is 1-year US bond, *USDFUTURE* is US dollar future.

sample results. Meanwhile, the negative nexus between *CBDCAI* and the other variables prevails using the preCovid-19 data, which resembles the full sample results.

IV. Conclusion

In this paper, we study the hedging potential of gold, US bond, and US dollar futures against CBDC uncertainty and attention indices. We find that the US dollar consistently shows a positive association with CBDC uncertainty. The association is mixed (both positive and negative) between CBDC attention index and the US dollar. Importantly, gold is not a hedge against CBDC uncertainty, which is in con-

trast to the literature (Baur & Lucey, 2010). Additionally, gold exhibits a negative association with CBDC attention index. Finally, the US bond hedges CBDC uncertainty only subsequent to 2019, while it shows a consistent negative association with the CBDC attention index. Our findings suggest that policy makers should be aware of the potential negative impacts of the CBDC indices, particularly the attention index. Future research may focus on other asset classes and alternative econometric models, such as quantile-based analysis, to capture spillovers from CBDC uncertainty and attention indices to financial markets in different market states.

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References

- Akhtaruzzaman, M., Boubaker, S., Lucey, B. M., & Sensoy, A. (2021). Is gold a hedge or a safe-haven asset in the COVID–19 crisis? *Economic Modelling*, 102, 105588. <https://doi.org/10.1016/j.econmod.2021.105588>
- Bank for International Settlements. (2018). *Central bank digital currencies*. <https://www.bis.org/cpmi/publ/d174.pdf>
- Bariviera, A. F., & Merediz-Solà, I. (2021). Where do we stand in cryptocurrencies economic research? A survey based on hybrid analysis. *Journal of Economic Surveys*, 35(2), 377–407. <https://doi.org/10.1111/joes.12412>
- Baur, D. G., & Dimpfl, T. (2021). *A safe haven index*. Available at SSRN 3641589.
- Baur, D. G., & Lucey, B. M. (2010). Is gold a hedge or a safe haven? An analysis of stocks, bonds and gold. *Financial Review*, 45(2), 217–229. <https://doi.org/10.1111/j.1540-6288.2010.00244.x>
- Corbet, S., Lucey, B., Urquhart, A., & Yarovaya, L. (2019). Cryptocurrencies as a financial asset: A systematic analysis. *International Review of Financial Analysis*, 62, 182–199. <https://doi.org/10.1016/j.irfa.2018.09.003>
- Dyhrberg, A. H. (2016). Hedging capabilities of bitcoin. Is it the virtual gold? *Finance Research Letters*, 16, 139–144. <https://doi.org/10.1016/j.frl.2015.10.025>
- Engle, R. F. (2002). Dynamic conditional correlation: A simple class of multivariate generalized autoregressive conditional heteroskedasticity models. *Journal of Business & Economic Statistics*, 20(3), 339–350. <https://doi.org/10.1198/073500102288618487>
- Glosten, L. R., Jagannathan, R., & Runkle, D. E. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. *The Journal of Finance*, 48(5), 1779–1801. <https://doi.org/10.1111/j.1540-6261.1993.tb05128.x>
- Kamal, J. B., & Hassan, M. K. (2022). Asymmetric connectedness between cryptocurrency environment attention index and green assets. *Journal of Economic Asymmetries*, 25, e00240. <https://doi.org/10.1016/j.jeca.2022.e00240>
- Nekhili, R., & Sultan, J. (2020). Jump Driven Risk Model Performance in Cryptocurrency Market. *International Journal of Financial Studies*, 8(2), 19. <https://doi.org/10.3390/ijfs8020019>
- Smales, L. A. (2022). Investor attention in cryptocurrency markets. *International Review of Financial Analysis*, 79, 101972. <https://doi.org/10.1016/j.irfa.2021.101972>
- Wang, Y., Lucey, B. M., Vigne, S. A., & Yarovaya, L. (2022). The effects of central bank digital currencies news on financial markets. *Technological Forecasting and Social Change*, 180, 121715. <https://doi.org/10.1016/j.techfore.2022.121715>
- Williamson, S. D. (2021). Central bank digital currency and flight to safety. *Journal of Economic Dynamics and Control*, 104146.