IS BITCOIN IMMUNE TO THE COVID-19 PANDEMIC?

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Abstract

This study examines how Bitcoin's trading characteristics react to the COVID-19 pandemic, using detailed futures trading data from the Chicago Mercantile Exchange. The results show that volume-weighted Bitcoin futures return responds positively to the spikes of public interest. Meanwhile, the surges of pandemic information do not harm market quality. Volume, bid-ask spread, and trading frequency remain stable, indicating that the positive price reaction is not a result of a few small, uninformed trades. Bitcoin's conditional beta on the S&P 500 index drops to near zero, while the conditional beta on gold more than doubles. These results indicate that traders have been using Bitcoin to hedge the risk associated with the pandemic outbreak.

JEL codes: E42, E44, G11, G13

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1. Introduction

One of the unique features that characterize cryptocurrencies is decentralization. Theoretically, decentralized cryptocurrencies can function as a hedge instrument when central authorities are in peril. However, there is mixed evidence on whether cryptocurrencies play such a role. Bouri, *et al.* (2017) argue that Bitcoin generally is not suitable for hedging but point out that Bitcoin's hedging properties depend on investment horizons. Smales (2019) argues that despite the lack of correlation between Bitcoin and other assets, the high volatility and low liquidity of the cryptocurrency disqualify it from safe-haven asset consideration. On the other hand, Corbet, *et al.* (2020) show that the volatility relationship between the main Chinese stock markets and Bitcoin evolved significantly after the COVID-19 pandemic outbreak and identify some hedging effects of the cryptocurrency.

Identifying the hedge properties of cryptocurrencies is difficult. Firstly, there has not been a significant crisis in the world economy from the point cryptocurrencies became popular until the end of 2019. Secondly, cryptocurrency markets are less established compared to traditional financial markets. Most of the cryptocurrency markets do not trade conventional financial products, and the markets are rarely regulated. The validity of the data from those markets can be questionable.¹ Lastly, the trading data is often not detailed enough.

¹ For example, Mt. Gox exchange handled 70% of Bitcoin transactions until 2014, when the exchange declared bankruptcy after a series of security breaches. Later, the CEO of the exchange was found guilty of falsifying data to inflate Mt. Gox's holdings.

We attempt to overcome these obstacles by analyzing the Bitcoin futures trading data from the Chicago Mercantile Exchange (CME) in the COVID-19 sample period. The COVID-19 pandemic created a substantial adverse effect on the world economy. If cryptocurrencies do matter in a crisis, their trading pattern should react to the event. From the market quality perspective, the CME is a well-established exchange, and the data from the CME is less likely to have inaccurate prices or mistakes in the quotes.

The CME constructed their Bitcoin futures contract to ensure arbitrage trades between the futures and the spot. When arbitrage trading is possible, the Cost-of-Carry model holds, and futures and spot prices reflect the same information.² Jia and Kang (2021) confirm the relationship between the futures and the spot. Kim (2021) documents that Bitcoin's convenience yield has been stable since the initiation of the futures contract. Similarly, Baig et al. (2020) show that the introduction of Bitcoin futures reduced price clustering, thus improving price discovery in the cryptocurrency market.

The CME also excels in data collection. The CME provides the Top-of-Book data that contains price, volume, and quotes with timestamps. From this data, we can construct trading activity measures that are less swayed by small, uninformed trades. Such robust variables are one of the features that differentiate our study from other works on cryptocurrencies.

We develop measures of pandemic information and examine how significant information events affect Bitcoin futures trading. We find that Bitcoin returns increase during the days of critical information. Meanwhile, we do not observe market quality deterioration signs, indicating that the pattern reflects market consensus rather than a few abnormal prices. We also find that Bitcoin's beta on the S&P 500 index significantly decreases to zero during the critical event days, while Bitcoin's beta on gold more than doubles. These results demonstrate that Bitcoin functions as a hedge against the COVID-19 crisis.

2. Data and Method

2.1 Trading Data

Most of the studies on cryptocurrencies rely on end-of-the-day or end-of-the-hour prices. However, a close look at the Top-of-Book data reveals that such prices may not represent overall trading activities. Figure 1 presents the hourly (Central Standard Time) averages of selected trading characteristics from the CME data. The prices and returns are volume weighted. The 16:00 hour has no observation because the futures market has a 1-hour break at the time.

We find that return, volume, and volatility vary considerably by the hour. For example, the volatility is exceptionally high at 12:00 AM, 9:00 AM, and 5:00 PM Central Standard Time. These hours are the end of a calendar day, the maturity time of the contract, and the first hour of trading after a break. The main driver of these movements is market structure rather than information. This result demonstrates that the relationship between trading and information would be better analysed by aggregating the intra-day trading data than using end-of-time observations.

Our data period is from January 1, 2020 to June 30, 2020. The average daily trading volume is 7,332 contracts or 36,660 Bitcoins in the sample period (one CME futures contract = five Bitcoins). Note that large Bitcoin spot markets have smaller trading volumes in the same

² Corbet, et al. (2018) and Bauer and Dimpfl (2018) examine the relationship between Bitcoin spot and futures markets. They show that the Cost-of-Carry model holds in general between the spot and futures prices.

period. The US-Dollar-based trading volumes of spot markets are 15,931 (Coinbase), 7,695 (Kraken), and 9,588 (Bitstamp) Bitcoins per day.³



Figure 1: Hourly Summary of Bitcoin Futures Trading

2.2 COVID-19 Information

We match the daily summary of trading activities with two measures of the COVID-19 information.⁴ First, we identify overall public interest in COVID-19 using the Google Trends search requests. We obtain data on daily search requests for "coronavirus" from Google

³ For the spot market trading volumes, we used the BTC/USD daily data on the <u>http://www.cryptodatadownload.com</u> website.

⁴ Karalevicius, et al. (2018) find that the Bitcoin prices react to the media sentiment regarding Bitcoin. Our analysis focuses on the Bitcoin futures' reaction to the information about the COVID-19 pandemic.

Trends.⁵ Google Trends data is presented in a normalized format (based on time and location of a query) and ranges from 0 to 100, with 100 assigned to the data point with the highest number of searches for a specified period (and location, if applicable). Figure 2 presents the Google Trends level in our sample period. March and April 2020 exhibit higher levels of public interest.

Our second variable attempts to capture significant events or milestones in the COVID-19 pandemic. To identify the most significant events, we perform internet searches for "coronavirus/COVID-19/SARS-CoV-2/pandemic + timeline/key events/major events/ milestones," etc. within major news outlets. We include newspapers, broadcast media, news agencies, COVID-19 milestones, and response documents published by international organizations (e.g., World Health Organization (WHO)) and central banks. The following sources have published the COVID-19 timelines: WHO, CNN, Reuters, New York Times, Associated Press, and Federal Reserve Bank of St. Louis.

Figure 2: Worldwide Google search for term "coronavirus" based on Google Trends data.



We compare all the events mentioned in the above sources and designate an event as a "major event/milestone" if at least 50% of sources mention it in their timeline document.⁶ The examples of the events/milestones of the COVID -19 pandemic include January 30, 2020, when the WHO declared the outbreak a Public Health Emergency of International Concern

⁵ "COVID-19" can be another search keyword. However, COVID-19 is the official name of the disease introduced by the World Health Organization on February 11, 2020. We would lose more than 1 months of trends by using "COVID-19". Additionally, the number of searches that use "COVID-19" is considerably smaller compared to "coronavirus" and, in general, follows a similar trend.

⁶ We try 33% or 66% as the cut-offs as well. Although the empirical results are similar with those cut-offs used, we believe 50% is the right balance. The 66% cut-off does not capture any events after March 2020. The 33% cut-off contains somewhat region-specific news.

(PHEIC). All six sources (100%) mention this event. Another example is March 13, 2020, when the former U.S. President, Donald Trump, declared a national emergency. This event appears in 83% of timeline documents. We create an indicator variable (*Coronavirus Event*) that equals to "1" on the date that significant development related to COVID-19 happened and "0" otherwise. For some events that occur on non-trading days, we assign "1" to the following trading day.⁷ Table A1 in the Appendix shows that most of the announcements contain negative information, except the stimulus package announcement on March 25, 2020. Similar to the Google search pattern, the timeline events are clustered in March and April 2020.

3. Tests on the relationship between the COVID-19 and Bitcoin

3.1 Information and Reaction

We first measure Bitcoin's reactions to the COVID-19 information with multivariate regressions. In addition to the information variables, we include variables used in the prior studies (e.g., Bouri *et al.*, 2017; Philippas *et al.*, 2019; Andrada-Félix *et al.*, 2020; Corbet, *et al.*, 2020, Baur and Hoang 2020; Kim 2021) as controls. Our controls are days to maturity (Days_to_Maturity), convenience yield of Bitcoin futures, a daily percent change in the exchange rates between the US dollar and euro (Euro) as well as the US dollar and Japanese yen (Yen), daily stock market return (*S&P500_ret*), extreme stock market indicator, and a daily percent change in COVID-19 cases around the world (*COVIDCasesWorld_rate*).

The convenience yield variable controls the futures-spot basis. According to the Cost-of-Carry model, a futures price has a high correlation with the spot price when the convenience yield of the spot contract is stable. Kim (2021) shows that the Bitcoin spot contract has a somewhat stable convenience yield, but we control for the convenience yield in the regression to account for the irregularities during the pandemic. We calculate the convenience yield from the Cost-of-Carry model using daily CME futures price, Bitcoin Real Time Index from the CME, and 1-month T-Bill rate. The storage cost is assumed as zero. The extreme stock market indicator is similar to Baur and Hoang (2020) and captures shocks from equity markets. The variable equals one when the S&P 500 index is below or above its 10 percentile or 90 percentile value in the sample period, and zero otherwise. The model is:

$$Trading \ Characteristics_t = a + b \cdot COVID_Info_t + c \cdot Y + \varepsilon_t$$
(1)

A Trading Characteristic at day t is regressed by the COVID information variables (*Coronavirus_ Google Trends, Coronavirus Event*) at day t. Y is the matrix of the control variables. We convert all level variables to a (percent) change variable. A level variable is likely to be non-stationary, and a time-series model with such a dependent variable generates spurious results.⁸

As the information variables are at the daily frequency, we aggregate the Top-of-Book data. The daily return is the volume-weighted average of returns between two consecutive transactions. Small, uninformed trades will have a limited effect on volume-weighted measures. Daily volume is the sum of traded contracts per day, and volatility is the standard deviation of returns between transactions. Bid-ask spread is the difference between the volume-weighted bid and ask quotes, divided by the quote midpoint. Lastly, we acquire the

⁷ Otherwise, we do not distinguish between the event date and the trading date. We find that the reactions of the futures market mostly occur on the same business day that the event happened.

⁸ Also, a Tobit estimation is necessary for a level variable because the dependent variable's sign is always above zero.

time between trades by taking the volume-weighted average of time between two consecutive transactions. We estimate our model using the OLS regressions with Newey–West standard errors.

	Return	Return	Return	∆ Volatility	∆ Volume	∆ Bid-ask spread	∆ Time btw. trades
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Coronavirus_ GoogleTrends	0.98ª	0.97 ª		-6.48	-0.02	8.44	0.16
(public interest)	(3.86)	(3.78)		(-1.26)	(-0.95)	(0.39)	(1.37)
Coronavirus_Event	-11.67		-8.86	527.74	0.37	1,410.39	-15.62 ^b
(main event)	(-0.66)		(-0.47)	(1.06)	(0.27)	(1.00)	(-1.99)
Days_to_Maturity	0.41	0.45	0.016	-14.88	0.04	24.51	0.065
	(0.68)	(0.76)	(0.03)	(-0.99)	(1.11)	(0.76)	(0.18)
Convenience Yield	-8.04	-8.29	0.43	375.47°	0.81	782.08	0.02
	(-0.78)	(-0.80)	(0.04)	(1.73)	(1.27)	(1.14)	(0.00)
Euro	1,349.76	1,330.97	791.35	350.88	-161.13	87,236	1,013.80
	(1.30)	(1.29)	(0.74)	(0.01)	(-1.55)	(1.12)	(1.35)
Yen	1,557.03	1,472.10	1,830.99	-6,325.10	-67.88	-15,672	201.51
	(1.34)	(1.28)	(1.43)	(-0.27)	(-0.74)	(-0.16)	(0.32)
S&P500_ret	144.60	137.96	52.19	-3,694.24	-25.61	-66,552ª	126.30
	(0.72)	(0.68)	(0.23)	(-0.64)	(-1.64)	(-2.91)	(1.53)
S&P500 Extreme	-36.97 ^b	-37.38 ^b	-5.50	1.55	0.82	153.61	-4.96
	(-2.23)	(-2.20)	(-0.41)	(0.00)	(0.87)	(0.12)	(-0.68)
COVIDCases	10.42	9.98	5.27	188.89	-0.46	8.44	12.09 ^b
World_rate	(1.46)	(1.49)	(0.73)	(1.64)	(-0.73)	(0.39)	(2.42)
Constant	-50.83ª	- 52.49 ª	-24.82 ^b	333.94	-0.30	-821.85	-3.99
	(-3.80)	(-4.14)	(-2.00)	(1.24)	(-0.37)	(-1.06)	(-0.70)
Observations	121	121	121	121	121	121	121
Adj. R-squared	6.85%	7.23%	-3.27%	-1.95%	-0.93%	14.61%	0.28%

Table 1: Impact of public interest and COVID-19 milestones on Bitcoin futures trading

This table presents the results of the OLS estimation of equation (1). The names of the dependent variables are in the first row. The Coronavirus_GoogleTrends (public interest) and Coronavirus_Event (main event) variables are the main explanatory variables. Further details on the variables are in section 3.1. The Greek letter delta (Δ) indicates that we use the difference between two consecutive observations. The coefficients on return, volatility, and spread are multiplied by 106 for visual convenience. T-values are in the parentheses, and the Newey –West standard errors are heteroscedasticity consistent.

Significance levels are indicated as follows: c = 10%, b = 5%, a = 1%.

Columns 1 and 2 in Table 1 show Bitcoin return is positively and significantly correlated with the public interest variable (*Coronavirus* _Google Trends). This pattern indicates that Bitcoin price increases when the public is more aware of (and/or more worried about) the crisis. Such a price reaction is consistent with the results of Corbet, *et al.* (2020). They measure the COVID-19 sentiment from Tweeter and find significant positive correlations between the measures and cryptocurrency returns. Compared to their study, we use volume-weighted returns and a more extended sample period (Jan 2020 - Mar 2020 vs. Jan 2020 - Jun 2020). Our result shows that Bitcoin price increase is a robust phenomenon in the pandemic period.

In addition, we do not observe any significant effect of the public interest variable on other trading characteristics. Volume, bid-ask spread, or time between transactions do not deteriorate significantly during the critical days. Such results demonstrate that the pandemic event has little impact on the market quality of Bitcoin futures. In unreported tests, we set various market quality variables as the dependent variable and check the relationship with the pandemic information. Other market quality variables, including volume volatility or skewness of volume, are not significantly associated with the pandemic information.

In column 6, the S&P 500 return has a particularly strong explanatory power for the bid-ask spread. The S&P 500 return coefficient is significant at the 1% level, and the adjusted R-squared is 15%. These numbers indicate a link between the stock market performance and the transaction cost of Bitcoin futures.

3.2 Bitcoin Betas

To further examine Bitcoin's usefulness as a hedge against the COVID-19 crisis, we analyze Bitcoin's betas. We construct the following model to determine if Bitcoin's betas change in critical times.

$$R_t = a_1 + b_1 \cdot R_{Bit,t} + b_2 \cdot R_{Bit,t} \times Pandemic_t + a_2 \cdot Pandemic_t + \varepsilon_t$$
(2)

Rt is the daily return of an asset, $R_{Bit,t}$ is the daily return of Bitcoin futures, and *Pandemict* is an indicator variable of the pandemic information. The *Pandemict* variable equals one in the days with a notable change in the pandemic information. When the *Pandemict* variable is zero, equation (2) becomes a simple beta estimation model, where the coefficient b_1 is the beta. When the *Pandemict* variable is one, the beta b_1 changes by the coefficient b_2 . Thus, the b_2 term captures a change in beta during critical times, and the $b_1 + b_2$ term is the beta conditional on the surge of the pandemic information.

For the *Pandemic*⁺ variable, we convert our *Coronavirus*_ *GoogleTrends* variable to an indicator that is equal to one whenever the variable is over 75 and zero otherwise. The number over 75 means the number of searches in a day is higher than the 75 percentiles of the sample period.⁹

We regress the Bitcoin return on the S&P 500 index, gold, and the Dollar index (DXY) returns. The S&P 500 index and gold returns are from Yahoo Finance and the DXY data is from Bloomberg. To reduce the noise in the end-of-the day prices, we calculate the daily return of Bitcoin futures from the daily volume-weighted average prices.¹⁰ The estimation method is the OLS with Newey –West standard errors. Table 2 presents the results.

Regressions on the S&P 500 returns show that Bitcoin's beta is 0.19 during relatively stable times. However, the interaction variable has a negative coefficient, as the beta drops to near zero in turbulent times.¹¹ Bitcoin has a positive correlation with the stock market in general, but a massive negative shock breaks the link.

⁹ We test with different thresholds such as 50 or 90 and acquire similar results.

¹⁰ We acquire similar results by cumulating the return between Bitcoin transactions. Still, the estimated betas will be easier to interpret if both the dependent variable and explanatory variable are from the differences in daily prices.
¹¹ Estimation using a subsample of critical information days indicates that Bitcoin's beta is statistically indistinguishable from zero.

	S&P 500	S&P 500	Gold	Gold	USD Index	USD Index
Bitcoin Return: b1	0.191⊧ (2.59)		0.063 ^b (2.48)		-0.008 (-0.52)	
Bitcoin Return x Pandemic: b2	-0.119 (-0.42)	0.072 (0.27)	0.078 (1.13)	0.141 ^ь (2.18)	-0.007 (-0.23)	-0.015 (-0.63)
b ₁ + b ₂	0.072		0.141		-0.015	
Constant: a1	0.000 (0.06)	0.001 (0.49)	0.001 (1.01)	0.001 (1.39)	-0.000 (-0.48)	-0.000 (-0.59)
Pandemic: a2	-0.010 (-0.49)	-0.010 (-0.53)	-0.002 (-0.18)	-0.002 (-0.22)	0.003 (1.08)	0.003 (1.09)
a 1 + a 2	0.010	-0.009	-0.001	-0.001	0.003	0.003
Adjusted R ²	4.1%	0.0%	10.2%	8.9%	2.2%	2.8%

Table 2: Conditional betas of Bitcoin futures

The conditional beta of Bitcoin is estimated using equation (2).

(2)

 $R_t = a_1 + b_1 \cdot R_{Bit,t} + b_2 \cdot R_{Bit,t} \times Pandemic_t + a_2 \cdot Pandemic_t + \epsilon_t$ Rt is the daily return of an asset, RBILT is the daily return of Bitcoin futures, and Pandemict is the indicator variable of the COVID-19's impact. We create the indicator variable by setting its value as 1 when the number of Google searches is over 75 percentiles. The daily return is the return from the daily volume-weighted average price. We regress the Bitcoin return on the returns of the Standard & Poors 500 index and gold. The estimation method is OLS, and the Newey –West standard errors are heteroscedasticity consistent. The $a_1 + a_2$ row and the $b_1 + b_2$ row report the sum of the coefficients for visual convenience. T-values are in the parentheses.

Significance levels are indicated as follows: c = 10%, b = 5%, c = 1%.

Bitcoin's beta with the gold price is positive and significant, demonstrating that Bitcoin's price moves similar to gold. When the pandemic situation escalates, the gold beta more than doubles from 0.06 to 0.14. In a crisis, Bitcoin begins to resemble gold, the traditional hedging instrument.

We do not find a significant relationship between the Dollar index and Bitcoin returns. This result may stem from several possibilities. First, Bitcoin price is based on the US Dollar, so Bitcoin return could already include the value change in the Dollar. Second, the USD index was stable during the data period. The standard deviation of daily return is 0.52%. The index may have a low volatility because most fiat currencies were simultaneously affected by the pandemic.

4. Conclusion

This paper examines the reactions of Bitcoin's trading characteristics to the COVID-19 pandemic. Using detailed trading data from an established futures exchange, we find that volume-weighted Bitcoin futures return responds positively to the spikes of public interest. Meanwhile, the surges of pandemic information do not harm market quality. Volume, bid-ask spread, and trading frequency remain stable, indicating that the positive price reaction is not a result of a few small, uninformed trades.

Our analysis of Bitcoin's beta verifies the existence of hedge-seeking trades. Bitcoin has a positive and significant beta with the S&P 500 index in general, but the beta drops to zero

during turbulent times. Similarly, we find that Bitcoin's beta on gold more than doubles in critical times.

Overall, this study demonstrates that Bitcoin has been functioning as a hedge after the pandemic outbreak. Media has been calling cryptocurrencies as "Digital Gold," mainly to describe speculative demand. After the COVID-19 crisis, perhaps the same nickname can have a different meaning, indicating that cryptocurrencies can have hedging properties similar to gold.

References

- Andrada-Félix, J., Fernandez-Perez, A., Sosvilla-Rivero, S., 2020. Distant or close cousins: Connectedness between cryptocurrencies and traditional currencies volatilities. Journal of International Financial Markets, Institutions and Money 67, 101219.
- Associated Press, 2020. Timeline of key events in the spread of the new coronavirus Associated Press, available at: <u>https://apnews.com/article/f143c90d86e5887fbb74cdc40b6796da</u> (accessed 10 September 2020)
- Baig, A. S., Haroon, O., Sabah, N., 2020. Price Clustering After the Introduction of Bitcoin Futures. Applied Finance Letters, 9, 36 - 42.
- Bauer, D., Dimpfl, T., 2019. Price discovery in bitcoin spot or futures? Journal of Futures Markets 39, 803-817
- Baur, D., Hoang, L., 2021. A crypto safe haven against Bitcoin. Finance Research Letters, 101431.
- Bouri, E., Molnár, P., Azzi, G., Roubaud, D., Hagfors, L. I., 2017. On the hedge and safe haven properties of Bitcoin: Is it really more than a diversifier? Finance Research Letters 20, 192-198.
- CNN Editorial Research (2020), "Coronavirus Outbreak Timeline Fast Facts", CNN, September 7, available at: <u>https://www.cnn.com/2020/02/06/health/wuhan-coronavirus-</u> <u>timeline-fast-facts/index.html</u> (accessed September 10, 2020)
- Corbet, S., Hou, Y. G., Hu, Y., Larkin, C., Oxley, L., 2020. Any port in a storm: Cryptocurrency safe-havens during the COVID-19 pandemic. Economics Letters 194, 109377.
- Corbet, S., Larkin, C., Lucey, B., 2020. The Contagion Effects of the COVID-19 Pandemic: Evidence from Gold and Cryptocurrencies. Finance Research Letters 35, 101554.
- Corbet, S., Lucey, B., Maurice, P. and Samuel, V. (2018), "Bitcoin Futures—What use are they?", Economics Letters, Vol. 172, pp. 23-27.
- Federal Reserve Bank of St. Louis. (2020), "Timeline of Events Related to the COVID-19 Pandemic", Federal Reserve Bank of St. Louis, available at: <u>https://fraser.stlouisfed.org/timeline/covid-19-pandemic</u> (accessed September 10, 2020)

- Jia, J., & Kang, S. B. (2021). Do the basis and other predictors of futures return also predict spot return with the same signs and magnitudes? Evidence from the LME. Journal of Commodity Markets, 100187.
- Karalevicius, V., Degrande, N., De Weerdt, J., 2018. Using sentiment analysis to predict interday Bitcoin price movements. Journal of Risk Finance 19, 56-75.
- Kim, S. T., 2021. Is it worth to hold Bitcoin?, Finance Research Letters, 102090.
- Philippas, D., Rjiba, H, Guesmi, K., Goutte, S., 2019. Media attention and Bitcoin prices. Finance Research Letters, 37-43.
- Reuters staff, Editing by de Kretser, L., Wu, T., 2020. Timeline: How the global coronavirus pandemic unfolded, Reuters, June 28, available at: <u>https://www.reuters.com/article/us-health-coronavirus-timeline/timeline-how-the-global-coronavirus-pandemic-unfolded-idUSKBN23Z0UW</u> (accessed September 10, 2020)
- Smales, L.A., 2019. Bitcoin as a safe haven: is it even worth considering? Finance Research Letters 30, 385–393
- Taylor, D.B., 2020. A Timeline of the Coronavirus Pandemic. New York Times, August 6, available at: <u>https://www.nytimes.com/article/coronavirus-timeline.html</u> (accessed September 10, 2020)
- World Health Organization (WHO), 2020. Timeline of WHO's response to COVID-19. World Health Organization, available at: <u>https://www.who.int/news-room/detail/29-06-2020-</u> <u>covidtimeline</u> (accessed 30 June, 2020)