**The role of Covid-19 for Chinese stock returns: evidence from a GARCHX model**

Nicholas Apergis, University of Derby, UK, n.apergis@derby.ac.uk

Emmanuel Apergis, University of Huddersfield, UK, e.apergis@hud.ac.uk

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**ABSTRACT**

This paper examines the effect of Covid-19 pandemic on the Chinese stock market returns and their volatility using the generalized autoregressive conditionally heteroskedastic GARCHX model. The GARCHX model allows us to include Covid-19 information within the GARCH framework. The findings document that daily increases in total confirmed Covid-19 cases in China, measured as total daily deaths and cases, have a significant negative impact on stock returns, with the negative impact of the Covid-19 on stock returns being more pronounced when total deaths proxy the effect of this infectious disease. The results also document that Covid-19 has a positive and statistically significant effect on the volatility of these market returns. Overall, new evidence is offered that infectious diseases, such as Covid-19, can seriously impact market returns, as well as their volatility. The findings could be essential in understanding the implications of Covid-19 for the stock market in China.

**Keywords**: stock market returns; Covid-19; China; GARCHX model

**JEL Classification**: G12; Q54

# I. Introduction

Much of the current attention has shifted to the global coronavirus outbreak that commenced in December 2019 from Wuhan, the capital city of Hubei province in China. The World Health Organization (WHO) officially declared Covid-19 (an infectious disease caused by novel coronavirus) outbreak to be a global pandemic on March 11, 2020. In particular, Covid-19 has put significant pressure on financial and labour markets worldwide, leading to an unprecedented financial and health crisis. It is expected that the global economy will experience the worst coronavirus recession since the Great Depression (IMF, 2020) [[1]](#footnote-1). It is noteworthy that the Chinese stock market is one of the largest markets worldwide. This work addresses a new very vital question, which could shed light on China’s current financial markets trends: whether the recent Covid-19 pandemic leads to significant adverse effects on stock market returns and their associated volatility. The findings provide new evidence that infectious diseases, such as Covid-19, can seriously impact stock market returns and their volatility. The findings could be of substantial interest for certain stakeholders, such as market participants, portfolio and hedge managers, regulators, and policy makers.

The study is mainly associated with two broad strands in the literature: studies on the impact of pandemic and natural disasters on stock returns, and the role of financial crisis for stock market developments. The first strand examine the impact of pandemic, such as Covid-19, on stock prices. Given the time scale of the paper, limited papers have investigated the stock market reaction to the Covid-19 pandemic (Al-Awadhi et al., 2020; Zhang et al., 2020)[[2]](#footnote-2). Zhang et al. (2020) provide a simple analysis to describe the general patterns of country-specific risks and systemic risks in the top ten countries that have the highest coronavirus cases as of March 27, 2020. Using a minimum spanning tree analysis, their work suggests that stock market risks have significantly increased in sample economies. Furthermore, the high uncertainty of Covid-19 and its negative impact on the real economy have increased the volatility in financial markets. Al-Awadhi et al. (2020) provide fresh evidence on the Chinese stock markets response to the Covid-19 outbreak, spanning the period January 10, 2020 to March 16, 2020. To this end, they use panel data methods to examine the impact of Covid-19 on all stocks traded on both the Hang Seng and Shanghai Stock Exchange Composite indexes. Their results document that the Covid-19 outbreak (measured as the daily growth in total confirmed cases, or as total daily cases of deaths) has a significant negative impact on stock returns in China. Our study, however, extends their analysis by considering a methodology that accounts for the simultaneous effect of the pandemic on both the mean and the volatility of Chinese stock returns directly through the structure of the model.

In terms of the literature on natural disasters, the impact of disasters on stock returns is conditional on the type of business activity of a firm. As a result, there is no consensus in the literature on how stock returns respond to such disasters. Previous studies have extensively examined the effects of disasters on stock prices (Kowalewski and Śpiewanowski, 2020; Donadelli et al., 2020; Shelor et al., 1992; Shelor et al., 1990). Shelor et al. (1990, 1992) find a negative impact on stock returns of real estate firms due to an earthquake in California. Wang and Kutan (2013) show that natural disasters result in a little change in the volatility of US equity returns. Using granular analysis, Donadelli et al. (2020) show that tornados have a negative effect on stock returns in the US. In a recent paper, Kowalewski and Śpiewanowski (2020) investigate how stock markets respond to disasters in potash mines, using data on 55 mining accidents worldwide between 1986 and 2019. They illustrate that the market value of these mining firms drops by 1.15% over the first two days of the accident.

The second strand of literature address how financial markets respond to financial crises. Naturally, stock markets respond differently to bear and bull markets, given their typical complex system. In principle, the specific time period, such as financial crisis or a market crash can have significant impact on stock returns and volatility. The Global Financial Crisis in 2007-2009 has been continuously labelled as the worst financial and economic crisis since the Great Depression in the 1930s. This crisis severely affected stock markets and macroeconomic indicators worldwide (Eichengreen and O’Rourke, 2009). In general, there is a consensus among economists that international stock markets respond strongly during the high volatility periods, such as market crises (Lin et al., 1994; Longin and Solnik, 2001). Engle (2004) investigates the daily U.S. stock market volatility using the S&P500 index over the period January 1963 through November 2003. He highlights that the 1987 international market crash has been ‘the most dramatic event’ in US equity market history; therefore, volatility in S&P 500 stock returns tends to be higher in bear markets (Lee et al., 2002).

The main objective of this paper is to examine the effect of Covid-19 on stock market returns and their volatility, spanning the period January 27, 2020 through April 30, 2020 period in China using daily data. We make use of the GARCHX method which does not require to assume linearity, independence, and constant variance in modeling stock returns. The GARCHX model is among the framework of standard GARCH models; however, it allows to include information on additional controls, such as the Covid-19 variable in both the mean and the conditional variance equations of the model.

The findings document that daily increases in total confirmed cases and total cases of daily deaths caused by Covid-19 have a significant negative impact on stock returns, with the negative impact of Covid-19 on stock returns being more pronounced when the analysis uses total cases of deaths to proxy the effect of this infectious disease. The results also document that Covid-19 has a positive and statistically significant effect on the volatility of the associated stock market returns. The findings also display that crude oil prices and interest rates have significant impacts on these returns.

The remainder of this paper goes as follows. Section 2 describes the data to be used in the analysis, while Section 3 outlines the methodology of the GARCHX model. Section 4 provides the main empirical findings and finally, Section 5 concludes.

# II. Data

We study the effect of Covid-19 on stock market returns and their volatility over the period January 22, 2020 through April 30, 2020 in China using daily data. The start date of January 22, 2020 reflects the date when the first Covid-19 case was officially announced in China. We employ two proxies for the Covid-19 event: i) total confirmed cases, and ii) death cases. The data are obtained from Refinitv Datastream. The analysis also uses the 1-month interbank loan rate as a proxy for the short-term interest rate. Data on these rates (short-term interest rates) are retrieved from Datastream. The analysis also uses daily crude oil price measured as spot West Texas Intermediate (WTI) prices also obtained from Datastream. Finally, the Shanghai Stock Exchange and the Shenzhen Stock Exchange are the two major emerging Chinese capital markets, linked via the national stock exchange automated quotation system. Two types of stocks are traded in the two markets: A shares and B shares. A type of shares are restricted to Chinese citizens and denominated in Chinese currency (RMB), while B shares can be bought and sold only by foreigners and are settled in foreign currency (U.S. dollars for Shanghai and Hong Kong dollars for Shenzhen). Here, the analysis focuses on the analysis of the A share market, since the B share market has lost its appeal to foreign investors, while A shares dominate B shares in terms of the number of listed companies, trading volume, and market capitalization. Hence, to the empirical ends of the analysis, we use the value-weighted return between A shares in the Shanghai and Shenzhen stock markets to represent the Chinese stock market returns. Stock market data are also sourced from Datastream. Table 1 presents certain summary statistics.

**Table 1.** Summary statistics.

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| **Variables** |  **Mean** |  **SD** |  **Min** |  **Max** |  **Skewness**  | **Kurtosis** |
| stock returns |  -0.0513 |  3.214 |  -0.0586 |  0.0124 |  0.54 |  4.13 |
| oil prices |  39.60 |  19.30 |  -37.60 |  59.90 |  -0.94 |  2.34 |
| T-bills |  1.19 |  0.61 |  1.04 |  1.58 |  0.94 |  4.96 |
| CCovid19-1 |  36,923.17 |  10,331.45 |  3.00 |  82,974.00 |  1.41 |  0.78 |
| CCovid19-2 |  1297.46 |  790.93 |  5.00 |  4,634.00 |  2.03 |  4.63 |

SD denotes standard deviation, CCovid19-1 denotes Chinese Covid-19 cases, CCovid19-2 denotes Chinese Covid-19 deaths.

# III. Methodology

The GARCH (generalized autoregressive conditional heteroskedasticity) model proposed by Bollerslev (1986), is a popular framework among scientific community to model risk and its forecasting in a time series. Following Bollerslev (1986), several variants of GARCH models have been introduced. The standard family of (symmetric) GARCH models includes integrated GARCH (IGARCH) recommended by Engle and Bollerslev (1986), exponential GARCH (EGARCH) recommended by Nelson (1991), and GARCHX recommended by Engle et al. (1990), Apergis (1998), and Connor and Linton (2001).

In order to examine the impact of the Covid-19 pandemic on stock returns and their volatility in China, the analysis considers the GARCHX model that builds upon the GARCH framework. The motivation of the model selection is based upon previous studies that have documented the correlation between stock returns and risk. The GARCHX model allows to include information on certain additional important controls that are allowed to impact the mean of stock returns. The standard GARCHX model is made up of two equations: a conditional mean and a conditional variance equation. We allow the Covid-19 factor to enter both the mean and the conditional volatility equations. Therefore, this modelling approach enables us to assess the impact of the Covid-19 event via both equations. The GARCHX model is a special case of the multivariate Factor-GARCH model by Engle et al. (1990), in the sense that only one factor, i.e., the Covid-19 factor is included.

GARCHX models are also a generalized version of models by Braun et al. (1995) and Glosten et al. (1993). The study by Babalos et al. (2019) also makes use of a modelling approach that is close to ours. More specifically, to establish any potential link between equity fund flows and stock market returns, they estimate a VAR-GARCH(1, 1)-in-mean model, which also allows the inclusion if an additional variable, i.e. a switch dummy variable that explicitly considers the global financial crisis event into the volatility equation. A simple, but widely used method to obtain time-series volatility, is to apply a return process to calculate errors and then square them. More specifically, an ARMA(p, q) returns process may be used to calculate errors. That is, for returns, rit, the following specification is used:

 p q

rt = a + Σbrt-i + Σcvt-i + εt (1)

 i=1 i=1

where the first sum represents the autoregressive (AR) component and the second sum the moving average (MA) component, with a and ε being a constant and an error term, respectively. In the first step of the GARCHX methodology, we add to Equation (1) a new variable that proxies the Covid-19 factor, turning the model into the GARCHX specification:

p q

rt = a + Σbrt-i + Σcvt-i + d Covid19t + ηt (2)

 i=1 i=1

Since the seminal paper of Hamilton (1983), many studies have shown that stock markets respond to oil price shocks. In a seminal contribution, Kilian (2009) proposes a model that shows that the impact of oil price shock is contingent on whether the oil price changes are due to supply shocks or demand shocks. Several papers have used the model of Kilian (2009) to examine the effect of oil price shocks on financial markets. In general, studies find that demand shocks have a large and significant impact on stock returns, while supply shocks have a small impact on those returns. Given that the literature has established a role of oil prices in determining stock prices and returns (Cologni and Manera, 2008; Kilian, 2009; Nguyen and Bhatti, 2012; Reboredo and Rivera-Castro, 2014), as well as a similar role for interest rates (Laopodis, 2013; Huang et al., 2016; Assefa et al., 2017), Equation (2) also includes both oil prices and short-term interest rates:

p q

rt = a + Σbrt-i + Σcvt-i + d1 Covid19t + d2 oilt + d3 ratet + ηt (3)

 i=1 i=1

Within a GARCH(1, 1) framework, the equation of conditional volatility turns out to be:

ht = f + ght-1 + mη2t-1 (4)

where h denotes the conditional volatility measure and η is the residuals from (2). In our GARCHX version modelling version, we also add the Covid-19 variable, and Equation (4) yields:

ht = f + ght-1 + mη2t-1 + k COVID19t (5)

with the restriction of the stability conditions remaining similar to those in the traditional GARCH(1, 1) model, that is g+m<1.

# IV. Empirical analysis

First, the results based on the General Least Squared Dickey-Fuller (Elliott et al., 1996) unit root test, reported in Table 2, document that the levels of series under investigation (stock prices) turn out to be stationary only when their first differences are obtained; furthermore, the Akaike information criterion recommends an AR(1) model as a proxy of Chinese stock returns.

**Table 2.** GLS unit root tests.

|  |  |
| --- | --- |
| **Variables** | **Levels First differences** |
| stock returns | -1.17(3) | -6.71(2)\*\*\* |
| oil prices | -1.27(3) | -6.52(2)\*\*\* |
| T-bills | -1.25(2) | -6.58(1)\*\*\* |
| CCOVID19-1 | -1.26(3) | -6.69(3)\*\*\* |
| CCOVID19-2 | -1.22(3) | -6.78(2)\*\*\* |

Rejection of the null hypothesis indicates stationarity. Lags in parentheses denote the number of lags included in the test and determined through the Akaike information criterion. \*\*\*: p≤0.01.

Next, the analysis provides the estimates of the parameters of the GARCHX model. The coefficient estimates for the model in Equations (3) and (5) are presented in Table 3. The findings with respect to the two alternative model specifications correspond to the two alternative proxies of the Covid-19 variable: i) CCovid19-1: daily total confirmed cases in China from Covid-19, ii) CCovid19-2: total daily deaths in China from Covid-19.

The results document that the estimated coefficients of the GARCHX model meet the required condition that g+m<1, which is a vital requirement for a mean reverting process. This sum g+m measures volatility persistence. Therefore, we can conclude that the conditional volatilities are mean reverting for the daily returns on the average index. Moreover, the estimates illustrate that all estimated coefficients in the conditional variance equation are statistically significant at the standard levels of significance. Therefore, we reject the null hypothesis that coefficients of the variance equation are zero. More importantly, the findings provide strong evidence that the Covid-19 factor exerts a significant negative impact on mean stock returns in China. These results hold across both models, corresponding to the two alternative definitions of the Covid-19 measure. However, the negative impact of the Covid-19 on stock returns is more pronounced when we use total cases of deaths to proxy the effect of this infectious disease. Similarly, the results of the conditional volatility equation document that Covid-19 has a positive and statistically significant effect on the volatility of stock returns. As in the case of the mean equation, we find that these effects are stronger when employing the total number of deaths as a proxy for Covid-19. In addition, the drivers of oil prices and short-term interest rates have the expected impact on mean stock returns. Finally, certain diagnostics across all models, such as the LM test statistic, denotes the absence of serial correlation in the residuals, implying that the GARCHX model is well specified.

**Table 3.** GARCHX estimates: the role of Covid-19 in stock returns.

|  |  |  |
| --- | --- | --- |
|  | **Model 1** | **Model 2** |
| **Mean equation** | **CCovid19-1** | **CCovid19-2** |
| Constant | 0.041 | 0.032 |
|  | [0.27] | [0.33] |
| stock returns(-1) | 0.615\*\*\* | 0.639\*\*\* |
|  | [0.00] | [0.00] |
| Covid-19 | -2.652\*\*\* | -3.675\*\*\* |
|  | [0.00] | [0.00] |
| Oil prices | -0.573\*\*\* | -0.642\*\*\* |
|  | [0.00] | [0.00] |
| T-bill rates | -0.497\*\* | -0.548\*\* |
|  | [0.03] | [0.02] |
| **Conditional volatility equation** |  |  |
| constant | 0.0036\* | 0.0040\* |
|  | [0.09] | [0.08] |
| h(-1) | 0.484\*\*\* | 0.503\*\*\* |
|  | [0.00] | [0.00] |
| η2(-1) | 0.342\*\*\* | 0.369\*\*\* |
|  | [0.00] | [0.00] |
| Covid-19 | 0.098\*\* | 0.129\*\*\* |
|  | [0.03] | [0.00] |
| *Diagnostics* |  |  |
| Log-likelihood | 3,453.9 | 3,618.1 |
| LM test for Heteroscedasticity | [0.65] | [0.73] |

Figures in brackets denote p-values, CCovid19-1 denotes Chinese Covid-19 incidences, and CCovid19-2 denotes Chinese Covid-19 deaths.

The final step of the empirical analysis investigates the forecasting performance of the GARCHX model. The model is estimated from January 22, 2020 to April 15, 2020, while the out-of-sample forecasting horizon span the period April 16, 2020 to April 30, 2020. The forecasting exercise uses a rolling sample of the past volatilities. On day t, the conditional volatility of one period ahead, t+1, is constructed by using the estimates which are obtained from only the past observations. By the recursive substitution of the conditional volatility, forecasts for up to 15 horizons are constructed. The forecasting performance was compared against the model with the Covid-19 factor. Table 4 reports the forecasting results which highlight that the GARCHX model with the Covid-19 factor (Panel I with respect to the Chinese confirmed cases and Panel II with respect to the Chinese confirmed deaths) performs better in terms of volatility forecasts.

Two popular measures derived from the forecast error are designed to evaluate the forecasts. These include the mean absolute forecasting error (MAFE) and the mean squared forecasting error (MSFE) (Diebold, 2004). The GARCHX model with the Covid-19 variable included shows smaller MAFE, as well as MSFE, than the GARCHX model without the Covid-19 factor. The lower the forecast error measure, the better the forecasting performance. However, it does not necessarily mean that a lower MAFE or MSFE completely testifies superior forecasting ability, since the difference may be not significantly different from zero. Therefore, it is important to check out whether any reductions in the two measures are statistically significant, rather than just compare them in each case (Harris and Sollis, 2003). To this end, the forecasting analysis makes use of the Diebold and Mariano (1995) test of equal forecast accuracy, which investigates whether two sets of forecast errors have equal mean value, i.e. the null hypothesis is that of equal forecast accuracy. The results also presented in Table 4 reject the null hypothesis of forecasting accuracy in both cases of the Covid-19 definition, thus providing solid support to the forecasting superiority of the model that explicitly considers the Covid-19 factor.

**Table 4.** Forecasting performance of the GARCHX model with Covid-19.

|  |  |  |  |
| --- | --- | --- | --- |
| Forecasting Horizon | I. Cases in China |   | II. Deaths in China |
| (days) | Without Covid-19 | With Covid-19 |   | Without Covid-19 | With Covid-19 |
|  | MAFE | MSFE | MAFE | MSFE |  | MAFE | MSFE | MAFE | MSFE |
| 1 | 0.1742 | 0.0765 | 0.1142 | 0.0432 | 1 | 0.1653 | 0.0645 | 0.1041 | 0.0365 |
| 2 | 0.1751 | 0.0768 | 0.1146 | 0.0448 | 2 | 0.1660 | 0.0651 | 0.1050 | 0.0369 |
| 3 | 0.1790 | 0.0801 | 0.1148 | 0.0455 | 3 | 0.1668 | 0.0660 | 0.1057 | 0.0376 |
| 4 | 0.1801 | 0.0812 | 0.1154 | 0.0461 | 4 | 0.1674 | 0.0674 | 0.1062 | 0.0392 |
| 5 | 0.1813 | 0.0817 | 0.1159 | 0.0469 | 5 | 0.1681 | 0.0677 | 0.1070 | 0.0397 |
| 6 | 0.1824 | 0.0819 | 0.1165 | 0.0484 | 6 | 0.1694 | 0.0686 | 0.1078 | 0.0412 |
| 7 | 0.1829 | 0.0826 | 0.1186 | 0.0489 | 7 | 0.1701 | 0.0703 | 0.1084 | 0.0418 |
| 8 | 0.1835 | 0.0833 | 0.1193 | 0.0496 | 8 | 0.1707 | 0.0710 | 0.1091 | 0.0425 |
| 9 | 0.1840 | 0.0832 | 0.1197 | 0.0512 | 9 | 0.1716 | 0.0726 | 0.1109 | 0.0421 |
| 10 | 0.1837 | 0.0853 | 0.1212 | 0.0514 | 10 | 0.1714 | 0.0715 | 0.1119 | 0.0416 |
| 11 | 0.1847 | 0.0862 | 0.1206 | 0.0508 | 11 | 0.1723 | 0.0723 | 0.1113 | 0.0430 |
| 12 | 0.1842 | 0.0861 | 0.1218 | 0.0519 | 12 | 0.1720 | 0.0736 | 0.1118 | 0.0434 |
| 13 | 0.1835 | 0.0869 | 0.1230 | 0.0513 | 13 | 0.1715 | 0.0728 | 0.1102 | 0.0421 |
| 14 | 0.1844 | 0.0872 | 0.1213 | 0.0506 | 14 | 0.1712 | 0.0716 | 0.1091 | 0.0411 |
| 15 | 0.1846 | 0.0864 | 0.1205 | 0.0500 | 15 | 0.1702 | 0.0704 | 0.1095 | 0.0405 |
| DM test |  |  |  |  | DM test |  |  |  |  |
| MAFE: [0.00], MSFE: [0.00] |   |   |   | MAFE: [0.00], MSFE: [0.00] |   |   |   |

MAFE and MSFE represent mean absolute forecast error and mean squared forecast error, respectively. DM is the Diebold-Mariano test statistic, using MAFE and MSFE as the error criterion. Figures in brackets denote p-values. The results are based on 15 out-of-sample forecasts.

# V. Conclusion

This study provided the first examination of the effects of Covid-19 on both the mean and the conditional volatility of the Chinese stock market returns, using a simple GARCHX conditional volatility model, spanning the period January 22, 2020 to April 30, 2020. The analysis used two alternative proxies of the Covid-19 factor: i) total confirmed cases, and ii) total daily deaths. The findings documented that Covid-19 had a significant negative impact on stock returns and their associated volatility across both alternative Covid-19 measures. Similar findings indicated that Covid-19 had a positive and statistically significant effect on the volatility of stock returns. The negative impact of Covid-19 on stock returns turned out to be more pronounced when the pandemic measure was proxied by the total cases of deaths. Furthermore, the model that included the Covid-19 factor highlighted a better out-of-sample forecasting performance.

 The empirical findings signify that the Covid-19 pandemic shock drives the Chinese market ‘crazy’, although the Chinese Covid-19 experience was not among the worst cases in an international context. However, the reflection of death cases provided an informative ‘opportunity’ for market participants to learn something about investors’ psychology and human behaviour. Borrowing what Keynes had named as the ‘beauty contest’ metaphor for this type of behaviour, we can clearly realize that financial markets are driven by humans, and, thus, are highly behavioural, with just ignoring trends in fundamentals. The Covid-19 event represents a fearsome and novel risk. As such, it stirred feverish behaviour by investors. It is important for all stakeholders associated with the stock market, i.e. individual investors, fund and portfolio managers, firms, policymakers and regulators, to learn about the nature of the challenge they are facing in these stressful times. Such stock price reactions suggest that broad actions, including fiscal policy or central bank interventions, are required to avoid further negative outcomes and propagations of the Covid-19 shock. The changes behind this event could bring potentially massive social and political upheavals, especially if billions of wealth are lost through the stock market, which necessitates the policymakers’ responses.

 Moreover, the results imply that news on this pandemic event is richer and diffuses much more rapidly across market environments. Therefore, the stock market impact of the Covid-19 pandemic is highly likely to trigger daily stock market jumps and high stock market volatility (events that deserve formal research in future empirical attempts). As Velde (2020) discusses, the negative stock market impact of a pandemic event was fairly modest in the past, even over time spans of several months. Today, however, explanations that stress greater information availability and its more rapid diffusion clearly rationalize the huge stock market effect since the outbreak of the Covid-19 pandemic. All the above, is the way such (adverse) news is reflected onto stock prices as an early and visible reflection of the more damages to come (through various sectors in the real economy, i.e. health markets, labour markets, tourism and transportation markets).

Finally, future research venues could explore how the Covid-19 event has impacted different Chinese sectors and individual companies and their corresponding listed stocks. In addition, the impact of Covid-19 factor could be also explored within an asymmetric conditional volatility framework. Apparently, this study can be extended to include many more stock markets that can be explored either on a time series or a panel basis.

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1. https://blogs.imf.org/2020/04/14/the-great-lockdown-worst-economic-downturn-since-the-great-depression/ [↑](#footnote-ref-1)
2. In a recent survey, Goodell (2020) finds that the research on the effects of pandemics is seriously limited. [↑](#footnote-ref-2)