Tourism Effects of Pandemics: New Insights from Novel Coronavirus

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Abstract

This study investigates the effect of coronavirus on tourism worldwide using data on confirmed cases of coronavirus by European Centre for Disease Prevention and Control [ECDCPC] and Google trends data. The analysis uses a variety of estimation approaches, including quantile regressions and causality tests. The study showed that cases of coronavirus have a negative relationship with tourism. In general, increasing cases of coronavirus would tend to reduce travel to tourist destinations. More interestingly, the effects are heterogeneous across the distribution of cases of coronavirus.

JEL Classification: Z30, Z31, L18
Keywords: Travel, tourism, pandemics, coronavirus

1. Introduction

The Coronavirus Disease 2019 (Covid-19), primarily caused by a novel coronavirus, namely severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), was first detected in December 2019 in the city of Wuhan in Hubei province, China (Fauci, Lane & Redfield, 2020). As shown in Table 1 and Figures 1 and 2 (in the appendix), the outbreak has since spread to all provinces of mainland China and 27 other countries, with more than 100 000 confirmed cases and 3 400 confirmed deaths as of March 7, 2020 (World Health Organization [WHO], 2020a).

The COVID-19 is a respiratory disease, which presents a range of illness from asymptomatic or mild through to severe disease and death. Since contact, droplets and fomites are the means of transmission, public health measures, such as hand hygiene and good respiratory etiquette (coughing into your elbow or into a tissue and immediately disposing of the tissue), are vital to prevent infection. According to a report by WHO (2020b), the speed of transmission for COVID-19 virus is estimated to be 5-6 days. The reproductive number (the number of secondary infections from one infected individual) is said to be between 2 and 2.5. Children are less infected than adults, and clinical attack rates in the 0-19 age group are low.

80% of infections are mild or asymptomatic, 15% are severe, requiring oxygen and 5% are critical infections, needing ventilation. Older age and underlying conditions intensify the risk for severe infection. Currently, the crude mortality ratio (the number of reported deaths divided by the reported cases) is between 3-4%. While a number of therapeutics are currently in clinical trials in China and more than 20 vaccines in development, there are currently no licensed vaccines or therapeutics available.

Since WHO declaration of a public health emergency of international concern in connection to COVID-19, more than 40 countries have reported extra health measures that considerably inhibit international traffic in connection to travel to and from China or other countries, from visa restrictions, quarantine for returning travelers, or denial of entry of passengers. Several countries that have denied entry to travelers or who have put on hold the flights to and from China or other affected countries, are now reporting cases of COVID-19 (WHO, 2020c). A cross-cutting economic activity, unlike any other, travel and tourism, are confronted by the COVID-19 challenge, especially because of the essential people-to-people nature of the sector. According to Monterrubio (2012): "Travel, tourism and epidemics are intrinsically linked. Although travel may significantly contribute to the actual paths an infection may take, the former may eventually become the victim of the latter. Past experiences have revealed that epidemic infections can have negative economic impact on the tourism industry" (p.1).

In a report update on the sector's response to the COVID-19 outbreak, the United Nations World Tourism Organization [UNWTO] (2020) has offered a first assessment highlighting a shrinkage in international arrivals and receipts in 2020. UNWTO has revised its 2020 prospects for international tourist arrivals to a negative growth of 1% to 3%, meaning an estimated loss of US\$ 30 to 50 billion in international tourism receipts. Amongst other regions, Asia and the Pacific is predicted to be the worst-hit region, with an anticipated fall in arrivals of 9% to 12%. In fact, the impact of the COVID-19 outbreak is estimated to be felt across the whole tourism value chain. For example, Canada's tourism industry has seen the impacts of the coronavirus on the number of foreign visitors for the summer travel season as all cases of the virus confirmed domestically have been connected to people who have recently returned from abroad and their close contacts. According to Global News (2020), bookings are down from China by about 70 per cent between October 2019 and March 2020 as several airlines have restricted the number of flights to the country, and several Canadian tourism marketing agencies have pulled all their ad money from China.

By implication, the discovery of coronavirus has reportedly altered travel and tourism patterns, causing significant economic damage to the affected areas, particularly the tourist destinations. As highlighted above, a report by UNWTO (2020) found that the virus' economic impact could range between US\$ 30 to 50 billion in international tourism receipts, with significant costs driven by dwindling tourism. Yet, the tourism literature has hardly evaluated the effects of cases of coronavirus on travel and tourism, though there are a few existing studies on the relationship with other pandemics (e.g., 1926 Smallpox Epidemic, SARS [severe acute respiratory syndrome]) and tourism (e.g., Zeng, Carter & De Lacy, 2005; Monterrubio, 2010; Jarvis, 2011; Novelli, Burgess, Jones & Ritchie, 2018; Dang, 2019). However, it would be expected that the virus would disproportionately reduce travel to infected regions and, in most cases, stifle travel to tourist destinations. However, this sort of relationship is hardly established in the literature. For this reason, this study examines the effects of cases of coronavirus on travel and tourism. Compared to existing studies, the main contributions of this novel study can be summed up in the two points: One, to the best of the researchers' knowledge, this is the first attempt to explore the effects of coronavirus on tourism. Two, by introducing Google trends, this study proposes a novel emerging online big data for future tourism studies.

The main aim of this study is, therefore to determine the effect of cases of coronavirus on tourism. The rest of the paper is organized as follows. Section 2 describes the data and the formulation process of the proposed econometric approach in detail. Section 3 discusses the results of the empirical analysis, where the effects of cases of coronavirus on tourism are estimated. Finally, Section 4 concludes the paper with key implications and the major directions for future research.

2. Data and Methodology

2.1 Data

The data on confirmed cases of coronavirus is from European Centre for Disease Prevention and Control [ECDCPC] (2020). In contrast, statistics on international tourists within the study period are fragmented, and there is no internationally comparable body of data. As such, this analysis relies on data drawn from Google trends to derive estimates of tourism behaviour. This approach adds to an emerging body of research using digital tools, such as social media and Google trends, to track disease, behaviour, and intentions to provide public health information (Ye, Li, Sharag-Eldin, Tsou & Spitzberg, 2017; Chu, Colditz, Sidani, Zimmer & Primack, 2019; Zadeh, Zolbanin, Sharda & Delen, 2019). In particular, Google search data are increasingly used to study many health outcomes such as the forecasting of Zika incidence in the 2016 Latin America outbreak (McGough, Brownstein, Hawkins & Santillana, 2017).

According to Yu, Zhao, Tang & Yang (2019, p. 213), "search engines are the most useful tools on the Internet for acquiring the latest relevant news about a target term and the related factors. Of all search engines, Google search is ranked at the top in terms of having the highest traffic. By processing a myriad of Google global search results, an emerging type of online big data, namely Google trends, is generated to reflect the public attention (or sentiment)". Accordingly, Google trends are considered a particular type of big data that cover large-scale information. Studies such as Ginsberg et al. (2009) contended that Google search queries are useful big data for detecting influenza epidemics. Lazer, Kennedy, King, and Vespignani (2014) emphasized Google flu trends as an example of the usage of emerging online big data. Considering the above, this study uses Google trends as informative predictors for travel restrictions and tourism.

To estimate the effect of coronavirus on the behaviour of tourists, this study first identified the point in time when the coronavirus became widely popular among the public. In order to accomplish this task, Google search trend data is used for the term "coronavirus" from December 2019 through March 2017. This term, though technical, has recently become widely used in Google searches and popular culture (Figure 3). The term "tourism destinations" are also searched for within the same period to determine if there was any significant change in the term's popularity among the public. Google search data shows that the term "tourist destinations" has reduced drastically in popularity since the same mid-January 2020 (Figure 3). This points to a relationship which will be confirmed in the analysis section.

2.2 Quantile regressions

Compared with the conventional ordinary linear squares (OLS), quantile regression is capable of providing a more robust picture of the relationship between the outcome Y and the regressor X at various points in the conditional distribution of Y (Le, Su & Nguyen, 2019). Koenker and Bassett (1978) derived a novel set of statistics for the linear model termed

'regression quantiles', which extended the classical OLS of conditional mean models to the estimation of a class of models for several conditional quantile functions.

Figure 3: Google search trends of 'coronavirus' and 'tourist attractions'
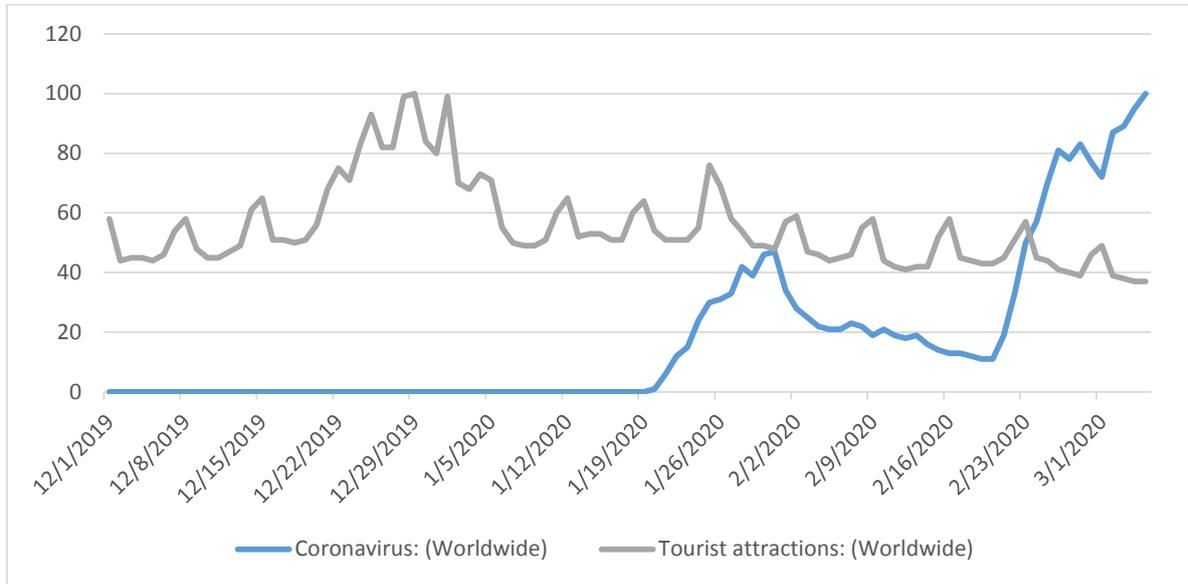
Quantile regression eliminates estimation bias when estimating the response of a variable with a heterogeneous distribution (Lee, Lee & Ryu, 2019). Koenker and Hallock (2001) have shown that this bias is a major shortcoming of the OLS method. Also, Deaton (1997) postulates that the properties of the estimates of quantile regression are better than those obtained from OLS.

The standard OLS model is defined as

$$y = X^T \beta + \varepsilon \tag{1}$$

where y is the dependent variable vector, X is the independent variable matrix, β is the coefficient matrix, and ε is the vector of residuals. The coefficient vector β can be estimated using a quadratic loss function; given observations $\{y_i, X\}_{i=1}^n$, the estimation is performed by minimizing the quadratic loss function over β:

$$\sum_{i=1}^n (y_i - X^T \beta)^2 \tag{2}$$

In OLS, the conditional expectation E[**y**|**X** = **x**] is minimized by this quadratic loss function. Conversely, the simplest form of the quantile regression, the median regression, estimates the conditional median of y, given that **X** = **x**, by minimizing the loss function:

$$\sum_{i=1}^n (y_i - X_i^T \beta)^2 \tag{3}$$

From equation (3), quantile regression defines the quantile loss function, λ_k, as

$$\lambda_k = \sum_{i=1}^n \left[k^{I(0,\infty)} (y_i - X_i^T \beta) |y_i - X_i^T \beta| - (1-k) I_{(0,\infty)} (y_i - X_i^T \beta) |y_i - X_i^T \beta| \right] \tag{4}$$

Where the identification function, $I_\rho(x)$, is defined as

$$I_\rho(x) = \begin{cases} 1, \text{if } \rho \in \text{A and} \\ 0, \quad \text{otherwise} \end{cases}$$

Equation (4) suggests that λ_k can be minimized instead of Equation (3). The quantile regression can be repeatedly conducted for different quantile values by replacing k in λ_k with the corresponding quantile value.

2.3 Granger causality test

The Granger causality test is employed to capture the effect of coronavirus on travel and tourism. The Granger causality from a stationary time series y_t to another stationary time series x_t can be defined as

$$\Pr(x_t|I_{t-1}) = \Pr(x_t|I_{t-1} - Y_{t-n}^n) \qquad (t = 1, 2, \ldots, T) \tag{5}$$

Where $\Pr(x_t|I_{t-1})$ is the conditional probability distribution of x_t based on the bivariate information data $I_{t-1} = (X_{t-m}^n, Y_{t-n}^n)$, where $X_{t-m}^n = (x_{t-m}, \ldots, x_t - 1)$ and $Y_{t-n}^n = (y_{t-m}, \ldots, y_{t-1})$.

The series y_t can predict the series x_t provided Equation (5) is statistically rejected. The causality is then model as

$$x_t = a_0 + a_1 x_{t-1} + \cdots + a_m x_{t-m} + b_1 y_{t-1} + \cdots + b_n x_{t-n} + \epsilon_t \tag{6}$$

$$y_t = c_0 + c_1 y_{t-1} + \cdots + c_m y_{t-m} + d_1 y_{t-1} + \cdots + d_n y_{t-n} + \varphi_t \tag{7}$$

where ϵ_t and φ_t are errors that are mutually independent and individually distributed, with zero means and constant variances. An F test is conducted to test the significance of the coefficients $b_i (i = 1, \ldots, n)$ and $d_j (j = 1, \ldots, m)$ individually. Causality is established if the coefficients deviate jointly from zero.

3. Empirical results

Descriptive statistics are descriptive coefficients that summarize a given data set (Evans, 2020). Table 2 reports the summary statistics of the data set: the mean, the minimum, the maximum, and the dispersion statistics. The correlation analysis in Table 3 shows correlation coefficients between the variables. Each cell in the table shows the correlation between the two variables. Evidently, cases of coronavirus are negatively and significantly related to Google trend of 'tourist destinations'. By implication, cases of coronavirus have a significant negative relationship with tourism.

Table 2. Descriptive Statistics

	Confirmed cases of Coronavirus	Google trend of 'tourist destinations'
Mean	93305.860	48.205
Median	96669.500	46.000
Maximum	141781.000	76.000
Minimum	44407.000	37.000
Std. Dev.	33658.090	8.245
Skewness	-0.194	1.203
Kurtosis	1.470	4.723

Table 3. Results of the Correlation Analysis

	Confirmed cases of Coronavirus	Google trend of 'tourist destinations'
Confirmed cases of Coronavirus	1.000	
Google trend of 'tourist destinations'	-0.518***	1.000

Notes: ***, ** and * denote statistical significance at the 1%, 5% and 10% levels.

To provide a better feel for the data and to show robustness to different specifications of the evidence, the analysis compares quantile and OLS regression results. Table 4 presents the results of the regressions, where the dependent variable is the Google trend of 'tourist destinations'. The Google trend of 'tourist destinations', representing tourism, is expected to

be highly negatively correlated with cases of coronavirus. The coefficient estimates obtained via OLS are shown in the first data column. The estimates are broadly consistent with a prior expectations and the correlation analysis. For example, tourism (Google trend of 'tourist destinations') is significantly and negatively associated with cases of coronavirus. The OLS estimates suggest that increasing cases of coronavirus would tend to increase reduce tourism.

Table 4. Quantile and OLS Estimates

Panel A	OLS	Quantiles				
		10%	25%	50%	75%	90%
Constant	0.673***	0.680***	0.651***	0.578***	0.682***	0.754***
	(0.053)	(0.062)	(0.067)	(0.081)	(0.117)	(0.126)
Confirmed cases of Coronavirus	-0.253***	-0.270***	-0.242***	-0.173**	-0.254***	-0.308***
	(0.047)	(0.055)	(0.059)	(0.071)	(0.103)	(0.110)
R^2	0.608	0.541	0.555	0.526	0.569	0.573
Pseudo R^2		0.527	0.540	0.508	0.549	0.553

Dependent variable: Google trend of 'tourist destinations'

*Notes: ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. Figures in brackets are standard errors. Huber Sandwich Standard Errors & Covariance. Sparsity method: Kernel (Epanechnikov) using residuals. Bandwidth method: Hall-Sheather, bw=0.098006*

Estimates obtained via quantile regressions are provided in the last five columns of the same table. The advantage of presenting the different quantiles is to bring clarity to possible heterogeneity across various quantiles and thus the varying impacts. In the regressions, it appears that there is much heterogeneity across various quantiles. For example, in the coronavirus and tourism relationship there is some degree of heterogeneity across various quantiles. The quantile coefficients of confirmed cases of coronavirus range from 17 per cent for the 50th percentile regression, to 31% per cent for the 90th percentile regression. In summary, the regressions suggest that cases of coronavirus has varying impacts on tourism, though cases of coronavirus tend to reduce tourism.

To appreciate the relationship between cases of coronavirus and tourism further, the Granger causality analysis is used to explore statistically whether cases of coronavirus cause Google trends of 'tourism destinations', with the lag orders varying from one to five. Evidently, from Table 5, cases of coronavirus Granger-cause Google trends of 'tourism destinations' across all lag orders from one to five. This indicates that cases of coronavirus reduces travel to tourist destinations.

Table 5. Results of the Granger causality analysis

	1	2	3	4	5
H_0: Cases of coronavirus does not Granger-cause Google trend of 'tourist destinations'					
F-stat	5.989**	7.706***	5.479***	4.470***	2.727**

*Notes: ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively.*

Overall, the empirical evidence from this study suggests that cases of coronavirus and tourism are highly interrelated to each other. Some possible reasons why cases of coronavirus have significant relationship 'tourist destinations' are as follows. First, the Google trends of 'tourist destinations' are a straight reflection of the public attention paid to the coronavirus epidemic. Second, cases of coronavirus will affect the trends of travel and tourism considerably in turn, due to concerns over safety and the fear of spreading or being infected with the virus. These findings are broadly consistent with earlier studies on the relationship between epidemics and tourism (e.g., Monterrubio, 2010; Novelli, Burgess, Jones & Ritchie, 2018; Dang, 2019). For example, according to Monterrubio (2012), hotel, restaurant and

aviation industries were the most affected in Mexico during the first weeks of the influenza A (H1N1) epidemic outbreak: "The impacts experienced by the industry were of an unprecedented nature and seem to have derived widely from international travel restrictions, the media's alarmist tones and government measures' (p. 1).

This study thus extends the extant literature by showing that pandemics such as coronavirus have a significant negative relationship with tourism. The findings have significant theoretical as well as practical implications. As regards theoretical implications, the findings suggest that future research focus on how pandemics or coronavirus interacts with other factors as part of an understanding of tourism behaviour. As regards practical implications, the results suggest that cases of coronavirus lead to negative repercussions on the tourism sector. International organizations, donor agencies and governments should consider tourism as a priority in recovery plans and actions from the coronavirus epidemic. Further, it is important to ensure that public health measures are implemented in ways that minimalize any unnecessary disruption to tourism.

4. Implications and Future Research

This paper examines the effects of coronavirus on tourism worldwide, in the hope of shedding further light on the epidemic–tourism nexus. The analysis uses a variety of estimation approaches, including OLS, quantile regressions and causality tests. The estimation results indicate that increasing cases of coronavirus would tend to reduce tourism. More interestingly, the effects are heterogeneous across the distribution of cases of coronavirus.

These results suggest that cases of coronavirus tend to reduce tourism. A direct implication of these findings is that, in pursuing public health measures for the eradication of coronavirus, international organizations, donor agencies and governments need to take into account the above differential impacts of their proposed actions. For example, if a policy action is likely to promote eradication of coronavirus but reduce tourism, supplementary actions may be needed to assist tourist destinations, and to prevent the scenario where public health measures might harm tourism by benefitting mainly public health without generating commensurate benefits for the tourism sector.

This analysis contains a few limitations. It is assumed that Google search for 'tourist destinations' are a proxy measure of intention to go on tour. Future studies could consider using survey to explore the effect of the coronavirus on tourism. However, this study is novel for the reason that it has evaluated tourism behavior change worldwide for a population that would understandably be otherwise difficult to study. Moreover, this study highlights an application of emerging online big data to help track epidemiologically-relevant tourism behavior across time in order to unravel how health-related information affects tourism.

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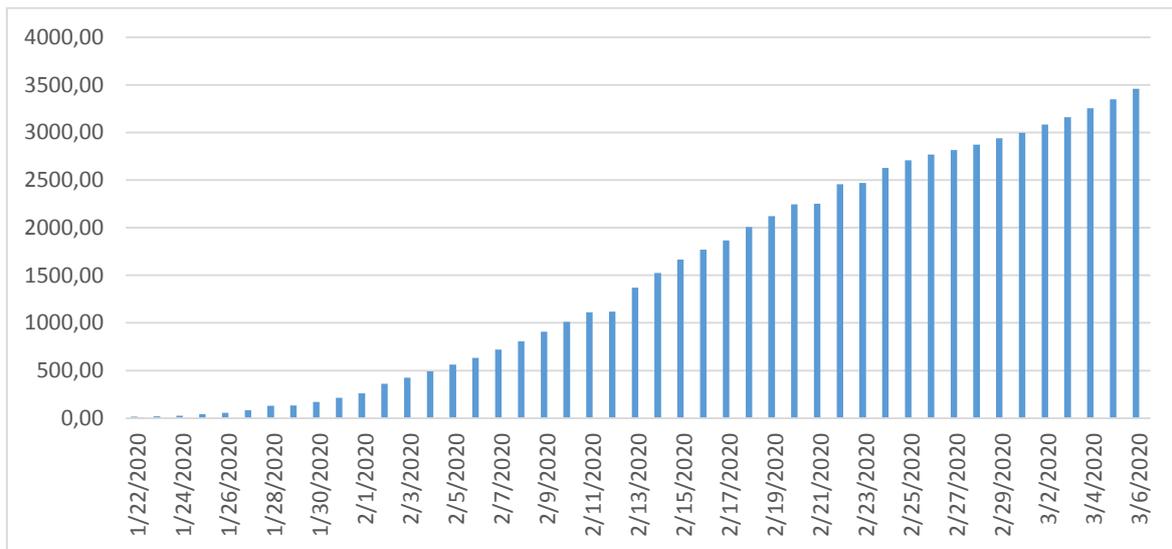
Appendix

Table 1. Reported Cases

Africa	Algeria (17), Senegal (4), Egypt (3), Morocco (2), Nigeria (1), South Africa (1) and Tunisia (1).
Asia	China (80 667), South Korea (6 284), Iran (3 513), Japan (349), Singapore (117), Kuwait (58), Bahrain (52), Malaysia (50), Thailand (47), Taiwan (44), Iraq (38), India (29), United Arab Emirates (29), Israel (17), Lebanon (16), Oman (16), Vietnam (16), Qatar (8), Palestine (7), Pakistan (5), Saudi Arabia (5), Philippines (3), Indonesia (2), Afghanistan (1), Bhutan (1), Cambodia (1), Jordan (1), Nepal (1) and Sri Lanka (1).
America	United States (233), Canada (45), Ecuador (13), Brazil (8), Mexico (5), Chile (4), Argentina (2), and Dominican Republic (1).
Europe	Italy (3 858), France (423), Germany (400), Spain (261), United Kingdom (115), Switzerland (87), Norway (86), Netherlands (82), Sweden (61), Belgium (50), Austria (41), Iceland (35), Greece (32), San Marino (22), Denmark (20), Ireland (13), Czech Republic (12), Finland (12), Croatia (10), Georgia (9), Portugal (9), Azerbaijan (6), Belarus (6), Romania (6), Slovenia (6), Estonia (5), Russia (4), Bosnia And Herzegovina (2), Hungary (2), Andorra (1), Armenia (1), Latvia (1), Liechtenstein (1), Lithuania (1), Luxembourg (1), Monaco (1), North Macedonia (1), Poland (1) and Ukraine (1).
Oceania	Australia (59) and New Zealand (4).

Figure 1. Confirmed cases of COVID-19 worldwide, as of 6 March 2020
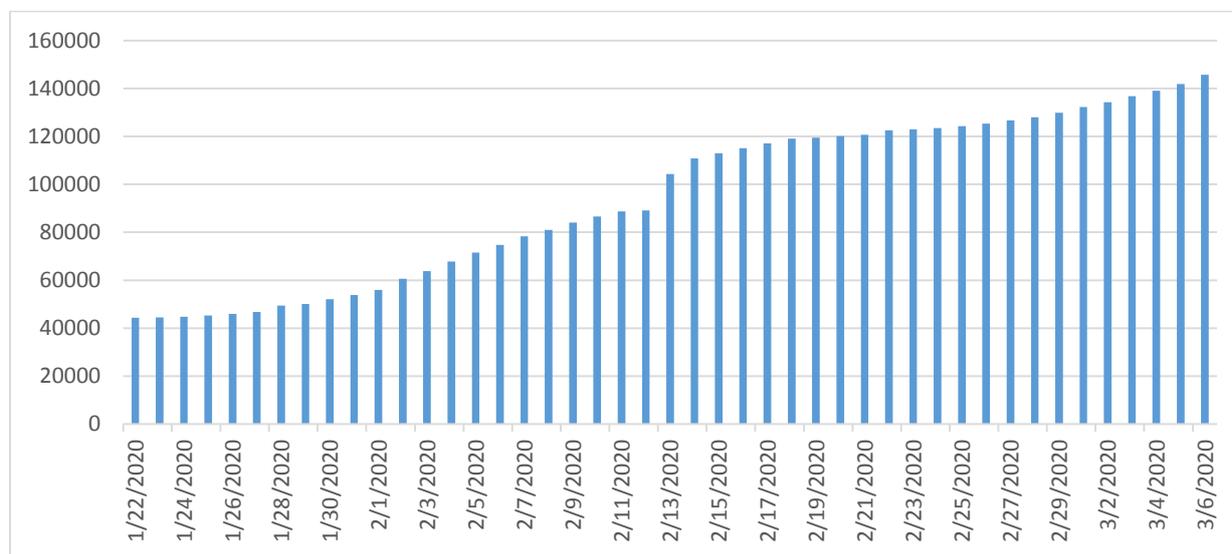
Data Source: ECDCPC (2020)

Figure 2. Death cases of COVID-19 worldwide, as of 6 March 2020

Data Source: ECDCPC (2020)