L-Università
ta' Malta

ISLANDS AND SMALL STATES INSTITUTE
UNIVERSITY OF MALTA, MSIDA, MALTA

OCCASIONAL PAPERS
ON ISLANDS AND SMALL STATES
ISSN 1024-6282

Number: 2020/02

TRAVEL CONNECTIVITY AND CLIMATE AS FACTORS AFFECTING THE CORONA VIRUS INFECTIONS ACROSS COUNTRIES: WITH IMPLICATIONS FOR SMALL STATES

Lino Briguglio and Melchior Vella

More information about the series of occasional paper can be obtained from the Islands and Small States Institute, University of Malta. Tel: 356-21344879, email: islands@um.edu.mt.

TRAVEL CONNECTIVITY AND CLIMATE AS FACTORS AFFECTING THE CORONA VIRUS INFECTIONS ACROSS COUNTRIES: WITH IMPLICATIONS FOR SMALL STATES[*]

Lino Briguglio[#] and Melchior Vella[§]

Abstract: The Corona virus outbreak has generated considerable interest as a subject of scholarly research. The present study is intended to add to the literature by testing the hypothesis that travel connectivity and warm climate of a country were important factors positively affecting the rate of recorded virus infection (RVI) across countries, between January and May 2020. Multiple regression analysis is used to test the stated hypothesis. The results indicate that RVI across countries was indeed positively influenced by travel connectivity and climate, keeping various other relevant factors constant, including population density and the number of days since the first virus infection was recorded. The results also shed light on whether country size matters in this regard. A two-way relationship between population size and the RVI, without keeping other things constant, indicated that the two variables are not correlated. However, the multiple regression results imply that while the high degree of travel connectivity and relatively high population density of many small states suggest that their exposure to virus infections would be relatively high, the opposite implication is suggested by the climate variable, in that many of these states, particularly small island developing states (SIDS), are located in the tropics, with relatively high temperatures all year round.

.

Keywords: Corona virus, travel connectivity, climate, small states.

Introduction

Objective of the paper

The Corona virus outbreak has generated considerable interest as a subject of scholarly research. The present study is intended to add to the literature by testing the hypothesis that travel connectivity and the warm climate of a country were important factors positively affecting the rate of recorded virus infection across countries, between January and May 2020. Multiple regression analysis is used to test the stated hypothesis. The study also sheds light on whether country size made a difference in this regard.

It should be stated at the outset that the findings presented in this study are general tendencies capturing the influences of variables which we assumed to have had systematic effects on the rate of transmission of the Corona virus in between January and May 2020. Various random factors, other than the selected explanatory variables, could have affected the rate of virus transmission.

Layout

This paper is organised in five sections. The section that follows presents a literature review

---

[*] This paper was completed on 19 June 2020

[#] Professor of Economics and Director of the Islands and Small State Institute at the University of Malta. Email: lino.briguglio@um.edu.mt .

[§] Visiting Assistant Lecturer at the University of Malta. Email: mvell31@um.edu.mt.

on themes relating to the explanatory variables selected for our analyses. The third section describes the methodology used to respond to the research question. The fourth section presents and discusses the results, while the concluding section derives a number of implications from the results.

Literature relating to the main explanatory variables

Travel connectivity

Travel connectivity, mostly as a result of tourism, is likely to be related to the rate of virus transmission as a result of contagion. This relationship has been treated in a number of academic studies. For example, Gössling *et al.*, (2020) emphasise the importance of recognising that travel and tourism are major contributors to disease spread and its economic consequences. The authors refer to several studies that have demonstrated the important role of air travel in accelerating and propagating viruses, citing Brown *et al.* (2016) for a review of these effects.

Brown *et al.*, (2016), who undertook a systematic study review to assess the evidence that air, ground and sea mass transportation systems or hubs are associated with spreading influenza and Corona viruses, concluded that transmission that occurs aboard aeroplanes can be transmitted at airports and at the travel destination.
Much earlier, in 2005, Mangili and Gendreu explained that because of the increasing ease and affordability of air travel and mobility of people, airborne, food-borne, vector-borne, and zoonotic infectious diseases transmitted during commercial air travel are an important public health issue. The authors further argue that the severe acute respiratory syndrome outbreak of 2002 showed how air travel can have an important role in the rapid spread of newly emerging infections and could potentially even start pandemics.

Climate

Climate differences and seasonality patterns have also been identified as having affected the rate of virus infections, *ceteris paribus*, on the assumption that the warmer the climate the lower is the chance of transmission. Various factors can explain this connection, including that people in temperate regions spend more time close together indoors during periods of colder weather, and that in Winter there is less sunshine to help in the production of vitamin D (Cookson, 2020). Kotz (2020) reported that researchers at the University of Maryrand (USA) found that the virus can spread anywhere, but it transmits most effectively between humans when humidity is low and the temperature is between 5^{o}C and 11^{o}C.

Ficetola and Rubolini (2000), referring to several studies and using an extensive global dataset showed that climate exhibits distinct impacts on the transmission of COVID-19, *ceteris paribus*. They also argue that the strong relationship between local climate and Covid-19 growth rates suggests the possibility of seasonal variation in the spatial pattern of outbreaks. Kroumpouzos *et al.*, (2020) also contended that higher temperatures and higher humidity tend to reduce virus viability, citing the findings of Chan *et al., (*2011) and Casanova *et al., (*2010) to back this statement. However, the authors argue that the seasonality and dynamics of COVID-19 are not well understood, and further studies are needed to identify the environmental conditions that favour its spread.

Wang *et al.*, (2020) in responding to the question as to whether the coming summer in the northern hemisphere will reduce the transmission intensity of COVID-19 as humidity and temperature increase, using data for 100 Chinese cities and 1005 US counties. However, their conclusion is that the change in weather alone will not be enough to contain the transmission of the virus, implying that public health intervention such as social distancing should continue to be implemented.

Population density and large gatherings.

Virus transmission is likely to occur at a high rate in densely populated areas, mostly large cities, as a result of contagion. This reality has given rise to practical measures in many countries to reduce contact rates drastically through lockdowns and by softer manners such as isolation of vulnerable persons. It has also led to may academic studies to assess of population density on virus transmission. Rocklöv and Sjödin (2020) proposed a number of formulae to assess this effect, but their parting shot argument is that keeping to more than 1-meter distance between people coughing and sneezing, as recommended by the WHO[1] becomes more difficult with higher population densities.

Other studies on this relationship are those produced by Singh (2020) and Sjödin et al., (2020), who found that areas with high population density are positively correlated with the rate of Corona infections. High population densities in cities also increases the possibilities for relatively large gatherings, which, in the literature is also associated with the rate of COVID-19 infections (Ebrahim and, Memish, 2020; Brooks-Pollock et al., 2020; Nunan and Brassey, 2020; Memish et al., 2020; WHO, 2020a).

Stage of development.

Intuitively, the stage of development of a country is likely to be negatively associated with the rate of virus infections, *ceteris paribus*. Advanced countries probably afford to carry out more tests than poorer ones, leading to a higher rate of recorded infections.[2] In addition, developed countries are likely to have a better capacity to withstand infections due to, amongst other things, improved ability to afford to buy protective devices (including masks), to adopt hygienic practices and to afford economic losses due to social distancing and lockdowns . However, at the same time, economically advanced countries are likely to have a higher degree of travel connectivity than poorer countries, and this would tend to be positively related to the rate of virus infection.[3]

The relationship between the rate of virus infections and the stage of development is investigated a number of studies including Barnett-Howell and Mobarak (2020), Schellekens and Sourrouille (2020). Barnett-Howell and Mobarak estimated the value of disease avoidance across rich and poor countries, and concluded that these policies tend to be less effective in poor countries with limited healthcare systems, which were already overwhelmed before the pandemic with other forms of diseases. Moreover, social distancing regulations are

---

[1] See: https://www.Who.Int/Emergencies/Diseases/Novel-Coronavirus-2019/Advice-For-Public.

[2] In the process of writing this paper, the authors assessed the relationship between number of tests per capita and GDP per capita and found a positive relationship, in that poorer countries tended to conduct fewer tests per capita, up to end May 2020.

[3] In the process of writing this paper, the present authors tested the correlation between GDP per capita and travel connectivity, measured as the ratio of tourists to the resident population, and found that they are highly correlated.

in poor countries tend to be very costly as they limit people's economic opportunities. Poorer people tend to be less willing to make those economic sacrifices, and place relatively greater value on their livelihood concerns compared to contracting COVID-19. The authors also argue that not only are the epidemiological and economic benefits of social distancing much smaller in poorer countries, such policies may exact a heavy toll on the poorest and most vulnerable. The authors further contend that workers in the informal sectors, prevent in poor countries, lack the resources and social protections to isolate themselves and sacrifice economic opportunities until the virus passes.

This argument is also treated by Wright *et al.,* (2020), but with reference to in-country income disparities. Their argument is that lack of compliance with social distancing rules creates local and regional interpersonal transmission risks. Using indices of population movement derived from cell phone location data in the United States, they investigate whether compliance with local shelter-in-place ordinances varies across US counties with different economic endowments. The authors conclude that poverty reduces compliance with social distancing and find evidence that low income areas comply less than counties with stronger economic endowments.

Schellekens and Sourrouille state that, in spite of their limited capacity to fight disease, the mortality toll resulting from COVID-19 infection remains highly concentrated in high-income countries. Developing countries represent 85 percent of the global population, with about a fourth of that percentage of the pandemic's death toll. The authors argue that the excessive skew towards rich countries is due to a time factor, and that the share of developing countries in global fatalities could rise.

Another factor that relates to the different rate of infections in poorer countries is that they tend to have a younger population profile. It has been found that the rate of transmission is slower among younger people (Zhanag *et al.*, 2020; Dowd *et al.*, 2020), implying that this may be to the advantage of poorer countries, *ceteris paribus*.

Government effectiveness.

Intuitively, government effectiveness is likely to be negatively related to the rate of virus transmission, *ceteris paribus*. This variable relates to the quality of public services, the quality of the civil service and of policy formulation and implementation, and the credibility of the government's commitment to such policies. However, the relationship might just as well be positive, if one relaxes the *ceteris paribus* condition, given that the better-governed countries tend to be also the developed countries. This is basically the same argument that we used above with regard to the stage of development (GPC).[4]

The term “non-pharmaceutical interventions” (NPI) is sometimes used to refer to government action. NPI include isolation of those infected, the closure of schools and universities, banning of mass gatherings, social distancing and national lockdowns. Some studies employ mathematical models to assess their impacts (e.g., Flaxman *et al.* 2020).

Imai *et al.,* (2020) contend that the timely implementation of control measures is key to their success and must strike a balance between early enough application to reduce the peak of the

---

[4] In the process of conducting this study, the present authors found that GVE and GPC are highly correlated with each other.

epidemic and ensuring that they can be feasibly maintained for an appropriate duration. The authors further argue that such measures can have large societal impacts and they need to be appropriately justified to the population. As the pandemic of COVID-19 progresses, quantifying the impact of interventions will be a vital consideration for the appropriate use of mitigation strategies.

China often features on discussion of government efficiency. Taghrir *et al.*, (2020) in investigating the efficacy of mass quarantine in China during the Corona virus COVID-19 pandemic found good quality evidence for the effectiveness of mass quarantine during the current stage of COVID-19 pandemic, and these strategies seem to have been highly effective in controlling the spread of the disease. This argument was counteracted by Gu and Li (2020) who contend that the result depends on the sharing of relevant knowledge and information. They state they China failed in this regard, as its actions were dominated by bureaucratic forces leading to lack of autonomy of scientific/professional communities—in this case, virologists, physicians, and epidemiologists—as one of the major contributing factors to the malfunction of the early warning system. They further argue that only by empowering scientific/professional groups to exert efficient community governance can a state modernize its early warning system and perform better in combatting epidemics.

Population and country size.

So far, there is no systematic study on the relationship between the COVID-19 outbreak and country size. The observations on the rate of infections in small states do not show a consistent tendency.[5] Baldacchino (2020) states that some of the jurisdictions with the highest mortality rates attributed to the Covid-19 outbreak are indeed small jurisdictions including San Marino, Andorra, Sint Maarten, Isle of Man and Luxembourg. However, the author noted that many UK Overseas Territories and French Overseas Departments reported no or a few infections.

Very often the question of country size in this regard is discussed in terms of the lack of capacity and the high dependence on tourism of small states (UN, 2000; Keane, 2020).

Methodology

Factors assumed to affect the rate of recorded transmission

The main factors that in this study are assumed to have affected the rate of recorded COVID-19 transmission (RVI) across countries between January and end of May 2020[6] are listed below. The manner in which these explanatory variables are measured is further explained in Appendix 1, which also gives the sources of the data.

---

[5] The present authors tested the correlation between country size in terms of population and the rate of virus infections in 174 sovereign states, and the correlation was practically zero.

[6] The rate of COVID-19 infections data is sourced was from Worldometer on 30 May 2020 covering 175 sovereign countries https://www.worldometers.info/coronavirus/#countries . The Worldometer database presented data on 215 jurisdictions, about 16% of which are not sovereign states, and were eliminated for the purpose of this study as most data required for their explanatory variables was not available. The data base does not cover a number of sovereign states, including ten Pacific Island Countries (PICS). Among the 180 sovereign states listed in the database, six were left out due to lack of data. The list of 174 countries covered in this study is presented in Appendix 2.

Travel connectivity

Travel connectivity (TRC), which in this study is represented by tourism density, measured as a ratio of international tourists to residents in 2019 (the most recent available data across countries). It is assumed that the higher the travel connectivity, the higher is the possibility of virus infections, *ceteris paribus*. Although most airports and seaports were closed by March 2020, tourism traffic in December 2019 and in January and February 2020 are likely to have triggered the initial infections. Another variable that could have been used for this purpose is the number of flight passengers in relation to the local residents, but this does not exclude transit passengers and thus may overstate the number of persons who landed in hub countries. Furthermore, many countries, including most EU members, receive tourists who do not travel by air.

Climate.

In this study this variable is denoted by CLM, and is measured by the average temperature during January-May 2020 in the largest city of each country. It is assumed that the warmer the climate, the lower are the chances of infections.

Population variables

In this study, population size is denoted by POP, and is considered as measuring country size. There may be conceptual arguments as to why small countries could tend to be more prone to infections than larger ones. For example, many small countries, especially the island ones, attract a relatively large number of tourists, thereby leading to a relatively high risk of contagion. Many small states also have a relatively high population density. These factors can be captured in two other explanatory variables the we use for this study, namely travel connectivity (TRC) and population density (PDN). In the present study, PDN is measured as the number of residents per km^2 in 2019 in the major city of a country. It is assumed that the higher the density the higher are the chances of transmission.

Another population variable that could possibly be associated with the relation between contagion and country size is the number of persons that live in the rural areas, which in this study is denoted by RUP. In large countries, a larger number of persons tend to live in such areas, remotely located away from major cities, when compared to small countries. It should be noted that this variable measures actual numbers and not density. It is assumed that the higher the number of persons living in rural areas, the lower will be the rate of virus infections per capita, *ceteris paribus*

GDP per capita and government effectiveness

GDP per capita is used to measure the stage of development of a country and in this study it is denoted by GPC. As argued above, advanced countries tend to have a superior capacity to fight the virus, and this suggests that GPC is negatively associated with RVI, everything else remaining constant. However, given that more advanced countries are likely to have a higher degree of travel connectivity with other countries, when compared to poorer countries, the relation between GPC and RVI would be positive. This matter is discussed further below.

Government effectiveness, denoted by GVE in this study, is measured by one of the indices included in the World Bank’s Worldwide Governance Indicators. It intended to capture the quality of policy formulation and implementation. Given the high degree of correlation between GVE and GPC, the arguments put forward with regard to GPC may apply also to GVE.

COVID-19 tests.

The number of COVID-19 tests per million persons in the country, as on 30th May 2020, is denoted by TPM. It is expected that the higher the number of tests, the higher is the chance of detecting infections.

The period of time, up to 30 May 2019, measured in days, since the first case of the Corona Virus was reported, is denoted by DST. It is assumed that the longer the period, the higher will be the rate of recorded virus infection.

Testing the hypothesis

Multiple regression analysis

The hypothesis stated above was tested by the regression method, which is commonly used to assess the effect of explanatory variables on a dependent variable.
In order to carry out the regression analysis, all observation values were converted into natural logarithms. The advantage of such transformation is that the estimated coefficients will be direct estimates of the elasticity of the explanatory variable with respect to the dependent variable.
Another advantage is that such a transformation can reduce the skewness of highly skewed distributions, and reduces the incidence of heteroscedasticity.

Multicollinearity and heteroscedasticity

On inspecting the correlation between the explanatory variables, it emerged that the number of tests per million population (TPM) [7], travel connectivity (TRC), GDP per capita (GPC) and Government Effectiveness (GVE) are highly correlated, and leaving the four of them would lead to multicollinearity. The best performing variable among the four was travel connectivity (TRC) in terms of improved correlation coefficient and t-statistics, and this was left in the equation. It is also theoretically meaningful and in the literature travel connectivity between countries this is considered as a major cause of the infections.[8]

Population density in the main cities (PDN) and the population size (POP) were also found to be highly correlated, and, again, in order to avoid multicollinearity, PDN was retained in the equation.[9]

---

[7] The Worldometer dataset on 30 May 2020 did not include the number of tests per million persons (TPM) for all countries and out of the 174 countries included in our regression exercise, 16 did not have such data. In regression and correlation runs involving TPM, the number of countries was reduced to 158.

[8] When TPM, GDC and GVE, were used instead of TRC in the regression analysis, the signs of the coefficients reported in the next Section remained the same, given that these variables are correlated, but the results were inferior with regard to the overall correlation coefficient and the standard errors.

[9] We tried using POP instead of PDN and the signs of the coefficients reported in the next Section remained the same, but, again here, the results were inferior in terms of the overall correlation coefficient and the standard errors of the estimates.

With the removal of the redundant variables, the equation was tested for multicollinearity, using the Variance Inflation Factors (VIF) test, the hypothesis that multicollinearity was present in the equation was rejected.

The specification of the regression model

After correcting for multicollinearity by retaining just one of each of the two sets of the highly correlated explanatory variables, the regression model was specified as follows:

$$RVI_i = \alpha_0 + \alpha_1 TRC_i + \alpha_2 CML_i + \alpha_3 DST_i + \alpha_4 PDN_i + \alpha_5 RUP_i + u_i$$

Where:

- all the variables have been defined above;
- u is a random variable assumed to capture those other factors that do not affect the rate of virus infections systematically;
- $\alpha_1, \alpha_2, \ldots, \alpha_5$ are coefficients to be estimated, indicating the effect of the given explanatory variable on the rate of virus infection. The signs on the coefficients are expected to be as follows: α_1 positive; α_2 positive; α_3 positive; α_4 negative; α_5 negative.
- The subscript i = 1, 2, …., 174 referring to the 174 countries under investigation.

Equation (1) was also tested for heteroscedasticity using Breusch Pagan test, which indicated that the assumption of constant variance of the error terms of the equation was rejected, meaning that the values of the standard errors were not consistent. The results were corrected for this problem using the Huber-White's Robust Standard Errors approach.

Results

The regression estimation results relating to Equation 1, after correcting for heteroscedasticity, are presented in Table 1. It can be seen that all estimated coefficients have the expected sign and are statistically significant at the 95% level, as indicated by the corresponding t-statistics.

Table 1: Regression results: Dependent Variable is RVI (rate of infection)

Explanatory Variables	**Coefficients**	**Coefficient Estimates**	**t Statistics**
Constant term	α_0	-1.045	-0.317
TRC (travel connectivity)	α_1	0.370	3.804
CLM (Climate)	α_2	-0.190	-2.212
DST (Days of testing)	α_3	1.713	2.073
PDN (population density)	α_4	0.394	3.917
RUP (Rural population)	α_5	-0.221	-2.373

Number of Observations = 174
$R^2 = 0.361$

Given the logarithmic transformation of the observations, the coefficients would be estimates of elasticities of the explanatory variables with respect to the dependent variable. Thus one can conclude that an increase of 1% in travel connectivity (TRC) is estimated to be associated with a .370% increase in the rate of reported cases. As regards climate, the results suggest that a 1% increase in temperature gives rise to a decrease in 0.190% in the rate of reported cases. The elasticities relating to the other explanatory variables can be likewise derived from the coefficients presented in Table 1.

It should be recalled that GDP per capita (GPC), Government effectiveness (GVE) and the number of tests per capita (TPM), where left out of the equation because they were highly correlated with travel connectivity (TRC). The coefficient on TRC is therefore difficult to interpret and is likely to capture the net effects of the two opposing influences on the rate of infections, namely the benefits of affordability and governance (GPC and GVE) and the downsides of travel connectivity.

Population size (POP) was also excluded from the equation due to the fact that it was highly correlated with population density in the main cities (PDN), and given the richness of meaning of PDN for our study, the latter variable was retained. The coefficient on PDN is positive, from which one can deduce that high density cities, tend to be more prone to infections, *ceteris paribus*, as expected.

Some weaknesses

The results just presented suffer from a number of weaknesses. The data excludes some countries, including 10 Pacific Island Countries (PICS) which did not feature in the Worldometer database, from which our data was sourced.[10]

There are a number of explanatory variables for which data was not possible to find across countries. One such variable is the extent to which the residents complied with the guidance or rule set by the health authorities.[11] Another possible variable is migration, particularly of the domestic type in large countries.[12]

Some of the data, notably TRC and PDN, were sourced from different databases, and this could have introduced discrepancies in their measurement. However, care was taken to ensure that the different sources were capturing the same tendencies.

Implications

The results confirm the hypothesis set in this study, namely that the rate of virus transmission was affected by travel connectivity. This has important policy implications for policy, in that tourism should be prohibited and social distancing in all its forms imposed as early as possible when a contagious virus is detected in the countries of origin of the tourists.

As hypothesised, climate was also found to be an important explanatory variable with regard to the rate of virus infections. This is not of course a matter of policy, given that climate is

---

[10] There is some information about the Pacific Island Countries (WHO, 2020b), which indicates that there were no cases and no deaths in ten PICS not listed in Worldometer dataset this study namely Kiribati, Marshall Islands, Melanesia FS, Nauru, Palau, Samoa, Solomon Islands, Tonga, Tuvalu and Vanuatu, as of 12 June 2020. On the effect of the pandemic on the Pacific Island Countries, see also Alegre, 2020; Craig *et al*,. 2020; and Oxford Analytica, 2020.

[11] In poor countries the rate of non-compliance with guidance and regulations issued by the authorities may be more frequent than in advanced countries, and therefore the GPC variable may to an extent capture this effect. This "disobedience effect" may be also influenced by political beliefs (Painter and Qiu, 2020).

[12] On this matter see Sirkeci and Yucesahin (2020).

not dependent on governance. However, this finding suggests that epidemiological analysis and projections relating to the rate of virus infections should take into account climate and weather processes. This finding can also be considered as a positive factor for many poor countries who have warm climates all year round, but have underdeveloped health systems, such as many countries in sub-Saharan Africa.

The results of our study also imply that some factors that may have affected the rate of COVID-19 infection across countries may offset other factors. For example, while travel connectivity (TRC) might have increased the rates of infection, a warmer climate (CLM) would have tended to decrease this rate.

Some of the findings would seem to be somewhat paradoxical. For example, the finding that travel connectivity (TRC) leads to an increase in the rate of infection as expected, implies that the stage of development (represented by GPC) is also likely to be positively correlated with the rates of infection, *ceteris paribus*, as these two variables are highly correlated. This seems to be a contradiction, given that advanced countries are likely to be in a position to apply and afford non-pharmaceutical interventions better than poorer countries. This seeming contradiction has been explained above, in that the effect of ability and affordability is probably offset by the high degree of openness to international travel. This reasoning also applies to government effectiveness (GVE) which is highly correlated with GDP per capita (GPC). [13]

As regards country size, some of our results suggest that small states tend to be more prone to virus infection than larger ones, although this relation was not tested directly. A simple correlation between the rate of infection (RVI) and population size (POP) showed that the two variables are not correlated neither positively nor negatively, but this is not the correct way of assessing this matter, given that this method does not keep other things constant. As already explained, we did not include POP in the regression equation to avoid the multicollinearity problem and also because we considered population density as a more relevant variable in this regard. However, the findings that the rate of infection is positively related to population density (PDN), as well as to travel connectively (TRC), and negatively related to the rural populations (RUL) would seem to indicate that small states tend to be prone to higher rates of virus infection than larger ones. Interestingly, our finding that temperature (CLM) and the rate of virus transmission are negatively related has the opposite implication for small states, given that most of these, notably small island developing states (SIDS), are located in the tropics, with relatively high temperatures all year round. This could explain why no correlation was found between the rate of virus infections and country size, when the citrus paribus assumption was not imposed.

References

Alegre, S. (2020). Pandemic in the Pacific - The double-edged sword of isolation in a time of crisis. Retrieved from: https://www.islandrights.org/pandemic-in-the-pacific-the-double-edged-sword-of-isolation-in-a-time-of-crisis/

Baldacchino, G. (2020). Editor's note : small states and territories and Coronavirus. Retrieved from: https://www.um.edu.mt/library/oar/handle/123456789/56493 .

---

[13] When travel connectivity (TRC) was substituted by TPM (tests per million persons) for 158 countries (due to lack of TPM data for 16 countries), the resulting estimated equations produced the same signs on the coefficients of the explanatory variables, indicating that the two variables are correlated.

Barnett-Howell, Z., and Mobarak, A. M. (2020). The Benefits and Costs of Social Distancing in Rich and Poor Countries. *arXiv preprint arXiv:2004.04867*. Retrieved from: https://arxiv.org/pdf/2004.04867.pdf

Brooks-Pollock, E., Read, J. M., House, T., Medley, G., Keeling, M. J., and Danon, L. (2020). The Population Attributable Fraction (PAF) of cases due to gatherings and groups with relevance to COVID-19 mitigation strategies. Retrieved from: https://www.medrxiv.org/content/medrxiv/early/2020/03/23/2020.03.20.20039537.full.pdf .

Brown, A., Ahmad, S., Beck, C., and Nguyen-Van-Tam, J. (2016). The roles of transportation and transportation hubs in the propagation of influenza and coronaviruses: A systematic review. *Journal of Travel Medicine*, 23(1), tav002. Retrieved from: https://doi.org/10.1093/jtm/tav002

Casanova, L. M., Jeon, S., Rutala, W. A., Weber, D. J., and Sobsey, M. D. (2010). Effects of air temperature and relative humidity on coronavirus survival on surfaces. *Applied* and *Environmental Microbiology*, 76(9), 2712-2717. Retrieved from: https://aem.asm.org/content/76/9/2712

Chakraborty, I., and Maity, P. (2020). COVID-19 outbreak: Migration, effects on society, global environment and prevention. *Science of The Total Environment*, 138882. Retrieved from: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7175860/

Chan, K. H., Peiris, J. S., Lam, S. Y., Poon, L. L. M., Yuen, K. Y., and Seto, W. H. (2011). The effects of temperature and relative humidity on the viability of the SARS coronavirus. *Advances in virology*, *2011*. Retrieved from: http://downloads.hindawi.com/journals/av/2011/734690.pdf .

Cookson, C. (2020). Scientists hopeful warmer weather can slow spread of coronavirus. Received from: https://www.ft.com/content/c8ed3692-6db3-11ea-9bca-bf503995cd6f

Craig, A. T., Heywood, A. E., and Hall, J. (2020). Risk of COVID-19 importation to the Pacific islands through global air travel. *Epidemiology* and *Infection*, 148. Retrieved from: https://www.cambridge.org/core/services/aop-cambridge-core/content/view/5FF4D23AB5FD537D752B38FB5AAB9721/S0950268820000710a.pdf/risk_of_covid19_importation_to_the_pacific_islands_through_global_air_travel.pdf .

Dowd, J. B., Andriano, L., Brazel, D. M., Rotondi, V., Block, P., Ding, X., ... and Mills, M. C. (2020). Demographic science aids in understanding the spread and fatality rates of COVID-19. *Proceedings of the National Academy of Sciences*, 117(18), 9696-9698. Retrieved from: https://www.pnas.org/content/pnas/117/18/9696.full.pdf

Ebrahim, S. H., and Memish, Z. A. (2020). COVID-19–the role of mass gatherings. Travel medicine and infectious disease. *Elsevier Public Health Emergency Collection,* PMC7102534. Retrieved from: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7102534/

Ficetola, G. F., and Rubolini, D. (2020). Climate affects global patterns of COVID-19 early outbreak dynamics. medRxiv. Retrieved from: https://www.medrxiv.org/content/medrxiv/early/2020/03/31/2020.03.23.20040501.full.pdf .

Flaxman, S., Mishra, S., Gandy, A., Unwin, H. J. T., Coupland, H., Mellan, T. A., ... and Schmit, N. (2020). Estimating the number of infections and the impact of non-pharmaceutical interventions on COVID-19 in European countries: technical description update. arXiv preprint arXiv:2004.11342. Retrieved from: https://arxiv.org/pdf/2004.11342.pdf .

Gössling, S., Scott, D., and Hall, C. M. (2020). Pandemics, tourism and global change: a rapid assessment of COVID-19. *Journal of Sustainable Tourism*, 1-20. m, DOI:

10.1080/09669582.2020.1758708. Retrieved from: https://www.tandfonline.com/doi/pdf/10.1080/09669582.2020.1758708

Gu, E., and Li, L. (2020). Crippled community governance and suppressed scientific/professional communities: a critical assessment of failed early warning for the COVID-19 outbreak in China. *Journal of Chinese governan*ce, 1-18. Retrieved from: https://www.tandfonline.com/doi/full/10.1080/23812346.2020.1740468?tab=permissions&scroll=top .

Imai, N., Gaythorpe, K. A., Abbott, S., Bhatia, S., van Elsland, S., Prem, K., ... and Ferguson, N. M. (2020). Adoption and impact of non-pharmaceutical interventions for COVID-19. Wellcome Open Research, 5(59), 59. Retrieved from: https://spiral.imperial.ac.uk/bitstream/10044/1/77789/5/ef719f59-8c63-4bbc-b777-3ef6c56a8ea1_15808_-_natsuko_imai.pdf .

Keane, J. (2020). The coronavirus pandemic and small states: a focus on small and vulnerable economies. Retrieved from: https://set.odi.org/wp-content/uploads/2020/03/The-coronavirus-pandemic-and-small-states-a-focus-on-Small-and-Vulnerable-Economies-.pdf .

Kotz, D. (2020) Researchers use climate to predict spread of COVID-19. University of Maryland, Baltimore. Retrieved from: https://www.bizjournals.com/baltimore/news/2020/03/27/researchers-use-climate-to-predict-spread-of-covid.html .

Kroumpouzos, G., Gupta, M., Jafferany, M., Lotti, T., Sadoughifar, R., Sitkowska, Z., and Goldust, M. (2020). COVID-19: A relationship to climate and environmental conditions? *Dermatologic Therapy*. Retrieved from: https://www.unboundmedicine.com/medline/citation/32276290/COVID-19:_A_Relationship_to_Climate_and_Environmental_Conditions .

Mangili, A., and Gendreau, M. A. (2005). Transmission of infectious diseases during commercial air travel. *The Lancet,* 365(9463), 989-996. Retrieved from: https://pubmed.ncbi.nlm.nih.gov/15767002/ .

Memish, Z. A., Ahmed, Q. A., Schlagenhauf, P., Doumbia, S., and Khan, A. (2020). No time for dilemma: mass gatherings must be suspended. *The Lancet* (London, England), 395(10231), 1191 . Retrieved from: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7146682/ .

Mooney, H. and Zegarra, M.A. (2020) COVID-19: Tourism-based shock scenarios for Caribbean countries Retrieved from: https://blogs.iadb.org/caribbean-dev-trends/en/covid-19-tourism-based-shock-scenarios-for-caribbean-countries/16/03/2020 .

Nunan, D., and Brassey, J. (2020). What is the evidence for mass gatherings during global pandemics? A rapid summary of best-available evidence. : Retrieved from: doi.org/10.1101/2020.03.20.20039537 .

Oxford Analytica. COVID-19 means economic distress for Pacific Islands. Emerald Expert Briefings, (oxan-db). Retrieved from: https://dailybrief.oxan.com/Analysis/DB251754/COVID-19-means-economic-distress-for-Pacific-Islands .

Painter, M., and Qiu, T. (2020). Political beliefs affect compliance with covid-19 social distancing orders. Available at SSRN 3569098. Retrieved from: https://voxeu.org/article/political-beliefs-and-compliance-social-distancing-orders .

Rocklöv, J., and Sjödin, H. (2020). High population densities catalyse the spread of COVID-19. *Journal of travel medicine*, 27(3), taaa038. Retrieved from: https://pubmed.ncbi.nlm.nih.gov/32227186/ .

Schellekens, P., and Sourrouille, D. M. (2020). COVID-19 Mortality in Rich and Poor

Countries: A Tale of Two Pandemics? World Bank Policy Research Working Paper, (9260). Retrieved from: http://documents.worldbank.org/curated/en/559181590712052524/COVID-19-Mortality-in-Rich-and-Poor-Countries-A-Tale-of-Two-Pandemics .

Singh, P. D. (2020). Close the Big Cities, Open the Small ones: How Corona correlates with Demographic Variables. (April 6, 2020). Retrieved from: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3569747 .

Sirkeci, I., and Yucesahin, M. M. (2020). Coronavirus and Migration: Analysis of Human Mobility and the Spread of COVID-19. Migration Letters, 17(2), 379-398. Retrieved from: https://journals.tplondon.com/index.php/ml/article/download/935/741

Sjödin, H., Wilder-Smith, A., Osman, S., Farooq, Z., and Rocklöv, J. (2020). Only strict quarantine measures can curb the coronavirus disease (COVID-19) outbreak in Italy, 2020. *Eurosurveillance*, 25(13), 2000280. Retrieved from: https://www.eurosurveillance.org/docserver/fulltext/eurosurveillance/25/13/eurosurv-25-13-2.pdf?expires=1592410270&id=id&accname=guest&checksum=6DFA0FD483FD6176AF139EA08A4D4835 .

Taghrir, M. H., Akbarialiabad, H., and Marzaleh, M. A. (2020). Efficacy of mass quarantine as leverage of health system governance during COVID-19 outbreak: a mini policy review. Archives of Iranian medicine, 23(4), 265-267. Retrieved from: http://www.aimjournal.ir/PDF/aim-23-265.pdf .

UN (2020). COVID-19 shocks too big to handle for small island nations, UN warns UN (Dept of Global Communications). Retrieved from: https://www.un.org/en/un-coronavirus-communications-team/covid-19-shocks-too-big-handle-small-island-nations-un-warns .

Wang, J., Tang, K., Feng, K., and Lv, W. (2020). High temperature and high humidity reduce the transmission of COVID-19. Available at SSRN 3551767. Retrieved from: https://arxiv.org/ftp/arxiv/papers/2003/2003.05003.pdf .

WHO (2020a) Key planning recommendations for Mass Gatherings in the context of COVID-19. Geneva. Retrieved from: https://apps.who.int/iris/bitstream/handle/10665/331502/WHO-2019-nCoV-POEmassgathering-2020.2-eng.pdf .

WHO (2020b). Novel Coronavirus (COVID-19) Health Sector Preparedness & Response Joint External Situation Report #19 – 12 June 2020. Retrieved from: https://www.who.int/docs/default-source/wpro---documents/dps/outbreaks-and-emergencies/covid-19/covid-19-external-situation-report-19.pdf?sfvrsn=ea24f9e7_2 .

Wright, A. L., Sonin, K., Driscoll, J., and Wilson, J. (2020). Poverty and economic dislocation reduce compliance with covid-19 shelter-in-place protocols. University of Chicago, Becker Friedman Institute for Economics, Working Paper, (2020-40). Retrieved from: https://bfi.uchicago.edu/cgi-sys/suspendedpage.cgi .

Zhang, J., Litvinova, M., Liang, Y., Wang, Y., Wang, W., Zhao, S., ... and Ajelli, M. (2020). Age profile of susceptibility, mixing, and social distancing shape the dynamics of the novel coronavirus disease 2019 outbreak in China. *medRxiv.* Retrieved from: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7217069/ .

Appendix 1: Sources of the data

Variable	Meaning and measurement	Source
CLM	Average temperature during January-May 2020 in the largest city of each country	World Climate Guide. Retrieved from: https://www.climatestotravel.com/world-climates/countries
DST	The period of time, up to 30 May 2020, measured in days, since the first case of the Virus was reported.	Our World in Data. Retrieved from: https://covid.ourworldindata.org/data/owid-covid-data.xlsx
GPC	Gross domestic product per capita, in US$.	IMF (World Economic Outlook, October 2019) https://www.imf.org/external/pubs/ft/weo/2019/02/weodata/weoselgr.aspx
GVE	Government Effectiveness, measured by a component of the World Bank's Worldwide Governance Indicators.	Worldwide Governance Indicators Retrieved from: https://info.worldbank.org/governance/wgi/
PDN	Population density. measured as the number of residents per km^2 in 2019 in the major city of a country.	For most countries the data was sourced from: https://o50328b.files.wordpress.com/2012/07/city-polulations.pdf . When more than one city was listed, the city with the largest population was chosen. Data was not available for the main city in 5 very small stats and this was sources from Wikipedia.
POP	Population size (number of thousand persons)	IMF (World Economic Outlook, October 2019) https://www.imf.org/external/pubs/ft/weo/2019/02/weodata/weoselgr.aspx
RUP	The number of persons residing in rural areas in 2018. In a few cases 2017 data was used.	World Bank database: https://data.worldbank.org/indicator/ST.INT.ARVL
RVI	Rate of recorded Virus Infections per million population.	Worldometer on 30 May 2020 https://www.worldometers.info/coronavirus/#countries.
TPM	The number of COVID-19 tests per million persons as on 30 May 2020).	Worldometer on 30 May 2020 https://www.worldometers.info/coronavirus/#countries.
TRC	Travel Connectivity. Measured as the ratio of incoming tourists to the resident population, in 2019.	Data for most countries was sourced from the Word Bank Database Retrieved from: https://data.worldbank.org/indicator/ST.INT.ARVL which in turn sourced from the World Tourism Organization, Yearbook of Tourism Statistic. There was no data for inbound tourism for 11 countries and to measure travel connectivity the annual number of passengers carried by registered air carriers was used, source at: https://data.worldbank.org/indicator/IS.AIR.PSGR

Appendix 2: Countries included in the study

Afghanistan	Denmark	Kyrgyzstan	Saint Kitts and Nevis
Albania	Dominica	Lao P.D.R.	Saint Lucia
Algeria	Dominican Republic	Latvia	Saint Vincent/Grenadines
Angola	Ecuador	Lebanon	São Tomé and Príncipe
Antigua and Barbuda	Egypt	Libya	Saudi Arabia
Argentina	El Salvador	Lithuania	Senegal
Armenia	Equatorial Guinea	Luxembourg	Serbia
Australia	Estonia	Madagascar	Seychelles
Austria	Eswatini	Malawi	Sierra Leone
Azerbaijan	Ethiopia	Malaysia	Singapore
Bahamas	Fiji	Maldives	Slovakia
Bahrain	Finland	Mali	Slovenia
Bangladesh	France	Malta	Somalia
Barbados	Gabon	Mauritania	South Africa
Belarus	Gambia	Mauritius	Spain
Belgium	Georgia	Mexico	Sri Lanka
Belize	Germany	Moldova	Sudan
Benin	Ghana	Mongolia	Suriname
Bhutan	Greece	Montenegro	Sweden
Bolivia	Grenada	Morocco	Switzerland
Bosnia and Herzegovina	Guatemala	Mozambique	Syria
Botswana	Guinea	Myanmar	Taiwan
Brazil	Guinea-Bissau	Namibia	Tajikistan
Brunei	Guyana	Nepal	Tanzania
Bulgaria	Haiti	Netherlands	Thailand
Burkina Faso	Honduras	New Zealand	Timor-Leste
Burundi	Hong Kong	Nicaragua	Togo
Cabo Verde	Hungary	Niger	Trinidad and Tobago
Cambodia	Iceland	Nigeria	Tunisia
Cameroon	India	North Macedonia	Turkey
Canada	Indonesia	Norway	Uganda
Central African Republic	Iran	Oman	Ukraine
Chad	Iraq	Pakistan	United Arab Emirates
Chile	Ireland	Panama	United Kingdom
China	Israel	Papua New Guinea	United States
Colombia	Italy	Paraguay	Uruguay
Comoros	Ivory Coast	Peru	Uzbekistan
Congo Dem. Rep.	Jamaica	Philippines	Venezuela
Congo Rep	Japan	Poland	Vietnam
Costa Rica	Jordan	Portugal	Yemen
Croatia	Kazakhstan	Qatar	Zambia
Cuba	Kenya	Romania	Zimbabwe
Cyprus	Korea South	Russia	
Czech Republic	Kuwait	Rwanda	