The Socio-Spatial Determinants of COVID-19 Diffusion: The Impact of Globalisation, Settlement Characteristics and Population

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The Socio-Spatial Determinants of COVID-19 Diffusion: The Impact of Globalisation, Settlement Characteristics and Population

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Abstract

Background: COVID-19 is an emergent infectious disease that has spread geographically to become a global pandemic. While much research focuses on the epidemiological and virological aspects of the COVID-19 transmission, there remains a gap in knowledge regarding the drivers of geographical diffusion between places. Here, we use quantile regression to model the roles of globalisation, human settlement and population characteristics as socio-spatial determinants of COVID-19 diffusion over a six-week period in March and April 2020.

Results: The quantile regression model suggest that globalisation and settlement population characteristics related to high human mobility predict disease diffusion. Human development level (HDI) and total population predict COVID-19 diffusion in countries with a high number of total confirmed cases per million whereas larger household size, older populations, and globalisation tied to human interaction predict COVID-19 diffusion in countries with a low number of total confirmed cases per million.

Conclusions: The analysis confirms that globalisation, settlement and population characteristics lead to greater disease diffusion, and primarily variables tied to high human mobility. These outcomes serve to inform policies around 'flattening the curve', particularly as they related to anticipated relocation diffusion from more- to less-developed countries and regions, and hierarchical diffusion from countries with higher population and density. Epidemiological strategies must be tailored to suit the range of human mobility patterns, as well as the variety of settlement and population characteristics.

Keywords: COVID-19; Coronavirus; Spatial Diffusion; Globalisation; Urbanisation; Quantile regression

Introduction

The Coronavirus disease (COVID-19) was declared a global pandemic by the World Health Organisation (WHO) on March 11th 2020 (1), just over two months after its outbreak in Wuhan, China. Widely understood to have diffused geographically from a single point of origin in late December 2019 (2, 3), COVID-19 has spread across more countries and in a more rapid manner than previous similar outbreaks (e.g., the 1918 Spanish Influenza pandemic and the SARS epidemic) (4), suggesting that the intensity of global connectivity (5, 6) was in part responsible for its quick diffusion between territories and therefore transmission between individuals. This has played out on an international scale, with early outbreaks beyond China in highly globalised countries such as Japan and Singapore, and on a national scale with highly globalised subnational regions more impacted than others. This is evidenced by a large number of early cases in countries' densest, and often most affluent, regions—Lombardia (Italy) (7), New York (the United States) (8), Madrid (Spain) (9), and Tehran (Iran) (10), which all by far outnumbered cases in other regions within their respective countries. The geographical concentration of the previous outbreaks in particular cities (11) suggests that connectivity at the urban scale also plays an important role in COVID-19 diffusion.

By the end of May 2020, only 12 states and territories have purportedly remained free of COVID-19, including 10 small and isolated Pacific island states, and two countries relatively closed to outside influence: Turkmenistan and North Korea (12). This suggests that in addition to urbanisation, globalisation is an influential factor driving COVID-19 diffusion. Countries with high numbers of confirmed cases (e.g. Italy, Spain, the United Kingdom and the United States) are highly globalised nations with high human mobility, whilst those with fewer cases are without exception less globalised, have significantly lower numbers of visitors, and in general less

domestic mobility (13). By April 8th 2020, there had been 20277716 confirmed cases recorded within the COVID-19 Data Repository by the Center for Systems Science and Engineering at Johns Hopkins University (14). At the time the first cases were recorded in early January 2020, spatial diffusion across borders was relatively slow. It took 45 days for the virus to spread to 30 countries, areas or territories (15). After this time, geographical diffusion accelerated and within the next 45 days COVID-19 to reach nearly all global territories (15). To control the spread of the virus within countries, governments have moved to limit international and intra-urban population movements to varying extents. China was the first country to quarantine, implementing a lock-down in the city of Wuhan on January 23rd 2020, and by early April 2020 an estimated one third to half of the world's population was in some form of lock-down (16, 17).

Despite extensive epidemiological research and mathematical modelling of the COVID-19 transmission (7, 18-23), there has been a lacuna of work aiming to understand how social and geographic factors converge to explain COVID-19 diffusion. In this paper, we demonstrate how globalisation, human settlement and population characteristics of countries explain both the number and diffusion patterns of COVID-19 cases, and how this relationship shifts over time.

Background

Infectious diseases diffuse over space and time through inherently geographical processes (24). The geographical concept of spatial diffusion is defined as the spread of a phenomenon across space (25), of which disease diffusion through interpersonal transmission is but one variant (24, 26). Here, we investigate the role of globalisation, settlement and population characteristics as socio-spatial determinants of COVID-19 diffusion between countries as an outcome of transmission between individuals. Although each new case is by definition a product of

interpersonal transmission—both direct and indirect—diffusion can occur across large distances as an outcome of human movement and mobility. Understandings of the viral transmission lie more firmly within the academic domains of virology and epidemiology than diffusion, which is a fundamentally geographic phenomenon that can be applied to many other forms of spread (for example, innovation diffusion (25)).

Different underlying processes characterise types of spatial diffusion (27, 28). *Expansion diffusion* identifies the general tendency for phenomena to spread 'outward', and infectious disease is most associated with *contagious diffusion*, indicating direct transmission between neighbours due to their physical proximity. The spread that occurs over a large distance from its origin is captured by *relocation diffusion*, which is often mobilised by air travel or other modes of extra-local transportation. *Hierarchical diffusion* characterises spread from large settlements to smaller ones. In large and dense agglomerations the spreading occurs faster compared to small towns due to larger populations and more intensive human contact. As infectious diseases spread through the populations, different types of diffusion come into play, often in combination (26, 28). Sirkeci and Yüceşahin (29) suggest that the spread of COVID-19 in March 2020 followed a relocation diffusion pattern (spreading between countries), with hierarchical diffusion being observed only in a few countries, including the United States, the United Kingdom, South Korea and Italy among others.

On a global scale, mobility and connectivity between countries collectively contribute to disease outbreaks across the globe, a finding supported by research on human rhinovirus, influenza, and SARS (30, 31). Indeed, globalisation in its diverse forms has rendered physical (Euclidian) distance increasingly less relevant as a proximity measure influencing diffusion. Though disease vectors do in fact require human contact (even if indirect via fomites), the speed and ubiquity of

global transportation and travel have led to time-space compression (5, 32), which progressively reduce the time-distance required to connect any two global points. Thus countries with higher levels of globalisation are more exposed to COVID-19, as are more globalised spaces within them such as world cities (11).

In recent studies (33, 34), globalisation has been shown to be positively linked to the COVID-19 cases in that more globalised countries experience higher exposure to COVID-19 outbreaks. Among its many related impacts, globalisation has increased the speed of global disease diffusion, as public health studies have repeatedly acknowledged (23, 35). One study (34) focused on the initial spread of COVID-19 based on Johns Hopkins University (JHU) data for March 16th, 2020 and found that more economically globalised countries were affected faster. COVID-19 has rapidly spread via international air (36) and sea (37) travel connecting countries with high levels of tourism and trade. Another study (33) focused on confirmed cases of COVID-19 by March 30th, 2020 across 138 countries and used a variety of sub-indices of globalisation (economic, social and political) (38) as the main explanatory variables. The study found that almost all KOF globalisation sub-indices have shown a robust and significant positive association with the number of COVID-19 confirmed cases, with social globalisation—that proxies migration and civil rights among other measures—being the most important predictor both in magnitude and statistical significance (33).

Once a pathogen has begun to spread within a country, settlement characteristics impact disease diffusion. In the case of infectious diseases, previous research suggests that large metropolitan areas experience more significant spread due to the larger number of people, their closer proximity and increased movement (31, 39-42). Both urbanisation and urban accessibility collectively increase vulnerability to infectious disease spread (43) by creating the requisite preconditions for higher numbers of human interactions wherein higher densities act to increase the intensity of such

interactions (44). However, human settlements from around the world can also be very heterogeneous with different patterns of human mobility and interactions and a highly variable impact of an epidemic (45). To this end, we test human settlement characteristics, including different levels of population density, urbanisation, and accessibility. Additionally, there are marked differences in population characteristics—population size, development levels, household size and age structure— affecting the spread of an infectious disease (45). We test this using four population characteristics of individual countries: Human Development Index (HDI), population aged over 65, mean household size and national population size. These variables have been selected based on recent studies that found them significant in explaining the COVID-19 outbreak at the early stages of its spread (8, 29, 46).

Data

We employ quantile regression (47, 48) to test the impact of globalisation, settlement characteristics and population characteristics on the cumulative total confirmed COVID-19 cases per one million inhabitants over a six-week period from the 10th week (ending March 4th) until the 15th week of 2020 (ending April 8th). Figure 1 shows the distribution of cases over the study period.

Figure 1. Distributions of cumulative confirmed COVID-19 cases per million population (log transformed). Graphs show the 10th week (ending March 4th) until the 15th week (ending April 8th) of 2020. The red line indicates the mean and the black lines quantiles.

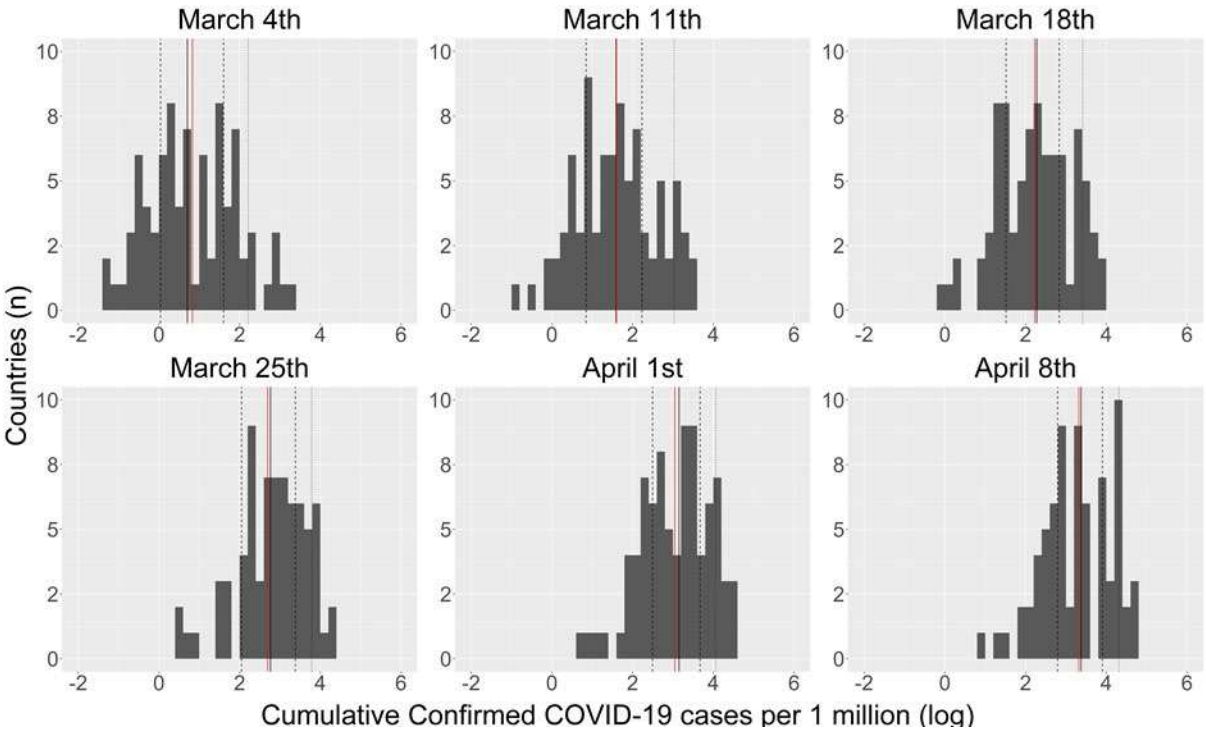


Table 1 lists the variables in the model, with the source, units and year of each.

Table 1. List of independent variables to explain the diffusion of confirmed COVID-19 cases.

Variable Description	Category	Units (Transformation)	Source	Year
Interpersonal Globalisation	Globalisation	Index Value (100 Point Scale)	Swiss Economic Institute (KOF)	2019
Trade Globalisation	Globalisation	Index Value (100 Point Scale)	Swiss Economic Institute (KOF)	2019
Financial Globalisation	Globalisation	Index Value (100 Point Scale)	Swiss Economic Institute (KOF)	2019
Urbanisation Rate	Settlement	National (Percent)	World Bank	2018
Population Density	Settlement	Log transformed value of Inhabitants per square kilometre	World Bank	2018
Urban Density	Settlement	Inhabitants per square kilometre in Densest Metropolitan Area	Demographia	2020
Areal Accessibility	Settlement	The area-weighted average for driving time to a location with at least 1,500 inhabitants per square kilometer	Weiss et al (2018)	2018
Human Development	Population	Index Value	United Nations Development Programme	2018

Population aged 65 and over	Population	Percent Age 65+	United Nations, Department of Economic and Social Affairs Population Division	2019
Household Size	Population	Mean Number of Household Members	United Nations, Department of Economic and Social Affairs Population Division	2019
Population	Population	Total population	United Nations	2019

During the six-week period of the study period, the number of cases increased by 1433 per cent and the number of countries and territories affected more than doubled, counting those enumerated within the COVID-19 Data Repository by the Center for Systems Science and Engineering at Johns Hopkins University (JHU) (14). Figures 2 and 3 show the geographical (Figure 2) and temporal spread (Figure 3) of COVID-19 over time.

Figure 2. Choropleth map of confirmed cases of COVID 19 per million population for the 84 countries included in the analysis over weeks 10 to 16 (ending March 4th and April 8th 2020, respectively).

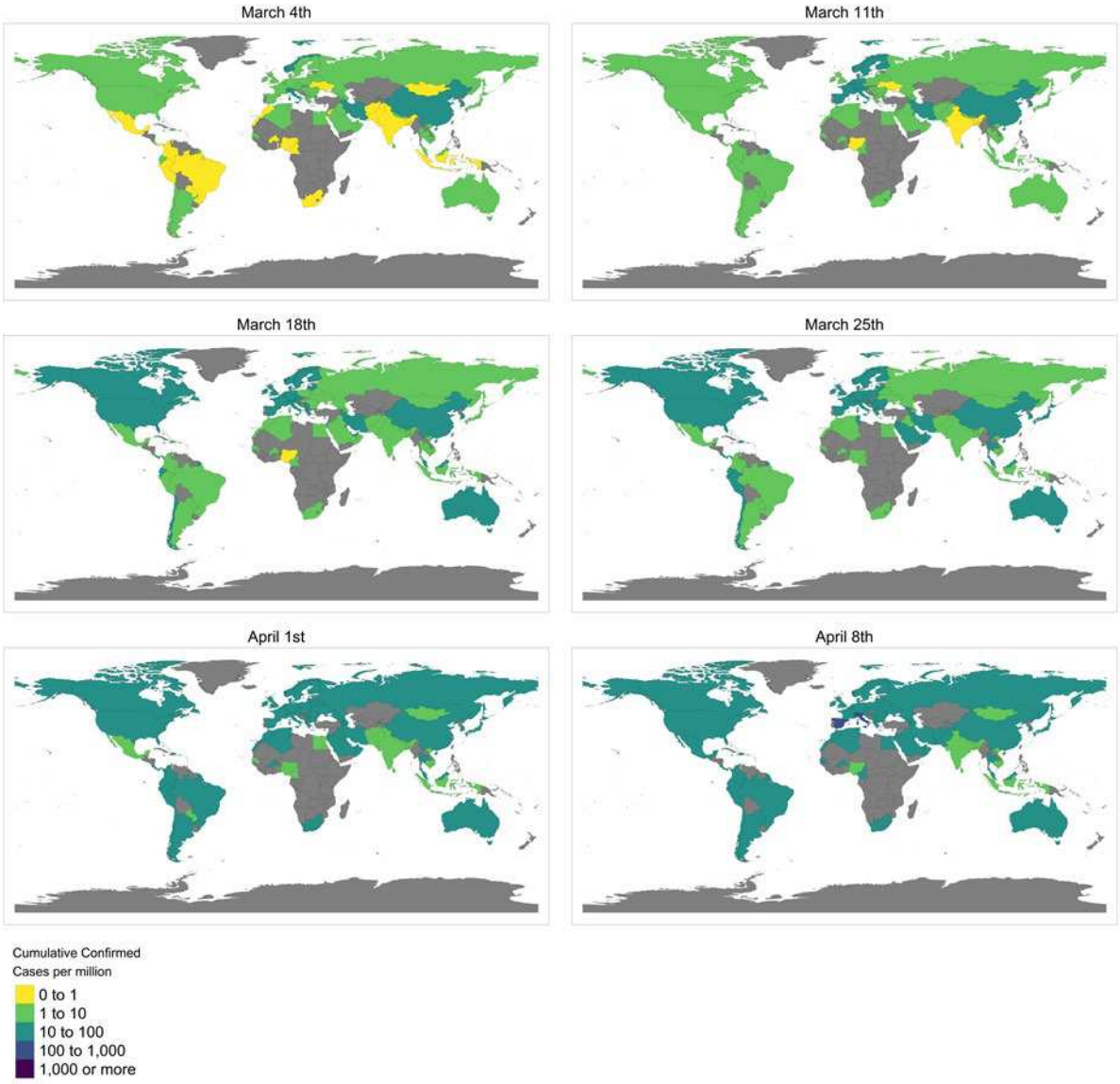
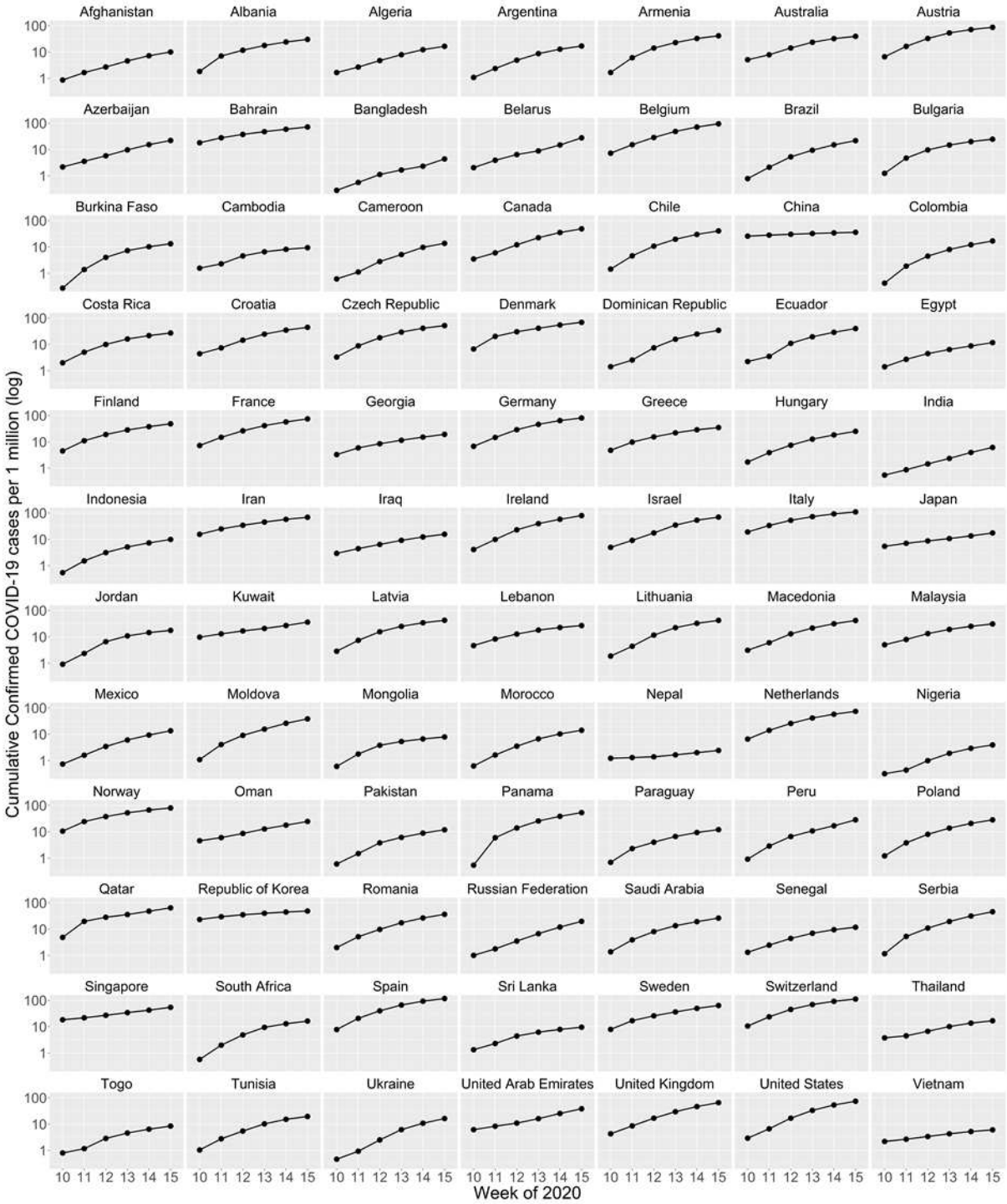


Figure 3. Diffusion of Covid-19 cases per million population (log transformed) over weeks 10 – 15 (ending 4th March and April 8th 2020, respectively) across 84 countries.



The dependent variable in the quantile regression model is the number of cumulative total of confirmed COVID-19 cases per one million inhabitants (log-transformed) by country (or territory) and by week. The denominator for the dependent variable is the 2019 mid-year population by

country drawn from the United Nations World Population Prospects (49). 84 countries had consistent available data for the duration of the study period and were therefore included in the model. Data on national COVID-19 cases were extracted from the JHU repository on May 13th 2020. Although some sources suggest that drawing data from this, and similar global repositories is problematic (50) due to data inconsistency, intentional misreporting, and disparate collection techniques (51), we align with a rapidly growing number studies published (52, 53) in other outlets recognizing the immense efforts of the Johns Hopkins team in both compiling, and triangulating the data set with a variety of data sources.

Quantile regression allows us to go beyond the mean relationship between the response and the predictor variables to reveal statistical relationships at different quantiles of the distribution (47, 48, 54, 55). In this way we detail our discussion on how the globalisation, settlement characteristics, and population characteristics affect global diffusion of COVID-19 cases along across its entire distribution. The technique explains the differential effects that socio-spatial factors have across points along the distribution that mean models cannot account for, which in this instance can identify contribute that explain COVID-19 diffusion at either end of the pandemic spectrum.

Although mean regression models are highly sensitive to outliers, different quantile estimations can also be influenced by outliers at different locations (quantile) (56, 57). For example at the 50th quantile in the last three weeks of the study, China, Iran and Japan stand out as influential observations which might have overly impacted the significance of each variable.

To understand the role of globalisation in COVID-19 diffusion, we test three variables from the KOF globalisation index (38, 58, 59): de facto interpersonal globalisation, de facto financial globalisation and de facto trade globalisation. These sub-indices proxy migration, tourism and

202 business flows, which have been positively associated with outbreaks of infectious diseases by
203 exposing countries to the outside world (33-35, 40, 60-62). Globalisation variable 1 is *de facto*
204 interpersonal globalisation is a KOF sub-index of social globalisation that includes indicators of
205 international traffic, transfers, international tourism, international students and migration (38). An
206 early study of the COVID-19 spatial diffusion (29) shows that the volume of migration flows has
207 been a strong indicator for the international spread of the pandemic. Globalisation variable 2 is *de*
208 *facto* trade globalisation, another KOF sub-index of economic globalization that reflects trade in
209 goods and services as well as trade partner diversity (38). Globalisation variable 3 is *de facto*
210 financial globalisation, a KOF sub-index of economic globalisation. It is comprised of measures
211 of foreign direct investment, portfolio investment, international debt, international reserves, and
212 international income payments (38).
213 To understand the role of settlement characteristics in COVID-19 diffusion, we test four variables
214 that measure various national-scale dimensions, including: urbanisation rate, population density,
215 maximum urban population density, and areal accessibility (measures the average drive time of
216 the national population from smaller to larger settlements (63)). These represent human interaction
217 within national boundaries, with recent publications demonstrating that diffusion happens more
218 rapidly in cities that are dense, well-connected, and accessible (11, 29, 42-44). Settlement variable
219 1 is urbanisation rate, defined as the proportion of a national population located in cities or
220 metropolitan regions (national definitions vary). We selected this variable as cities are more prone
221 to early disease diffusion than rural areas due to higher concentration of interaction and movement
222 in urban areas (42). COVID-19 has been preliminary found to diffuse faster in more populous
223 urban areas in the United States (64). Settlement variable 2 is population density, defined as the
224 population per square kilometre across a national territory. Population density proxies the higher

225 intensity of human interaction which makes disease transmission more likely. The literature shows
226 a significant effect of population density on the outbreak of infectious diseases (44). While a
227 previous study (29) found no significant relationship between population density and total
228 confirmed COVID-19 cases, there is a broader literature that shows an association between
229 population density and the outbreak of infectious diseases (44).
230 Settlement Variable 3 is urban density [maximum], defined as the population per square kilometre
231 of the densest city in a country. This variable has been selected based on previous studies that
232 documented a higher sensitivity of large cities (global cities) to the spread of infectious diseases
233 (11, 31). Settlement Variable 4 is areal accessibility, defined as an area-weighted average of
234 driving time to locations with at least 1,500 inhabitants per square km (63). This variable has been
235 selected based on a previous study (43) in which the authors argue that extended urbanisation may
236 result in increased vulnerability to an infectious disease spread. Urban accessibility captures the
237 variations in suburbanisation and peri-urbanisation across countries.
238 To understand the role of national population characteristics in COVID-19 diffusion, we employ
239 HDI, population age structure (65+), median household size, and population size. Research
240 suggests that COVID-19 is more likely to spread in more-developed countries with higher levels
241 of international migration than in countries with lower levels of development and migration (33).
242 Affluent, healthy and educated populations (HDI) are more likely to be highly mobile. Although
243 larger household sizes and national populations have also been shown to increase COVID-19
244 cases, these are not clear-cut relationships (8). Older populations or populations with higher
245 mortality rates are more likely to get tested than younger populations that may be asymptomatic
246 (46, 65). Population variable 1 is HDI (Human Development Index), which captures a holistic
247 picture of individual countries and has been used as an indicator of the macro environment in a

248 previous study (29) written in the early period of the pandemic. The study found that each unit
249 increase in the HDI score is associated with five more confirmed COVID-19 cases. Populations in
250 countries with higher HDI are more affluent, healthier, and better educated, meaning that their
251 overall mobility potential would be higher. Population variable 2 is population aged 65 and over
252 (%), which is the proportion of the population aged 65 years and over. We hypothesise that in early
253 stages of the pandemic, case detection is higher in countries with older populations due to the
254 higher burden of mortality among older adults (46). COVID-19 transmission may remain
255 undetected longer in younger populations (65). Population variable 3 is household size (mean) is
256 the average number of people per dwelling. Individuals in larger households interact with more
257 people including once stay-home measures are applied. The analysis of demographic and
258 socioeconomic determinants of COVID-19 testing in New York shows a very strong correlation
259 between the cases of infection in the population and household size (8). Population variable 4 is
260 population (n), which is a demographic variable with a direct relation to the pool size for the
261 potentially infected population. Population size was considered as a moderating variable in a
262 previous study (29) that found that "a one person increase in population size indicates over 1.6
263 more COVID-19 cases" (p. 385) thus more populous countries have greater potential for exposure.
264 Even when normalised on a per capita basis, the likelihood of new cases is still higher in large
265 countries than small countries. The table below (Table 2) provides summary statistics on
266 globalisation, settlement characteristics and population variable data.
267
268 **Table 2. Descriptive Summary of Independent Variables**

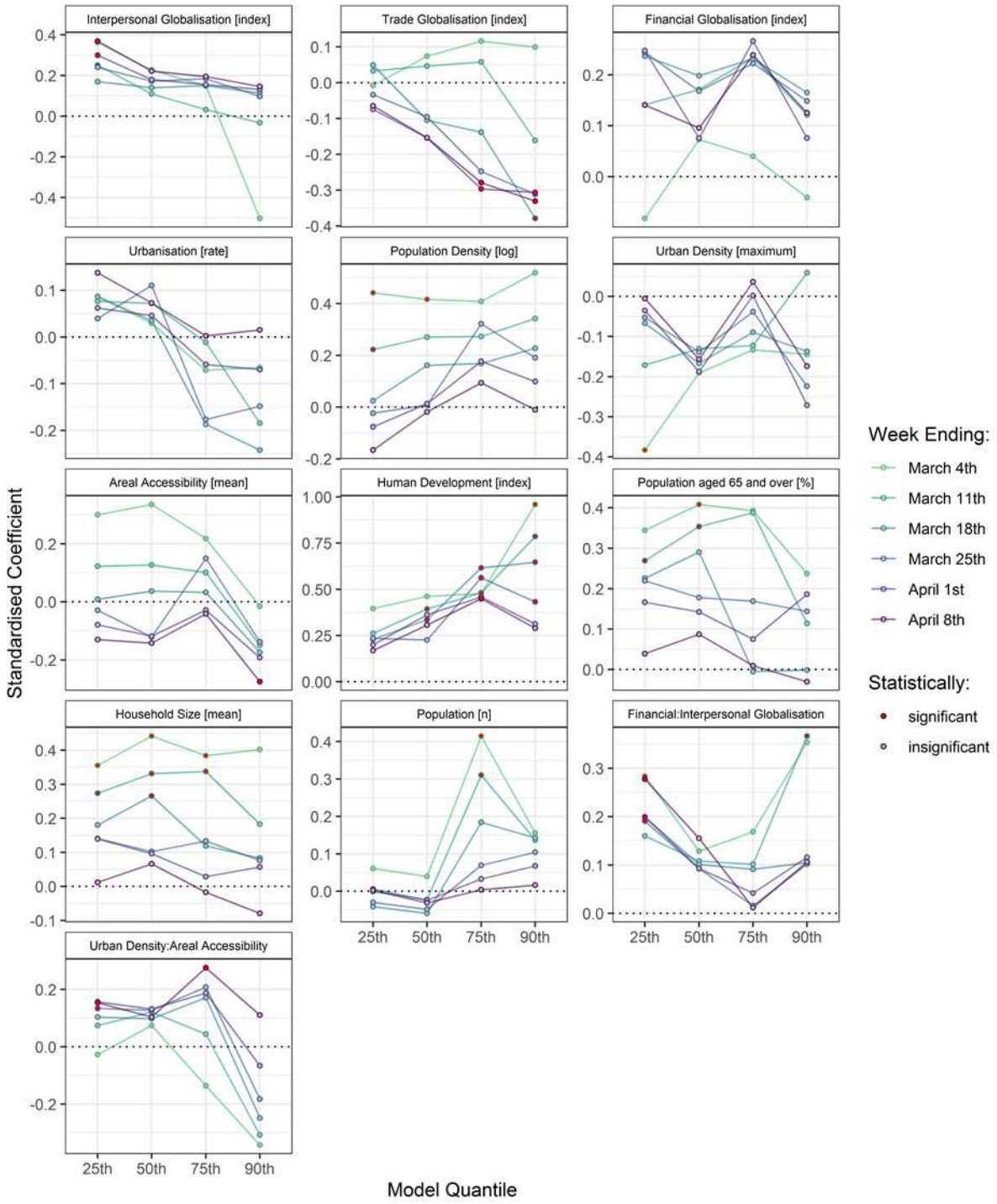
Independent Variable	Median	Mean	St. Dev.	Min	Max
Confirmed cases per million by March 4th[log]	0.71	0.83	1.10	-1.29	3.25
Confirmed cases per million by March 11th [log]	1.59	1.60	1.00	-0.83	3.52

Confirmed cases per million by March 18th [log]	2.28	2.23	0.91	-0.01	3.97
Confirmed cases per million by March 25th [log]	2.77	2.69	0.88	0.50	4.29
Confirmed cases per million by April 1st [log]	3.15	3.04	0.86	0.70	4.53
Confirmed cases per million by April 8th [log]	3.38	3.32	0.83	0.89	4.76
Interpersonal Globalisation [index]	68.50	64.80	20.70	22.70	96.50
Trade Globalisation [index]	62.80	57.80	21.50	21.20	99.20
Financial Globalisation [index]	72.70	69.20	19.10	21.30	97.30
Urbanisation [rate]	72.00	68.60	19.60	18.50	100.00
Population Density [log]	1.97	1.95	0.57	0.31	3.90
Urban Density [maximum]	5650	7686	6251	1300	41000
Areal Accessibility [mean]	111	158	116	30	577
Human Development [index]	0.80	0.79	0.12	0.43	0.95
Aged over 65 [%]	11.00	11.40	6.70	1.09	27.60
Population [million]	18	76	219	1	1432
Household Size [mean]	3.36	3.78	1.16	2.05	8.66

Results

Globalisation, settlement characteristics, and population characteristics all influence COVID-19 diffusion, but do so differently at different points on the distribution and at different points in time. Figure 4 visualises the standardised relationship of each factor with the number of (log-transformed) confirmed cases per million at the 25th, 50th, 75th and 90th quantiles for each of week of the six week period.

Figure 4. Standardised coefficient value of confirmed COVID-19 cases at the 25th, 50th, 75th and 90th quantiles the 10th week (ending March 4th) until the 15th week of 2020 (ending April 8th).



In the early stages (Weeks 10, 11), population characteristics were the most significant variables in explaining COVID-19. HDI was found to be the most important and significant variable affecting COVID-19 diffusion, particularly in countries with a high number of new cases per capita

285 (75th and 90th quantiles) and within the earlier weeks (corroborating findings of an earlier study
286 (29)), decreasing in importance over time. Aged population (65+) is significant only in early weeks
287 at the 25th and 50th quantiles, but strong collinearity with HDI suggests these are related in causality
288 (See Additional file 7). Both HDI and Population aged 65+ tend toward zero in later weeks,
289 indicating a muted impact as time goes on. Population size and household size are significant and
290 positive in earlier weeks and both tend toward zero in later weeks. Population size is significant at
291 the 75th quantile whereas household size is significant throughout the 25th, 50th and 75th quantiles.
292 Settlement characteristics had mixed effects in explaining COVID-19 diffusion. Population
293 density initially (Week 10) had a strong positive effect at the mean, and at the 25th, 50th, and 75th
294 quantiles but waned both in strength and significance with time. Maximum urban density exerts
295 negative influence on COVID-19 diffusion throughout the distribution, but is strongest at the mean
296 and only significant in the first week of our study. Again, early COVID-19 diffusion is tied to
297 density, but the influence of a single (or multiple) densely populated settlements has less impact
298 and significance over time. In contrast, areal accessibility is negatively associated with COVID-
299 19 diffusion in later weeks but only at the 90th quantile, meaning its effect is significant in countries
300 with a high number of new cases per million. A negative relationship suggests that the highest
301 number of total cases are associated with greater access to cities, and that as this is reduced, so are
302 the number of confirmed cases per million.
303 Globalisation has the weakest effect of the three classes of variables, and its effects are mixed both
304 in terms of which portion of the distribution is impacted and the type of globalisation.
305 Interpersonal globalisation has a weak positive effect at the mean and 25th quantile, particularly in
306 early weeks. While financial globalisation was not a reliable predictor, it interacted with
307 interpersonal globalisation towards the start of the study period at both tails of the distribution.

Trade globalisation is the most prominent in scaled terms and given that it explains suppressed COVID-19 spread, suggesting that countries with strong import and export ties are better placed to slow the spread following the closure of borders.

Greater significance in terms of which globalisation and settlement characteristics explain diffusion was added through two interaction terms, added based on goodness-of-fit. The globalisation interaction term is between de facto financial globalisation and de facto interpersonal globalisation. This interaction term takes into account the combined effect of international travel and the level of financial globalisation. This interaction effect is significant and positive, particularly throughout the lower quantiles and in the early weeks. This is to say that countries with a low number of COVID-19 cases per million are likely to receive new cases if conditions of both high financial globalisation and interpersonal globalisation are met, generally both related to intensity of human mobility flows.

The settlement interaction term is between urban density of the largest city of the country and the (lack of) accessibility of smaller settlements. This interaction term accounts for the hierarchical connectivity between settlements of different sizes within the country and thus it proxies the primacy, as many countries are poorly connected overall but have large and dense capital or primate cities. This interaction yields a mostly positive effect (up to the 75th quantile), and is significant and positive in the distribution in the final week of the analysis. Thus we can attribute diffusion of COVID-19 to urban primacy, especially in countries at the low end of the distribution, and particularly in later weeks. In other words, countries with poorly connected urban systems are more prone to disease diffusion, perhaps counter to intuition.

Discussion

With a vaccine against SARS-CoV-2 unavailable, COVID-19 is, and will continue to be, a significant detriment to human health outcomes. Of the variables tested in our diffusion model, population and settlement characteristics have both the strongest, and most significant impact on new COVID-19 cases per one million inhabitants. Notably, among countries with high early infection rates HDI is by far the strongest predictor of new cases. HDI has a strong, albeit weakening, positive association with COVID-19 diffusion across the six week period, suggesting some level of hierarchical diffusion from more developed countries to less developed countries, and relocation diffusion between more-developed countries with high mobility (e.g. within Europe). Particularly in the early weeks, other population and settlement characteristics such as population aged 65+, household size, and population density explain diffusion, but their effect is almost immediately dampened in successive weeks. The lasting impact of HDI, and the muted impacts of other population and settlement characteristics, is perhaps best explained by COVID-19's impacts on mobility. Although more-developed countries may have been more successful in implementing early lock-down measures, they also had much higher overall levels of both international and internal mobility, hence why settlement characteristics play such an important role in Week 10 but not afterward.

Of the globalisation variables, interpersonal globalisation has the strongest and most significant effect, particularly when interacting with the financial globalisation variable. Conversely, trade globalisation has a negative impact, and the impacts of all three globalisation types appear to be stronger toward the latter weeks. The impact of globalisation in later weeks may be somewhat counterintuitive, as one might expect more globalised countries to experience COVID-19 diffusion in earlier stages, but it also reflects the fact that the economies of more globalised countries are tied to 'openness', with strong disincentives for shutting borders and enforcing other 'global'

restrictions. To this end, trade globalisation is not associated with human mobility as much as financial globalisation and interpersonal globalisation, with the latter incorporating both tourism and migration.

Conclusion

Globalisation, settlement, and population characteristics are all important in explaining COVID-19 diffusion, but significant at different points on the distribution and points in time. The quantile regression model reveals that urbanisation and density generally exert a positive effect on disease diffusion early on, that over time tends toward zero. Conversely, variants of globalisation exert diverse effects, with trade globalisation exerting a negative effect on COVID-19 diffusion that diverges from the positive effects associated with financial and interpersonal globalisation. The impacts of settlement characteristics is mixed, but generally has the greatest effect at the upper and lower ends of the distribution, and more so in the initial weeks.

Our model suggests that the impacts of non-local diffusion outweigh the geographical effects of diffusion tied to adjacency. There is no evidence to suggest that neighbouring countries spread disease across borders, at least not to the degree that openness via globalisation, or local transmission via urbanisation, do. Although both infectious and contagious diffusion are present throughout the study period via interpersonal contact, our results indicate that relocation diffusion precedes hierarchical diffusion as the disease is first carried across long distances via global mobility, and later diffused within countries from single or multiple points of entry, which are typically the largest and/or most globalised cities. Though this may seem self-evident, further research should focus on the impacts and effects of policy on diffusion, which is likely to have had a strong impact across the study period (16, 66, 67).

377 Perhaps the finding that more-developed countries experience higher disease diffusion before less-
378 developed countries may be perceived as auspicious, given that countries with more economic
379 wealth and more advanced health care systems are better able to cope with pandemic conditions.
380 However, there is clear evidence of diffusion: from more-developed to less-developed, and to a
381 lesser extend from urbanised on non-urbanised. As COVID-19 is a disease whose diffusion is
382 reliant on interpersonal transmission, we find that both relocation diffusion (tied to global
383 mobility) and hierarchical diffusion (tied to population and settlement characteristics) are
384 simultaneously acting on countries.
385 To date, the primary public health initiatives to curb disease diffusion have been travel bans (border
386 closures) and stay-home orders, which restrict gatherings. Both have shown clear effectiveness in
387 curbing disease diffusion (16, 66) as the recent case of New Zealand vanquishing COVID-19 has
388 proven (68). As disease diffusion progresses, implanting these measures at increasingly small
389 scales will be necessary as restricting human mobility has proven the most effective measure
390 against spread.
391
392
393 **Methods**
394 An Ordinary Least Squares regression (OLS; formula 1) was repeated for each period (weeks 10
395 to 15). We introduce two interaction terms - one at the global-scale and another at the local-scale.
396 At the global-scale, the interaction term is between de facto financial and interpersonal
397 globalisation. Financial globalisation captures direct foreign investment, international reserves,
398 and international income payments that induce movement of skills and labour. Financially
399 globalised nations are typically global centres of business and related services and thus, generate

global business travel and interaction. As such, the interaction between financial and interpersonal globalisation captures international travel related to business. In contrast, we anticipate that the national-scale interaction between maximum urban density (the largest National City) and areal accessibility will have growing importance in later weeks once national borders close and thus COVID-19 exposure will typically occur within national borders and at home. As such, this interaction represents the connectivity between the smaller urban growth centres and the economic centre of the country.

$$y_n = \beta_0 + \beta_1 x_1 + \beta_1 x_1 + \cdots + \beta_n x_n + \varepsilon_n \qquad (1)$$

Once the least parsimonious set of variables was identified, quantile regression was used to explain the global diffusion and transmission of COVID-19 according to key globalisation and national variables. This regression revealed how the influences of log-transformed rate of COVID-19 confirmed cases vary across the quantiles of the distribution (69). As such, this regression does not assume there is normality nor uniformity in how COVID-19 is diffused and transmitted between and within countries. This regression revealed how the influences of log-transformed rate of COVID-19 confirmed cases vary across the quantiles of the distribution (69). As such, this regression does not assume there is normality nor uniformity in how COVID-19 is diffused and transmitted between and within countries. The τ were placed at the 25th, 50th, 75th, and 90th quartiles according to the conventions of disease mapping (70-72). Again the quantile regression was iterated for each week using formula 2 (69):

$$Q^{\tau}(y_i|x_i) = \beta_0^{(\tau)} + \beta_1^{(\tau)} x_1 + \cdots + \beta_n^{(\tau)} x_n + \varepsilon^{(\tau)} \qquad (2)$$

Where i = 1, 2, …….,n

$$Q^{\tau}(y_i|x_i) = \beta_0^{(\tau)} + \beta_1^{(\tau)} x_1 + \cdots + \beta_n^{(\tau)} x_n + \varepsilon^{(\tau)} \qquad (2)$$

Where i = 1, 2, …….,n

The output tables for these regression models in Additional Files 1-6. Lastly, the specific R functions used for modelling are quantreg::rq for quantile regression.

Koenker and Machado (1999) suggest a goodness of fit, $R_1(\tau)$ analogous to R-squared in simple linear regression and argues that $R_1(\tau)$ gives a local measure of goodness of fit for a particular quantile rather than a global measure of goodness of fit over the entire conditional distribution (73). The median (50th quantile) is the point at which the model is weakest, suggesting likewise that a mean model would have been a poor fit. The model is strongest at the 25th and 90th quantiles, indicating that the model is best fit to serve countries with a low number of cases (these are mostly small countries with low HDI) and the 90th is where most of the existing cases are (generally larger countries with high HDI). The quantile regression model is the best fit in the first week, with progressively less significance and explanatory power. This suggests that policy may be most effective in early weeks, as known socio-spatial conditions can be targeted through specific public interventions.

Declarations

Ethics approval and consent to participate

Not applicable.

Consent for publication

Not applicable.

Availability of data and materials

The dataset supporting the conclusions of this article is available from the COVID-19 Data Repository by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University, https://github.com/CSSEGISandData/COVID-19.

Competing interests

The authors declare that they have no competing interests.

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Authors' contributions

All authors contributed equally to the research conception and design. TS, SM, AK, JC contributed to data collection, harmonization, data analysis and interpretation. JL, PWJ, ECE contributed to drafting the work. All authors read and approved the final manuscript.

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Additional file 1. Week 10 (ending April 4th) comparison of standardised coefficients at 25th, 50th, 75th and 90th quantiles and the mean function

	Dependent variable:				
	OLS	*quantile regression*			
	Mean Model	25th quantile	50th quantile	75th quantile	90th quantile
Intercept	0.663***	0.257	0.644***	1.070***	1.490***
	(0.108)	(0.162)	(0.171)	(0.190)	(0.195)
Interpersonal Globalisation [index]	0.134	0.362	0.227	0.149	-0.503
	(0.171)	(0.238)	(0.254)	(0.225)	(0.419)
Trade Globalisation [index]	0.082	-0.008	0.074	0.116	0.099
	(0.127)	(0.152)	(0.185)	(0.205)	(0.239)
Financial Globalisation [index]	-0.134	-0.082	0.073	0.040	-0.041
	(0.159)	(0.237)	(0.245)	(0.231)	(0.262)
Urbanisation [rate]	-0.024	0.086	0.030	-0.071	-0.065
	(0.129)	(0.162)	(0.180)	(0.203)	(0.264)
Population Density [log]	0.505***	0.441**	0.416**	0.408	0.519
	(0.156)	(0.185)	(0.204)	(0.247)	(0.349)
Urban Density [maximum]	-0.357**	-0.383**	-0.191	-0.133	-0.145
	(0.147)	(0.163)	(0.202)	(0.495)	(0.689)
Areal Accessibility [mean]	0.311**	0.300	0.335	0.218	-0.015
	(0.155)	(0.197)	(0.229)	(0.367)	(0.416)
Human Development [index]	0.636***	0.396	0.462	0.477	0.959**
	(0.210)	(0.290)	(0.322)	(0.337)	(0.394)
Population aged 65 and over [%]	0.337*	0.344	0.408*	0.393	0.237
	(0.179)	(0.220)	(0.238)	(0.271)	(0.365)
Household Size [mean]	0.344**	0.356*	0.442**	0.384**	0.402
	(0.144)	(0.208)	(0.194)	(0.179)	(0.277)
Population [n]	0.165*	0.061	0.039	0.415**	0.156
	(0.091)	(0.151)	(0.188)	(0.173)	(0.213)
Financial:Interpersonal Globalisation	0.211**	0.284*	0.129	0.169	0.354
	(0.102)	(0.145)	(0.153)	(0.177)	(0.229)
Urban Density:Areal Accessibility	0.048	-0.027	0.074	-0.136	-0.343
	(0.090)	(0.112)	(0.130)	(0.377)	(0.452)
Observations	84	84	84	84	84
R^2	0.678				
Adjusted R^2	0.619				
Residual Std. Error	0.679				

F Statistic	11.400***
Note:	*p**p***p<0.01

Additional file 2. Week 11 (ending March 11th) comparison of standardised coefficients at 25th, 50th, 75th and 90th quantiles and the mean function

	Dependent variable:				
	OLS	*quantile regression*			
	Mean Model	25th quantile	50th quantile	75th quantile	90th quantile
Intercept	1.460***	1.210***	1.440***	1.790***	2.100***
	(0.089)	(0.101)	(0.121)	(0.148)	(0.174)
Interpersonal Globalisation [index]	0.104	0.251*	0.110	0.031	-0.033
	(0.141)	(0.145)	(0.149)	(0.201)	(0.316)
Trade Globalisation [index]	0.049	0.033	0.047	0.058	-0.161
	(0.105)	(0.111)	(0.125)	(0.170)	(0.208)
Financial Globalisation [index]	0.030	0.141	0.171	0.234	0.121
	(0.131)	(0.146)	(0.155)	(0.168)	(0.212)
Urbanisation [rate]	-0.014	0.077	0.072	-0.012	-0.184
	(0.106)	(0.104)	(0.116)	(0.161)	(0.238)
Population Density [log]	0.262**	0.223*	0.271	0.273	0.342
	(0.129)	(0.121)	(0.170)	(0.250)	(0.301)
Urban Density [maximum]	-0.205*	-0.171	-0.130	-0.123	0.059
	(0.121)	(0.107)	(0.124)	(0.242)	(0.599)
Areal Accessibility [mean]	0.141	0.123	0.127	0.101	-0.149
	(0.128)	(0.131)	(0.156)	(0.240)	(0.336)
Human Development [index]	0.629***	0.261	0.393*	0.481*	0.786**
	(0.174)	(0.182)	(0.199)	(0.255)	(0.304)
Population aged 65 and over [%]	0.235	0.269**	0.354*	0.388	0.114
	(0.148)	(0.133)	(0.195)	(0.282)	(0.332)
Household Size [mean]	0.292**	0.274**	0.332**	0.338**	0.183
	(0.118)	(0.110)	(0.135)	(0.167)	(0.225)
Population [n]	0.100	-0.001	-0.023	0.310**	0.137
	(0.075)	(0.113)	(0.122)	(0.131)	(0.162)
Financial:Interpersonal Globalisation	0.160*	0.160	0.108	0.102	0.367*
	(0.084)	(0.101)	(0.113)	(0.145)	(0.211)
Urban Density:Areal Accessibility	0.122	0.075	0.122	0.044	-0.308

	(0.075)	(0.072)	(0.081)	(0.194)	(0.405)
Observations	84	84	84	84	84
R^2	0.735				
Adjusted R^2	0.686				
Residual Std. Error	0.560				
F Statistic	14.900^{***}				
Note:					$^{*}p^{**}p^{***}p<0.01$

631

632 **Additional file 3.** Week 12 (ending March 18th) comparison of standardised coefficients at 25th, 50th,
633 75th and 90th quantiles and the mean function

	Dependent variable:				
	OLS	*quantile regression*			
	Mean Model	25th quantile	50th quantile	75th quantile	90th quantile
Intercept	2.100^{***}	1.780^{***}	2.100^{***}	2.380^{***}	2.840^{***}
	(0.082)	(0.113)	(0.123)	(0.151)	(0.162)
Interpersonal Globalisation [index]	0.140	0.170	0.139	0.150	0.114
	(0.130)	(0.140)	(0.156)	(0.227)	(0.286)
Trade Globalisation [index]	-0.024	0.049	-0.105	-0.138	-0.379^{*}
	(0.096)	(0.116)	(0.116)	(0.162)	(0.199)
Financial Globalisation [index]	0.113	0.236	0.198	0.232	0.165
	(0.120)	(0.157)	(0.152)	(0.188)	(0.184)
Urbanisation [rate]	0.023	0.086	0.035	-0.187	-0.242
	(0.098)	(0.106)	(0.112)	(0.193)	(0.215)
Population Density [log]	0.105	0.025	0.161	0.168	0.227
	(0.118)	(0.128)	(0.159)	(0.249)	(0.265)
Urban Density [maximum]	-0.149	-0.067	-0.167	-0.090	-0.137
	(0.111)	(0.115)	(0.113)	(0.221)	(0.437)
Areal Accessibility [mean]	0.004	0.008	0.037	0.033	-0.174
	(0.118)	(0.131)	(0.138)	(0.257)	(0.290)
Human Development [index]	0.485^{***}	0.229	0.336^{*}	0.616^{**}	0.646^{**}
	(0.160)	(0.189)	(0.193)	(0.295)	(0.280)
Population aged 65 and over [%]	0.108	0.226	0.291	-0.005	-0.001
	(0.136)	(0.151)	(0.191)	(0.279)	(0.292)
Household Size [mean]	0.146	0.180	0.265^{*}	0.119	0.083
	(0.109)	(0.125)	(0.142)	(0.180)	(0.194)
Population [n]	0.060	-0.041	-0.059	0.185	0.143

	(0.069)	(0.119)	(0.111)	(0.154)	(0.155)
Financial:Interpersonal Globalisation	0.142*	0.199*	0.101	0.091	0.105
	(0.077)	(0.104)	(0.115)	(0.149)	(0.162)
Urban Density:Areal Accessibility	0.138**	0.104	0.098	0.171	-0.249
	(0.069)	(0.072)	(0.071)	(0.212)	(0.315)
Observations	84	84	84	84	84
R^2	0.729				
Adjusted R^2	0.679				
Residual Std. Error	0.515				
F Statistic	14.500***				
Note:					*p**p***p<0.01

Additional file 4. Week 13 (ending March 25th) comparison of standardised coefficients at 25th, 50th, 75th and 90th quantiles and the mean function

	Dependent variable:				
	OLS	*quantile regression*			
	Mean Model	25th quantile	50th quantile	75th quantile	90th quantile
Intercept	2.580***	2.270***	2.590***	2.930***	3.190***
	(0.077)	(0.124)	(0.144)	(0.141)	(0.124)
Interpersonal Globalisation [index]	0.184	0.240	0.172	0.184	0.097
	(0.122)	(0.158)	(0.186)	(0.216)	(0.231)
Trade Globalisation [index]	-0.072	-0.034	-0.095	-0.248	-0.311*
	(0.091)	(0.116)	(0.138)	(0.151)	(0.157)
Financial Globalisation [index]	0.141	0.244	0.168	0.223	0.148
	(0.114)	(0.161)	(0.182)	(0.185)	(0.159)
Urbanisation [rate]	0.053	0.040	0.110	-0.176	-0.148
	(0.092)	(0.101)	(0.131)	(0.195)	(0.188)
Population Density [log]	-0.009	-0.024	0.008	0.322	0.191
	(0.112)	(0.142)	(0.192)	(0.244)	(0.213)
Urban Density [maximum]	-0.112	-0.053	-0.139	-0.039	-0.224
	(0.105)	(0.110)	(0.132)	(0.248)	(0.329)
Areal Accessibility [mean]	-0.096	-0.029	-0.121	0.150	-0.138
	(0.111)	(0.132)	(0.167)	(0.307)	(0.227)
Human Development [index]	0.408***	0.235	0.226	0.562*	0.432*
	(0.151)	(0.183)	(0.223)	(0.285)	(0.241)

Population aged 65 and over [%]	0.037	0.219	0.178	0.169	0.144
	(0.128)	(0.170)	(0.235)	(0.221)	(0.233)
Household Size [mean]	0.070	0.141	0.102	0.134	0.077
	(0.103)	(0.142)	(0.172)	(0.162)	(0.157)
Population [n]	0.044	-0.030	-0.048	0.070	0.104
	(0.065)	(0.108)	(0.134)	(0.165)	(0.128)
Financial:Interpersonal Globalisation	0.130*	0.191*	0.093	0.016	0.102
	(0.073)	(0.111)	(0.133)	(0.157)	(0.135)
Urban Density:Areal Accessibility	0.151**	0.134**	0.128	0.209	-0.182
	(0.065)	(0.065)	(0.084)	(0.321)	(0.250)
Observations	84	84	84	84	84
R^2	0.741				
Adjusted R^2	0.693				
Residual Std. Error	0.487				
F Statistic	15.400***				
Note:					*p**p***p<0.01

Additional file 5. Week 14 (ending April 1st) comparison of standardised coefficients at 25th, 50th, 75th and 90th quantiles and the mean function

	Dependent variable:				
	OLS	*quantile regression*			
	Mean Model	25th quantile	50th quantile	75th quantile	
Intercept	2.920***	2.600***	2.950***	3.270***	3.450***
	(0.073)	(0.128)	(0.149)	(0.127)	(0.113)
Interpersonal Globalisation [index]	0.220*	0.299*	0.180	0.155	0.131
	(0.116)	(0.169)	(0.195)	(0.179)	(0.207)
Trade Globalisation [index]	-0.089	-0.074	-0.154	-0.297**	-0.307**
	(0.086)	(0.121)	(0.137)	(0.141)	(0.140)
Financial Globalisation [index]	0.142	0.247	0.076	0.266	0.076
	(0.108)	(0.167)	(0.191)	(0.174)	(0.151)
Urbanisation [rate]	0.078	0.062	0.046	-0.059	-0.069
	(0.088)	(0.109)	(0.161)	(0.182)	(0.179)
Population Density [log]	-0.101	-0.076	0.013	0.177	0.099
	(0.106)	(0.148)	(0.203)	(0.227)	(0.196)
Urban Density [maximum]	-0.079	-0.035	-0.187	0.002	-0.271

	(0.100)	(0.120)	(0.149)	(0.254)	(0.288)
Areal Accessibility [mean]	-0.172	-0.079	-0.118	-0.028	-0.192
	(0.105)	(0.141)	(0.169)	(0.362)	(0.209)
Human Development [index]	0.364**	0.199	0.363	0.458	0.313
	(0.143)	(0.193)	(0.258)	(0.277)	(0.228)
Population aged 65 and over [%]	-0.018	0.167	0.143	0.075	0.186
	(0.122)	(0.174)	(0.240)	(0.207)	(0.214)
Household Size [mean]	0.023	0.139	0.096	0.029	0.057
	(0.098)	(0.141)	(0.186)	(0.142)	(0.141)
Population [n]	0.044	0.006	-0.024	0.033	0.067
	(0.062)	(0.119)	(0.135)	(0.158)	(0.123)
Financial:Interpersonal Globalisation	0.136*	0.200*	0.093	0.042	0.116
	(0.069)	(0.119)	(0.135)	(0.199)	(0.113)
Urban Density:Areal Accessibility	0.168***	0.157**	0.132	0.188	-0.066
	(0.061)	(0.072)	(0.086)	(0.455)	(0.212)
Observations	84	84	84	84	84
R^2	0.755				
Adjusted R^2	0.710				
Residual Std. Error	0.462				
F Statistic	16.600***				
Note:					*p**p***p<0.01

Additional file 6. Week 15 (ending April 8th) comparison of standardised coefficients at 25th, 50th, 75th and 90th quantiles and the mean function

	Dependent variable:				
	OLS	*quantile regression*			
	Mean Model	25th quantile	50th quantile	75th quantile	90th quantile
Intercept	3.200***	2.810***	3.160***	3.530***	3.650***
	(0.070)	(0.116)	(0.137)	(0.111)	(0.104)
Interpersonal Globalisation [index]	0.241**	0.368**	0.221	0.194	0.146
	(0.111)	(0.149)	(0.178)	(0.155)	(0.187)
Trade Globalisation [index]	-0.095	-0.065	-0.154	-0.279**	-0.331***
	(0.082)	(0.115)	(0.123)	(0.109)	(0.124)
Financial Globalisation [index]	0.148	0.141	0.095	0.239	0.125
	(0.103)	(0.171)	(0.165)	(0.145)	(0.141)
Urbanisation [rate]	0.098	0.138	0.073	0.003	0.015
	(0.084)	(0.104)	(0.144)	(0.163)	(0.163)

Population Density [log]	-0.172*	-0.166	-0.019	0.094	-0.010
	(0.101)	(0.121)	(0.183)	(0.160)	(0.172)
Urban Density [maximum]	-0.011	-0.005	-0.157	0.036	-0.174
	(0.095)	(0.114)	(0.136)	(0.210)	(0.172)
Areal Accessibility [mean]	-0.238**	-0.130	-0.142	-0.041	-0.275*
	(0.100)	(0.130)	(0.149)	(0.173)	(0.162)
Human Development [index]	0.360**	0.169	0.307	0.449*	0.290
	(0.136)	(0.192)	(0.232)	(0.240)	(0.221)
Population aged 65 and over [%]	-0.071	0.039	0.087	0.009	-0.030
	(0.116)	(0.147)	(0.215)	(0.192)	(0.186)
Household Size [mean]	-0.005	0.012	0.066	-0.017	-0.079
	(0.093)	(0.128)	(0.164)	(0.125)	(0.129)
Population [n]	0.034	0.002	-0.031	0.004	0.016
	(0.059)	(0.111)	(0.119)	(0.067)	(0.102)
Financial:Interpersonal Globalisation	0.134**	0.278***	0.155	0.012	0.106
	(0.066)	(0.100)	(0.121)	(0.097)	(0.090)
Urban Density:Areal Accessibility	0.169***	0.154**	0.104	0.276*	0.110
	(0.059)	(0.066)	(0.075)	(0.148)	(0.112)
Observations	84	84	84	84	84
R^2	0.766				
Adjusted R^2	0.722				
Residual Std. Error	0.440				
F Statistic	17.600***				
Note:					*p**p***p<0.01

Additional file 7. Correlogram and Multicollinearity Diagnostics

This depicts collinearities among the independent variables that is particularly pronounced between the human development index and globalization indices.

Figures

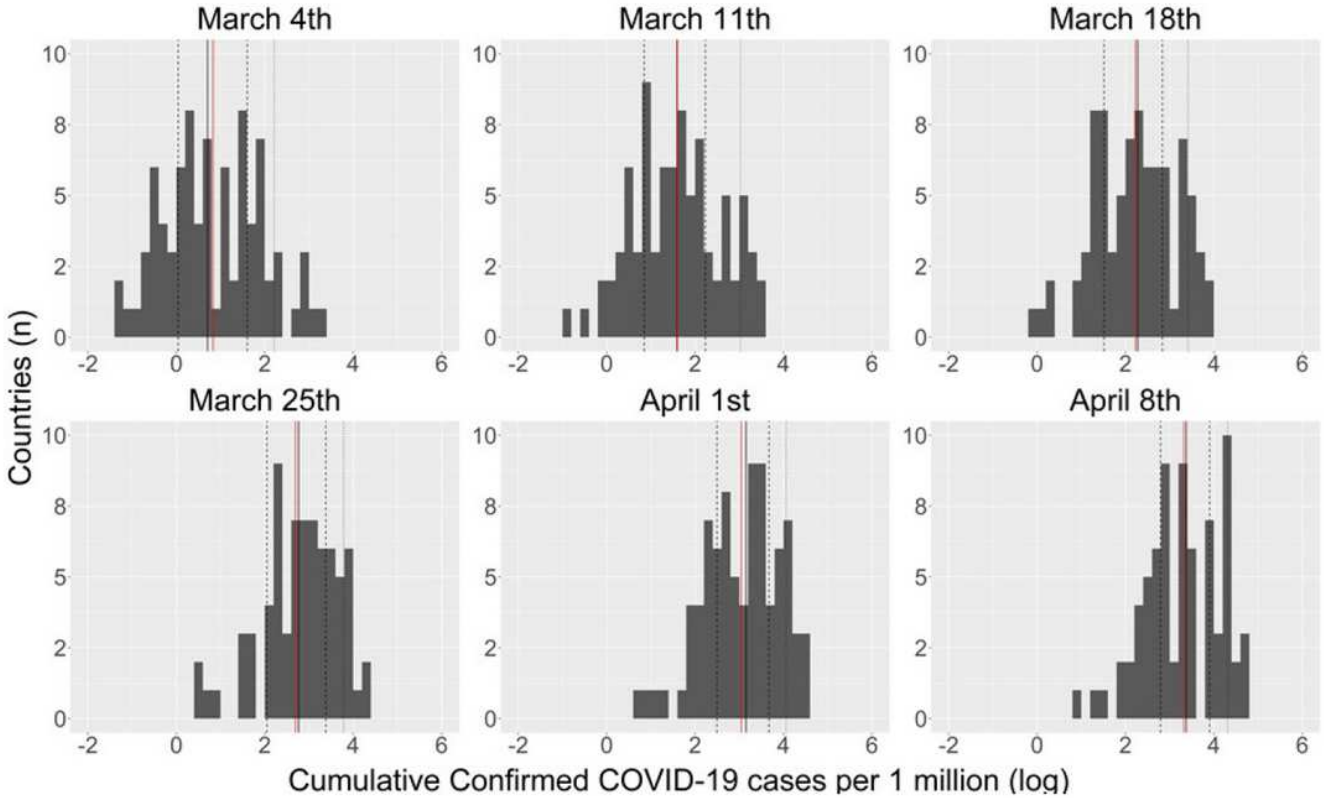

Figure 1

Distributions of cumulative confirmed COVID-19 cases per million population (log transformed). Graphs show the 10th week (ending March 4th) until the 15th week (ending April 8th) of 2020. The red line indicates the mean and the black lines quantiles.

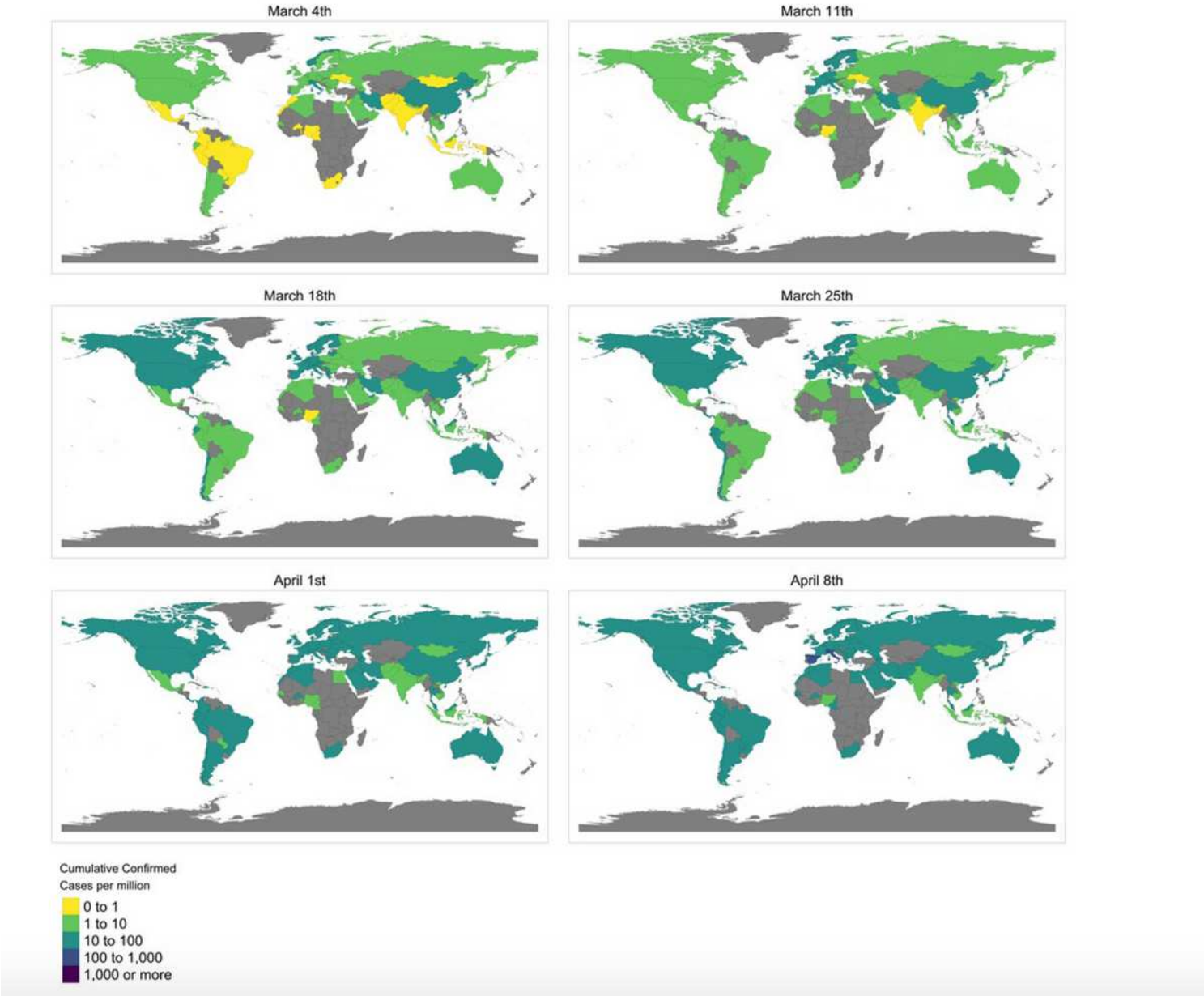

Figure 2

Choropleth map of confirmed cases of COVID 19 per million population for the 84 countries included in the analysis over weeks 10 to 16 (ending March 4th and April 8th 2020, respectively).

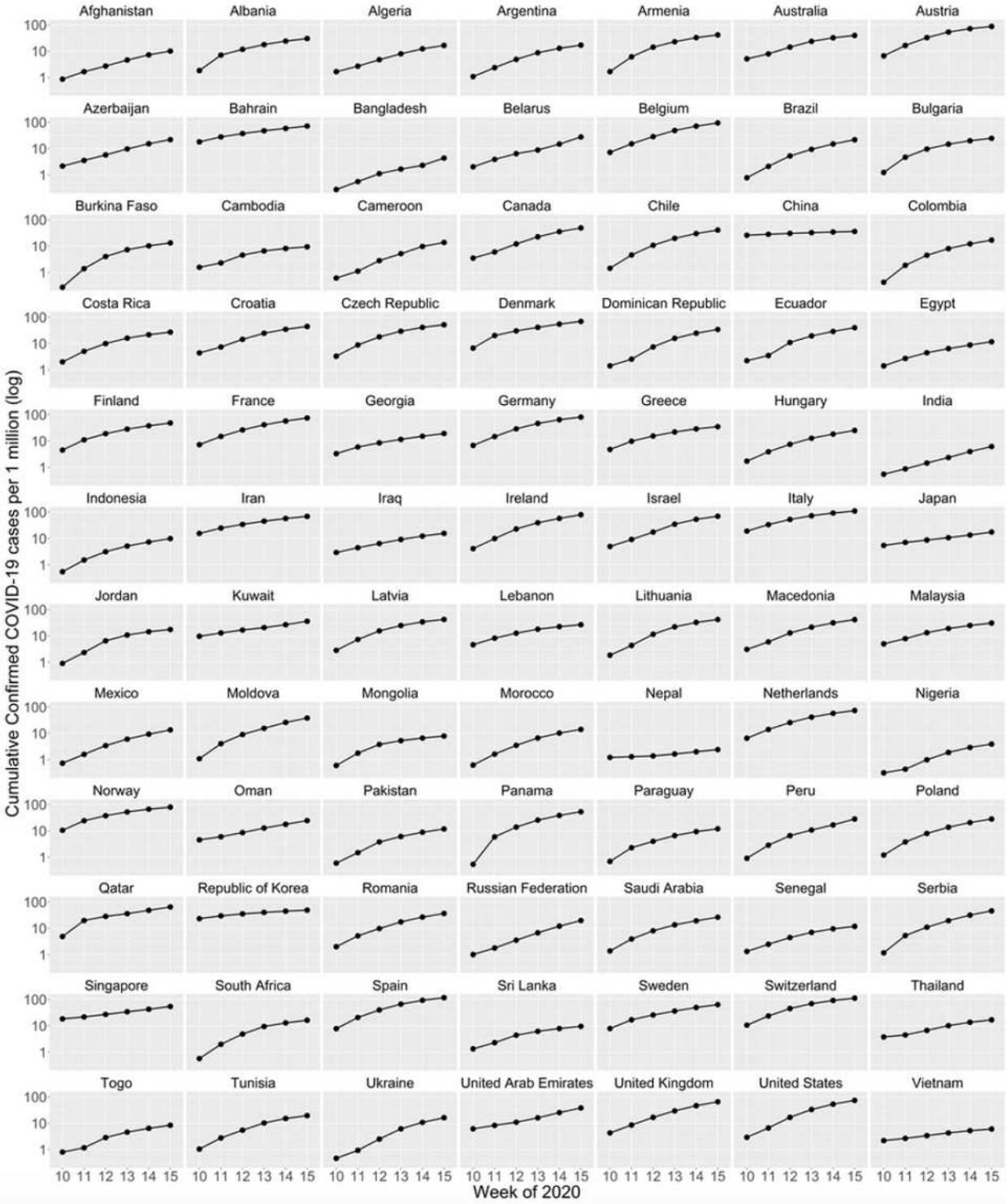

Figure 3

Diffusion of Covid-19 cases per million population (log transformed) over weeks 10 – 15 (ending 4th March and April 8th 2020, respectively) across 84 countries.

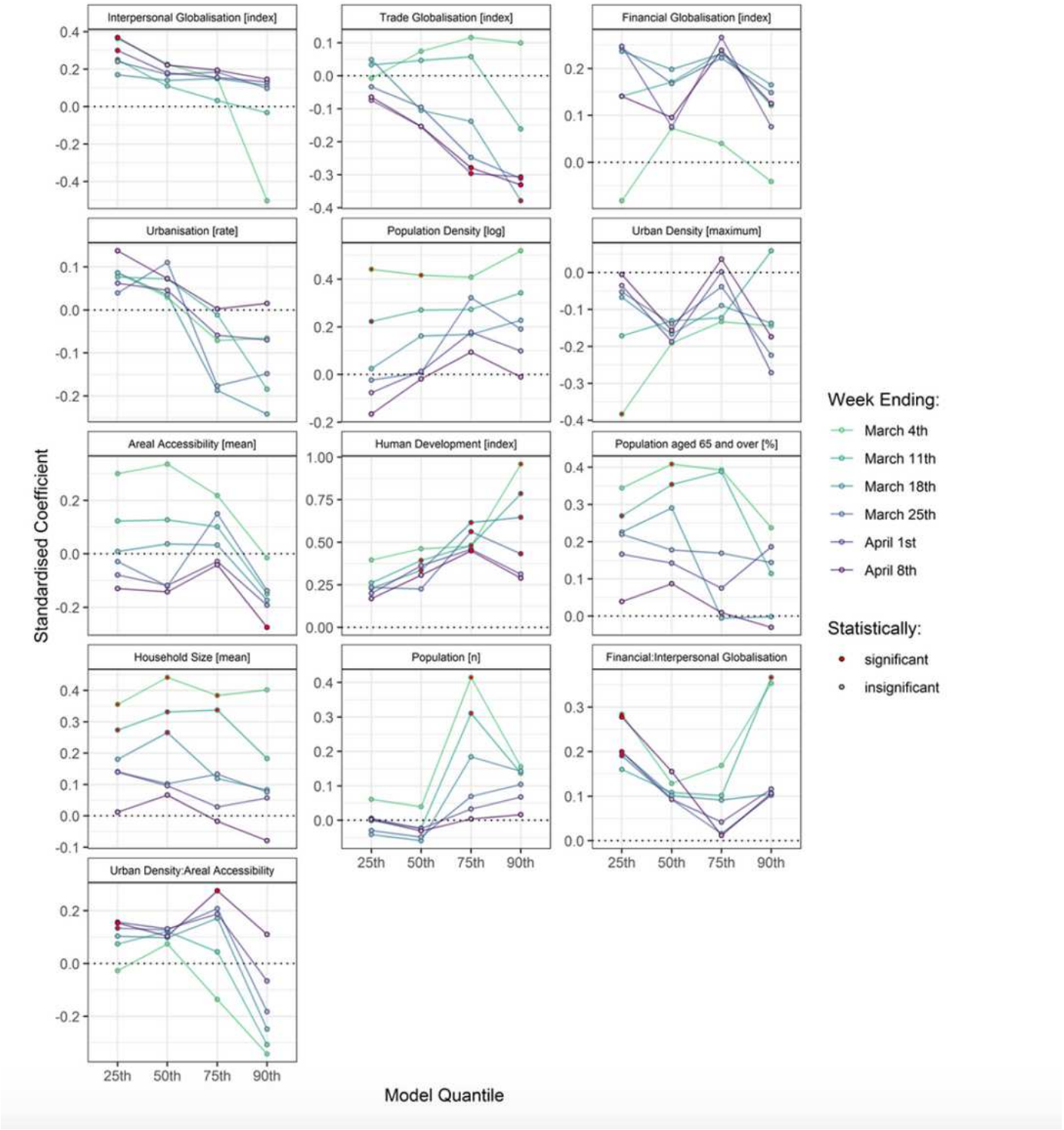

Figure 4

Standardised coefficient value of confirmed COVID-19 cases at the 25th, 50th, 75th and 90th quantiles the 10th week (ending March 4th) until the 15th week of 2020 (ending April 8th).