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GRA 19703

Master Thesis

Thesis Master of Science

Should the Timing of Covid-19 Restrictions be Determined by Country Characteristics?

A Global Cross-Country Analysis

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Start: 15.01.2021 09.00

Finish: 01.07.2021 12.00

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Should the Timing of Covid-19 Restrictions be Determined by Country Characteristics?
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MSc in Business, Major in Economics

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June 2021

BI Norwegian Business School

Acknowledgement

First and foremost, we would like to thank our supervisor, Associate Professor Per Botolf Maurseth, for his insightful feedback throughout the writing process. His knowledge and suggestions have been a major contribution to our final thesis, through both help to formulate our research problem in the early stage, as well as detailed comments and specific suggestions for areas of improvement during the process.

Our experience of completing this master's degree has without a doubt been influenced by the Covid-19 pandemic and the containment measures that followed. As campus has been closed for months at different stages and we were not allowed to visit each other for some time, we are proud to finish. Thus, we would like to express gratitude towards our boyfriends, who have lived with us and supported us throughout this process. We want to especially thank them, our families and friends for their patience and support.

Abstract

The Covid-19 pandemic was declared on 11 March 2020 by the World Health Organization. Previous studies on viral diseases have suggested that the socioeconomic factors of countries can provide an explanation for which countries are more susceptible to Covid-19 infection cases. Our objective in this study was to determine whether this is the case, and whether the factors of importance change during different stages of the first year of the pandemic. We believed investigating this would provide important information to policymakers as containment measures should be implemented when a country is susceptible to more cases. We investigated this using a two-step procedure, where the first step was a panel data analysis of the number of cases and the second step was a cross-country analysis of the socioeconomic factors. We find that socioeconomic factors can explain a country's susceptibility to a higher number of infections, and these factors do in fact differ during the various periods of the pandemic. Our key results are that countries with developed economies are more susceptible in the early stage of the pandemic, while countries with more inequality become susceptible after the former countries have gained control of the virus. We conclude that policymakers should, when facing a pandemic of a virus transmitted in a similar way to Covid-19, consider the characteristics of their country and time their policy implementation accordingly.

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1 Introduction

The Covid-19 pandemic that shook the world at the start of 2020 was not the first, and most likely will not be the last, pandemic the world will experience. This fact provides a strong rationale for further research on the topic—more specifically into how the disease has spread across the world and how policymakers should react to control it.

Several previous studies, some presented in our literature review, have found that socioeconomic factors are important determinants of how a country will be affected by a disease. One cannot predict which part of a population will be most at risk during the next pandemic, as this may be determined by the disease itself. However, one may investigate whether there is a relationship between the characteristics of countries and the number of registered infections of Covid-19, hereafter referred to as "the number of cases." This relationship may provide valuable information about a country's susceptibility to a higher number of cases.

To this end, we would like to study the socioeconomic factors of countries and their number of cases throughout the first year of the pandemic. We hope to identify a relationship between the characteristics of countries and the number of cases using socioeconomic factors. Further, we believe that there will be a difference in the characteristics of those countries susceptible to cases in the early stage of the pandemic as compared to the countries susceptible at the later stages of the first year. Additionally, the Covid-19 pandemic is characterized by waves of cases. More specifically, there are periods when countries experience more growth in the number of cases compared to other periods. Therefore, we study this relationship at different time periods during the year.

An increase in the number of cases gives reason to implement stricter containment measures; hence, we believe that drawing the inference between the characteristics of countries and their number of cases may provide valuable information to policymakers. This may help decision-makers understand how to react, when to react, and how to prioritize should a new global pandemic occur. When the pandemic was declared in March 2020, numerous countries introduced strict containment measures such as lockdowns; however, many of these countries were not struggling with the disease at this point. As the socioeconomic differences across countries may have an impact on their susceptibility to an increasing number of cases, this might imply that introducing the same policies simultaneously across the world is excessively cautious. For some countries, these strict measures might be unnecessary; they may, in fact, do more harm than good, as the feasibility of continuing such measures over longer periods of time vary across countries. Some countries are more reliant on their labour-intensive economic activity, and the consequences of the strict measures might be more severe for these countries.

Our hypothesis, based on studies mentioned in the literature review, is that the countries with high economic activity will experience a higher number of cases during the early stage of the pandemic. We also believe that a high level of international tourism will be positively correlated with a high number of cases in the early stage. Moreover, we believe that countries characterized by more unfavorable socioeconomic factors, such as inequality, will struggle with the disease in the later periods.

Relevant literature is discussed in Chapter 2, and an overview of the data with hypotheses and data limitations are presented in Chapter 3. In Chapter 4, the research method and estimating methodology is outlined and explained. We present our results in Chapter 5 with a discussion of the results that also identifies the limitations of the study. The conclusions are outlined in Chapter 6.

2 Literature Review

How socioeconomic factors determine the spread and severity of pandemics and various diseases has been studied by several researchers over the past decade. Since the beginning of the Covid-19 pandemic in March 2020, numerous studies have been conducted on the virus, trying to relate it to socioeconomic factors in an effort to explain why and how the virus spreads.

The link between the socioeconomic factors of countries and how the countries should prepare for future pandemics has been studied by numerous researchers prior to the start of the Covid-19 pandemic. Socioeconomic factors have been used to predict risky areas for pandemics and diseases. For instance, a paper from 2019 used socioeconomic factors to predict risky areas for Ebola outbreaks (Redding et al., 2019). In 2017 an Infectious Disease Vulnerability Index was constructed, mostly based on the experience of the Zika and Ebola viruses; the index uses socioeconomic factors to identify which countries are most vulnerable to virus outbreak (Moore et al., 2017). Furthermore, a 2017 article finds that social inequality is an underestimated factor in how the world prepares for future pandemics (Mamelund, 2017).

Not only are socioeconomic factors demonstrated to be important considerations when preparing for future pandemics, these factors can also be used to explain the spread and severity of diseases. A paper studying the 2009 pandemic influenza in China found that socioeconomic factors had not received enough attention, given that they could explain how incidences had accumulated (Xu et al., 2019). Furthermore, a recent paper from China finds that economic activity and population flow are important factors in the spread of Covid-19 (Qiu et al., 2020). This result is similar to the results of a study from France in 2016, which shows that high economic activity and growth in trade can lead to viruses spreading faster (Adda, 2016). Mukherji (2020) conducted a study in July 2020, regarding the social and economic factors underlying the incidence on Covid-19 cases in U.S. counties. In this study, a vulnerability index for each county was developed. This study found that counties with higher income had more cases, but higher mortality rates occurred in counties when a higher number of cases were combined with lower income. The study also found that the American counties with higher income inequality and higher population density had a higher number of deaths.

These studies suggest that how policymakers should react and what measures they should implement during pandemics can be based on the socioeconomic factors of individual countries. A 1998 study found that macro variables directly affect individuals and their choices (Diez-Roux, 1998). This finding has become a major research topic as it can determine the effect of the measures implemented by policymakers. A study from April 2020 investigated and used socioeconomic factors to construct maps of the counties in the U.S., suggesting this should be used to determine the suitable measures for containing the spread of Covid-19 (Chin et al., 2020). Another paper from 2020 analyzed more than 160 countries and the timing and strictness of policies. This study finds that the effect of the measures differs between countries (Hale et al., 2020).

Moreover, how pandemics can affect the socioeconomic factors of countries has been studied, as this can determine which countries to prioritize during a pandemic. A study on how Covid-19 will affect poor communities is one example, suggesting that one should focus on reducing the effect of the pandemic for these communities (Buheji et al., 2020). Similar results are found in a study of Pakistan, addressing the issue of food insecurity due to the pandemic (Ali et al., 2020).

The socioeconomic factors of countries are, without a doubt, important to consider both when dealing with an ongoing pandemic and preparing for future pandemics. In keeping with this growing research focus, we would like to contribute to the literature by studying the socioeconomic factors of countries globally and how these factors shaped the outcomes of Covid-19. More specifically, we aim to identify which countries experienced a higher number of cases compared to others during different periods of the first year of the Covid-19 pandemic.

3 Data

We have chosen to use data in our study which is easy to access and comes from well-known and reliable sources. The World Health Organization has been a key player in the international efforts to manage the pandemic. Since we want to study all the countries of the world, we choose to use them as our data source on Covid-19 infections and related deaths (WHO Coronavirus Disease [COVID-19] Dashboard, 2021). Since we believe country characteristics can help explain the number of Covid-19 infections, we need data on our characteristics of interest. We found that The World Bank DataBank is a suitable option since they have 189 member countries and their DataBank contains data for almost every variable we are interested in (World Bank, 2021). In Table 1, we have listed the variables of interest, which data from The World Bank DataBank we use to create this variable, and their hypothesis. In addition to data from The World Bank, we believe that the stringency of the Covid-19 containment policy in different countries had an effect on the registered infections. To find the effect of the government actions undertaken, we use the Oxford Covid-19 Government Response Tracker (OxCGRT) which captures the policies related to containing the virus (Hale et al., 2021).

Table 1

Data Hypotheses

Variable	Data	Definition	Hypotheses
Economic strength	GDP per capita (current US$)	Sum of value added by all producers less value of intermediate goods and services used in production. Divided by midyear population.	Based on other studies on viral diseases from the literature review; we believe this will increase the spread of Covid-19.
Life expectancy	Life expectancy at birth, total (years)	Average years a newborn is expected to live if the mortality patterns at the time of birth stays constant; so this reflects the mortality level of a population.	When the health situation in a country is good, this generally means people live longer lives. We believe this foundation is built on economic strength and will have

			a similar effect on the spread.
Population density	Population density (people per sq. km of land area)	Midyear population divided by land area. Residents are counted, except for refugees. Land area under water is not counted.	People living closer together will have more interaction with each other and thereby increase the infection rates.
Migrant stock	International migrant stock, total	Number of people born in another country than where they live. This number includes refugees.	Immigrants have been shown to be at larger risk of Covid-19 infections than native-born residents. High migrant stock will lead to more registered cases of Covid-19 (OECD, 2020). However, we cannot say if the effect of this is genetic or attached to living conditions.
Total Population	Population, total	Total population regardless of legal status or citizenship.	We use this as a control variable since the data we use on infection rates are not controlled for population size. A larger population will experience more infections.
Urban population	Urban population (% of total population)	People living in urban areas defined by national statistical offices.	People living closer together will have more interaction with each other and thereby increase the infection rates.
Physicians per 1,000	Physicians (per 1,000 people)	Physicians include generalist and special medical practitioners.	We believe a good health foundation is built on economic strength leading to more health practitioners and will

			have a similar effect on the spread.
Medical Expenditure	Current health expenditure per capita, PPP (current international $)	Current expenditure on health per capita, estimates prepared by the World Health Organization.	We believe this foundation is built on economic strength and the medical expenditure will have a similar effect on the spread.
Population over 65	Population ages 65 and above (% of total population)	Population based on the definition counting all residents regardless of legal status or citizenship.	When the health situation in a country is good, this generally means people live longer lives. We believe this foundation is built on economic strength and will have a similar effect on the spread.
Tourism	International tourism, number of arrivals	Overnight visitors who travel to a country other then the country they have residence for a period not exceeding 12 months. Data come from World Tourism Organization (WTO).	International tourists travel between countries. In periods where the travel restrictions were not enforced, we believe the countries which normally have a high level of tourists had this during the pandemic as well, leading to higher spread.

Governance	Government Effectiveness : Estimate	Estimate of the perceptions of the quality of public services, civil service, policy formulation and implementations, and the degree of independence from political pressures. The estimate gives scores on the aggregate indicator in units of a standard normal distribution, meaning the estimate is from -2.5 to 2.5.	The effect of the implemented containment measures will depend on the quality of governance and the trust in the government. We believe high quality governance will lead to containment of the virus.
Gini	Gini index (World Bank estimate)	Measure of the distribution of income among individuals or households within an economy. The Lorenz curve plots cumulative percentages of total income received against the cumulative number of recipients. Gini index measures the area between the Lorenz curve and a line of absolute equality. Gini index of 0 represents perfect equality and 100 is perfect inequality.	We believe higher inequality will lead to more Covid-19 infections. There can be a lower number of people in absolute poverty but an increase in the Gini index. Thus, we cannot say anything about the general income level, only the level of inequality.
Poverty	Poverty headcount ratio at $1.90 a day (2011 PPP) (% of population)	The percentage of the population living on less than $1.90 a day at prices from 2011.	This variable is added as a possible explanation variable in the periods where most of the world had declining infection rates. We believe poverty headcount could help explain the

			characteristics of the countries with growth in these periods.

Note: The data listed in this table are obtained from the World Bank Databank, the definitions are provided in the metadata for each variable (World Bank, 2021). The currency listed in this table is USD.

The data on Covid-19 infections from the World Health Organization will be subject to some obvious flaws. The confirmed cases of Covid-19 may not reflect the actual infections. Studies have found that there has been substantial under-ascertainment of cases, especially during the first wave (Musa et al., 2021; Omori et al., 2020; Russell et al., 2020). Findings from Japan showed that the severe cases had twice the likelihood of being diagnosed (Omori et al., 2020). Even so, the majority of the reported cases of Covid-19 are not severe, and most people will experience mild symptoms and fully recover (*Corona - High Risk Groups and Their Relatives*, 2020). This tells us that there might be severe underreporting, and we cannot say with certainty that the reported cases of Covid-19 are the same as the number of infected people. However, we use the number as a proxy in our estimation.

Cross-country comparisons are a problem with most data, and the reported cases of Covid-19 are no different. Different countries have different methods for testing and for containing the virus which makes it difficult to compare the number of cases between countries (Middelburg & Rosendaal, 2020). The paper by Middelburg and Rosendaal on how to make cross-country comparisons emphasizes that comparisons like this can only be made when both the arrival of the virus and the population size are taken into consideration. We believe that our decisions to divide the first year of the pandemic into short periods helped us take the arrival of the virus into account and we control for population size in the cross-country analysis.

Because of reporting anomalies, smoothing the data on reported cases can provide more accurate representation of the timing of waves. The data is smoothed over seven days so that the over- and under-reporting that can come from weekends, for example, are eliminated (McConnell, 2020). Some of the countries had large corrections of registered cases leading to days with negative numbers of reported cases. These corrections were largely eliminated during the smoothing process. Countries which, after smoothing, still had days with negative reported numbers are removed from the sample for the periods where large corrections occurred.

A persistent challenge for all official data used in this thesis is that each country differs in its collection procedures, estimation methods, and the definitions they use (World Bank, 2021); these differences impose limitations on the comparisons between countries. Since all population estimates we use are from the World Bank, and as their data is affected by the level of trust in the government, the government's commitment to enumeration, and protections against misusing census data, our results will also inevitably be affected by this. The economic variables used in this analysis also have a measurement problem. Even though GDP is the most widely used measure for analyzing economic growth, there are problems defining and measuring it. Measuring GDP is especially problematic in developing economies, and one reason for this is that some of the economic activity is conducted outside the formal sectors (Henderson et al., 2012). Another problem for our economic variables is that comparing GDP levels would also require purchasing power parity, which is also subject to uncertain estimates (Deaton & Heston, 2010). In Table 2, the limitations specific for each variable are listed; these limitations occur in addition to the general limitations for cross-country comparisons.

Table 2

World Bank Data Limitations

Variable	Limitations
Economic strength	Different countries use different definitions, methods, and reporting standards. Developing countries may have additional problems. These limitations are affected by the limitations for total GDP and for total population.
Life expectancy	One of the sources for this data is the United Nations Population Division. This is five-year data, and this data may not reflect events as much as the observed data.
Population density	This is mainly based on population censuses, and this is for many countries not available. Another problem with comparing population density across countries is that much of the land area consists of deserts and mountains, which will affect this measure.
Migrant stock	Several countries lack data on their foreign-born residents, and the data is built on estimation. There are some discontinuities in the trend of the migrant stock.
Total population	In addition to the limitations for all our data, this data depends on U.S. estimates where five-year period data is used and actual events are not events in the data.
Urban population	There is no universal definition of urban and rural area. There might be national differences in these definitions.
Medical expenditure	Human resources can be concentrated in urban areas, making the distribution across the country and its inhabitants unequal.
Physicians per 1000	This data is in a version which include dimensions that are made for international comparisons.

Population over 65	Based on five-year period data used in the United Population Division's Population Prospects, the data might not reflect actual events or age composition.
Tourism	The data is on international tourists. A person making several trips is counted every time. Data for some countries are unavailable or incomplete and then tourists, same-day visitors, cruise passengers, and crew members are counted. Data collection methods are different across countries; therefore, comparing across countries should be done with caution.
Governance	The data is based on the Worldwide Governance Indicators (WGI) project. The data includes hundreds of individual underlying variables taken from many data sources. The views on governance are based on surveys and public and private sector experts all over the world. There are difficulties measuring governance using any kind of data; however, the WGI is a meaningful tool for cross-country comparisons (Kaufmann et al., 2010).
Gini index	The Gini index is not unique. It is also possible that there is a lower number of people in absolute poverty but an increase in the Gini index. This is because it can still be increasing inequality, even if the number of people living in absolute poverty decrease. This data also suffers from differences in collection methods between countries and time periods. To make the data more comparable, World Bank has used consumption wherever this is possible.
Poverty	There are challenges to measuring poverty. There is low availability and low quality of the data as income and consumption are hard to gain access to, especially in the poorest countries. Comparisons of countries at different levels of development might be a problem.

Note: The data listed in this table are obtained from the World Bank DataBank. The limitations are provided in the metadata for each variable (World Bank, 2021).

The data on stringency on containment measures are in time-series format, but we want to use it in our cross-sectional analysis since we believe this could be an explanatory variable for the registered number of Covid-19 cases. We use the mean value of the measure of government responses for the periods used in this paper; then, we use the previous periods' mean measure of government response in our model. We do this to avoid the endogeneity that stems from government measures relying on infection rates in the same period. As with all data comparing countries, this data also has to rely on the judgement and differences of the countries, and it does not measure how well the government implements the containment measures.

Since data collection methods depend heavily on a country's collection processes and recourses for testing, the process of comparing countries has real limitations. Nevertheless, we decided to conduct cross-country comparisons, despite the limitations this imposes on the thesis.

4 Methodology

4.1 Research design

Even though many countries experience growth in cases simultaneously, the number of cases varies across countries. The main goal of this study is to investigate whether socioeconomic factors can explain the varying number of cases. There are distinctive wave patterns in the number of reported cases for each country, which provides the rationale for studying the number of reported cases at different time periods during the first year. We investigate whether socioeconomic factors can explain the varying number of cases in two steps, where the first step is a panel data analysis and the second is a cross-sectional analysis.

For the panel data analysis, we divide the first year of the pandemic into shorter time periods. This allows us to investigate each period separately. Following this, we construct a model to estimate the number of cases at time t in each period. In the model, we include a variable for the number of cases at time $t-1$, as the number of cases today is determined by the number of cases the previous day. In addition, we include a variable for the epidemiological factors that can explain the number of cases. We will use an epidemiological model to construct the epidemiological factors. This model can only explain how the epidemiological factors contribute to growth in cases. Thus, we remove the countries which do not experience growth in each period, and the model solely estimates the number of cases for the countries that experience growth. The model also includes time fixed effects, included as a time dummy variable.

Moreover, we believe that there are omitted variables in our model. The time-constant omitted variables are accounted for in the error term. The error term in the model is a composite error term, consisting of both an unobserved country-specific variable that is fixed over time and an idiosyncratic error that is time-varying. The unobserved country-specific variable will account for the time-constant omitted variables. This country-specific variable is what we will investigate in the next step. We will extract estimates of the unobserved country-specific variable for each period from the composite error term post-estimation and convert these estimates into an index, ranging from 0–100. A country with a high value on the index will indicate that the country is susceptible to a higher number of cases, due to time-constant, country-specific characteristics.

The second step in our analysis is a cross-sectional analysis. This analysis investigates the possible explanatory value of the socioeconomic factors regarding variation in the indices. More specifically, we investigate whether the socioeconomic factors included in our study may be some of the time-constant omitted variables accounted for in the unobserved country-specific variable. We use the index values of countries as the dependent variable and regress on the socioeconomic factors using Ordinary Least Squares regression (OLS). The socioeconomic factors that significantly correlate with the index value will indicate that these factors may be the omitted variables in our model that can explain the variation in the number of cases across countries.

4.2 Step 1 - Panel Data Analysis

Due to the distinctive wave patterns, we want to study the differential number of cases across countries during short time periods. We divide the first year following the date the pandemic was declared, 11 March, into periods of 20 days. This results in 18 time periods. The periods are presented in Table A1 in Appendix A. Further, we construct a model to estimate the number of cases in each period.

4.2.1 The estimation model

The model we construct to estimate the number of cases is based on both its autoregressive path and the epidemiological factors of the spread of the disease. In addition, we include time-fixed effects. Moreover, the error term is a composite error term, consisting of both an unobserved country-specific variable as well as an idiosyncratic error.

4.2.1.1 Epidemiological factors

Inspired by the paper by Mukherji (2020) discussed in the literature review, we use a compartment model which divides the population into three compartments—susceptible (S), infected (I), and recovered (R) (Blackwood & Childs, 2018). This model is named the SIR model. This epidemiological model is widely used to explain and investigate spread of a disease within a community. The simple model is used to predict the number of individuals within the three compartments at any point of time. The total population is referred to as N, such that N = S + I + R. The model makes several assumptions—for instance, that immunity following a recovery will last forever, that there is a closed as well as large and constant population, and that all individuals within a population have equal probability of being in contact (Cooper et al., 2020; Weiss, 2013). Assuming a constant population is a large simplification. The case facility rate of Covid-19 is not constant and difficult to estimate; the reported case-fatality rate varies from 0.4% to 15% (Azizi et al., 2020). However, we believe that the total Covid-19 related deaths are so few that they will not have a substantial impact on the size of the total population. These simplifying assumptions lead to limitations of the model which we will discuss further and evaluate in the limitations section in Chapter 5.

In this model, an individual will move from the susceptible compartment to the infected compartment as a result of an interaction with an infected individual ($S_0 = N,\ S_1 = N - \ I_1,\ S_2 = N - I_1 - I_2$....). Following this, the individual will move to the recovered compartment when the individual has either recovered or died. In our estimation, we use the fact that interactions between susceptible and infected individuals can lead to new cases. We implement this in the model using an interaction term between the susceptible and infected individuals divided by the total population. We arrive at the number of individuals in the susceptible compartment based on the assumption that one can only get infected by the Covid-19 virus once (Weiss, 2013). Thus, the susceptible variable is equal to the number of cumulative cases subtracted from the population size within the countries.

As a proxy for the number of infected individuals, we use the number of registered cases seven days ago ($I = I_{i,t-j} = I_{t-7}$). The logic behind using a lag of seven days is based on the incubation period and the time it takes to recover. A meta-analysis based on data from January 2020 to January 2021 found that the mean incubation period was 6.38 days (Elias et al., 2021). We assume that those infected seven days ago were not isolated in the incubation period, which makes it possible that interactions will result in new cases. We also assume that infections and recoveries happen at the same rate, such that the infected individuals will eventually move to the recovered compartment or die.

4.2.1.2 The model equation

When estimating the number of cases, our model equation is as follows:

$$C_t = \beta_0 + \beta_1 C_{t-1} + \beta_2 \left(\frac{S_{it} * I_{i,t-j}}{N} \right) + \delta t + \varepsilon_{it} \tag{1}$$

where C_t is the number of new registered cases at time t and C_{t-1} is the number of new registered cases at time $t - 1$. Furthermore, $\frac{S_{it}*I_{i,t-j}}{N}$ is a variable representing the epidemiological factors, while t is a time dummy variable. $\varepsilon_{it} = \gamma_i + v_{it}$ is a composite error term, where γ_i is the unobserved country-specific variable and v_{it} is the idiosyncratic error.

As the number of cases in our model follows an AR(1) process, where the dependent variable is determined by past values of itself, we need to use a dynamic panel estimation method. Furthermore, when estimating models with an unobserved country-specific variable this is usually dealt with by first-differencing the equation, which removes the country-specific variable as it is time-constant (Wooldridge, 2012, p. 461). However, the lagged dependent variable is a predetermined variable, as it is correlated with past error terms, which results in an endogeneity problem when we transform the equation by first-differencing (Wooldridge, 2012, p. 461). This occurs as the idiosyncratic error v_{it-1} in the difference term $(v_{it} - v_{it-1})$ is correlated with C_{t-1} in the difference term for the lagged dependent variable $(C_{t-1} - C_{t-2})$.

Moreover, we have constructed the variable representing the epidemiological factors in our model to be endogenous. This is due to how we find the number of individuals in the susceptible compartment—by subtracting the number of cumulative cases from the total population size. The number of cumulative cases includes the number of cases today. Thus, the variable representing the epidemiological factors is simultaneously determined with the number of registered cases today, and simultaneity is a form of endogeneity (Wooldridge, 2012, p. 554). We thereby conclude that this variable is endogenous in the model equation both prior to and after the first-differencing transformation of the equation.

4.2.2 Choice of estimation method

Following what is mentioned about the components of the model equation above, our choice of method needs to allow for an unobserved country-specific variable as well as independent variables that are not strictly exogenous. Additionally, we want to study the significance of the socioeconomic factors at different time periods and thereby want to construct an index for each of these time periods. Thus, the estimation method also needs to fit data from a short panel, which means a larger number of cross-sectional units than time periods (T < N).

4.2.2.1 Instrumental variable approach

A widely used estimation method which takes the endogeneity issue into account is the instrumental variables method. There are two criteria for an instrument to be valid—namely, the relevance and exclusion criteria (Wooldridge, 2012, p. 514). Instruments that meet these requirements are often not easily available. However, Anderson & Hsiao (1982) suggested instrumenting with the second lag of the lagged dependent variable for the difference term after the model is transformed into the first-difference equation. Thus, C_{t-2} may be used as an instrument for the difference term $(C_{t-1} - C_{t-2})$.

The second lag of the dependent variable meets both of the requirements of valid instruments. The relevance requirement means that the instrument must be related to the endogenous variable it is supposed to instrument. More specifically, $Cov(C_{t-2}, (C_{t-1} - C_{t-2})) \neq 0$ (Wooldridge, 2012, p. 514). As C_{t-2} is a part of the difference term $(C_{t-1} - C_{t-2})$, the second lag of the lagged dependent variable is related to the lagged difference term. Furthermore, the exclusion requirement states that the instrument has no effect on the dependent variable—which means that it is exogenous. More specifically, it is uncorrelated with the idiosyncratic error difference term, $Cov(C_{t-2}, (v_{it} - v_{it-1})) = 0$ (Wooldridge, 2012, p. 514). This is satisfied as long as the idiosyncratic error is not serially correlated (Roodman, 2009b).

As a result of the analysis above, we would like to use lags as instruments since instruments that meet the necessary criteria are difficult to obtain. Moreover, using longer lags as instruments can improve efficiency. This is possible without losing observations if one uses a set of instruments where the instruments are time-specific, starting from the second lag and where missing observations are replaced by zeros (Holtz-Eakin et al., 1988, as cited in Roodman, 2009b, p. 107). This set of instruments allows for the use of lags of endogenous as well as lags of predetermined variables as instruments, where the second lag of the endogenous variables and the first lag of the predetermined variables can be used as instruments (Holtz-Eakin et al., 1988, as cited in Roodman, 2009b, p. 108).

We find that Difference and System Generalized Method of Moments (GMM) estimators incorporates these type of instruments sets, as well as allowing for the other considerations we mentioned about estimating our model equation. More specifically, these estimators allow for endogenous and predetermined regressors, a dynamic process as well as an unobserved country-specific variable. In addition, these estimators fit data from a short panel (Roodman, 2009b).

4.2.2.2 Method of Moments

As we will work in the GMM framework, understanding the Method of Moments (MM) estimator is essential. The principle behind finding the MM estimator is to use population moments and replace them with the corresponding sample moments. For instance, an unbiased estimator for the population mean, μ, is the sample average (Wooldridge, 2012, p. 759). Thus, one can replace the sample moment $E(\bar{Y}) = E(\frac{1}{N}\sum_{i=1}^{N} Y_i)$, with the population moment $E(Y) = \mu$, to estimate μ. This estimator is an example of a MM estimator (Wooldridge, 2012, p. 768).

The MM approach can be applied to obtain an estimate of a parameter of interest when one makes use of instruments. For instance, using an example from Wooldridge (2012, p. 524), consider if one has the following model: $Y_1 = \beta_0 + \beta_1 x_1 + \beta_2 \beta x_2 + u$, where both x_1 and x_2 are endogenous and u is assumed to have an expected value equal to zero. If valid instruments, one can use z_1 and z_2 as instruments for the endogenous regressors, respectively. Wanting to find estimates of β_0, β_1 and β_2, one can use the assumption of zero mean of the error term, and the assumption of exogeneity of each instrument, more specifically: $E(u) = 0, E(z_1 u) = 0$ and $E(z_2 u) = 0$.

These assumptions will then become the moment conditions which need to hold. To solve for the unknown parameters, one makes use of the sample counterparts. The system of equations for the sample moments is:

$$\sum_{i=1}^{n}(y_{i1} - \hat{\beta}_0 - \hat{\beta}_1 x_{i2} - \hat{\beta}_2 x_{i1}) = 0$$

$$\sum_{i=1}^{n} z_{i1}(y_{i1} - \hat{\beta}_0 - \hat{\beta}_1 x_{i2} - \hat{\beta}_2 x_{i1}) = 0$$

$$\sum_{i=1}^{n} z_{i2}(y_{i1} - \hat{\beta}_0 - \hat{\beta}_1 x_{i2} - \hat{\beta}_2 x_{i1}) = 0 \qquad (2)$$

This is a case where the number of moments equals the number of parameters to be estimated. When this is the case, it is possible to find a unique solution using MM. The estimated parameter will then be equal to the true value of the parameter. However, this is not possible when there are more moment conditions than parameters one is trying to estimate. This will lead to overidentification as there are more equations than unknowns, resulting in the need to use GMM (Hayashi 2000, p. 205).

4.2.2.3 Difference and System GMM

Arellano and Bond (1991) make use of all the available lags as instruments instead of only the second lag as suggested by Anderson and Hsaio (1982). This method includes first-differencing the equation before using all the available lags as instruments for the differences in the transformed equation. In this case, the moment conditions are that the instruments are assumed to be exogeneous to the difference term $(v_{it} - v_{it-1})$. Using all lags as instruments, they made use of all linear moment conditions, $E(C_{t-s}\Delta v_{it}) = 0\ for\ t = 3, \ldots, T\ and\ s \geq 2$ $(\text{Blundell \& Bond, 1998})$. These moment restrictions imply that the instrument exclusion requirement is met for all the available lags of the endogenous variables. Thus, the moment restrictions depend on the absence of serial correlation in the idiosyncratic error. When all available lags are used as instruments and the number of available lags exceeds the number of regressors, this results in an overidentified specification as explained above, and the GMM estimator is needed. Their approach is referred to as Difference GMM.

Arellano and Bover (1995) extended this approach even further. They suggested the use of all the available lagged differences as instruments in the untransformed equation as well, hereafter referred to as the level equation. Their approach consists of using both the level and the transformed equation simultaneously to estimate the unknown parameters. In the level equation, the unobserved country-specific variable is not removed. Thus, this method implies using the additional moment conditions: $E(\varepsilon_{it}\Delta C_{i,t-1}) = 0\ for\ t = 3,..,T$ (Blundell & Bond, 1998). These restrictions imply that if not correlated with the unobserved country-specific variable in the composite error term, the differences of all the available lagged endogenous variables can be used as instruments in the level equation. They found that using both equations simultaneously to estimate the parameters gives even better estimates (Blundell & Bond, 1998). This is referred to as system GMM as the method consists of using a system of equations.

We find that these estimators are both available in Stata using the command Xtabond2. Roodman (2009) explains the use of this command, and we will make use of this paper in the following section to explain how the GMM estimator is obtained, using a simpler model with no unobserved country-specific variable.

4.2.2.4 Generalized Method of Moments

For simplicity, the model in our explanation of obtaining the GMM estimator is given by: $y = x_{\mathrm{k}}\theta + \varepsilon$, where ε contains no unobserved country-specific variable. As mentioned, we follow derivations and definitions from Roodman (2009b) in our explanation.

The use of instruments requires that the exogeneity assumption holds. More specifically, this is:

$$E\left(z_j\varepsilon\right) = 0 \tag{3}$$

The corresponding sample moments is $\frac{1}{N}\boldsymbol{Z'\widehat{E}}$, where given an estimate for θ the residuals are $\boldsymbol{\widehat{E}} = (\hat{e}_1, \dots, \hat{e}_N)' = \boldsymbol{Y} - \boldsymbol{X}\hat{\theta}$. Here, $\boldsymbol{X}$ and $\boldsymbol{Y}$ represents matrices of N observations, and $\boldsymbol{Z}$ is a matrix of instruments as described in section 4.2.2.1. For N observations, the corresponding sample moment conditions can be written as $\boldsymbol{E_N}(\boldsymbol{z}\varepsilon) \equiv \frac{1}{N}\boldsymbol{Z'\widehat{E}} = 0$, where $\boldsymbol{z}$ is the column vector of j instruments.

The specification will be overidentified when the number of instruments exceeds the number of regressors, j > k. Forcing all the sample moment conditions to zero will, in this case, result in a system of equations with more equations than unknowns. All moment conditions cannot be fitted all at once; however, what can be done is to make the fit as good as possible for all of them, which implies minimizing $\boldsymbol{E_N}(\boldsymbol{z}\varepsilon)$. In the GMM estimation method, this is done by constructing a quadratic form which can be minimized, which consists of a symmetric weighting matrix $\boldsymbol{W}$.

$$\boldsymbol{E_N}(\boldsymbol{z}\varepsilon)\boldsymbol{W}(\boldsymbol{E_N}(\boldsymbol{z}\varepsilon))' = N(\frac{1}{N}\boldsymbol{Z}'\widehat{\boldsymbol{E}}\ )'\boldsymbol{W}(\frac{1}{N}\boldsymbol{Z}'\widehat{\boldsymbol{E}}) = \frac{1}{N}\widehat{\boldsymbol{E}}'\ \boldsymbol{Z}\ \boldsymbol{W}\ \boldsymbol{Z}'\widehat{\boldsymbol{E}} \tag{4}$$

The minimization problem becomes:

$$\hat{\theta}_{GMM} = \arg\min_{\hat{\theta}} \frac{1}{N}\widehat{\boldsymbol{E}}'\ \boldsymbol{Z}\ \boldsymbol{W}\ \boldsymbol{Z}'\widehat{\boldsymbol{E}} \tag{5}$$

The solution is found by taking the derivative with respect to $\hat{\theta}$ setting it equal to zero.

$$0 = \frac{d\hat{\theta}_{GMM}}{d\hat{\theta}} = \frac{d}{d\widehat{\boldsymbol{E}}}\frac{1}{N}\widehat{\boldsymbol{E}}'\ \boldsymbol{Z}\ \boldsymbol{W}\ \boldsymbol{Z}'\widehat{\boldsymbol{E}}\ \frac{d(\boldsymbol{Y} - \boldsymbol{X}\hat{\theta})}{d\hat{\theta}}$$

Using matrix identities, when $\boldsymbol{W}$ is not a function of $\widehat{\boldsymbol{E}}$ and $\boldsymbol{W}$ is symmetric, we have that $\frac{d(\widehat{\boldsymbol{E}}'\boldsymbol{W}\widehat{\boldsymbol{E}})}{d\widehat{\boldsymbol{E}}} = 2\widehat{\boldsymbol{E}}'\boldsymbol{W}$, such that:

$$0 = \frac{2}{N}\widehat{\boldsymbol{E}}'\boldsymbol{Z}\boldsymbol{W}\boldsymbol{Z}'(-\boldsymbol{X})$$

As is done in the xtabond2 paper, we remove $-\frac{2}{N}$ and we can solve for the GMM estimator:

$$0 = \widehat{\boldsymbol{E}}'\boldsymbol{Z}\boldsymbol{W}\boldsymbol{Z}'\boldsymbol{X} = (\boldsymbol{Y} - \boldsymbol{X}\hat{\theta})'\ \boldsymbol{Z}\boldsymbol{W}\boldsymbol{Z}'\boldsymbol{X} = \boldsymbol{Y}'\boldsymbol{Z}\boldsymbol{W}\boldsymbol{Z}'\boldsymbol{X} - \hat{\theta}'\boldsymbol{X}'\boldsymbol{Z}\boldsymbol{W}\boldsymbol{Z}'\boldsymbol{X}$$

$$\rightarrow \qquad \hat{\theta}\ = (\boldsymbol{X}'\ \boldsymbol{Z}\boldsymbol{W}\boldsymbol{Z}'\boldsymbol{X})^{-\mathbf{1}}\ \boldsymbol{X}'\ \boldsymbol{Z}\boldsymbol{W}\boldsymbol{Z}'\mathbf{Y} \tag{6}$$

This is the GMM estimator.

4.2.2.4.1 GMM estimator assumptions

The GMM estimator $\hat{\theta}$ has the following assumptions, as explained in Hayashi (2000, Chapter 3) for our notations.

For a simplicity of the explanation of assumptions, we define

$$\boldsymbol{\Sigma}_{\boldsymbol{XZ}} \equiv E(\boldsymbol{x}\boldsymbol{z}'),\ \mathbf{S}_{\boldsymbol{XZ}} \equiv \left(\frac{\mathbf{1}}{\boldsymbol{N}}\boldsymbol{X}\boldsymbol{Z}'\right) = \boldsymbol{E_N}(\boldsymbol{z}\boldsymbol{x}'), \mathbf{S}_{\boldsymbol{YZ}} \equiv \left(\frac{\mathbf{1}}{\boldsymbol{N}}\boldsymbol{Y}\boldsymbol{Z}'\right), \boldsymbol{S}_{\boldsymbol{EZ}} \equiv \frac{1}{N}\boldsymbol{E}\ \boldsymbol{Z}'$$

which gives us the following expression for the GMM estimator:

$$\hat{\theta}\ = (\ \mathbf{S}'_{\boldsymbol{XZ}}\widehat{\boldsymbol{W}}\ \mathbf{S}_{\boldsymbol{XZ}})^{-\mathbf{1}}\ \mathbf{S}'_{\boldsymbol{XZ}}\widehat{\boldsymbol{W}}\ \mathbf{S}_{\boldsymbol{YZ}} \tag{7}$$

where $\boldsymbol{W} \equiv \text{plim}\widehat{\boldsymbol{W}}$ as $\widehat{\boldsymbol{W}}$ is a symmetric positive matrix.

The bias of the estimator is the calculated errors from the true errors in the model:

$$\hat{\theta} - \theta_0 = (\, \mathbf{S}'_{XZ}\widehat{\boldsymbol{W}}\, \mathbf{S}_{XZ})^{-1}\, \mathbf{S}'_{XZ}\widehat{\boldsymbol{W}}\boldsymbol{S}_{EZ}) \tag{8}$$

Assumption 1: Identification assumption

The order condition: The order condition simply means that there has to be an overidentified or just identified system of equations for there to be a possible solution for the estimator.

The rank condition: There needs to be at least as many functionally independent moment conditions, as there are a number of parameters to be estimated. This means there has to be a guarantee that there is a solution to the equation system.

Uniqueness: θ_0, the true parameters of the population, is the only vector which satisfies the population moment conditions.

Assumption 2: The GMM estimator is consistent

Under the law of large moments, the sample GMM estimator $\hat{\theta}$ converges in probability to θ_0 as N goes to infinity since the sample moments converge in probability to the population moments, as N goes to infinity:

$\mathbf{S}_{xz} \xrightarrow{p} \mathbf{\Sigma}_{xz}$ as $N \to \infty$ or $p \lim_{N\to\infty} \mathbf{S}_{xz} = \mathbf{\Sigma}_{xz}$

which in turn $\theta_0 = p \lim_{N\to\infty} \hat{\theta}$

Assumption 3: Asymptotic normality

The consistent estimator $\hat{\theta}$ as asymptotically normal if

$\sqrt{n}(\hat{\theta} - \theta_0)\ \vec{d}\ N\left(0, Avar(\hat{\theta})\right)$

The $Avar(\hat{\theta})$is the variance of the limiting distribution.

$$Avar(\hat{\theta}) = (\mathbf{\Sigma}'_{xz}\boldsymbol{W}\mathbf{\Sigma}_{xz})^{-1}\mathbf{\Sigma}'_{xz}\boldsymbol{W}\, Var(\boldsymbol{z}\varepsilon)\, \boldsymbol{W}\mathbf{\Sigma}_{xz}(\mathbf{\Sigma}'_{xz}\boldsymbol{W}\mathbf{\Sigma}_{xz})^{-1} \tag{9}$$

Consistent estimate of $Avar(\hat{\theta})$:

If there is available consistent estimator $\widehat{Var}(\boldsymbol{z}\varepsilon)$, then $\widehat{Avar(\hat{\theta})}$ is consistently estimated by:

$$\widehat{Avar}(\hat{\theta}) = \left(\boldsymbol{S}'_{\boldsymbol{xz}}\widehat{\boldsymbol{W}}\boldsymbol{S}_{\boldsymbol{xz}}\right)^{-1}\boldsymbol{S}'_{\boldsymbol{xz}}\widehat{\boldsymbol{W}}\,\widehat{Var(\boldsymbol{z}\varepsilon)}\,\widehat{\boldsymbol{W}}\boldsymbol{S}_{\boldsymbol{xz}}\left(\boldsymbol{S}'_{\boldsymbol{xz}}\widehat{\boldsymbol{W}}\boldsymbol{S}_{\boldsymbol{xz}}\right)^{-1} \quad (10)$$

We can prove the asymptotic normality by multiplying both sides of the equation of the sampling error with $\sqrt{n}$ since $\hat{\theta}$ is asymptotically normal if $\sqrt{n}(\hat{\theta} - \theta_0)\ \overrightarrow{d}\ N\left(0, Avar(\hat{\theta})\right)$.

4.2.2.4.2 Efficiency and feasibility of the GMM estimator

There are alternative ways of finding the weighting matrix, as there is inefficiency involved in making the weighting matrix, which weights the moments. To be efficient, **W** must weigh the inverse proportion of the moments to their variances and covariances (Arellano & Bover, 1995). The weights are decided by the inverse of the variance of the population moments, which under the assumptions of the GMM estimator described above is the asymptotic variance of the sample moments (Roodman, 2009b).

The efficient estimator is the one that minimizes the sample moments $\boldsymbol{E_N}(\boldsymbol{z}\varepsilon) = \frac{1}{N}\boldsymbol{Z}'\widehat{\boldsymbol{E}}$ as derived above using the quadratic form. The efficient GMM moment weighting matrix:

$$\boldsymbol{W_{efficient}} = Var(\boldsymbol{z}\varepsilon)^{-1} = \left(\operatorname*{plim}_{N\to\infty} N\,Var\left(\frac{1}{N}\boldsymbol{Z}'\boldsymbol{E}\right)\right)^{-1} = Avar\left(\frac{1}{N}\boldsymbol{Z}'\boldsymbol{E}\right)^{-1}$$

which substituted into the GMM estimator formula becomes:

$$\hat{\theta} = (\boldsymbol{X}'\,\boldsymbol{Z}Var(\boldsymbol{z}\varepsilon)^{-1}\boldsymbol{Z}'\boldsymbol{X})^{-\mathbf{1}}\,\boldsymbol{X}'\,\boldsymbol{Z}Var(\boldsymbol{z}\varepsilon)^{-1}\boldsymbol{Z}'\mathbf{Y} \quad (11)$$

This is the efficient GMM estimator.

However, this estimator is not feasible unless we know $Var(\boldsymbol{z}\varepsilon)$. The approach to this problem is to find the expression that is built around the covariance matrix of the disturbance term $E(\boldsymbol{E}\boldsymbol{E}') = \boldsymbol{\Omega}$.

$$Var(\boldsymbol{z}u) = \operatorname*{plim}_{N\to\infty} NVar(\tfrac{1}{N}\boldsymbol{Z}'\boldsymbol{E}) = \operatorname*{plim}_{N\to\infty} NE\left(\tfrac{1}{N^2}\boldsymbol{Z}'\boldsymbol{E}\boldsymbol{E}'\boldsymbol{Z}\right) = \operatorname*{plim}_{N\to\infty}\tfrac{1}{N}\boldsymbol{E}(\boldsymbol{Z}'\boldsymbol{\Omega}\boldsymbol{Z})$$

Using that $\frac{1}{N}\left(\boldsymbol{Z}'\widehat{\boldsymbol{\Omega}}\boldsymbol{Z}\right)$ is a consistent estimator of $\operatorname*{plim}_{N\to\infty}\frac{1}{N}\boldsymbol{E}(\boldsymbol{Z}'\boldsymbol{\Omega}\boldsymbol{Z})$ from the assumptions above, the weighting matrix is: $(\boldsymbol{Z}'\widehat{\boldsymbol{\Omega}}\boldsymbol{Z})^{-\mathbf{1}}$.

To find the estimated $\widehat{\boldsymbol{\Omega}}$ which yields an efficient GMM estimator, there must be an initial estimation of the GMM estimator, which is called the one-step GMM estimation. To obtain the one-step GMM estimator, $\boldsymbol{W}$ is set equal to $(\boldsymbol{Z}'\mathbf{H}\boldsymbol{Z})^{-\mathbf{1}}$, using $\mathbf{H}$ as an estimated $\boldsymbol{\Omega}$ based on simple-error assumptions such as homoscedasticity. The residuals from the one-step estimation are used to construct $\widehat{\boldsymbol{\Omega}}$, which again is used to construct the weighting matrix in the two-step estimation.

$$\hat{\theta}_2 = (\boldsymbol{X}'\,\boldsymbol{Z}(\boldsymbol{Z}'\widehat{\boldsymbol{\Omega}}\boldsymbol{Z})^{-\mathbf{1}}\boldsymbol{Z}'\boldsymbol{X})^{-\mathbf{1}}\,\boldsymbol{X}'\,\boldsymbol{Z}(\boldsymbol{Z}'\widehat{\boldsymbol{\Omega}}\boldsymbol{Z})^{-\mathbf{1}}\boldsymbol{Z}'\mathbf{Y} \tag{12}$$

This estimate is robust to all heteroskedasticity patterns and is both a feasible and efficient estimation.

4.2.2.4.3 Standard errors

The asymptotic variance of the linear GMM estimator, if the assumptions above hold, is equation (9):

$$Avar(\hat{\theta}) = (\boldsymbol{\Sigma}'_{\boldsymbol{xz}}\boldsymbol{W}\boldsymbol{\Sigma}_{\boldsymbol{xz}})^{-1}\boldsymbol{\Sigma}'_{\boldsymbol{xz}}\boldsymbol{W}\,Var(\boldsymbol{z}\varepsilon)\,\boldsymbol{W}\boldsymbol{\Sigma}_{\boldsymbol{xz}}(\boldsymbol{\Sigma}'_{\boldsymbol{xz}}\boldsymbol{W}\boldsymbol{\Sigma}_{\boldsymbol{xz}})^{-1}$$

which shows the asymptotic variance dependence on the weighting matrix $\mathbf{W}$.

The standard errors from the standard formula for the variance of the GMM estimate can be downward-biased, which again can cause the two-step GMM estimation to not work (Arellano & Bond, 1991). The two-step estimation as explained above can actually overweight the observations that fit the model and give less weight to the observations that do not fit, since the weights are based on the moment's own variances and covariances. This means that the bias of the estimator is associated with the weighting matrix. Windmeijer (2005) devised a small-sample correction for these implausibly small standard errors that can occur using two-step estimation. He used Taylor expansion and replaced infeasible terms in the estimate with feasible approximations. This results in a feasible correction of the estimate of the variance of the two-step GMM estimator that contained the robust one-step estimate. The corrected errors seem better than the cluster-robust one-step estimation.

4.2.3 Implementation of the estimator

What remains is to decide between using the Arellano-Bond (Difference GMM) estimator and the Arellano-Bover (System GMM) estimator (Arellano & Bond, 1991; Arellano & Bover, 1995). We base our decision on the fact that the literature states that one should use system GMM if the estimate of the parameter for the lagged dependent variable with difference GMM is not within an upper and lower bound limit (Bond, 2002; Roodman, 2009b). These limits are found by estimating the parameters with pooled OLS and fixed effects estimation, respectively. This follows from the fact that the fixed-effects estimator and the difference GMM estimator have been proven to be downward-biased in finite samples (Bond, 2002).

However, we cannot estimate the parameter for the lagged dependent variable with the Difference GMM estimator before we have made a judgment about which specifications to include. More specifically, we need to make a judgment about whether to use one-step or two-step estimation, whether we need to correct for bias in the standard errors, and how many lags to include as instruments. Following what is mentioned in section 4.2.2.4.2 and 4.2.2.4.3, we decide to use two-step estimation and Windmeijer correction of the standard errors. In two-step estimation, the errors are already robust; however, we also use the Windmeijer correction of the standard errors in our estimation to correct for the bias associated with two-step estimation. Moreover, we need to decide on the number of instruments.

Roodman (2009a) wrote a note on the theme of too many instruments. He explains the problem of too many instruments, they can fail to remove the endogenous components of the endogenous variables. Since we have a finite sample, this problem is something we need to be aware of. Our sample may not include enough information for it to be possible to estimate the size of the matrix in a good way. There is not enough information on how many instruments are too many and at what level these negative effects are initiated. A rule of thumb is that the instrument count should not be higher than the number of groups in the panel data. The number of instruments can be reduced by imposing limits on the number of lags (Roodman , 2009b).

We base our decision on how many lags to include on the relevant Covid-19 statistics—more specifically, the fact that the incubation period averages approximately seven days. Thus, we assume that after seven days most people will have experienced symptoms and will therefore isolate themselves and no longer contribute to new cases. As a result, we believe that using the number of cases prior to seven days earlier might not be valid instruments. As the number of countries experiencing growth vary across the time periods, some periods still result in too many instruments with a lag limit of seven. For the periods with too many instruments, we change the model by clustering the variables for the level and difference equation, which results in fewer instruments but the same number of lags.

Moreover, our estimation of the number of cases only includes the number of countries which experience growth during each period. In the first period, many countries experience growth. In this period, we exclude the countries which only have a few registered cases. We do this by constructing a threshold, where the countries with a mean of smoothed registered cases in the first period below the median were excluded. Furthermore, we take period 7 and 17 out of our sample, as the number of countries with growth in these periods is too low (25 countries), while the estimators we have decided to use requires a large N.

Finally, we can decide on whether to use the Difference or the System GMM estimator. As the estimate of the parameter for the lagged dependent variable is below the lower bound in all samples but one, the system GMM is proven to be a better fit for our data. The output of these tests is presented in Table A2 in Appendix A.

Hence, we will use System GMM in our estimation, and the system of equations is as follows:

The level equation (1):

$$C_t = \beta_0 + \beta_1 C_{t-1} + \beta_2 \left(\frac{S_{it} * I_{i,t-j}}{N}\right) + \gamma_i + \delta_t + \varepsilon_{it}$$

The Transformed equation:

$$C_t - C_{t-1} = \beta_1 (C_{t-1} - C_{t-2}) + \beta_2 \left(\frac{S_{it} * I_{i,t-j}}{N} - \frac{S_{it-1} * I_{i,t-j-1}}{N}\right) + \delta t + (\varepsilon_{it} - \varepsilon_{it-1}) \quad (13)$$

We estimate the parameters using the command Xtabond2 in Stata. When performing the estimation, Xtabond2 performs two tests which should be noticed and which we elaborate on in the next section.

4.2.3.1 Validity testing

In the following sections, we will describe two tests which should be considered when using the Arellano-Bover estimator, namely, the Hansen test and the autocorrelation test. We will comment on the results of these tests in section 5.2.1.

4.2.3.1.1 Hansen Test

Since we have the assumption of the exogeneity of instruments and have an overidentified model, we need to test the validity of the instruments. The Hansen J statistics for identifying restrictions is an automatic output from using Xtabond2, which was developed by Lars Peter Hansen (1982). The null of the test is that $\frac{1}{N}\boldsymbol{Z'\widehat{E}}$ is randomly distributed around zero, which is a null we would like to not reject. The overidentification statistic as described in the Xtabond2 paper (Roodman, 2009b) is:

$$\left(\frac{1}{N}\boldsymbol{Z'\widehat{E}}\right)' \boldsymbol{var}(\boldsymbol{z}\varepsilon)^{-1}\frac{1}{N}\boldsymbol{Z'\widehat{E}} = \left(\frac{1}{N}\boldsymbol{Z'\widehat{E}}\right)' \boldsymbol{W_{efficient}}\frac{1}{N}\boldsymbol{Z'\widehat{E}} \tag{14}$$

If this holds, then the statistic is a chi-square distributed random variable with the degrees of freedom which is equal to the degree of overidentification, which refers to how many more moment conditions there are to parameters (Hansen, 1982). Chi-square distributions come from independent standard normal random variables, which is why this test is helpful for testing the exogeneity for the instruments as a whole (Wooldridge, 2012, p. 845).

4.2.3.1.2 Autocorrelation

Arellano-Bond developed a test for autocorrelation since autocorrelation in the idiosyncratic error term, v_{it}, would lead to lags that are invalid as instruments. We will outline the reasoning behind this test (Arellano & Bond, 1991). The test is used for the residual in differences. This is also true for system GMM since the basis of the test is in difference and will not make a difference. $E\left(v_{it}v_{i(t-1)}\right)$ does not need to be zero, because v_{it} are the first differences of serially uncorrelated errors and are expected since the model includes a lagged dependent term. However, the GMM estimation has an assumption that $E\left(v_{it}v_{i(t-2)}\right) = 0$. The average covariances are assumed to be independent random variables with zero mean, which is the null hypothesis of the test. The average covariances are denoted $\phi_i = v_{i(-2)}v_{i*}$. $\hat{v}_{-2}$ is the vector of residuals lagged two times, which has an order of $\sum_{i=1}^{N}(T_i - 4)$, and v_* is a vector of v matching v_{-2}. The first test is the one degree of freedom test, which is simply to check if $E(\phi_i) = 0$.

To test for second-order serial correlation, they created a test statistic that is based on the residuals from the first difference equation: $m_2 = \frac{\hat{v}_{-2}\hat{v}_*}{\hat{v}^{1/2}}$ with a normal distribution and mean of zero and variance equal to 1. When assuming the errors are uncorrelated across individuals, the central limit theorem will ensure that $\sum_{i=1}^{N} \hat{v}_{i(-2)}\hat{v}_{i*} = \frac{\hat{v}_{-2}\hat{v}_*}{\hat{v}^{1/2}}$, which is asymptotically normally distributed. m_2 is only defined if $T_i \geq 5$ stems from the order of the vector of the two times lagged residuals.

4.2.4 Developing the indices

The purpose of the estimation of the number of cases is to find estimates of the unobserved country-specific variable. We can find the estimates by looking at the composite error term:

$$\varepsilon_{it} = \gamma_i + v_{it} \tag{15}$$

where γ_i is the unobserved country-specific variable and v_{it} is the idiosyncratic error. Taking the average of the residuals, one removes the time varying part of this equation, $E(v_{it}) = 0$, thereby leaving γ_i. $\bar{\varepsilon}_i$ can be used as an estimate for the unobserved country-specific variable, if these are uncorrelated with the v_{it} term (Mukherji, 2020). We found this requirement satisfied, as subtracting the average $\bar{\varepsilon}_i$ from ε_{it} resulted in very small numbers, meaning small idiosyncratic errors. Table A3 presents the value of the idiosyncratic errors for each period found in Appendix A.

Following the estimation of the unobserved country-specific variable, we convert these estimates into an index ranging from 0–100 for each period by normalizing the estimates, resulting in 16 indices covering the first year of the pandemic. In the second step of our analysis, we will use these indices to find out whether the socioeconomic factors included in our study may be some of the time-constant omitted variables the unobserved country-specific variable accounts for.

4.3 Step 2 - Cross-sectional regression analyses

The next step in this study is to investigate whether the socioeconomic factors can explain the variation in the index values calculated in step 1. We decided to use

Ordinary Least Squares (OLS) regression to determine the significance of each socioeconomic factor. We perform two separate analyses using the indices as the dependent variable—one on the average of the indices and one where we use the index value for each period as the dependent variable. These analyses will investigate whether the socioeconomic factors included in our study may be some of the time-constant omitted variables accounted for in the unobserved country-specific variable we used to construct the indices.

The first cross-sectional analysis is on the average of the indices. We take the average of the index values across periods for each country. We use the average index value as the dependent variable and regress on the socioeconomic factors for each country. This gives us a sample size of 92 countries.

For the second cross-sectional analysis we perform 16 separate regressions for each period. We use the index value for each country as the dependent variable and regress on the socioeconomic factors. As the GMM estimation only included the countries that experienced a growth in cases during the period, the sample size varies between the periods, from a minimum of 39 to a maximum of 60 countries.

There are several opinions and rules of thumb considering what the minimum sample size of a regression should be, often in terms of the number of predictors. However, a paper from 2020 weighs many of these opinions and recommendations and concludes that a minimum of N > 25 is sufficient (Jenkins & Quintana-Ascencio, 2020). We thereby conclude that we have a large enough sample in all periods; however, we aim for constructing several models and reducing the number of predictors in each model.

4.3.1 Assumptions of the OLS model

There are a few assumptions needed to produce unbiased OLS estimates and to be able to state that this estimator is best linear unbiased (BLUE)—namely, the Gauss-Markov assumptions (Wooldridge, 2012, p. 105). The four assumptions needed to demonstrate the unbiasedness of OLS include that the model should be linear in parameters, the sample should be random, there is no perfect collinearity among the independent variables, and the conditional mean of the error on the independent variables is zero. A fifth assumption is needed to make sure OLS is the best linear unbiased estimator (BLUE), namely the homoskedasticity assumption. This assumption states that given any values of the independent variables, the error has the same variance. By choosing to use the robust estimator of variance in our regression specification, we could relax this last assumption.

4.3.1.1 Multicollinearity

The assumption about no perfect collinearity is connected to the issue of multicollinearity; however, the existence of multicollinearity does not violate this assumption (Wooldridge, 2012, p. 95). Multicollinearity implies that there exists high correlation, though not perfect correlation, between the independent variables. Even though this is an issue which is harder to determine whether it is severe or not, less correlation between the independent variables is better (Wooldridge, 2012, p. 96).

We investigate this issue by testing the Variance Inflation Factor (VIF). We conclude that including some of our socioeconomic factors cause a higher level of multicollinearity compared to others, which we need to keep in mind when constructing the models for the OLS regression. In some cases, a VIF value higher than 10 is chosen to be viewed as an issue; however, simply looking at such thresholds is not always convenient. Other factors, such as sample size, may play an important role in whether the standard deviation of the estimate becomes too high (Wooldridge, 2012, p. 98).

4.3.2 Log-transforming and mean-centering the variables

We log-transform the independent variables that are not estimates or in percentages to reduce skewness in the data (UCLA, n.d.). The interpretation of the coefficient will change when we log transform the variables (Wooldridge, 2012, p. 216). We are simply interested in looking at which socioeconomic factors are positively or negatively correlated with the index values; thus, the new interpretation of the coefficients is not something we need to consider.

Moreover, we suscept that inequality will have a different effect on the index value when combined with both population density and migrant stock. Thus, we add two separate interaction terms in our economic model: an interaction between inequality and population density as well as an interaction between inequality and migrant stock (Wooldridge, 2012, p. 198–199). Including such interaction terms can create a higher level of multicollinearity, as the variables that are included in the interaction term will be highly correlated with the product of the two variables. However, a solution to this may be centering the variables (Afshartous

& Preston, 2011). More specifically, we subtract the mean from each of the variables that are included as interaction terms. By looking at the VIF-values, we see that this reduces the multicollinearity to a level which is of no concern.

4.3.3 The regression models

We choose to construct two baseline models—an economic model and a health model—where none of the variables of concern due to multicollinearity was included. We then simply add the variables of concern one by one. The variables added are different for the economic model and the health model, and this procedure results in a total of 11 models. We conclude that by constructing separate models, there is no need to drop any of the variables we want to investigate. We can simply check whether our results are robust to including these variables. When constructing such separate models, adding a variable never results in a VIF value higher than 10. Which of the variables we include in each model is shown in the following regression equations:

The Economic Base Model, Model 1:

$$I_i = \beta_0 + \beta_1 Economicstrength_i + \beta_2 PopulationDensity_i + \beta_3 MigrantStock_i + \beta_4 TotalPopulation_i + \beta_5 UrbanPopulation_i + \beta_6 GiniIndex_i + \varepsilon_i$$

Model 2:$I_i = EconomicBaseModel_i + \beta_7 GiniIndex_i \cdot PopulationDensity_i$

Model 3: $I_i = EconomicBaseModel_i + \beta_7 Governance_i$

Model 4: $I_i = EconomicBaseModel_i + \beta_7 Tourism_i$

Model 5: $I_i = EconomicBaseModel_i + \beta_7 Poverty_i$

Model 6:$I_i = EconomicBaseModel_i + \beta_7 GiniIndex_i \cdot MigrantStock_i$

Model 7: $I_i = EconomicBaseModel_i + \beta_7 StingencyIndex_i$

The Health Base Model, Model 8:

$$I_i = \beta_0 + \beta_1 LifeExpectancy_i + \beta_2 PopulationDensity_i + \beta_3 MigrantStock_i + \beta_4 TotalPopulation_i + \beta_5 UrbanPopulation_i + \beta_6 PopulationOver65 + \varepsilon_i$$

Model 9: $I_i = HealthBaseModel_i + \beta_7 PhysiciansPer1000_i$

Model 10: $I_i = HealthBaseModel_i + \beta_7 MedicalExpenditure_i$

Model 11: $I_i = HealthBaseModel_i + \beta_7 StingencyIndex_i$

5 Results

5.1 Cross-sectional analysis on the total amount of cases and deaths

A simple way to investigate whether the socioeconomic factors of countries might explain the varying number of cases across countries would be to regress on the number of total cases in each country. This method can also be used to investigate the number of total deaths. We performed two OLS regressions on the total amount of registered cases and total amount of deaths as dependent variables in the models we described in the previous chapter, except for the models that include last periods stringency of containment measures since they vary over time. The regressions on total number of cases and Covid-19 related deaths are shown in Table 3.

Table 3

Regressions on Total Number of Cases and Covid-19 related Deaths

	Total Number of Cases					Number of Covid-19 related deaths				
Model	1	3	4	5	7	1	3	4	5	7
ln Economic strength	.53654***	1.01244***	.229147	.276893		.596725***	1.34536***	.230847	.369174*	
	(.177273)	(.20649)	(.18611)	(.20115)		(.19924)	(.25834)	(.19629)	(.22071)	
ln Life Expectancy					2.96591					1.43640
					2.5975					(3.2621)
ln Population density	.192241	.19371	.173429	.18493	.142286	.284401	.285531	.26460	.279107	.23217
	(.135837)	(.12865)	(.12161)	(.12890)	.14003	(.18297)	(.17829)	(.16344)	(.17885)	(.17731)
ln Migrant Stock	.220125	.290425*	.20607	.375983**	.211954	.117078	.222684	.112518	.259619	.057432
	(.1763185)	(.17269)	(.18253)	(.18597)	.15620	(.22287)	(.21316)	(.22586)	(.23386)	(.18655)
ln Total Population	.727935***	.673565***	.515106**	.629618***	.742864***	.949169***	.864474***	.690945***	.861462***	1.00513***
	(.1947852)	(.18568)	(.20036)	(.20449)	.17558	(.23486)	(.21824)	(.23136)	(.24748)	(.2084)
%Urban Population	2.145***	2.12726***	2.01657***	1.41849*	2.10732***	2.26016***	2.22258***	2.12872***	1.62873*	2.2506***
	(.7158659)	(.67781)	(.69215)	(.72144)	.66848	(.84556)	(.76863)	(.80052)	(.92033)	(.8485)
ln Medical Expenditure										
ln Physicians per 1000										
%Population over 65					1.79737***					2.65253***
					.57717					(.69887)
ln Tourism			.417254***					.501554***		
			(.14624)					(.17423)		
Governance		-3.98988***					-6.28948***			
		(1.4563)					(1.7841)			
Gini index	.8832	.698899	1.00813	1.79096**		1.21338	.887268	1.4478	2.04865**	
	(.6881024)	(.65369)	(.65857)	(.71246)		(.88503)	(.80794)	(.87410)	(.90695)	
Poverty				-2.72449**					-2.40325**	
				(1.0859)					(1.1924)	
ln Migrant Stock · Gini										
ln Population Density · Gini										
Observations	92	92	92	92	92	91	91	91	91	91
R^2	0.6799	0.7027	0.7126	0.712	0.6991	0.6278	0.674	0.6653	0.6481	0.6553

Note: Robust standard errors in parentheses. Used variance inflation factor (VIF) for diagnosing collinearity in the models. No VIF values regarded as problematic. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

The full regressions can be seen in Appendix B, Table B1 and B2. The connection between the results related to total number of cases and deaths is clear. This implies that where there are more cases of Covid-19, there are also more deaths caused by the infection. Because of this, the results of the regressions are similar; and economic strength, percentage of urban population, and level of international tourism are positively correlated with both number of cases and deaths. The same is true for population over 65, which is surprising for the characteristics of the deaths related to Covid-19, considering that older people are at greater risk of a serious infection and death (Himmels et al., 2021). We consider this to be a consequence of cross-country comparison, where the characteristics of the countries attracting Covid-19 are also characteristics which lead to an older population. The same train of thought might explain the negative correlation of poverty.

However, a weakness in this analysis is that it does not consider the autoregressive path of cases nor the epidemiological factors of spread. This downside in the simple cross-country analysis provides the rationale for the two-step approach we explained in the Methodology chapter, which incorporates both the autoregressive path of cases and the epidemiological factors. In the next sections, we will present the results from the first-step panel data analysis, followed by the second-step cross-sectional analyses.

5.2 Panel data results

The full results of the 16 GMM system estimations are shown in Appendix C. In every period, two days were omitted from the analysis due to collinearity.

Table 4

GMM Dynamic Panel-Data Estimation, Two-Step System GMM

	Variables	Number of observations	Coefficient	Robust Std.Error	t-value	p-value	[95%Conf Interval]	
Period 1	$lnSmooth\ Cases_{t-1}$	969	0.8932042***	0.0457596	19.52	0.000	0.8012934	0.985115
	$\frac{S \cdot I_{t-7}}{N}$		-0.0238392	0.019353	-1.23	0.224	-0.0627108	0.0150323
Period 2	$lnSmooth\ Cases_{t-1}$	798	0.9627284***	0.0304146	31.65	0.000	0.9013048	1.024152
	$\frac{S \cdot I_{t-7}}{N}$		0.0019498	0.0193672	0.10	0.920	-0.037163	0.0410625
Period 3	$lnSmooth\ Cases_{t-1}$	760	0.9095594***	0.1152317	7.89	0.000	0.6764812	1.142638
	$\frac{S \cdot I_{t-7}}{N}$		-0.1014088**	0.0431757	-2.35	0.024	-0.1887398	-0.0140777
Period 4	$lnSmooth\ Cases_{t-1}$	760	0.9384911***	0.0439686	21.34	0.000	.8495562	1.027426
	$\frac{S \cdot I_{t-7}}{N}$		.0029869	.036267	0.08	0.935	-.07037	.0763438
Period 5	$lnSmooth\ Cases_{t-1}$	1026	0.9497536***	0.0696236	13.64	0.000	0.8101063	1.089401
	$\frac{S \cdot I_{t-7}}{N}$		-.0061311	0.0278588	-0.22	0.827	-0.0620087	0.0497465
Period 6	$lnSmooth\ Cases_{t-1}$	988	1.01384***	0.0429466	23.61	0.000	0.9276209	1.100059
	$\frac{S \cdot I_{t-7}}{N}$		-0.0671492***	0.0215164	-3.12	0.003	-0.1103451	-0.0239533
Period 8	$lnSmooth\ Cases_{t-1}$	912	0.9654136***	0.0504846	19.12	0.000	0.8638516	1.066976
	$\frac{S \cdot I_{t-7}}{N}$		-0.0430903*	0.0250197	-1.72	0.092	-0.0934235	0.0072429
Period 9	$lnSmooth\ Cases_{t-1}$	874	0.8833237***	0.0822324	10.74	0.000	0.7176991	1.048948
	$\frac{S \cdot I_{t-7}}{N}$		-0.0417754	0.0498447	-0.84	0.406	-0.1421677	0.0586169
Period 10	$lnSmooth\ Cases_{t-1}$	1007	1.015545***	0.0571499	17.77	0.000	0.9008656	1.130225
	$\frac{S \cdot I_{t-7}}{N}$		-0.0361971	0.0284019	-1.27	0.208	-0.0931897	0.0207955
Period 11	$lnSmooth\ Cases_{t-1}$	1140	0.9919995***	0.0402936	24.62	0.000	0.9113722	1.072627
	$\frac{S \cdot I_{t-7}}{N}$		-0.041476	0.0278205	-1.49	0.141	-0.0971447	0.0141926
Period 12	$lnSmooth\ Cases_{t-1}$	1045	0.9871144***	0.0715235	13.8	0.000	0.8437184	1.13051
	$\frac{S \cdot I_{t-7}}{N}$		-0.0334594	0.0443421	-0.75	0.454	-0.12236	0.0554412
Period 13	$lnSmooth\ Cases_{t-1}$	969	1.053443***	0.0292451	36.02	0.000	0.9947021	1.112183
	$\frac{S \cdot I_{t-7}}{N}$		-0.0444098*	0.025228	-1.76	0.084	-0.0950817	0.0062621
Period 14	$lnSmooth\ Cases_{t-1}$	950	0.8902508***	0.0272929	32.62	0.000	0.8354036	0.945098
	$\frac{S \cdot I_{t-7}}{N}$		0.0505348**	0.0245372	2.06	0.045	0.0012254	0.0998441
Period 15	$lnSmooth\ Cases_{t-1}$	836	0.9899477***	0.0301045	32.88	0.000	0.9292362	1.050659
	$\frac{S \cdot I_{t-7}}{N}$		-0.0060647	0.0254645	-0.24	0.813	-0.0574187	0.0452893
Period 16	$lnSmooth\ Cases_{t-1}$	760	0.9826608***	0.0360479	27.26	0.000	0.9097471	1.055575
	$\frac{S \cdot I_{t-7}}{N}$		0.030531	0.0297282	1.03	0.311	-0.0295999	0.090662
Period 18	$lnSmooth\ Cases_{t-1}$	798	1.16224***	0.3307167	3.51	0.001	0.4943439	1.830136
	$\frac{S \cdot I_{t-7}}{N}$		-0.2860568	0.4349078	-0.66	0.514	-1.164371	0.5922573

Note: Windmeijer corrected standard errors.

Table 4 shows that the lagged value is always significant at the 1% level. However, the SIR-variable only has significant explanatory value in a few periods, namely in periods 3, 6, 13 and 14.

5.2.1 Validity test results

The GMM estimations autocorrelation tests do not show any sign of second-order correlation and the null hypothesis is not rejected for any period, as can be seen in Table 5. Hence, there was no need to include a second lag of the lagged dependent variable in our model equation.

Moreover, the Hansen J statistic has satisfying values in most periods. The null hypothesis is not rejected in most periods except periods 11, 12 and 18, as reported in Table 5. The Xtabond2 paper states that one should worry if the p-value is too high—specifically, a value higher than 0.25 (Roodman, 2009b). For most periods, we are able to reject the null and not have values that are too high. However, this test should not be trusted completely since the point of the estimation is to get $\frac{1}{N}\boldsymbol{Z}'\widehat{\boldsymbol{E}}$ as close as possible to zero and then test this with the Hansen J statistic. However, the more moment conditions included, the weaker the test becomes. This is a problem related to the number of instruments, where too many instruments give p-values that are too high, which is related to the weakness of the test.

We would like to check whether the "not satisfying" test results in periods 11, 12, 15 and 18 will influence the index values in these periods. We did this by increasing the number of lags, which give better test results, and we were able to reject the null for the robustness checks. By comparing the index values prior to and after this adjustment on the number of lags, we can see that index values are very similar. Thus, we keep the baseline model with a limit on seven lags to avoid p-hacking.

Table 5

Validity Test Results

		Hansen J tatistic	Prob > χ^2	Arellano-Bond test for AR(2) in first differences z	Prob > z
Period	1	32.69	0.171	0.20	0.844
Period	2	17.72	0.220	1.63	0.103
Period	3	17.45	0.233	-0.96	0.335
Period	4	22.68	0.066	0.93	0.352
Period	5	21.17	0.097	-0.68	0.494
Period	6	31.43	0.213	-0.32	0.748
Period	8	36.97	0.075	0.68	0.499
Period	9	21.50	0.089	0.21	0.837
Period	10	29.97	0.269	0.69	0.492
Period	11	48.13	0.005	0.35	0.724
Period	12	40.90	0.032	-1.31	0.191
Period	13	27.26	0.396	0.07	0.940
Period	14	32.34	0.182	1.34	0.181
Period	15	10.03	0.760	-0.17	0.867
Period	16	16.09	0.308	1.46	0.144
Period	18	25.24	0.032	0.40	0.689

Note: Full regressions where these tests are represented is found in appendix C.
$^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

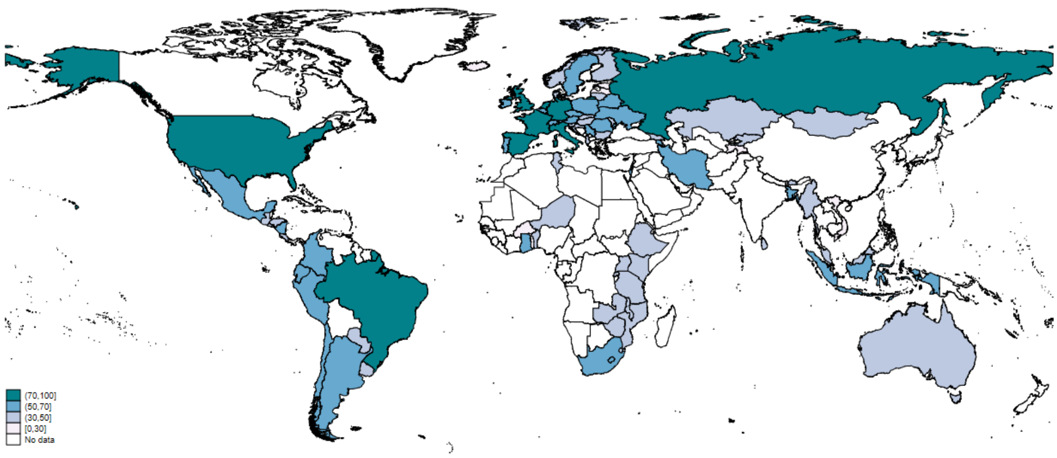
5.2.2 System GMM estimation results

Following the GMM estimation, we find the estimates of the unobserved country-specific variables by the procedure described in section 4.2.4. We convert these to an index ranging from 0–100 by normalizing the values. A country with a higher index value indicates that this country is susceptible to a higher number of cases during this period, based on other factors than what is explained by our model, namely the autoregressive path and the epidemiological factors.

A table of the indices for the countries are found in Appendix C in Tables C17 to C20. The table shows that the countries that generally have a high index are the countries that are known to have a high number of cases. This is also shown in the map in Figure 1. The values used to create the map are the countries' average index values. From the map, we can see that the countries with high index values on average are the same countries that are known to be Covid-19 hot spots—for instance, the United States, the United Kingdom, and Brazil. Similarly, one can see that the countries on the map with low index values on average also are the countries known to have fewer Covid-19 cases, such as Australia, Norway, and most of the African countries included in our study.

Figure 1

Map of the Average Index Score



Note: Results of our GMM estimation, the values are the countries average score on the index. Made in Stata using shapefiles obtained from World Bank (World Bank, 2020)

5.3 Cross-sectional analyses results

5.3.1 Cross-sectional analysis on the averages

The first cross-sectional analysis we perform is on the average of the indices. The countries with high and low average index values are shown in Figure 1. The R^2 of this analysis is lower compared to the simple analysis we performed on the total number of cases and deaths, as can be seen in the comparison in Table 6.

Table 6

R^2 of Index Average, Total Cases, and Total Deaths

	Average of index	Total Cases	Total Deaths
Model 1	0.5574	0.6799	0.6278
Model 2	0.5921	0.6794	0.6371
Model 3	0.6173	0.7027	0.674
Model 4	0.5576	0.7126	0.6653
Model 5	0.575	0.712	0.6481
Model 6	0.6245	0.6618	0.624
Model 7	0.5561	0.6991	0.6553
Model 8	0.5599	0.7466	0.6857
Model 9	0.5594	0.7039	0.6659

Note: These results can also be seen in the full regression tables in Appendix B, Tables B1, B2 and Appendix D Table D1.

The analysis on the average of the indices gave no robust significant results for the models of health variables, which can be seen in Table D1 in Appendix D. The regressions on the economic models show that there are no results which hold for all the models, as presented in Table 7. However, economic strength and migrant stock are positively correlated with the average of the indices in three of the models. The variable for inequality, poverty, governance, and the interaction terms are negatively correlated when included.

Table 7

Regressions on the Average of the Indices

Model	1	2	3	4	5	6
ln Economic strength	2.81109	3.10723*	7.88521***	2.6611	1.54461	2.91009*
	(1.7573)	(1.7125)	(1.8062)	(1.7775)	1.5371	(1.5335)
ln Population density	1.2512	3.4697***	1.26689	1.24203	1.2156	1.37363
	(1.0446)	(1.1248)	(1.0128)	(1.0346)	(1.0214)	(1.1126)
ln Migrant Stock	1.78562	2.18419	2.53519*	1.77877	2.54583*	3.6869**
	(1.4941)	(1.4676)	(1.4155)	(1.5183)	(1.5187)	(1.6987)
ln Total Population	4.32783	4.0102**	3.7481**	4.2240**	3.84828**	4.7388***
	(1.6584)	(1.6287)	(1.5657)	(1.6097)	(1.6859)	(1.5309)
%Urban Population	10.3476	6.85545	10.1589	10.285	6.80420	12.3933*
	(7.7933)	(7.9293)	(7.2988)	(7.8722)	(8.2799)	(6.3949)
ln Tourism				.203546		
				(1.1885)		
Governance			-42.5417***			
			(10.981)			
Gini index	5.13651	-4.52715**	3.17141	5.19745	9.56415	-5.63513***
	(6.9487)	(1.9045)	(6.3999)	(7.0410)	(7.4738)	(1.8120)
Poverty					-13.2889**	
					(6.0167)	
ln Migrant Stock · Gini						-5.75101***
						(1.92457)
ln Population Density · Gini		-6.72429***				
		(2.3657)				
Observations	92	90	92	92	92	90
R^2	0.5574	0.5921	0.6173	0.5576	0.575	0.6245

Note: Robust standard errors in parentheses. Used variance inflation factor (VIF) for diagnosing collinearity in the models. No VIF values regarded as problematic. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Regarding the effectiveness of governance, the countries which have an effective governance are not the countries susceptible to a higher number of cases. The poverty headcount is also negatively significant, which implies that the countries that struggle with a high number of people living below the poverty line are not the ones most vulnerable to a higher number of cases. Both interaction terms—between population density and inequality and between migrant stock and inequality—are negatively significant.

However, none of the baseline model variables are robust in their significance, and we believe this is due to what we have mentioned in the introduction—that different countries struggle with the virus at different stages of the pandemic. This analysis does not allow for the opportunity to distinguish which of the socioeconomic factors may explain the number of cases during different time periods during the year. This provides the rationale for our second cross-sectional analysis, where we perform 16 separate regressions on the index for each period.

5.3.2 Cross-sectional analysis on the index value for each period

The results from the second cross-sectional analysis which contain the results we are interested in are fully reported in Appendix D. Common for almost all periods is that R^2 are quite high; an exception is period 15.

Table 8

R^2 for all Models for all Periods

	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 8	Period 9	Period 10	Period 11	Period 12	Period 13	Period 14	Period 15	Period 16	Period 18
Model 1	0.7423	0.5792	0.783	0.5363	0.5353	0.6064	0.6017	0.5644	0.6253	0.6828	0.7332	0.5837	0.8094	0.3393	0.7465	0.5165
Model 2	0.7451	0.5759	0.7993	0.6223	0.5175	0.5813	0.6274	0.5927	0.6366	0.7153	0.7319	0.5879	0.8248	0.4263	0.7442	0.5701
Model 3	0.7508	0.6054	0.7966	0.6279	0.5984	0.6701	0.6542	0.6489	0.6288	0.6877	0.749	0.6167	0.8094	0.3431	0.7477	0.5921
Model 4	0.7448	0.6038	0.7995	0.5638	0.5513	0.6067	0.6043	0.5697	0.6397	0.7449	0.7704	0.6548	0.8094	0.3418	0.7623	0.5797
Model 5	0.7429	0.5857	0.7899	0.6018	0.5804	0.7419	0.6512	0.5976	0.6254	0.7456	0.7729	0.6518	0.8272	0.3393	0.7542	0.5749
Model 6	0.7536	0.5335	0.7975	0.5811	0.5275	0.5966	0.605	0.5918	0.6457	0.6986	0.7328	0.6114	0.8254	0.3315	0.7689	0.5504
Model 7	Not available	0.5761	0.7662	0.6477	0.6256	0.6578	0.6792	0.5682	0.6314	0.7033	0.7306	0.595	0.8039	0.3812	0.7304	0.5589
Model 8	0.7719	0.5861	0.7518	0.5635	0.4829	0.6051	0.6535	0.5823	0.5993	0.7405	0.8183	0.6714	0.8099	0.2453	0.8064	0.5626
Model 9	0.7793	0.5879	0.7649	0.6175	0.5685	0.6392	0.6687	0.6019	0.6353	0.7675	0.855	0.7098	0.8386	0.2727	0.8116	0.5954
Model 10	0.8076	0.6004	0.7574	0.5788	0.4852	0.6124	0.7175	0.6071	0.6046	0.7423	0.8184	0.6831	0.8347	0.3144	0.8064	0.5627
Model 11	Not available	0.5797	0.7279	0.6455	0.5785	0.6345	0.6983	0.593	0.599	0.7636	0.8411	0.6943	0.8044	0.2995	0.7728	0.6374

Note: The regressions resulting in the numbers represented in the table are found in Appendix D.

5.3.2.1 Early-stage

Table 9 for the first period, 11 March to 30 March, shows that the economic strength variable, the population density, the migrant stock, and life expectancy are all positively significant. Furthermore, the medical expenditure variable is positively significant. These results are shown in Models 1 and 10 shown below.

In the second and third period, from 31 March to 9 May also presented in Table 9, the percentage of people living in urban areas becomes positively significant. These results are quite robust in the second period and robust in the third. In the second period, the economic strength variable is not significant, while it becomes robust positively significant in period 3. Moreover, the life expectancy variable is robust positively significant in period 2, from 31 March to 19 April; however, this is not the result in the third period. The variable for effective governance is negatively significant in period 2, and physicians per 1000 becomes positively significant in period 3. These results can be seen in Models 1 and 10 for the first period, Models 1 and 8 for the second period, and Models 1 and 9 for the third period.

Table 9

Early-Stage Regressions

	Period 1		Period 2		Period 3	
Model	1	10	1	8	1	9
ln Economic strength	13.9388***		1.88996		10.0272***	
	(3.55571)		(-3.4427)		(2.9359)	
ln Life Expectancy		142.686**		95.8495***		35.8389
		(61.81649)		(34.962)		(39.339)
ln Population density	4.74876**	3.85214**	4.95010	4.16367	1.56406	1.61244
	(1.775506)	(1.568739)	(-3.5118)	(3.2939)	(2.178)	(2.4268)
ln Migrant Stock	4.42379**	4.27004**	3.5395	6.03911***	3.096	3.9637
	(2.061256)	(1.759005)	(2.5105)	(2.0636)	(2.9228)	(2.521)
ln Total Population	7.96749***	7.98899***	6.29841**	4.24001*	4.36459	3.5847
	(1.968313)	(1.640331)	(2.6564)	(2.1052)	(2.9521)	(2.7881)
%Urban Population	.540495	-17.4551	42.3880**	26.4974	36.1726***	45.0476***
	(13.39503)	(13.62944)	(19.997)	(17.791)	(12.463)	(14.028)
ln Medical Expenditure		14.3048**				
		(5.403512)				
ln Physicians per 1000						4.27699*
						(2.5089)
%Population over 65		-10.1557		-9.92597		-3.0313
		(10.43237)		(10.595)		(12.246)
Gini index	.896067		-23.215*		-7.11573	
	(11.10798)		(12.742)		(11.092)	
Observations	51	51	42	42	40	40
R^2	0.7423	0.8076	0.5792	0.5861	0.783	0.7649

Note: Robust standard errors in parentheses. Used variance inflation factor (VIF) for diagnosing collinearity in the models. No VIF values regarded as problematic.

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

The full Table D2 in Appendix D shows that the results from the first period are robust throughout the models, except for population density, which is not significant in one of the health models—Model 9.

Countries with high GDP per capita are the countries that are susceptible to a higher number of cases during the first period, which fits well with our hypothesis about this variable. Similarly, countries with high population density, life expectancy, and migrant stock struggle with a higher number of cases during the first period, which also matches our hypotheses on these variables. This result also corresponds to what is found in the related literature.

The full Tables D3 and D4 in Appendix D shows the robustness of Urban population. This may be explained by the global lockdown that occurred in mid-March and the fact that it is more difficult to contain the virus in urban areas, with more people living within a limited space and public transportation more widely used. All countries implemented somewhat strict measures during the first months of the pandemic (Hale et al., 2021). However, the results can tell us that countries with more effective governance during the second period could implement measures containing the spread more efficiently.

In the analysis for the fourth period, 10 May to 29 May, none of the variables in the baseline models are significant and robust. However, as seen in Table 10, the effectiveness of the government, the poverty headcount, and the interaction term between inequality and population density is negatively significant. In addition, the number of physicians per 1000 is positively significant. The stringency variable representing the strictness of containment measures are negatively significant in this period for both models where they are included, where they also impact the significance of the migrant stock and population density. These results can be seen in Models 2, 3, 5, 7, 9 and 11.

Table 10

Results for Regressions in the Fourth Period

Model	2	3	5	7	9	11
ln Economic strength	1.68713	14.5542**	-.828145	8.24857		
	(6.1699)	(6.1341)	(6.3215)	(5.7961)		
ln Life Expectancy					39.5248	70.8414
					(50.107)	(54.2002)
$lnStringency_{t-1}$				-23.4988**		-18.3329*
				(9.800935)		(10.271)
ln Population density	-5.10525**	-2.50324	-1.64802	-3.93928	-1.8162	-4.84176**
	(2.1545)	(2.1079)	(2.260)	(2.6181)	(1.9967)	(2.264)
ln Migrant Stock	-4.71623*	-1.1942	.016740	-4.08237*	-2.42167	-1.96332
	(2.3142)	(2.1184)	(2.4881)	(2.1978)	(2.4217)	(2.304)
ln Total Population	13.7068***	11.4028***	10.706***	15.596***	13.0682***	14.43855***
	(2.2610)	(2.2855)	(2.9927)	(2.9296)	(2.1925)	(2.519)
%Urban Population	25.7259	9.99893	3.69926	4.469	7.88933	15.1831
	(24.642)	(22.936)	(25.459)	(22.457)	(13.136)	(12.789)
ln Physicians per 1000					8.43259**	
					(3.3666)	
%Population over 65					-26.626	-.465207
					(18.742)	(18.961)
Governance		-77.2111***				
		(23.864)				
Gini index	-7.08963	-4.05263	19.1287	.923732		
	(5.5557)	(17.785)	(19.532)	(19.146)		
Poverty			-45.7146***			
			(16.605)			
ln Population Density · Gini	-28.4141***					
	(6.5942)					
Observations	39	40	40	37	40	37
R^2	0.637	0.6279	0.6018	0.6477	0.6175	0.6455

Note: Robust standard errors in parentheses. Used variance inflation factor (VIF) for diagnosing collinearity in the models. No VIF values regarded as problematic.

*$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

The countries with stronger measures in the previous period, as well as the countries with more effective governance, are those less susceptible to a higher number of cases during period 4. Our interpretation of this is that stronger containment measures contribute to limiting the increase in the number of cases. Furthermore, countries with more effective governance could implement these measures more efficiently, resulting in less vulnerability to a higher number of cases. The result of the full regression can be seen in Table D5 in Appendix D.

5.3.2.2 Early summer

For the fifth and sixth periods, 30 May to 8 July, inequality becomes positively significant as seen in Table 11. The results are quite robust in the fifth period and less robust in the sixth. Moreover, the governance effectiveness and poverty headcount variables are negatively significant in both periods. In addition, the physicians per 1000 variable is positively significant in both periods. The stringency variable is robust positively significant in the fifth period, but only positively significant in the economic model in the sixth period. Population over 65 is negatively significant in the sixth period, except in the model where the stringency variable is included. These results can be seen in Models 3, 5, 7, 9 and 11 for the fifth period, and in Models 3, 5, 7, 9 and 11 for the sixth. The results of the regressions are fully represented in Appendix D, Tables D6 and D7.

Table 11

Early Summer Regressions

	Period 5					Period 6				
Model	3	5	7	9	11	3	5	7	9	11
ln Economic strength	6.98749	-2.35769	1.50692			8.08049**	-6.82637*	1.86735		
	(4.7714)	(4.706)	(3.7530)			(3.9919)	(3.469)	(3.5354)		
ln Life Expectancy				-77.1261*	-29.8314				-1.43808	16.4589
				(39.271)	(43.564)				(55.316)	(53.81)
$lnStringency_{t\text{-}1}$			27.4118***		30.6052***			19.9385*		20.3035
			(8.9975)		(9.2215)			(11.039)		(12.564)
ln Population density	-.193542	-.328922	-1.3483	.318690	-1.86239	3.6243*	3.82923**	1.48258	2.70183	.95302
	(2.3611)	(2.4282)	(2.5939)	(2.2915)	(2.6514)	(2.0215)	(1.6856)	(2.3475)	(1.8119)	(2.1629)
ln Migrant Stock	2.67276	3.31401	2.25096	-.471402	1.36338	3.91979*	7.0648***	1.92021	1.45086	1.84647
	(2.4961)	(2.9149)	(2.5310)	(2.3702)	(2.1905)	(2.1404)	(2.2377)	(1.9222)	(2.0241)	(1.9819)
ln Total Population	6.28449**	5.45614	7.20435**	9.10364***	8.51734***	7.47796***	5.56025***	9.08446***	10.5622***	9.42017***
	(2.6979)	(3.2801)	(2.9177)	(2.6571)	(2.5794)	(1.7308)	(1.9987)	(1.9528)	(1.7973)	(2.1749)
%Urban Population	19.9497	4.59258	12.2023	19.680	24.9859**	19.9008*	-.728399	14.3939	16.6749	20.4916
	(14.316)	(16.143)	(14.4971)	(13.696)	(12.157)	(11.319)	(12.821)	(11.909)	(11.253)	(12.365)
ln Physicians per 1000				10.4529***					7.16462*	
				(3.3759)					(3.594)	
%Population over 65				-24.1084***	2.63079				-35.8977***	-10.8052
				(7.2011)	(9.671)				(10.318)	(16.193)
Governance	-61.2854**					-72.759***				
	(23.138)					(22.65)				
Gini index	23.961**	41.8852***	26.0686***			27.0119*	55.10449***	22.5902		
	(9.2305)	(8.5419)	(9.1672)			(14.754)	(11.266)	(14.629)		
Poverty		-36.4609***					-63.4965***			
		(13.032)					(14.218)			
Observations	54	54	51	54	51	52	52	50	52	50
R^2	0.5984	0.5804	0.6256	0.5685	0.5785	0.6701	0.7419	0.6578	0.6392	0.6345

Note: Robust standard errors in parentheses. Used variance inflation factor (VIF) for diagnosing collinearity in the models. No VIF values regarded as problematic. **p* < 0.1, ***p* < 0.05, ****p* < 0.01

Countries with more inequality are susceptible, in the fifth and sixth periods, to an increase in the number of cases than previously, representing a shift in the countries experiencing growth. This fits well with our hypothesis that countries with more inequality will become susceptible to a higher number of cases in the later periods. This socioeconomic factor may imply that more people are living in unfavorable conditions, whose daily life exposes them to more contact with others. However, looking at the headcount of people living under the poverty line, the countries with a high number of people living in poverty are not the countries that are susceptible to a higher number of cases during these periods. This may be connected to what we mentioned about the Gini variable in Chapter 3, namely that more inequality does not necessarily imply that more people are living in poverty.

Moreover, the countries with more physicians per 1000 people seem to be more vulnerable to a higher number of cases during the third period through the sixth. This may be explained by a country’s ability to set up the infrastructure for mass-testing. Testing more people, including the individuals without severe symptoms or even the asymptomatic individuals, will lead to a higher number of registered cases compared to countries without these resources available.

5.3.2.3 Late summer to early autumn

In the eighth period through the tenth, 29 July to 26 September, the percentage of the population living in urban areas becomes positively significant. The government effectiveness is negatively significant in all periods except in the tenth period, 7 September to 26 September. The poverty headcount is negatively significant, and the population density is positively significant in period 8, 29 July to 17 August, while this is not significant in the latter periods. Medical expenditure is negatively significant, and the stringency variable is positively significant in both the economic and health model in the eighth and ninth periods, while these results cannot be seen in the tenth. In period 10, physicians per 1000 becomes positively significant. These results can be seen in Models 3, 5, 7, 10 and 11 for period 8, in Models 3, 7, 10 and 11 for period 9, and in Models 1 and 9 for period 10, which are represented in Table 12. The significance of the stringency of political measures for the health models are left out of this table due to lack of space; these results can be viewed in full in Appendix D in Tables D8, D9, and D10 for the tenth period.

Table 12

Regressions for Late Summer to Early Autumn

	Period 8				Period 9			Period 10	
Model	3	5	7	10	3	7	10	1	9
ln Economic strength	7.88222*	-2.41294	-.148788		11.1008**	1.09155		-1.54219	
	(4.2359)	(2.3003)	(2.697)		(4.4922)	(3.5352)		(3.2501)	
ln Life Expectancy				283.522***			175.793**		-42.8398
				(63.926)			(82.417)		(67.661)
$lnStringency_{t-1}$			15.5097*			17.1472**			
			(8.6363)			(8.2197)			
ln Population density	3.48094**	3.49167**	2.09374	2.25051	.330957	-.032789	-1.42479	1.6372	2.16325
	(1.5879)	(1.6945)	(1.4652)	(1.6979)	(2.2323)	(2.6588)	(2.285)	(2.5041)	(2.615)
ln Migrant Stock	2.51213	3.6248	.896585	5.01731*	.141207	.323856	2.68022	-0.639912	-1.40729
	(3.2152)	(3.0459)	(3.4252)	(2.7606)	(2.2756)	(2.4435)	(3.1827)	(2.4753)	(2.6471)
ln Total Population	7.16593**	6.85827**	8.96729***	7.38895***	11.0092***	10.4956***	9.81508***	10.7349***	11.230***
	(3.3391)	(3.3480)	(3.1499)	(2.6971)	(2.8047)	(3.3448)	(2.7633)	(2.5163)	(2.3868)
%Urban Population	48.2126***	36.7212**	58.24***	58.6859***	51.5498***	42.1476***	37.4317**	52.8999***	44.7486**
	(13.379)	(15.623)	(13.159)	(13.243)	(13.549)	(13.482)	(16.024)	(15.197)	(17.836)
ln Medical Expenditure				-18.1283***			-13.203*		
				(5.7542)			(7.1526)		
ln Physicians per 1000									8.36958*
									(4.1828)
%Population over 65				-22.8895			3.56921		-5.0366
				(13.949)			(18.732)		(13.788)
Governance	-62.9189**				-79.5489***				
	(26.525)				(26.863)				
Gini index	28.2946	41.6819**	13.5663		7.10108	-8.13591		-27.9939**	
	(18.048)	(16.247)	(22.121)		(16.057)	(20.332)		(13.129)	
Poverty		-38.8547**							
		(14.781)							
Observations	48	48	46	48	46	44	46	53	53
R^2	0.6542	0.6512	0.6792	0.7175	0.6489	0.5682	0.6071	0.6253	0.6353

Note: Robust standard errors in parentheses. Used variance inflation factor (VIF) for diagnosing collinearity in the models. No VIF values regarded as problematic. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

The countries with a higher percentage of the population living in urban areas are the countries susceptible to a higher number of cases. This may be explained by the same reasons as previously mentioned, except that some countries by now had relaxed their containment measures. When relaxing their measures, countries with more people living in urban areas may experience that opening up society will lead to a large increase in the interactions between people and thus a higher number of cases. Moreover, the countries with more people living within a sq. km of land area were more vulnerable to a higher number of cases during the eighth period. This fits well with our hypothesis that overcrowding will lead to a higher number of cases. During period 8 and 9, 29 July to 6 September, the countries with more effective governance and those spending more money on medical expenditure are not the countries susceptible to a higher number of cases. These results may be related as the countries with more effective governance may in fact be those prioritizing to spend money on supplies that may contain the spread.

5.3.2.4 Autumn

In the eleventh and the twelfth period, 27 September to 5 November, economic strength becomes positively significant again. The main results are presented in Table 13. In period 11, life expectancy is robust and positively significant, and the population density variable is positively significant in all models except when stringency is included in the health model. In both periods, tourism and physicians per 1000 are positively significant, and the poverty headcount is negatively significant. In period 12, the population over 65 and the stringency variables are robust positively significant. This can be seen in Models 1, 4, 5 and 9 for period 11, and in Models 4, 5, 7, 9 and 11 for period 12. The full regressions can be seen in Appendix D, Tables D11 and D12.

Table 13

Regressions for Autumn

	Period 11				Period 12				
Model	1	4	5	9	4	5	7	9	11
ln Economic strength	4.73702**	1.87484	1.96303		5.61691**	5.40871**	10.7599***		
	(1.7962)	(1.6743)	(1.7149)		(2.2192)	(2.316)	(2.0746)		
ln Life Expectancy				59.7251**				40.3077	84.6347***
				(25.388)				(28.083)	23.195
$lnStringency_{t\text{-}1}$							13.6166*		15.230**
							(7.4176)		6.2295
ln Population density	4.1904**	4.22275**	4.38049**	4.28477**	.763403	.080060	-.476622	1.24423	-1.01473
	(2.0049)	(1.760)	(1.9851)	(1.8516)	(1.758)	(1.7435)	(2.071)	(1.7258)	1.5067
ln Migrant Stock	-.148848	-.264327	1.89697	.957166	-.042506	1.68912	-1.26864	1.88124	.85435
	(1.828)	(1.6228)	(1.8829)	(1.3499)	(2.0351)	(2.1823)	(2.0428)	(1.5242)	1.5849
ln Total Population	8.66422***	6.45908***	6.41826***	7.6008***	7.00523***	7.86798***	9.42705***	8.02855***	7.4414***
	(1.9539)	(1.9459)	(1.8646)	(1.3869)	(2.1851)	(1.9976)	(2.2345)	(1.4796)	1.8064
%Urban Population	14.4885*	11.6359	5.04683	1.36201	2.50525	.760052	-2.41651	-6.78879	-9.74481
	(7.828)	(8.3911)	(8.3263)	(7.8993)	(10.502)	(9.7918)	(11.219)	(8.7708)	9.1024
ln Physicians per 1000				5.19245**				6.94223***	
				(2.0887)				(2.5491)	
%Population over 65				2.44581				21.971***	39.8626***
				(7.2694)				(6.8254)	8.9763
ln Tourism		4.29886***			4.16609**				
		(1.2724)			(1.6064)				
Gini index	-14.2335*	-12.2155	3.20211		-19.6375*	-8.65286	-27.9849**		
	(7.9578)	(7.3365)	(8.3193)		(9.9264)	(12.239)	(10.594)		
Poverty			-37.1795***			-35.1112**			
			(10.346)			(13.606)			
Observations	60	60	60	60	55	55	51	55	51
R^2	0.6828	0.7449	0.7456	0.7675	0.7704	0.7729	0.7306	0.855	0.8411

Note: Robust standard errors in parentheses. Used variance inflation factor (VIF) for diagnosing collinearity in the models. No VIF values regarded as problematic. $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

For the first time, we see a significant effect of the tourism variable. We believed that this variable would be positively correlated with the number of Covid-19 cases—but in the earlier periods. This may be explained by the fact that the travel restrictions were eased in Europe during summer 2020 (European Commission, 2020a). These restrictions were reintroduced October 2020 (European Commission, 2020b), which fits well with our results, namely that countries with a high level of tourism struggled with a higher number of cases at this time.

5.3.2.5 Winter

From the fourteenth period, 26 November and throughout the sample (except for the sixteenth, which is very different), the results seem to be less consistent. For instance, both economic strength and percentage of population older than 65 are robust positively significant in period 14, while this effect cannot be seen in period 15 and 18, which can be seen in Table 14. Moreover, the poverty headcount is negatively significant in periods 14 and 18, but not in period 15. In the fourteenth and fifteenth period, medical expenditure is positively significant, while physicians per 1000 is only positively significant in periods 14 and 18. In the eighteenth period, the level of tourism becomes positively significant, and effectiveness of the government is negatively significant. These results can be seen in Models 5, 9 and 10 for period 14, in Model 10 for period 15, and in Model 3, 4, 5 and 9 for period 18. The full results from the regressions are presented in Appendix D, Tables D14, D15 and D17.

Table 14

Regressions for Winter

	Period 14			Period 15	Period 18			
Model	5	9	10	10	3	4	5	9
ln Economic strength	7.51153**				10.1993***	-2.52353	-2.90661	
	(3.0239)				(2.5034)	(3.8655)	(3.4949)	
ln Life Expectancy		8.17556	3.67652	-79.9866				-30.8434
		(37.662)	(29.833)	(55.887)				(38.245)
ln Population density	-1.68518	-.130983	-1.21387	2.05018	2.20359	2.68922	2.92869	2.9354
	(1.1842)	(1.2073)	(1.1957)	(2.8896)	(3.2253)	(2.7357)	(3.1738)	(3.1089)
ln Migrant Stock	-.73004	-.830973	-2.2126**	.039052	-.600855	-1.34643	.934810	-1.69740
	(1.7872)	(1.2194)	(1.0688)	(3.0485)	(3.9136)	(3.8805)	(4.1115)	(3.5179)
ln Total Population	8.50487***	9.12602***	9.40366***	4.9306	8.60517**	7.27681**	8.10022**	10.3029***
	(1.4471)	(1.0890)	(1.118)	(3.5007)	(3.3583)	(2.9972)	(3.5107)	(2.7794)
%Urban Population	.962469	6.57199	6.0096	-10.1187	33.2661**	32.3059*	26.5633	18.1765
	(8.2059)	(8.5931)	(8.0786)	(16.837)	(14.595)	(16.182)	(18.289)	(12.4082)
ln Medical Expenditure			8.02517**	12.3279*				
			(3.3499)	(6.5375)				
ln Physicians per 1000		5.9302*						6.21976**
		(2.9713)						(2.7023)
%Population over 65		22.9465**	18.6138*	-2.33653				11.4947
		(8.8244)	(9.8235)	(16.616)				(10.647)
ln Tourism						4.55573**		
						(1.9399)		
Governance					-67.5707***			
					(20.614)			
Gini index	-2.44959				-12.6842	-2.843	.731371	
	(9.1104)				(14.669)	(15.432)	(14.296)	
Poverty	-19.7803**						-43.3070***	
	(9.6771)						(11.941)	
Observations	50	50	50	44	42	42	42	42
R^2	0.8272	0.8386	0.8347	0.3144	0.5921	0.5797	0.5749	0.5954

Note: Robust standard errors in parentheses. Used variance inflation factor (VIF) for diagnosing collinearity in the models. No VIF values regarded as problematic. *p < 0.1, **p < 0.05, ***p < 0.01

5.3.2.6 Periods with divergent results

There is a gap between 27 September and 4 January, more specifically period 13, 6 November to 25 November, where the countries experiencing growth are differential. This also occurs in period 16, 5 January to 24 January. In both periods, the rest of the world is in decline, while countries characterized by more unfavorable factors are still experiencing growth, as can be seen in Table 15. Thus, most of the variables become significant in the opposite direction. For instance, economic strength has a significant negative effect in both periods.

Moreover, the poverty headcount is positively significant, while the level of tourism, medical expenditure, and physicians per 1000 are negatively significant in period 13. Additionally, the population density and population over 65 is robust negatively significant in the thirteenth period. Stringency is also negatively significant in the health model in period 13, while it is only in the economic model that is negatively significant in the sixteenth period. In period 16, life expectancy is robust negatively significant, and the urban population is robust negatively significant, except when the stringency variable is included. These results can be seen in Models 4, 5, 9, 10 and 11 for the thirteenth period, and in Models 7 and 8 for the sixteenth. The full results of the regressions can be seen in Appendix D, Tables D13 and D16.

Table 15

Regressions for Periods with Divergent Results

	Period 13					Period 16	
Model	4	5	9	10	11	7	8
ln Economic strength	-4.65792**	-3.02161				-7.53658***	
	(2.2849)	(3.1990)				(2.6557)	
ln Life Expectancy			-5.17969	-11.7561	-.891503		-125.2124***
			(33.854)	(37.205)	(34.382)		(29.714)
$lnStringency_{t-1}$					-10.379**	-17.6886**	
					(5.0223)	(7.8463)	
ln Population density	-7.03482***	-7.35519***	-7.53406***	-7.4384***	-6.63631***	1.41926	1.34121
	(2.0017)	(2.3569)	(2.2231)	(2.3541)	(2.4204)	(2.3216)	(1.9956)
ln Migrant Stock	1.00551	-2.21207	.165434	.660049	.377493	3.10599	.492359
	(1.7530)	(2.1723)	(1.6596)	(1.8869)	(1.716)	(1.8388)	(1.3714)
ln Total Population	-5.94199***	-5.57098**	-8.25748***	-8.32304***	-7.78065***	-7.38712***	-8.07594***
	(1.8111)	(2.5772)	(1.4632)	(1.6194)	(1.8008)	(2.2454)	(1.5995)
%Urban Population	-7.74023	-1.80626	-2.25752	-5.21295	-15.2362	-16.890	-30.6898**
	(10.029)	(13.134)	(11.959)	(11.4801)	(11.553)	(11.218)	(11.900)
ln Medical Expenditure				-4.8685*			
				(2.7529)			
ln Physicians per 1000			-6.50055**				
			(3.0156)				
%Population over 65			-25.7283**	-29.926***	-43.1906***		8.56448
			(10.483)	(9.322)	(10.573)		(8.6069)
ln Tourism	-5.42739***						
	(1.7831)						
Gini index	16.0057*	-.412233				8.20136	
	(8.0639)	(9.4513)				(15.597)	
Poverty		46.0231**					
		(19.397)					
Observations	51	51	51	51	50	35	40
R^2	0.6548	0.6518	0.7098	0.6831	0.6943	0.7304	0.8064

Note: Robust standard errors in parentheses. Used variance inflation factor (VIF) for diagnosing collinearity in the models. No VIF values regarded as problematic. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

5.3.2.7 Concluding remarks

The interaction terms we included—between inequality and population density and between inequality and migrant stock—did not give us the results we expected. When the terms are significant, they are significant in the opposite direction than what we believed, meaning they have negative correlation with the number of cases.

Some of our variables, such as migrant stock, were based on the literature on Covid-19 (OECD, 2020). It may be the case that this variable is an important determinant of regional differences and across cities. However, this variable does not seem important for describing the varying number of cases across countries. This may be due to what we mentioned in our hypothesis about this variable—that we cannot say whether the status migrant is connected to living conditions, and this connection may vary across countries.

Stronger government measures seem to have a positive effect on how susceptible countries are to a higher number of cases during all periods but period 4. However, we must remember that a high number of cases within a country may be a reason for stronger measures. The stronger measures in the previous period may imply that the country was experiencing a higher number of cases during the previous period. As the path of cases also is determined by earlier numbers of cases, this may explain why countries with stronger measures in the previous period may still be susceptible to a higher number of cases during this period.

Moreover, during periods five to nine, 30 May to 6 September, the countries with more effective governments are less susceptible to a higher number of cases, while the stricter containment measures have a positive effect on the number of cases. This can be related to the government's ability within these countries to implement the necessary containment measures. Furthermore, a more effective government will adjust their containment measures according to their ongoing level of infections.

Moreover, as the R^2 in period 15 is quite low, it seems that we may have excluded one or more socioeconomic factors that may explain the varying number of cases from 16 December to 4 January.

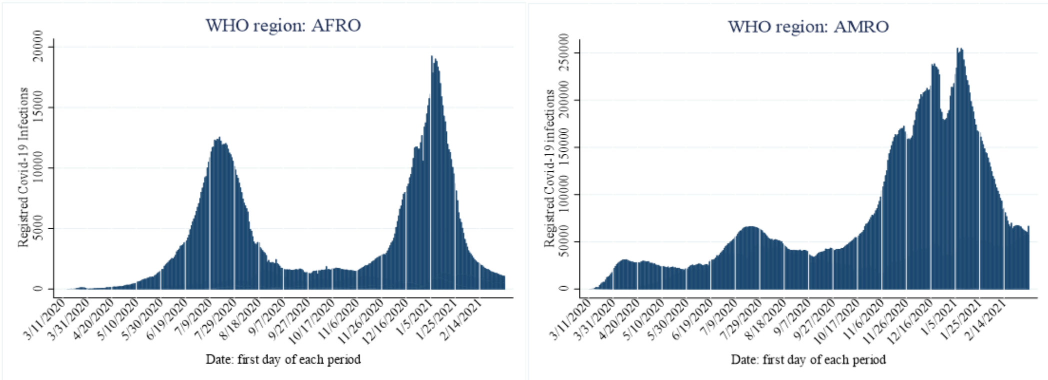
5.4 Comparing regression results in relation to regional infection waves

Following the results presented in the previous section, we study these results in combination with the regional waves of Covid-19 infection. This may provide us with deeper understanding of the characteristics of countries susceptible to a higher number of cases and the timing of waves. We compare our results with the waves in different WHO regions, namely the African Region (AFRO), Region of the Americas (AMRO), European Region (EURO), Western Pacific Region (WPRO), South-East Asia Region (SEARO), and Eastern Mediterranean Region (EMRO).

By looking at the socioeconomic factors that become significant in period 5, we can conclude that there is a shift in the countries which are susceptible to a higher number of cases. As seen in Figure 2, the countries that are categorized in the WHO region AFRO experienced large growth during this period, while countries within other regions experienced the opposite, except for the WHO-region AMRO.

Figure 2

Registered Covid-19 Infections in WHO Regions AFRO and AMRO



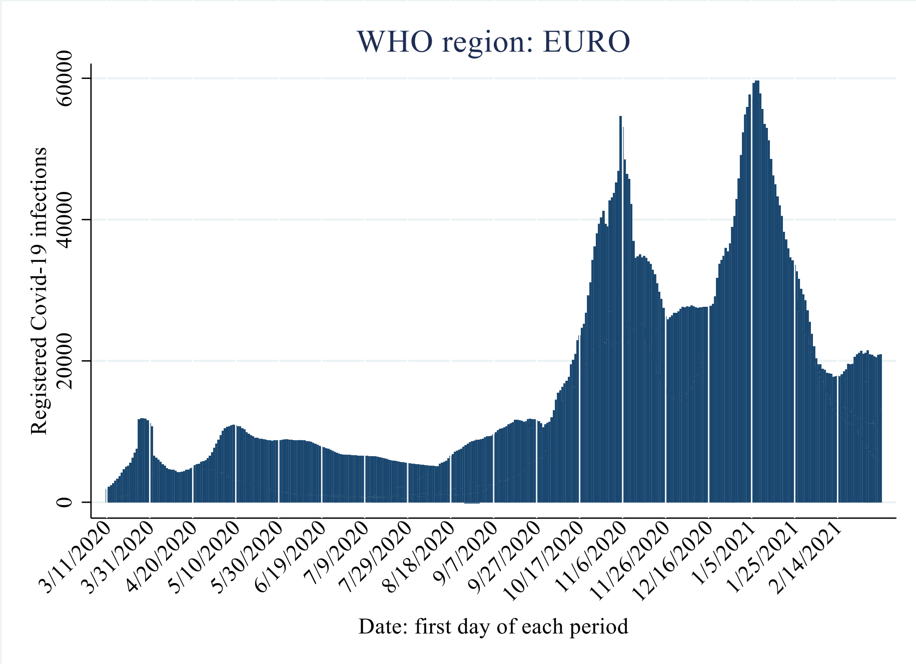
Note: Figure created using number of cases from the countries in our sample.

By looking at the indices, we can see that South Africa is the only country within the AFRO region which has a high index value. This may be the reason why poverty does not have a positive correlation with the number of cases in these periods.

During both periods 11 and 12—from 27 September to 5 November—countries with higher GDP per capita and higher life expectancy are also the countries which are susceptible to a higher number of cases. This seems to correspond with the beginning of the second wave in Europe as seen in Figure 3.

Figure 3

Registered Covid-19 infections in WHO Region EURO

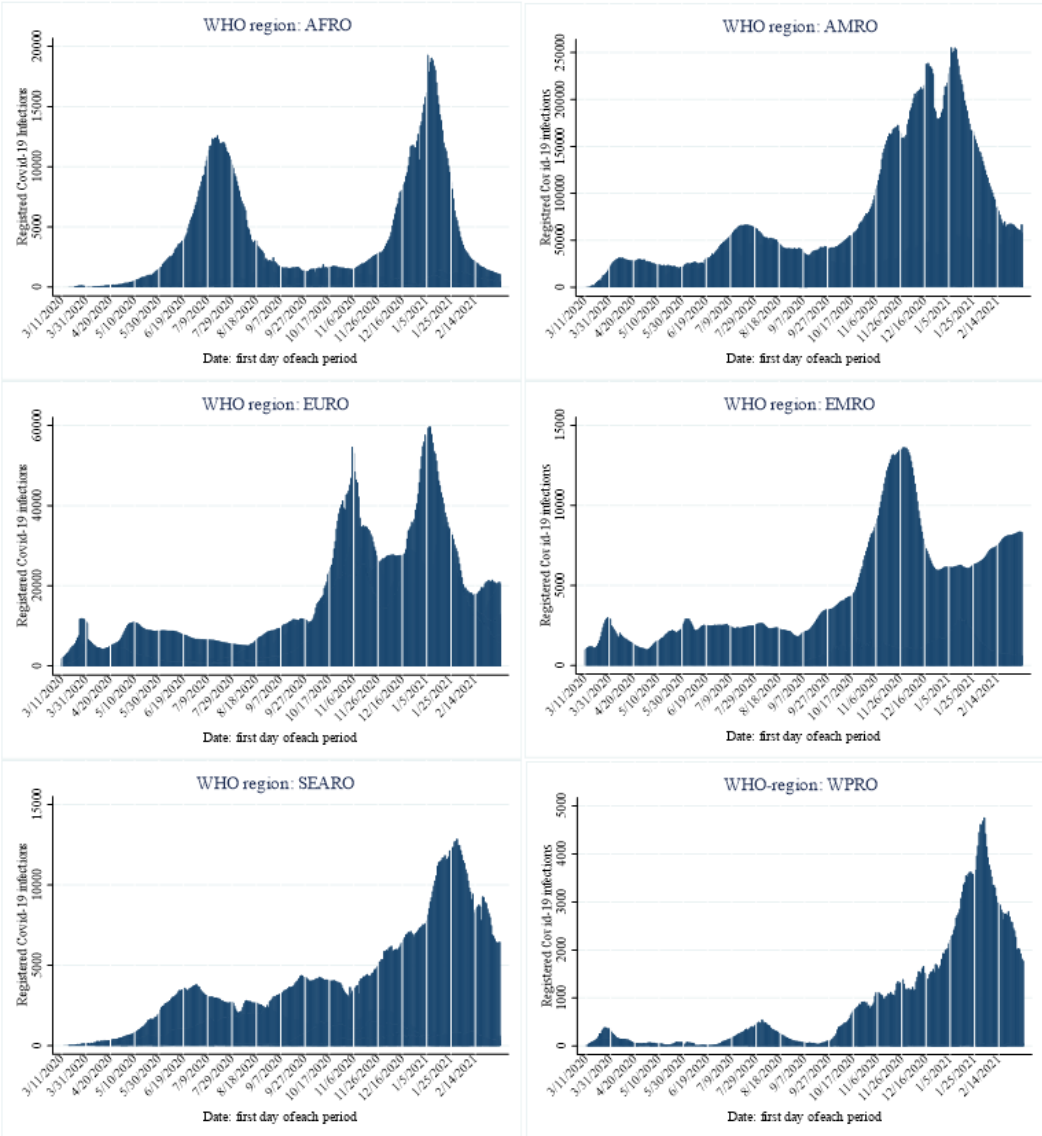


Note: Figure created using number of cases from the countries in our sample.

Looking at the last three periods, the socioeconomic factors which characterize the countries more vulnerable to a higher number of cases are less consistent. The virus has at this time spread to all regions of the world included in our study, and most countries have struggled with waves and increasing number of cases, as shown in the graphs in Figure 4. This may be the reason why we have less distinctive results at the end of our sample period.

Figure 4

Registered Covid-19 Infections in all WHO Regions



Note: Figure created using number of cases from the countries in our sample.

Another interesting result is that similar countries seem to have waves of cases moving in the same direction during the same periods. Thus, their characteristics seem to matter more than their geographical location. For instance, in periods 13 and 16, where many African countries experienced growth and had high scores on the indices, South Africa had a low score on the index in period 13 and did not experience growth in period 16. Thus, it seems as though South Africa's waves, in later periods, were moving more like other countries with similar characteristics. Governance was not significant, and stringency was not robust, but was significant for some models in these periods. Thus, we are not able to distinguish whether this is a result of similar countries implementing the same policies simultaneously or the effectiveness of their governance—that is, their ability to implement measures effectively.

5.5 Limitations and weaknesses of the analyses

We discussed the limitations in the data we use in our analysis in the Data chapter; however, there are other limitations and weaknesses in our analysis which need to be considered.

As mentioned previously in section 4.2.1.1, the SIR model assumes that immunity following a recovery will last forever (Weiss, 2013). This assumption does not fit the data on Covid-19 cases, however, as there are individuals who have been infected more than once. Moreover, another assumption is that all individuals within a population have equal probability of being in contact (Weiss, 2013). However, one could state that this assumption does not hold during the Covid-19 pandemic, as there are large differences among the population when it comes to the possibility of limiting contact with other individuals. For instance, some individuals are able to work from home, while others work in the services sector, where limiting contact is more difficult. Thus, one could state that using the simple SIR model is not the best fit for estimating the number of cases during the Covid-19 pandemic, and one should instead use a more complex epidemiological model to find the epidemiological factors.

In our analysis, we included only the countries for which we could obtain all the socioeconomic factors. Thus, many countries were excluded from our analysis, which may cause limitations in the value of our results. For instance, we have excluded India, which is a well-known hot-spot for Covid-19 infections. This country, as well as other countries excluded from our study, may have characteristics that are very different from those included. Thus, there is a possibility that including these countries would have given us different results than what we obtained in the cross-sectional analysis.

We chose to use Xtabond2 in our estimation; however, there are other commands in Stata which make use of the same estimators—for instance, Xtdpdgmm. A weakness in the Xtabond2 command is that it will report too few degrees of freedom for the overidentification tests when time dummies are omitted due to perfect collinearity. This is corrected for in Xtdpdgmm (Kripfganz, 2019). Thus, it might have been better to use this command in our estimation. However, as we discussed in section 5.2.1, the test results did not have a large effect on our index values, and we can conclude that this is not a severe issue for our analysis.

The sample size can affect whether the findings from research are valid (Ioannidis, 2005). Thus, we understand that the small sample sizes in the second cross-sectional analysis may affect whether the results we find in the cross-sectional analysis are valid. In addition to considering multicollinearity, we decided to reduce the number of regressors in each model as there are many different opinions on the minimum sample size required, based on the number of predictors. However, a study considered these recommendations and found that a minimum sample size of 25 is sufficient—evidence that our sample size was, in fact, sufficient (Jenkins & Quintana-Ascencio, 2020).

Another reasoning for why our findings may be valid even though the sample size is small, is the fact that the small sample cross-sectional analysis results correspond to the results in our analysis on the total number of cases, deaths, and the average indices. These analyses include all 92 countries, and the models consist of a maximum of seven predictors. Thus, it is more likely that the sample size in these analyses is sufficient. Nevertheless, the results correspond to the small sample analysis, and we can conclude that the sample size is sufficient.

6 Conclusion

Our study seems to have the similar results and findings as other studies on viral diseases and socioeconomic factors. We have performed a cross-country comparison which has its limitations. However, some of the explanatory variables that are significant in explaining the varying number of cases within countries seem to be valid across countries as well. In the beginning of a pandemic, with a virus transmitted through aerosols or droplets like Covid-19, countries with developed economies and a population living in urban areas seem to have the highest number of cases. How a country is governed and the containment measures they undertake have an impact on how fast the country controls a wave. After a period with strict measures, it appears that easing the containment measures in these countries will lead to a spread of the virus to other parts of the world. Thus, countries with other characteristics receive the virus which leads to waves of cases in these countries as well. In late fall and during winter, all parts of the world experienced infection waves. This makes it harder to distinguish which of the socioeconomic factors may explain the varying number of cases across countries.

According to our hypothesis, the countries with high economic activity, where we have used GDP per capita as a proxy, would be more affected by the virus in the beginning of the pandemic. This fits well with our results. However, in contrast to our hypothesis, a high level of tourism was not a socioeconomic factor which could explain why a country was susceptible to a higher number of cases in the early stage. This factor could instead explain the number of cases during fall, after the travel restrictions were eased. Furthermore, we believed that unfavorable factors like inequality would become important for the spread of the virus in the later periods. In our results, we can see that countries with more inequality struggle with a higher number of cases in later periods compared to countries with less inequality. However, it does not seem as though these countries are more vulnerable compared to other countries throughout the year. Our results may be affected by the fact that we excluded some countries—for instance, India—which is a well-known hot-spot for Covid-19.

Finally, our goal in this study was to provide information to policy makers on which measures to implement at which time. There are reasons to conclude that there should be a different timing of the measures for different countries. When the pandemic was announced in the middle of March 2020, all countries implemented strict policies to contain the virus. We cannot say what would have happened without these strict measures. However, it seems that countries with less developed economies might not reap the benefits of the early-stage lockdowns, only the negative effects of shutting down their labour-intensive economic activity. This finding in the early stage of the pandemic is also consistent with other studies on the subject (Nabi & Islam, 2020).

Therefore, one could conclude that implementing the same level of strictness of the measures at the same time may not be the optimal strategy for containing the global spread of the virus. Policy makers, when facing a virus that is transmitted in a similar way as Covid-19, should instead focus on the characteristics of their country and adapt their measures accordingly.

7 Reference list

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Appendix A Tables

Table A 1

The Periods of the First year of Covid-19

Periods	Date from	Date to
1	3/11/2020	3/30/2020
2	3/31/2020	4/19/2020
3	4/20/2020	5/9/2020
4	5/10/2020	5/29/2020
5	5/30/2020	6/18/2020
6	6/19/2020	7/8/2020
7	7/9/2020	7/28/2020
8	7/29/2020	8/17/2020
9	8/18/2020	9/6/2020
10	9/7/2020	9/26/2020
11	9/27/2020	10/16/2020
12	10/17/2020	11/5/2020
13	11/6/2020	11/25/2020
14	11/26/2020	12/15/2020
15	12/16/2020	1/4/2021
16	1/5/2021	1/24/2021
17	1/25/2021	2/13/2021
18	2/14/2021	3/5/2021

Note: 20-day periods staring from the pandemic was declared 3/11/2020.

Table A 2

Upper and Lower Bound Test for Difference GMM

	Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 8	Period 9
Upper Bound (Pooled OLS)	0.9986517	1.000328	0.998578	0.9504151	0.9842195	1.041454	1.03756	1.01726
Lower bound (Fixed effect model)	0.8653721	0.8751788	0.8711482	0.7768515	0.8050397	0.857274	0.8710083	0.8341987
Diff. GMM	0.754092	0.9121547	0.8445631	0.7394647	0.7015938	0.7826323	0.7592008	0.7260753
	Period 10	Period 11	Period 12	Period 13	Period 14	Period 15	Period 16	Period 18
Upper Bound (Pooled OLS)	1.033067	1.006311	1.003593	1.018514	0.9470255	1.023346	0.9870984	1.038874
Lower bound (Fixed effect model)	0.9324983	0.886555	0.7944928	0.8259189	0.7199118	0.8397033	0.8027978	0.8831471
Diff. GMM	0.8264708	0.7679095	0.5980585	0.7465348	0.6228099	0.616317	0.7587831	0.7583183

Note: Coefficients of the first lagged dependent variable.

Table A 3

Average Difference Between the Residuals and the Average Residuals

Period 1	Period 2	Period 3	Period 4	Period 5	Period 6	Period 8	Period 9
-8.24E-10	5.61E-10	-9.80E-11	-1.46E-10	7.46E-10	-4.19E-10	4.06E-11	1.05E-09
(.0055188)	(.0090649)	(.0093966)	(.0111908)	(.0062243)	(.0050088)	(.0043129)	(.0067248)
Period 10	**Period 11**	**Period 12**	**Period 13**	**Period 14**	**Period 15**	**Period 16**	**Period 18**
-1.57E-10	-9.31E-11	2.47E-10	1.24E-10	6.56E-10	8.09E-11	-3.84E-10	5.99E-10
(.0027351)	(.0035431)	(.0043492)	(.0032324)	(.0067506)	(.005271)	(.00586)	(.0050091)

Note: Standard errors in parentheses.

Appendix B Cross Sectional Analyses, First Pandemic Year

Table B 1

Regressions on Total Amount of Cases

	Economic						Health		
Model	1	2	3	4	5	6	7	8	9
ln Economic strength	.53654***	.539256***	1.01244***	.229147	.276893	.458653***			
	(.177273)	(.1673)	(.20649)	(.18611)	(.20115)	(.16787)			
ln Life Expectancy							2.96591	-2.06179	.619013
							2.5975	2.9802	3.3069
ln Population density	.192241	.425469**	.19371	.173429	.18493	.191251	.142286	.244048*	.16191
	(.135837)	(.16184)	(.12865)	(.12161)	(.12890)	(.12885)	.14003	.13806	.14562
ln Migrant Stock	.220125	.212567	.290425*	.20607	.375983**	.36041*	.211954	.187284	.156458
	(.1763185)	(.17339)	(.17269)	(.18253)	(.18597)	(.19549)	.15620	.15891	.17467
ln Total Population	.727935***	.719468***	.673565***	.515106**	.629618***	.759546***	.742864***	.821744***	.792754***
	(.1947852)	(.19253)	(.18568)	(.20036)	(.20449)	(.18983)	.17558	.17031	.18152
%Urban Population	2.145***	1.92423***	2.12726***	2.01657***	1.41849*	2.34398***	2.10732***	1.55421**	1.7365**
	(.7158659)	(.69339)	(.67781)	(.69215)	(.72144)	(.69669)	.66848	.66971	.75459
ln Medical Expenditure									.370379
									.32789
ln Physicians per 1000								.706839***	
								.24068	
%Population over 65							1.79737***	.953303*	1.33982**
							.57717	.50474	.61657
ln Tourism				.417254***					
				(.14624)					
Governance			-3.98988***						
			(1.4563)						
Gini index	.8832	-.618311***	.698899	1.00813	1.79096**	-.598641***			
	(.6881024)	(.17768)	(.65369)	(.65857)	(.71246)	(.18671)			
Poverty					-2.72449**				
					(1.0859)				
ln Migrant Stock · Gini						-.530897***			
						(.17632)			
ln Population Density · Gini		-.930771***							
		(.23782)							
Observations	92	89	92	92	92	89	92	92	92
R^2	0.6799	0.6794	0.7027	0.7126	0.712	0.6618	0.6991	0.7466	0.7039

Note: Robust standard errors in parentheses. Used variance inflation factor (VIF) for diagnosing collinearity in the models. No VIF values regarded as problematic. **p* < 0.1, ***p* < 0.05, ****p* < 0.01

Table B 2

Regressions on Total Amount of Deaths Caused by Covid-19

	Economic						Health		
Model	1	2	3	4	5	6	7	8	9
ln Economic strength	.596725***	.586899***	1.34536***	.230847	.369174*	.494357**			
	(.19924)	(.18933)	(.25834)	(.19629)	(.22071)	(.18773)			
ln Life Expectancy							1.43640	-2.99095	-2.42849
							(3.2621)	(3.8106)	(4.2985)
ln Population density	.284401	.45229**	.285531	.26460	.279107	.293042*	.23217	.321333*	.263792
	(.18297)	(.17244)	(.17829)	(.16344)	(.17885)	(.16067)	(.17731)	(.17909)	(.18425)
ln Migrant Stock	.117078	.0384555	.222684	.112518	.259619	.413906	.057432	.03277	-.037271
	(.22287)	(.20153)	(.21316)	(.22586)	(.23386)	(.25801)	(.18655)	(.19614)	(.21266)
ln Total Population	.949169***	.96916***	.864474***	.690945***	.861462***	.974803***	1.00513***	1.07451***	1.0873***
	(.23486)	(.23020)	(.21824)	(.23136)	(.24748)	(.22137)	(.2084)	(.2111)	(.22141)
%Urban Population	2.26016***	2.13048***	2.22258***	2.12872***	1.62873*	2.71183***	2.2506***	1.74936**	1.62485*
	(.84556)	(.80516)	(.76863)	(.80052)	(.92033)	(.78909)	(.8485)	(.86676)	(.92903)
ln Medical Expenditure									.613247
									(.39563)
ln Physicians per 1000								.625393**	
								(.26839)	
%Population over 65							2.65253***	1.90246**	1.89171**
							(.69887)	(.73193)	(.7312)
ln Tourism				.501554***					
				(.17423)					
Governance			-6.28948***						
			(1.7841)						
Gini index	1.21338	-.681969***	.887268	1.4478	2.04865**	-.786929***			
	(.88503)	(.21768)	(.80794)	(.87410)	(.90695)	(.27794)			
Poverty					-2.40325**				
					(1.1924)				
ln Migrant Stock · Gini						-.803183***			
						(.25454)			
ln Population Density · Gini		-1.03498***							
		(.30135)							
Observations	91	88	91	91	91	89	91	91	91
R^2	0.6278	0.6371	0.674	0.6653	0.6481	0.624	0.6553	0.6857	0.6659

Note: Robust standard errors in parentheses. Used variance inflation factor (VIF) for diagnosing collinearity in the models. No VIF values regarded as problematic. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

Appendix C Dynamic panel data estimation

Table C 1

Period 1 Dynamic Panel-Data Estimation, Two-step System GMM

Group vaiable: country				Number of obs =		969
Time variable:date				Number of groups =		51
Number of instruments = 47				Obs per group: min =		19
F(20, 50) = 3255.88				avg =		19.00
Prob > F = 0.000				max =		19
Variables	Coefficient	Robust Std.Error	t-value	p-value	[95%Conf Interval]	
$lnSmooth\ Cases_{t-1}$	0.8932042***	0.0457596	19.52	0.000	0.8012934	0.985115
$\frac{S \cdot I_{t-7}}{N}$	-0.0238392	0.019353	-1.23	0.224	-0.0627108	0.0150323
day1	Omitted					
day2	-0.1730996	0.1632601	-1.06	0.294	-0.5010173	0.154818
day3	-0.1368359	0.1524695	-0.90	0.374	-0.44308	0.1694082
day4	-0.1122517	0.1369597	-0.82	0.416	-0.3873434	0.1628399
day5	-0.0877495	0.1432112	-0.61	0.543	-0.3753975	0.1998986
day6	-0.0660604	0.1204942	-0.55	0.586	-0.3080801	0.1759593
day7	-0.0489149	0.0952229	-0.51	0.610	-0.2401758	0.1423459
day8	-0.0600874	0.0969352	-0.62	0.538	-0.2547876	0.1346127
day9	-0.1044432	0.0854212	-1.22	0.227	-0.2760166	0.0671303
day10	-0.0385254	0.0696769	-0.55	0.583	-0.1784756	0.1014248
day11	-0.0092794	0.0679185	-0.14	0.892	-0.1456977	0.1271389
day12	0.0003294	0.0589482	0.01	0.996	-0.1180716	0.1187304
day13	0.0211033	0.0419817	0.50	0.617	-0.0632195	0.1054261
day14	-0.0082242	0.0397174	-0.21	0.837	-0.0879989	0.0715504
day15	0.023229	0.0360856	0.64	0.523	-0.049251	0.095709
day16	0.0608642**	0.0266127	2.29	0.026	0.0074109	0.1143174
day17	-0.0035019	0.0238271	-0.15	0.884	-0.05136	0.0443563
day18	0.001463	0.0177785	0.08	0.935	-0.0342462	0.0371722
day19	Omitted					
day20	-0.0068776	0.0236817	-0.29	0.773	-0.0544438	0.0406885
Constant	0.7317247**	0.301962	2.42	0.019	0.1252161	1.338233
*p<0.1, **p<0.05, ***p<0.01						
Arellano-Bond test for AR(1) in first differences: z = -3.64 Pr > z = 0.000						
Arellano-Bond test for AR(2) in first differences: z = 0.20 Pr > z = 0.844						
Sargan test of overid. restrictions: chi2(26) = 74.49				Prob > chi2 = 0.000		
Hansen test of overid. restrictions: chi2(26) = 32.69				Prob > chi2 = 0.171		

Note: Windmeijer corrected standard errors.

Table C 2

Period 2 Dynamic Panel-Data Estimation, Two-step System GMM

Group vaiable: country				Number of obs	=	798
Time variable:date				Number of groups	=	42
Number of instruments = 35				Obs per group: min	=	19
F(20, 41) = 10457.90					avg =	19.00
Prob > F = 0.000					max =	19
Variables	Coefficient	Robust Std.Error	t-value	p-value	[95%Conf	Interval]
$lnSmooth\ Cases_{t-1}$	0.9627284***	0.0304146	31.65	0.000	0.9013048	1.024152
$\frac{S \cdot I_{t-7}}{N}$	0.0019498	0.0193672	0.10	0.920	-0.037163	0.0410625
day1	Omitted					
day2	-0.006794	0.0530541	-0.13	0.899	-0.1139389	0.100351
day3	-0.044678	0.0619334	-0.72	0.475	-0.169755	0.0803989
day4	-0.026858	0.0564797	-0.48	0.637	-0.1409211	0.0872052
day5	-0.0311913	0.0597225	-0.52	0.604	-0.1518033	0.0894208
day6	-0.0277364	0.0576997	-0.48	0.633	-0.1442633	0.0887904
day7	0.0089531	0.0489096	0.18	0.856	-0.0898218	0.107728
day8	-0.0152436	0.0512496	-0.30	0.768	-0.1187443	0.0882571
day9	-0.0627398	0.0599347	-1.05	0.301	-0.1837803	0.0583008
day10	-0.017923	0.0416891	-0.43	0.670	-0.1021158	0.0662698
day11	-0.1033166	0.0668485	-1.55	0.130	-0.2383199	0.0316868
day12	0.0395935	0.0555004	0.71	0.480	-0.0724918	0.1516789
day13	-0.0638368	0.0460626	-1.39	0.173	-0.1568621	0.0291885
day14	-0.0220743	0.0390101	-0.57	0.575	-0.1008568	0.0567081
day15	0.0055954	0.0577659	0.10	0.923	-0.1110653	0.1222561
day16	-0.0295268	0.0516859	-0.57	0.571	-0.1339086	0.074855
day17	-0.0569203	0.0485054	-1.17	0.247	-0.1548791	0.0410384
day18	-0.0083837	0.0382059	-0.22	0.827	-0.0855422	0.0687747
day19	Omitted					
day20	-0.0627222	0.0379412	-1.65	0.106	-0.1393461	0.0139017
Constant	0.2374601*	0.1366705	1.74	0.090	-0.0385516	0.5134719
*p<0.1, **p<0.05, ***p<0.01						
Arellano-Bond test for AR(1) in first differences: z = -3.18 Pr > z = 0.001						
Arellano-Bond test for AR(2) in first differences: z = 1.63 Pr > z = 0.103						
Sargan test of overid. restrictions: chi2(14) = 17.38					Prob > chi2 =	0.236
Hansen test of overid. restrictions: chi2(14) = 17.72					Prob > chi2 =	0.220

Note: Windmeijer corrected standard errors.

Table C 3

Period 3 Dynamic Panel-Data Estimation, Two-step System GMM

Group vaiable: country		Number of obs =	760
Time variable:date		Number of groups =	40
Number of instruments = 35		Obs per group: min =	19
F(20, 39) =	730.06	avg =	19.00
Prob > F =	0.000	max =	19

Variables	Coefficient	Robust Std.Error	t-value	p-value	[95%Conf Interval]	
$lnSmooth\ Cases_{t\text{-}1}$	0.9095594***	0.1152317	7.89	0.000	0.6764812	1.142638
$\frac{S \cdot I_{t\text{-}7}}{N}$	-0.1014088**	0.0431757	-2.35	0.024	-0.1887398	-0.0140777
day1	Omitted					
day2	-0.1887496*	0.1006129	-1.88	0.068	-0.3922584	0.0147591
day3	-0.1559793*	0.0774892	-2.01	0.051	-0.312716	0.0007575
day4	-0.1771595**	0.0769486	-2.30	0.027	-0.3328028	-0.0215163
day5	-0.1551338**	0.0687896	-2.26	0.030	-0.294274	-0.0159936
day6	-0.2072558***	0.0759528	-2.73	0.009	-0.3608847	-0.0536268
day7	-0.1613206**	0.0670769	-2.41	0.021	-0.2969963	-0.0256448
day8	-0.1557928**	0.0617993	-2.52	0.016	-0.2807936	-0.030792
day9	-0.1757829**	0.0747339	-2.35	0.024	-0.3269466	-0.0246192
day10	-0.169693**	0.0795855	-2.13	0.039	-0.3306699	-0.008716
day11	-0.1189694**	0.0576038	-2.07	0.046	-0.235484	-0.0024547
day12	-0.1751609**	0.0669427	-2.62	0.013	-0.3105652	-0.0397565
day13	-0.0812789	0.0614958	-1.32	0.194	-0.2056659	0.043108
day14	-0.1337801**	0.0542498	-2.47	0.018	-0.2435106	-0.0240495
day15	-0.0811633	0.0605611	-1.34	0.188	-0.2036596	0.0413331
day16	-0.0426325	0.0561485	-0.76	0.452	-0.1562036	0.0709386
day17	-0.071969	0.0472099	-1.52	0.135	-0.1674601	0.0235222
day18	Omitted					
day19	-0.064466*	0.0376099	-1.71	0.094	-0.1405391	0.0116071
day20	-0.0737103*	0.0431438	-1.71	0.095	-0.1609769	0.0135563
Constant	0.9466001**	0.4468317	2.12	0.041	0.0427977	1.850402

*p<0.1, **p<0.05, ***p<0.01

Arellano-Bond test for AR(1) in first differences: z = -2.44 Pr > z = 0.015

Arellano-Bond test for AR(2) in first differences: z = -0.96 Pr > z = 0.335

Sargan test of overid. restrictions: chi2(14) = 37.99 Prob > chi2 = 0.001

Hansen test of overid. restrictions: chi2(14) = 17.45 Prob > chi2 = 0.233

Note: Windmeijer corrected standard errors.

Table C 4

Period 4 Dynamic Panel-Data Estimation, Two-step System GMM

Group vaiable: country					Number of obs =	760
Time variable:date					Number of groups =	40
Number of instruments = 35					Obs per group: min =	19
F(20, 39) = 4487.02					avg =	19.00
Prob > F = 0.000					max =	19
Variables	Coefficient	Robust Std.Error	t-value	p-value	[95%Conf Interval]	
$lnSmooth\ Cases_{t-1}$	0.9384911***	0.0439686	21.34	0.000	.8495562	1.027426
$\frac{S \cdot I_{t-7}}{N}$	.0029869	.036267	0.08	0.935	-.07037	.0763438
day1	Omitted					
day2	-.0566829	0.053813	-1.05	0.299	-0.1655299	0.0521641
day3	-0.0105285	0.0472536	-0.22	0.825	-0.106108	0.085051
day4	-0.0666406	0.0509605	-1.31	0.199	-0.169718	0.0364369
day5	-0.0639366	0.0502481	-1.27	0.211	-0.165573	0.0376997
day6	-0.0767178	0.0536166	-1.43	0.160	-0.1851675	0.031732
day7	-0.0429035	0.0572458	-0.75	0.458	-0.1586941	0.0728871
day8	-0.0131151	0.0448182	-0.29	0.771	-0.1037684	0.0775382
day9	-0.0119675	0.0526991	-0.23	0.822	-0.1185615	0.0946266
day10	-0.1017178	0.060871	-1.67	0.103	-0.224841	0.0214054
day11	-0.0296276	0.0554437	-0.53	0.596	-0.141773	0.0825179
day12	-0.1014863	0.062769	-1.62	0.114	-0.2284485	0.025476
day13	-0.0068647	0.0515645	-0.13	0.895	-0.1111638	0.0974344
day14	-0.0528518	0.0610008	-0.87	0.392	-0.1762377	0.070534
day15	-0.0578802	0.0464903	-1.24	0.221	-0.1519158	0.0361554
day16	0.0683477	0.0575484	1.19	0.242	-0.048055	0.1847503
day17	0.0230562	0.0361721	0.64	0.528	-0.0501087	0.0962212
day18	Omitted					
day19	-0.0247135	0.0239404	-1.03	0.308	-0.0731375	0.0237106
day20	-0.010189	0.0233172	-0.44	0.665	-0.0573525	0.0369744
Constant	0.3545624	0.2761449	1.28	0.207	-0.2039934	0.9131181
*p<0.1, **p<0.05, ***p<0.01						
Arellano-Bond test for AR(1) in first differences: z = -2.25 Pr > z = 0.025						
Arellano-Bond test for AR(2) in first differences: z = 0.93 Pr > z = 0.352						
Sargan test of overid. restrictions: chi2(14) = 49.35					Prob > chi2 = 0.000	
Hansen test of overid. restrictions: chi2(14) = 22.68					Prob > chi2 = 0.066	

*Note:*Windmeijer corrected standard errors.

Table C 5

Period 5 Dynamic Panel-Data Estimation, Two-step System GMM

Group vaiable: country				Number of obs =		1026
Time variable:date				Number of groups =		54
Number of instruments = 35				Obs per group: min =		19
F(20, 53) = 3182.30				avg =		19.00
Prob > F = 0.000				max =		19
Variables	Coefficient	Robust Std.Error	t-value	p-value	[95%Conf	Interval]
$lnSmooth\ Cases_{t\text{-}1}$	0.9497536***	0.0696236	13.64	0.000	0.8101063	1.089401
$\frac{S \cdot I_{t\text{-}7}}{N}$	-.0061311	0.0278588	-0.22	0.827	-0.0620087	0.0497465
day1	Omitted					
day2	-0.0177638	0.0282614	-0.63	0.532	-0.074449	0.0389215
day3	0.000922	0.0221621	0.04	0.967	-0.0435296	0.0453736
day4	Omitted					
day5	0.0176975	0.0283143	0.63	0.535	-0.0390939	0.0744888
day6	0.0155907	0.024742	0.63	0.531	-0.0340356	0.065217
day7	-0.003724	0.021638	-0.17	0.864	-0.0471242	0.0396762
day8	0.0353346	0.0326439	1.08	0.284	-0.0301407	0.10081
day9	0.0313008	0.0268913	1.16	0.250	-0.0226364	0.085238
day10	0.0434992	0.0290042	1.5	0.140	-0.0146759	0.1016742
day11	0.0334176	0.0287191	1.16	0.250	-0.0241856	0.0910209
day12	0.0332303	0.0291605	1.14	0.260	-0.0252584	0.0917189
day13	0.0428744	0.0311911	1.37	0.175	-0.0196871	0.105436
day14	0.0622549*	0.0354861	1.75	0.085	-0.0089213	0.1334311
day15	0.0432587	0.0427706	1.01	0.316	-0.0425283	0.1290457
day16	0.0623796	0.0462876	1.35	0.184	-0.0304616	0.1552208
day17	0.0444129	0.0415532	1.07	0.290	-0.0389323	0.1277581
day18	0.0558794	0.0517886	1.08	0.285	-0.0479954	0.1597543
day19	0.0428321	0.0464733	0.92	0.361	-0.0503814	0.1360457
day20	0.0665819	0.044754	1.49	0.143	-0.0231832	0.156347
Constant	0.2773309	0.2310921	1.2	0.235	-0.1861812	0.7408431
*p<0.1, **p<0.05, ***p<0.01						
Arellano-Bond test for AR(1) in first differences: z = -3.12 Pr > z = 0.002						
Arellano-Bond test for AR(2) in first differences: z = -0.68 Pr > z = 0.494						
Sargan test of overid. restrictions: chi2(14) = 80.30					Prob > chi2 =	0.000
Hansen test of overid. restrictions: chi2(14) = 21.17					Prob > chi2 =	0.097

*Note:*Windmeijer corrected standard errors.

Table C 6

Period 6 Dynamic Panel-Data Estimation, Two-step System GMM

Group vaiable: country				Number of obs	=	988
Time variable:date				Number of groups	=	52
Number of instruments = 47				Obs per group: min	=	19
F(20, 51) = 9848.10				avg	=	19.00
Prob > F = 0.000				max	=	19

Variables	Coefficient	Robust Std.Error	t-value	p-value	[95%Conf Interval]	
$lnSmooth\ Cases_{t-1}$	1.01384***	0.0429466	23.61	0.000	0.9276209	1.100059
$\frac{S \cdot I_{t-7}}{N}$	-0.0671492***	0.0215164	-3.12	0.003	-0.1103451	-0.0239533
day1	Omitted					
day2	-0.0320464	0.0241119	-1.33	0.190	-0.0804531	0.0163602
day3	0.0073602	0.0226999	0.32	0.747	-0.0382118	0.0529322
day4	Omitted					
day5	-0.0070841	0.025257	-0.28	0.780	-0.0577896	0.0436214
day6	0.0049391	0.0203952	0.24	0.810	-0.036006	0.0458841
day7	0.0069713	0.0251091	0.28	0.782	-0.0434374	0.05738
day8	0.0120497	0.02478	0.49	0.629	-0.0376983	0.0617977
day9	0.027661	0.0225865	1.22	0.226	-0.0176833	0.0730053
day10	0.0034738	0.0220514	0.16	0.875	-0.0407963	0.0477439
day11	-0.0028985	0.0269591	-0.11	0.915	-0.0570211	0.0512241
day12	0.0158852	0.0253151	0.63	0.533	-0.0349371	0.0667074
day13	0.0053494	0.0260458	0.21	0.838	-0.0469398	0.0576386
day14	0.0074574	0.0273521	0.27	0.786	-0.0474542	0.062369
day15	-0.003586	0.0289162	-0.12	0.902	-0.0616376	0.0544656
day16	-0.0191697	0.0416653	-0.46	0.647	-0.1028163	0.0644769
day17	0.0406929	0.033705	1.21	0.233	-0.0269728	0.1083586
day18	0.03192	0.0287343	1.11	0.272	-0.0257666	0.0896066
day19	0.0535614	0.0412299	1.3	0.200	-0.0292112	0.136334
day20	0.030983	0.0329234	0.94	0.351	-0.0351134	0.0970793
Constant	0.2869314	0.2300138	1.25	0.218	-0.1748406	0.7487033

*p<0.1, **p<0.05, ***p<0.01

Arellano-Bond test for AR(1) in first differences: z = -2.85 Pr > z = 0.004

Arellano-Bond test for AR(2) in first differences: z = -0.32 Pr > z = 0.748

Sargan test of overid. restrictions: chi2(26) = 103.66 Prob > chi2 = 0.000

Hansen test of overid. restrictions: chi2(26) = 31.43 Prob > chi2 = 0.213

Note: Windmeijer corrected standard errors.

Table C 7

Period 8 Dynamic Panel-Data Estimation, Two-step System GMM

Group vaiable: country					Number of obs =	912
Time variable:date					Number of groups =	48
Number of instruments = 47					Obs per group: min =	19
F(20, 47) = 8326.89					avg =	19.00
Prob > F = 0.000					max =	19
Variables	Coefficient	Robust Std.Error	t-value	p-value	[95%Conf Interval]	
$lnSmooth\ Cases_{t-1}$	0.9654136***	0.0504846	19.12	0.000	0.8638516	1.066976
$\frac{S \cdot I_{t-7}}{N}$	-0.0430903*	0.0250197	-1.72	0.092	-0.0934235	0.0072429
day1	Omitted					
day2	-0.0490821	0.0332665	-1.48	0.147	-0.1160057	0.0178415
day3	-0.0474001	0.0359813	-1.32	0.194	-0.1197852	0.0249849
day4	-0.0334696	0.0407402	-0.82	0.415	-0.1154284	0.0484892
day5	0.0152501	0.0336896	0.45	0.653	-0.0525245	0.0830247
day6	-0.0399852	0.0293904	-1.36	0.180	-0.099111	0.0191407
day7	-0.0266217	0.0362769	-0.73	0.467	-0.0996014	0.046358
day8	0.0023998	0.0303308	0.08	0.937	-0.0586179	0.0634176
day9	-0.0115303	0.0249048	-0.46	0.646	-0.0616324	0.0385718
day10	-0.0072489	0.0283462	-0.26	0.799	-0.064274	0.0497762
day11	0.0062314	0.0282683	0.22	0.826	-0.0506371	0.0631
day12	-0.0117212	0.0231885	-0.51	0.616	-0.0583705	0.0349281
day13	0.0229812	0.0268062	0.86	0.396	-0.0309459	0.0769083
day14	0.0276396	0.0205234	1.35	0.185	-0.0136482	0.0689274
day15	0.0202754	0.0329532	0.62	0.541	-0.0460179	0.0865687
day16	0.0487122**	0.0233299	2.09	0.042	0.0017786	0.0956458
day17	0.0169012	0.0175791	0.96	0.341	-0.0184634	0.0522658
day18	Omitted					
day19	0.0114923	0.0179172	0.64	0.524	-0.0245523	0.047537
day20	0.0224447	0.0189249	1.19	0.242	-0.0156272	0.0605166
Constant	0.3909899	0.2637802	1.48	0.145	-0.1396674	0.9216472
*p<0.1, **p<0.05, ***p<0.01						
Arellano-Bond test for AR(1) in first differences: z = -2.43 Pr > z = 0.015						
Arellano-Bond test for AR(2) in first differences: z = 0.68 Pr > z = 0.499						
Sargan test of overid. restrictions: chi2(26) = 125.32					Prob > chi2 = 0.000	
Hansen test of overid. restrictions: chi2(26) = 36.97					Prob > chi2 = 0.075	

*Note:*Windmeijer corrected standard errors.

Table C 8

Period 9 Dynamic Panel-Data Estimation, Two-step System GMM

Group vaiable: country				Number of obs	=	874
Time variable:date				Number of groups	=	46
Number of instruments = 35				Obs per group: min =		19
F(20, 45) = 2730.99				avg =		19.00
Prob > F = 0.000				max =		19
Variables	Coefficient	Robust Std.Error	t-value	p-value	[95%Conf Interval]	
$lnSmooth\ Cases_{t-1}$	0.8833237***	0.0822324	10.74	0.000	0.7176991	1.048948
$\frac{S \cdot I_{t-7}}{N}$	-0.0417754	0.0498447	-0.84	0.406	-0.1421677	0.0586169
day1	Omitted					
day2	-0.0892263**	0.0438753	-2.03	0.048	-0.1775957	-0.0008569
day3	-0.0573442	0.0545449	-1.05	0.299	-0.1672031	0.0525148
day4	-0.0624677	0.0404966	-1.54	0.130	-0.144032	0.0190966
day5	-0.0919532**	0.0395991	-2.32	0.025	-0.1717098	-0.0121966
day6	-0.0712435*	0.0397569	-1.79	0.080	-0.151318	0.0088309
day7	-0.0528585	0.0315957	-1.67	0.101	-0.1164954	0.0107785
day8	-0.104178*	0.060203	-1.73	0.090	-0.2254331	0.017077
day9	-0.0633378	0.0385367	-1.64	0.107	-0.1409547	0.0142791
day10	-0.0894579***	0.027517	-3.25	0.002	-0.14488	-0.0340359
day11	-0.0533427	0.0365718	-1.46	0.152	-0.1270021	0.0203167
day12	-0.058533*	0.0312079	-1.88	0.067	-0.1213888	0.0043229
day13	-0.024741	0.0343088	-0.72	0.475	-0.0938424	0.0443604
day14	-0.0442208	0.0306223	-1.44	0.156	-0.1058974	0.0174557
day15	0.0210805	0.0405279	0.52	0.606	-0.0605468	0.1027078
day16	-0.0176047	0.0166825	-1.06	0.297	-0.051205	0.0159957
day17	-0.0047042	0.0192103	-0.24	0.808	-0.0433957	0.0339872
day18	Omitted					
day19	0.0292046	0.0222216	1.31	0.195	-0.0155521	0.0739613
day20	0.0071836	0.0254831	0.28	0.779	-0.044142	0.0585091
Constant	0.8735304	0.6197829	1.41	0.166	-0.3747765	2.121837
*p<0.1, **p<0.05, ***p<0.01						
Arellano-Bond test for AR(1) in first differences: z = -1.43 Pr > z = 0.154						
Arellano-Bond test for AR(2) in first differences: z = 0.21 Pr > z = 0.837						
Sargan test of overid. restrictions: chi2(14) = 83.42				Prob > chi2 = 0.000		
Hansen test of overid. restrictions: chi2(14) = 21.50				Prob > chi2 = 0.089		

*Note:*Windmeijer corrected standard errors.

Table C 9

Period 10 Dynamic Panel-Data Estimation, Two-step System GMM

Group vaiable: country				Number of obs =		1007
Time variable:date				Number of groups =		53
Number of instruments = 47				Obs per group: min =		19
F(20, 52) = 104846.86					avg =	19.00
Prob > F = 0.000					max =	19
Variables	Coefficient	Robust Std.Error	t-value	p-value	[95%Conf	Interval]
$lnSmooth\ Cases_{t-1}$	1.015545***	0.0571499	17.77	0.000	0.9008656	1.130225
$\frac{S \cdot I_{t-7}}{N}$	-0.0361971	0.0284019	-1.27	0.208	-0.0931897	0.0207955
day1	Omitted					
day2	-0.0065652	0.0207266	-0.32	0.753	-0.0481563	0.0350258
day3	0.0042055	0.022651	0.19	0.853	-0.041247	0.0496581
day4	-0.0075527	0.0157636	-0.48	0.634	-0.0391846	0.0240792
day5	-0.0119348	0.0153196	-0.78	0.439	-0.0426759	0.0188062
day6	-0.0094155	0.0166059	-0.57	0.573	-0.0427377	0.0239066
day7	-0.0073243	0.0172918	-0.42	0.674	-0.0420229	0.0273743
day8	-0.0065197	0.0197892	-0.33	0.743	-0.0462295	0.0331902
day9	0.0056002	0.0165829	0.34	0.737	-0.0276758	0.0388762
day10	-0.0041454	0.0174736	-0.24	0.813	-0.0392088	0.0309179
day11	0.0048453	0.0219091	0.22	0.826	-0.0391186	0.0488092
day12	-0.0109621	0.0184057	-0.6	0.554	-0.0478958	0.0259716
day13	-0.0189921	0.0215131	-0.88	0.381	-0.0621613	0.0241771
day14	-0.0084805	0.0172182	-0.49	0.624	-0.0430313	0.0260703
day15	0.0106042	0.0168517	0.63	0.532	-0.0232112	0.0444195
day16	-0.0102398	0.0182652	-0.56	0.577	-0.0468916	0.026412
day17	0.000921	0.0198109	0.05	0.963	-0.0388326	0.0406745
day18	Omitted					
day19	-0.0110873	0.0129023	-0.86	0.394	-0.0369778	0.0148031
day20	-0.0055021	0.0102563	-0.54	0.594	-0.026083	0.0150787
Constant	0.1566851	0.2063173	0.76	0.451	-0.2573209	0.5706911
*p<0.1, **p<0.05, ***p<0.01						
Arellano-Bond test for AR(1) in first differences: z = -2.08 Pr > z = 0.038						
Arellano-Bond test for AR(2) in first differences: z = 0.69 Pr > z = 0.492						
Sargan test of overid. restrictions: chi2(26) = 200.45					Prob > chi2 =	0.000
Hansen test of overid. restrictions: chi2(26) = 29.97					Prob > chi2 =	0.269

Note: Windmeijer corrected standard errors.

Table C 10

Period 11 Dynamic Panel-Data Estimation, Two-step System GMM

Group vaiable: country				Number of obs =		1140
Time variable:date				Number of groups =		60
Number of instruments = 47				Obs per group: min =		19
F(20, 59) = 12112.88					avg =	19.00
Prob > F = 0.000					max =	19
Variables	Coefficient	Robust Std.Error	t-value	p-value	[95%Conf	Interval]
$lnSmooth\ Cases_{t-1}$	0.9919995***	0.0402936	24.62	0.000	0.9113722	1.072627
$\frac{S \cdot I_{t-7}}{N}$	-0.041476	0.0278205	-1.49	0.141	-0.0971447	0.0141926
day1	Omitted					
day2	-0.0225032	0.0161253	-1.4	0.168	-0.0547698	0.0097635
day3	Omitted					
day4	-0.0207445	0.013707	-1.51	0.136	-0.0481722	0.0066832
day5	-0.0054878	0.019216	-0.29	0.776	-0.043939	0.0329633
day6	0.0164454	0.0285312	0.58	0.567	-0.0406454	0.0735362
day7	0.0062616	0.0371059	0.17	0.867	-0.0679871	0.0805103
day8	0.0385704	0.0312096	1.24	0.221	-0.0238798	0.1010206
day9	0.0168415	0.0191319	0.88	0.382	-0.0214412	0.0551243
day10	0.0198531	0.0275426	0.72	0.474	-0.0352596	0.0749658
day11	0.032265	0.0250159	1.29	0.202	-0.0177917	0.0823217
day12	0.0183563	0.0233587	0.79	0.435	-0.0283843	0.0650968
day13	-0.0016128	0.0343693	-0.05	0.963	-0.0703856	0.0671599
day14	0.0169286	0.0262606	0.64	0.522	-0.0356187	0.0694759
day15	0.013618	0.0302889	0.45	0.655	-0.04699	0.0742259
day16	0.0246363	0.0353722	0.7	0.489	-0.0461433	0.0954158
day17	0.0292569	0.0343971	0.85	0.398	-0.0395715	0.0980854
day18	0.0428228	0.0404354	1.06	0.294	-0.0380882	0.1237338
day19	0.0347115	0.0409561	0.85	0.400	-0.0472415	0.1166644
day20	0.0454536	0.0458684	0.99	0.326	-0.0463289	0.1372361
Constant	0.3208122	0.2885901	1.11	0.271	-0.2566553	0.8982796
*p<0.1, **p<0.05, ***p<0.01						
Arellano-Bond test for AR(1) in first differences: z = -2.14 Pr > z = 0.032						
Arellano-Bond test for AR(2) in first differences: z = 0.35 Pr > z = 0.724						
Sargan test of overid. restrictions: chi2(26) = 137.54					Prob > chi2 =	0.000
Hansen test of overid. restrictions: chi2(26) = 48.13					Prob > chi2 =	0.005

Note: Windmeijer corrected standard errors.

Table C 11

Period 12 Dynamic Panel-Data Estimation, Two-step System GMM

Group vaiable: country	Number of obs = 1045
Time variable:date	Number of groups = 55
Number of instruments = 47	Obs per group: min = 19
F(20, 54) = 23934.26	avg = 19.00
Prob > F = 0.000	max = 19

Variables	Coefficient	Robust Std.Error	t-value	p-value	[95%Conf	Interval]
$lnSmooth\ Cases_{t-1}$	0.9871144***	0.0715235	13.8	0.000	0.8437184	1.13051
$\frac{S \cdot I_{t-7}}{N}$	-0.0334594	0.0443421	-0.75	0.454	-0.12236	0.0554412
day1	Omitted					
day2	0.0167502	0.0406176	0.41	0.682	-0.0646831	0.0981835
day3	0.0045377	0.0330389	0.14	0.891	-0.0617012	0.0707766
day4	0.01266	0.0346375	0.37	0.716	-0.0567841	0.0821041
day5	0.0170268	0.0284153	0.6	0.552	-0.0399424	0.073996
day6	0.0166354	0.0280942	0.59	0.556	-0.0396902	0.0729609
day7	-0.00342	0.023472	-0.15	0.885	-0.0504785	0.0436386
day8	-0.004637	0.0229088	-0.2	0.840	-0.0505664	0.0412925
day9	0.0053468	0.0325909	0.16	0.870	-0.059994	0.0706876
day10	-0.0059603	0.0162985	-0.37	0.716	-0.0386368	0.0267163
day11	0.0373738	0.02937	1.27	0.209	-0.0215095	0.0962572
day12	-0.0134825	0.0238161	-0.57	0.574	-0.061231	0.0342659
day13	-0.0220972	0.0188113	-1.17	0.245	-0.0598115	0.0156172
day14	0.0251427	0.0245728	1.02	0.311	-0.0241228	0.0744081
day15	0.0094108	0.0213162	0.44	0.661	-0.0333257	0.0521473
day16	-0.0072999	0.0157608	-0.46	0.645	-0.0388985	0.0242987
day17	0.0224213	0.020949	1.07	0.289	-0.0195789	0.0644215
day18	Omitted					
day19	0.0109694	0.0106144	1.03	0.306	-0.0103112	0.0322499
day20	0.0501969	0.0389364	1.29	0.203	-0.027866	0.1282598
Constant	0.3363474	0.3419764	0.98	0.330	-0.349274	1.021969

*p<0.1, **p<0.05, ***p<0.01

Arellano-Bond test for AR(1) in first differences: z = -2.86 Pr > z = 0.004

Arellano-Bond test for AR(2) in first differences: z = -1.31 Pr > z = 0.191

Sargan test of overid. restrictions: chi2(26) = 272.97 Prob > chi2 = 0.000

Hansen test of overid. restrictions: chi2(26) = 40.90 Prob > chi2 = 0.032

Note: Windmeijer corrected standard errors.

Table C 12

Period 13 Dynamic Panel-Data Estimation, Two-step System GMM

Group vaiable: country				Number of obs =		969
Time variable:date				Number of groups =		51
Number of instruments = 47				Obs per group: min =		19
F(20, 50) = 271669.86					avg =	19.00
Prob > F = 0.000					max =	19
Variables	Coefficient	Robust Std.Error	t-value	p-value	[95%Conf	Interval]
$lnSmooth\ Cases_{t-1}$	1.053443***	0.0292451	36.02	0.000	0.9947021	1.112183
$\frac{S \cdot I_{t-7}}{N}$	-0.0444098*	0.025228	-1.76	0.084	-0.0950817	0.0062621
day1	Omitted					
day2	0.013249	0.0115481	1.15	0.257	-0.0099461	0.0364441
day3	Omitted					
day4	-0.0028512	0.0087409	-0.33	0.746	-0.0204077	0.0147054
day5	0.0163346	0.0156985	1.04	0.303	-0.0151968	0.047866
day6	0.0051164	0.0111914	0.46	0.650	-0.0173623	0.027595
day7	0.0230066	0.0154433	1.49	0.143	-0.0080123	0.0540254
day8	0.0085777	0.0153872	0.56	0.580	-0.0223285	0.0394838
day9	0.0064854	0.0149101	0.43	0.665	-0.0234624	0.0364332
day10	0.012365	0.0125922	0.98	0.331	-0.0129272	0.0376572
day11	0.0180236*	0.0104135	1.73	0.090	-0.0028926	0.0389398
day12	-0.0066884	0.0169343	-0.39	0.695	-0.0407019	0.0273251
day13	0.0003022	0.0126435	0.02	0.981	-0.0250931	0.0256974
day14	-0.0104214	0.0141308	-0.74	0.464	-0.0388041	0.0179612
day15	0.006517	0.018723	0.35	0.729	-0.0310892	0.0441233
day16	-0.0002719	0.0106149	-0.03	0.980	-0.0215926	0.0210488
day17	0.0093938	0.0158894	0.59	0.557	-0.022521	0.0413086
day18	-0.0034345	0.0092564	-0.37	0.712	-0.0220265	0.0151575
day19	0.0064718	0.0135981	0.48	0.636	-0.0208409	0.0337844
day20	0.0174646	0.0175631	0.99	0.325	-0.0178119	0.0527412
Constant	-0.05102	0.0703967	-0.72	0.472	-0.1924161	0.090376
*p<0.1, **p<0.05, ***p<0.01						
Arellano-Bond test for AR(1) in first differences: z = -2.47 Pr > z = 0.013						
Arellano-Bond test for AR(2) in first differences: z = 0.07 Pr > z = 0.940						
Sargan test of overid. restrictions: chi2(26) = 183.15					Prob > chi2 =	0.000
Hansen test of overid. restrictions: chi2(26) = 27.26					Prob > chi2 =	0.396

Note: Windmeijer corrected standard errors.

Table C 13

Period 14 Dynamic Panel-Data Estimation, Two-step System GMM

Group vaiable: country				Number of obs =		950
Time variable:date				Number of groups =		50
Number of instruments = 47				Obs per group: min =		19
F(20, 49) = 18380.60				avg =		19.00
Prob > F = 0.000				max =		19
Variables	Coefficient	Robust Std.Error	t-value	p-value	[95%Conf Interval]	
$lnSmooth\ Cases_{t-1}$	0.8902508***	0.0272929	32.62	0.000	0.8354036	0.945098
$\frac{S \cdot I_{t-7}}{N}$	0.0505348**	0.0245372	2.06	0.045	0.0012254	0.0998441
day1	Omitted					
day2	0.0024513	0.019302	0.13	0.899	-0.0363375	0.0412401
day3	-0.0066961	0.0155579	-0.43	0.669	-0.0379609	0.0245687
day4	Omitted					
day5	0.0227904	0.0279796	0.81	0.419	-0.0334367	0.0790175
day6	-0.0033917	0.0167147	-0.2	0.840	-0.0369811	0.0301978
day7	0.023941	0.019362	1.24	0.222	-0.0149685	0.0628505
day8	0.0281735	0.0211691	1.33	0.189	-0.0143674	0.0707143
day9	0.0188926	0.0183747	1.03	0.309	-0.0180327	0.0558178
day10	0.0269144*	0.0147756	1.82	0.075	-0.0027782	0.056607
day11	-0.0076703	0.0480976	-0.16	0.874	-0.104326	0.0889854
day12	0.0097096	0.0197615	0.49	0.625	-0.0300025	0.0494218
day13	0.0342989*	0.018949	1.81	0.076	-0.0037804	0.0723783
day14	0.0561228	0.0610505	0.92	0.362	-0.0665628	0.1788085
day15	0.0474541	0.0351369	1.35	0.183	-0.0231562	0.1180644
day16	0.0491306	0.0297021	1.65	0.104	-0.010558	0.1088192
day17	0.0407706*	0.0239073	1.71	0.094	-0.007273	0.0888141
day18	0.0483807*	0.0266631	1.81	0.076	-0.0052008	0.1019621
day19	0.0405243*	0.0237785	1.7	0.095	-0.0072604	0.088309
day20	0.0613574**	0.0289963	2.12	0.039	0.0030871	0.1196276
Constant	0.420816**	0.2093528	2.01	0.050	0.0001058	0.8415263
*p<0.1, **p<0.05, ***p<0.01						
Arellano-Bond test for AR(1) in first differences: z = -1.72 Pr > z = 0.086						
Arellano-Bond test for AR(2) in first differences: z = 1.34 Pr > z = 0.181						
Sargan test of overid. restrictions: chi2(26) = 134.64					Prob > chi2 = 0.000	
Hansen test of overid. restrictions: chi2(26) = 32.34					Prob > chi2 = 0.182	

Note: Windmeijer corrected standard errors.

Table C 14

Period 15 Dynamic Panel-Data Estimation, Two-step System GMM

Group vaiable: country				Number of obs =		836
Time variable:date				Number of groups =		44
Number of instruments = 35				Obs per group: min =		19
F(20, 43) = 25237.04				avg =		19.00
Prob > F = 0.000				max =		19
Variables	Coefficient	Robust Std.Error	t-value	p-value	[95%Conf Interval]	
$lnSmooth\ Cases_{t-1}$	0.9899477***	0.0301045	32.88	0.000	0.9292362	1.050659
$\frac{S \cdot I_{t-7}}{N}$	-0.0060647	0.0254645	-0.24	0.813	-0.0574187	0.0452893
day1	Omitted					
day2	0.0132913	0.0168673	0.79	0.435	-0.0207249	0.0473075
day3	Omitted					
day4	0.0075828	0.0110297	0.69	0.495	-0.0146607	0.0298263
day5	0.010381	0.0105131	0.99	0.329	-0.0108207	0.0315826
day6	0.0047652	0.0103652	0.46	0.648	-0.0161381	0.0256686
day7	0.0067958	0.013815	0.49	0.625	-0.0210648	0.0346563
day8	-0.0088002	0.0158899	-0.55	0.583	-0.0408453	0.0232449
day9	-0.0622357***	0.0181147	-3.44	0.001	-0.0987674	-0.0257039
day10	-0.0436617**	0.0182553	-2.39	0.021	-0.080477	-0.0068464
day11	0.0051602	0.0188174	0.27	0.785	-0.0327886	0.0431091
day12	-0.0089784	0.0209632	-0.43	0.671	-0.0512546	0.0332979
day13	0.0534389**	0.022852	2.34	0.024	0.0073535	0.0995244
day14	0.0245583	0.0181179	1.36	0.182	-0.0119799	0.0610965
day15	-0.0261269	0.0229138	-1.14	0.261	-0.0723369	0.0200831
day16	0.0523572**	0.0212648	2.46	0.018	0.0094727	0.0952416
day17	0.025993	0.0203961	1.27	0.209	-0.0151396	0.0671256
day18	0.0228035	0.0194266	1.17	0.247	-0.016374	0.0619809
day19	0.0237749	0.0188434	1.26	0.214	-0.0142264	0.0617763
day20	0.03119*	0.017232	1.81	0.077	-0.0035617	0.0659417
Constant	0.1304271	0.1008997	1.29	0.203	-0.0730565	0.3339106
*p<0.1, **p<0.05, ***p<0.01						
Arellano-Bond test for AR(1) in first differences: z = -2.92 Pr > z = 0.004						
Arellano-Bond test for AR(2) in first differences: z = -0.17 Pr > z = 0.867						
Sargan test of overid. restrictions: chi2(14) = 30.79					Prob > chi2 = 0.006	
Hansen test of overid. restrictions: chi2(14) = 10.03					Prob > chi2 = 0.760	

*Note:*Windmeijer corrected standard errors.

Table C 15

Period 16 Dynamic Panel-Data Estimation, Two-step System GMM

Group vaiable: country				Number of obs =		760
Time variable:date				Number of groups =		40
Number of instruments = 35				Obs per group: min =		19
F(20, 39) = 55077.24				avg =		19.00
Prob > F = 0.000				max =		19
Variables	Coefficient	Robust Std.Error	t-value	p-value	[95%Conf Interval]	
$lnSmooth\ Cases_{t-1}$	0.9826608***	0.0360479	27.26	0.000	0.9097471	1.055575
$\frac{S \cdot I_{t-7}}{N}$	0.030531	0.0297282	1.03	0.311	-0.0295999	0.090662
day1	Omitted					
day2	-0.0201233	0.0240491	-0.84	0.408	-0.0687672	0.0285206
day3	0.0155504	0.021626	0.72	0.476	-0.0281922	0.0592931
day4	Omitted					
day5	-0.0191982	0.0197696	-0.97	0.337	-0.059186	0.0207897
day6	-0.040774*	0.0240869	-1.69	0.098	-0.0894944	0.0079465
day7	-0.0357031*	0.0192498	-1.85	0.071	-0.0746395	0.0032332
day8	-0.0540226**	0.023213	-2.33	0.025	-0.1009753	-0.0070698
day9	-0.0423814	0.0267989	-1.58	0.122	-0.0965874	0.0118245
day10	-0.0577286*	0.0321856	-1.79	0.081	-0.1228301	0.0073729
day11	-0.0582783	0.0361971	-1.61	0.115	-0.1314939	0.0149372
day12	-0.0760414***	0.0277492	-2.74	0.009	-0.1321695	-0.0199133
day13	-0.0818086**	0.0348726	-2.35	0.024	-0.1523452	-0.0112721
day14	-0.063495**	0.0296364	-2.14	0.038	-0.1234403	-0.0035496
day15	-0.0561366*	0.0310914	-1.81	0.079	-0.1190249	0.0067517
day16	-0.0670601**	0.0292453	-2.29	0.027	-0.1262142	-0.007906
day17	-0.0814956**	0.0386345	-2.11	0.041	-0.1596413	-0.00335
day18	-0.0748933**	0.0341201	-2.19	0.034	-0.1439078	-0.0058788
day19	-0.0743978**	0.0310832	-2.39	0.022	-0.1372695	-0.0115261
day20	-0.0742514**	0.0328453	-2.26	0.029	-0.1406872	-0.0078155
Constant	-0.0148815	0.0962927	-0.15	0.878	-0.209652	0.1798889
*p<0.1, **p<0.05, ***p<0.01						
Arellano-Bond test for AR(1) in first differences: z = -2.35 Pr > z = 0.019						
Arellano-Bond test for AR(2) in first differences: z = 1.46 Pr > z = 0.144						
Sargan test of overid. restrictions: chi2(14) = 39.74				Prob > chi2 = 0.000		
Hansen test of overid. restrictions: chi2(14) = 16.09				Prob > chi2 = 0.308		

Note: Windmeijer corrected standard errors.

Table C 16

Period 18 Dynamic Panel-Data Estimation, Two-step System GMM

Group vaiable: country				Number of obs	=	798
Time variable:date				Number of groups	=	42
Number of instruments = 35				Obs per group: min	=	19
F(20, 41) = 3333.28				avg	=	19.00
Prob > F = 0.000				max	=	19

Variables	Coefficient	Robust Std.Error	t-value	p-value	[95%Conf	Interval]
$lnSmooth\ Cases_{t-1}$	1.16224***	0.3307167	3.51	0.001	0.4943439	1.830136
$\frac{S \cdot I_{t-7}}{N}$	-0.2860568	0.4349078	-0.66	0.514	-1.164371	0.5922573
day1	Omitted					
day2	-0.0126038	0.0202513	-0.62	0.537	-0.0535021	0.0282946
day3	0.0032404	0.0123509	0.26	0.794	-0.0217029	0.0281836
day4	Omitted					
day5	-0.0111948	0.0120104	-0.93	0.357	-0.0354503	0.0130607
day6	-0.0092289	0.0149499	-0.62	0.540	-0.0394208	0.020963
day7	-0.0085037	0.0198735	-0.43	0.671	-0.0486391	0.0316318
day8	0.0204353	0.0329776	0.62	0.539	-0.0461643	0.087035
day9	-0.0029054	0.0350615	-0.08	0.934	-0.0737135	0.0679027
day10	-0.0067114	0.0319274	-0.21	0.835	-0.0711902	0.0577673
day11	-0.0083149	0.0317461	-0.26	0.795	-0.0724275	0.0557977
day12	-0.0068967	0.0381126	-0.18	0.857	-0.0838667	0.0700732
day13	-0.0119947	0.0381136	-0.31	0.755	-0.0889667	0.0649773
day14	0.0128772	0.03354	0.38	0.703	-0.0548582	0.0806125
day15	0.0137158	0.0239217	0.57	0.570	-0.0345951	0.0620267
day16	0.0025476	0.0246817	0.1	0.918	-0.0472981	0.0523932
day17	0.0048499	0.0219405	0.22	0.826	-0.0394598	0.0491595
day18	0.0125013	0.0293306	0.43	0.672	-0.046733	0.0717356
day19	0.0064394	0.0370376	0.17	0.863	-0.0683596	0.0812384
day20	0.0519518*	0.0283737	1.83	0.074	-0.00535	0.1092537
Constant	0.7887529	0.704078	1.12	0.269	-0.6331614	2.210667

*p<0.1, **p<0.05, ***p<0.01

Arellano-Bond test for AR(1) in first differences: z = -1.42 Pr > z = 0.157

Arellano-Bond test for AR(2) in first differences: z = 0.40 Pr > z = 0.689

Sargan test of overid. restrictions: chi2(14) = 254.95 Prob > chi2 = 0.000

Hansen test of overid. restrictions: chi2(14) = 25.24 Prob > chi2 = 0.032

Note: Windmeijer corrected standard errors.

Table C 17

Countries Top Half Average of Index Score for the First 9 Periods

Country	index1	index2	index3	index4	index5	index6	index8	index9
United States	100	91.59634			97.54026	100		
United Kingdom	74.67934	72.85466					72.98646	77.53062
Germany	86.97035				61.46999		73.22344	
Italy	88.89655						62.60851	75.45399
Spain	96.91524					53.71451	92.65199	99.14301
Russian Federation	34.18534	95.66348	100					91.93066
France	80.66085					50.66846	81.48212	93.27737
Netherlands	59.30122						66.11433	65.67075
Brazil	45.34751	77.38309	95.78318	100	100	95.5909		
Peru	25.81118	83.08825	86.93548	83.03315			96.63506	
Poland	34.68992	50.80363			60.74635		67.6259	
Bangladesh		100	71.36206	73.77283	82.6039			
Czech Republic	40.2746				46.28507	39.63263	54.27796	62.63303
Iran, Islamic Rep	74.31667		80.28765	73.33022	77.62014			
Ukraine	14.91313	58.98909	69.51725		68.98729		77.51298	82.09132
Argentina	20.10859	34.95253	57.26982	64.1552	75.28187	71.54788	93.67226	100
South Africa	26.93152	40.108	65.23442	70.37049	84.41541	84.21703		
Colombia	16.83539	44.94099	65.54433	66.28092	78.10873	73.65138	100	
Chile	36.66724	50.14138	75.76649	85.05121	90.72313			79.01884
Romania	31.31817	48.8689			59.2445	51.69234		74.00689
Switzerland	64.19918				36.29828	37.92731	52.97722	58.09768
Mexico	26.71215	62.96653	79.6379	77.89752	83.71732	78.11761		
Belgium	63.04816					35.67706		63.50534
Sweden	38.92207	53.4118	72.07196	55.86249	72.13013		57.22315	
Indonesia	28.70215	53.40869	66.67068	60.2221	71.99448	64.6496	79.40004	84.80367
Belarus		82.49369	75.85056					50.29028
Austria	56.63255				38.43577	35.39202	52.30163	56.66902
Ecuador	38.68133	49.52193			69.2254	57.048	71.89116	
Israel	45.93945			22.77267	61.69388	62.06484		80.30147
Nicaragua				75.15038			29.19558	
Serbia	23.2529	58.97532			50.60582	50.06603		
Armenia	14.06782		51.73147	56.73699	65.82103			
Ireland	40.49849	60.84084				16.44452	44.77586	45.67264
Portugal	53.96225				60.09243	48.72091	52.2733	57.75641
Ghana		44.71531	56.53209		62.39083	54.36323		
St Lucia								
Honduras			46.43171	44.23744	63.36833	56.53338		66.69325
Moldova	7.474084	41.41898	55.047	44.88427	62.00947		59.59774	62.50986
Denmark	29.71061				41.67178		47.41422	46.99959
Tanzania		46.3428						
Kenya			34.42303	41.42376	52.63849	47.87309		
Timor-Leste		0						
Kazakhstan	8.903414	45.12897	59.42444	55.99556	62.74087	65.94994		
Kyrgyz Republic		26.8474		32.74058	49.42048	58.59876		
Croatia	18.89698				26.47946	34.845	47.31076	55.59253

Note: The Countries are sorted by their average score for the whole year, 16 periods.

Table C 18

Countries Lower Half of Average Index Score for the First 9 Periods

Country	index1	index2	index3	index4	index5	index6	index8	index9
Guatemala		33.75514	41.52956	55.6843	64.88699	58.81288		
Ethiopia		9.387129	19.41716	37.77556	57.66255		71.35484	
Cote d'Ivoire		34.28471		30.64332	64.17362			39.68425
Hungary	10.57538	37.99684				14.43739	32.32655	50.45178
Bulgaria	4.28911	23.90775	45.51708		57.23001	44.52654		46.58903
Slovak Republic	3.861084	33.69337			20.13881	20.42804	34.1846	41.60194
Costa Rica	0			19.41044	49.97545	50.77258	66.78313	71.41395
Paraguay		11.05724	31.72015			38.97647	59.25424	66.49852
Mongolia				32.13383				
Norway	40.57414				35.03672		37.96978	38.6735
Zimbabwe				30.22886		26.45451		40.79307
Malaysia	37.96921			33.9123				17.72676
Albania		22.89241		23.60246	45.43304	34.38522	48.67152	
Georgia		20.56005		11.92277			19.45632	22.28426
Finland	21.50187	40.39006					29.33028	26.81517
Myanmar		16.05895					1.123229	38.07684
Malta					20.23933		37.64399	
Zambia			23.88328			30.42744		
El Salvador		22.82564	39.70111	36.91714	50.6113	47.43818		
Eswatini			23.46692		39.53707	28.83748		
Slovenia	12.46084				26.00868	22.24131	25.96688	31.01879
Maldives		32.42987	39.91537	28.40437		22.39297	47.44077	
Lithuania	12.45375					4.903337	27.70438	
Malawi			7.328374	24.18923		36.34552		
Luxembourg	33.44514				23.18214	30.86157		16.00392
Uganda			12.80853	30.5249			32.4915	44.85923
Mozambique			13.01657	16.4592	42.91776	21.97997	39.61882	40.53231
Gambia, The					0		44.97623	
Tunisia	3.555373			2.639524	18.46151	5.578021	40.43607	49.3424
Australia	44.87712				31.49658	41.43899		
Bhutan				0			0	
Cyprus						5.631443	20.70773	
Cabo Verde		35.36012	25.91571		39.18362	27.59052	36.06981	36.1698
Rwanda			23.14802	4.548429	41.02317	24.47789	29.99169	
Benin		5.99917	22.8239		42.72754			
Uruguay	4.612805					7.236036		
Niger					30.87022			
Sri Lanka		14.56055	38.86097	35.81762		30.77986		15.26357
Latvia	6.728534					0		6.093617
Burkina Faso			27.04916			15.57071	13.34442	12.55337
Estonia	14.55809			8.506961		2.640237		22.21148
Tajikistan			28.54819	49.06974				
Togo			17.16367				21.07288	
Iceland	21.60278						14.20569	
Comoros			0	0.2867699	34.42521			0
Vietnam			3.324317		15.83187			
Mauritius								

Note: The Countries are sorted by their average score for the whole year, 16 periods.

Table C 19

Countries Top Half Average of Index Score for the Last 9 Periods

Country	index10	index11	index12	index13	index14	index15	index16	index18
United States	100	100	100	0	100	80.04469		
United Kingdom	86.67609	93.24398	86.13663		76.71565	88.72009		
Germany	62.65204	83.03051	87.18504		78.34021			82.76276
Italy	56.79073	87.16759	92.86167			57.64461		87.81085
Spain	79.86845	87.32655	85.85828		65.89079	69.31929	16.91256	
Russian Federation	80.64542	90.21741	84.30991	6.911328	79.44219			
France	89.65102	93.25098	95.81923		69.93037	59.90916	4.560553	90.97735
Netherlands	82.05569	85.29512			71.12441			75.0164
Brazil				16.76929	86.27011		0	100
Peru							37.24016	
Poland	69.20515	85.8428	88.7921					81.6794
Bangladesh		68.87618	60.48722	23.68201				54.86227
Czech Republic	78.45513	86.81367	79.71313		64.58966	66.71272		82.1006
Iran, Islamic Rep	73.33533	78.53249	78.78126	14.75424			2.669834	82.9379
Ukraine	69.8325	81.47775	78.54623	13.78029				77.97387
Argentina	81.57432	88.06972				60.77386	2.362921	
South Africa		70.53415		30.32489	72.1344	72.88203		
Colombia		82.10969	78.1614		68.68374	61.68451	1.244811	
Chile					53.09615	51.18309	16.90051	74.99968
Romania	56.4432	78.47884	77.35709					72.24917
Switzerland		80.29594	79.10561		61.49139			63.29997
Mexico			72.78829	24.54667	70.93584		15.26281	
Belgium	72.85023	90.06204			55.55605		16.19629	69.29522
Sweden	49.20592	64.67804	72.53844	17.93888	65.36494			73.42297
Indonesia	71.87353			18.74942	66.31334	55.29667	11.92039	
Belarus	40.12645	62.52347	56.538	29.29111	54.38322			
Austria	53.13675	70.00654	77.62783					66.84326
Ecuador						43.87172	27.22622	64.55657
Israel	87.49634			27.99304	59.2232	72.71577	4.217268	
Nicaragua								
Serbia		53.73611	71.6836	38.58279				70.44782
Armenia	47.21125	69.23136	64.99556					46.75887
Ireland	47.58007	68.64516			36.63283	100		
Portugal	52.58869	72.48584	73.22562	7.156808		56.68739	21.67463	
Ghana			36.54087		28.4809		70.39552	
St Lucia			14.25042			36.56273	100	
Honduras	40.82696	62.8951		36.133		33.33385	37.92342	
Moldova	44.67702	63.2089	54.73363	27.33925	50.3949			61.14214
Denmark	51.58544		61.34262	22.12899	65.49825			55.16057
Tanzania								
Kenya	25.86868	60.90854	58.74918					47.61755
Timor-Leste							90.76302	
Kazakhstan		54.13676	56.90686	24.26718		32.64366	31.72872	
Kyrgyz Republic	31.9843	60.0765	50.73206					
Croatia		65.96077	68.75903	23.2794				52.67797

Note: The Countries are sorted by their average score for the whole year, 16 periods.

Table C 20

Countries Lower Half of Average Index Score for the Last 9 Periods

Country	index10	index11	index12	index13	index14	index15	index16	index18
Guatemala	43.68452			23.32037	40.82197		30.64589	
Ethiopia		64.03316		28.28687				60.71014
Cote d'Ivoire				58.22852	14.87251	42.92406	58.63147	48.75468
Hungary	58.7103	68.7812	74.55943	11.55102				70.36143
Bulgaria	27.87234	64.78999	72.03201	11.42268				63.54094
Slovak Republic	56.13684	70.70621	66.07867		58.56588	46.94082		
Costa Rica	49.98733			23.75401		34.05978		
Paraguay				29.21925	45.97916		20.32858	62.63565
Mongolia		0		98.50591		37.83141		33.84828
Norway	18.54003	48.66364	55.70412			35.98283		50.92763
Zimbabwe		30.21711		67.20298	25.13649	58.1576		
Malaysia	38.54256	68.05396	58.50297	22.14147	50.78557	48.028	21.16461	
Albania		54.84645	49.2838	30.62167	45.37841		28.27894	
Georgia	73.33904	67.59219	67.92956	20.27256				
Finland	33.10281	54.30997		44.55356			31.17982	55.16948
Myanmar	76.02407	68.43817		23.66212				
Malta		51.38878	37.86536			29.75657		45.5248
Zambia		43.25296	32.15673		22.21178	66.6907	39.56789	
El Salvador	27.30452	49.48132	41.5726	32.0377	34.6176		22.82146	
Eswatini				63.64138	20.0566	43.53043		
Slovenia	42.19846	64.88043	64.26784	19.11075	50.80479	42.62555		
Maldives			27.64472	41.15985		19.68074	59.15355	43.52826
Lithuania	40.43776	54.33684	64.47588	25.40146	59.37579			
Malawi					0	63.4086	76.08871	
Luxembourg	21.63928	53.83241	60.43991	27.2528				44.31402
Uganda	29.30863		44.78485	33.07666	44.77116			
Mozambique	42.55167				24.63505	36.74254	61.06903	
Gambia, The						24.18132	66.28529	
Tunisia	67.89178	70.17847			47.96876	48.49435	14.84429	
Australia				51.79821		17.77143		13.62336
Bhutan	0			100		66.86694		
Cyprus	28.21573	46.51606	44.7187	33.19359	39.60196	36.3867		43.31825
Cabo Verde	19.07032	45.81834			20.14324		45.16365	33.9334
Rwanda				71.65908	26.29723	18.19908	57.8413	
Benin		30.43013	17.47138				78.13612	
Uruguay		39.96512	28.78182	54.01491	45.67299	37.41993	19.37568	57.74633
Niger			0	82.91125	19.82761		37.51403	25.34689
Sri Lanka	2.34642	57.91228	56.18095	26.78744	47.56506		28.93813	
Latvia	27.98405	52.39668	49.46806	41.41004	44.78202	37.30672		
Burkina Faso		32.51759		62.75644	42.4525			
Estonia	17.48866		45.16092	40.37761	43.86007			60.06519
Tajikistan	9.600727				22.27156			
Togo		32.62452	21.54549	47.37717	9.448673	4.052588	49.42588	37.91129
Iceland	47.59446	45.81205				0		
Comoros			12.47965			36.92482	80.84599	
Vietnam						12.38959		
Mauritius			13.23096					0

Note: The Countries are sorted by their average score for the whole year, 16 periods.

Appendix D Cross Sectional Analysis on Indices

Table D 1

Regressions on Average of the Indices

	Economic						Health		
Model	1	2	3	4	5	6	7	8	9
ln Economic strength	2.81109	3.10723*	7.88521***	2.6611	1.54461	2.91009*			
	(1.7573)	(1.7125)	(1.8062)	(1.7775)	1.5371	(1.5335)			
ln Life Expectancy							25.1129	15.6571	12.1839
							(21.679)	(24.9408)	(27.378)
ln Population density	1.2512	3.4697***	1.26689	1.24203	1.2156	1.37363	1.03075	1.22214	1.13886
	(1.0446)	(1.1248)	(1.0128)	(1.0346)	(1.0214)	(1.1126)	(1.0519)	(1.1065)	(1.10004)
ln Migrant Stock	1.78562	2.18419	2.53519*	1.77877	2.54583*	3.6869**	2.10344	2.05705	1.79772
	(1.4941)	(1.4676)	(1.4155)	(1.5183)	(1.5187)	(1.6987)	(1.3233)	(1.3533)	(1.4756)
ln Total Population	4.32783	4.0102**	3.7481**	4.2240**	3.84828**	4.7388***	4.0973***	4.24563***	4.37212***
	(1.6584)	(1.6287)	(1.5657)	(1.6097)	(1.6859)	(1.5309)	(1.5047)	(1.5721)	(1.5946)
%Urban Population	10.3476	6.85545	10.1589	10.285	6.80420	12.3933*	11.4512*	10.41096	9.40845
	(7.7933)	(7.9293)	(7.2988)	(7.8722)	(8.2799)	(6.3949)	(6.8635)	(7.0166)	(7.5673)
ln Medical Expenditure									2.04041
									(2.4433)
ln Physicians per 1000								1.32939	
								(1.3088)	
%Population over 65							3.23663	1.64913	.715974
							(5.2655)	(5.1301)	(5.3111)
ln Tourism				.203546					
				(1.1885)					
Governance			-42.5417***						
			(10.981)						
Gini index	5.13651	-4.52715**	3.17141	5.19745	9.56415	-5.63513***			
	(6.9487)	(1.9045)	(6.3999)	(7.0410)	(7.4738)	(1.8120)			
Poverty					-13.2889**				
					(6.0167)				
ln Migrant Stock · Gini						-5.75101***			
						(1.92457)			
ln Population Density · Gini		-6.72429***							
		(2.3657)							
Observations	92	90	92	92	92	90	92	92	92
R^2	0.5574	0.5921	0.6173	0.5576	0.575	0.6245	0.5561	0.5599	0.5594

Note: Robust standard errors in parentheses. Used variance inflation factor (VIF) for diagnosing collinearity in the models. No VIF values regarded as problematic. $*p < 0.1$, $**p < 0.05$, $***p < 0.01$

Table D 2

Regressions Period 1, 3/11/2020 to 3/30/2020

	Economic							Health			
Model	1	2	3	4	5	6	7	8	9	10	11
ln Economic strength	13.9388***	13.8412***	19.0612***	14.7741***	13.9636***	13.32959***					
	(3.55571)	(3.55617)	(4.514628)	(3.537854)	(3.54343)	(3.218146)					
ln Life Expectancy								236.501***	240.801***	142.686**	
								(67.21927)	(60.6886)	(61.81649)	
$lnStringency_{t-1}$							Not available				Not available
ln Population density	4.74876**	3.16184	4.82826***	4.93547**	4.74939**	4.994439***		3.65188*	3.1483	3.85214**	
	(1.775506)	(2.092988)	(1.7441)	(1.859596)	(1.83346)	(1.676688)		(1.943376)	(1.950887)	(1.568739)	
ln Migrant Stock	4.42379**	4.120985*	4.48527**	4.42245**	4.49203**	1.1504789		6.96801***	7.71572***	4.27004**	
	(2.061256)	(2.050043)	(2.009064)	(2.094318)	(2.163829)	(2.686527)		(1.64983)	(1.658606)	(1.759005)	
ln Total Population	7.96749***	8.184898***	7.67529***	8.93345***	7.86322***	8.74109***		6.22143***	5.01208**	7.98899***	
	(1.968313)	(2.03869)	(1.924515)	(2.225428)	(2.099127)	(2.092034)		(1.871764)	(2.096733)	(1.640331)	
%Urban Population	.540495	-.3445538	3.11945	-1.04204	-1.26512	2.5784815		-1.66788	.346401	-17.4551	
	(13.39503)	(14.04915)	(13.9609)	(13.96948)	(14.19235)	(14.44088)		(13.11086)	(13.18163)	(13.62944)	
ln Medical Expenditure										14.3048**	
										(5.403512)	
ln Physicians per 1000									-7.69002		
									(5.709819)		
%Population over 65								3.09637	10.2728	-10.1557	
								(11.13032)	(12.45664)	(10.43237)	
ln Tourism				-1.40153							
				(2.038017)							
Governance			-33.1529								
			(25.95575)								
Gini index	.896067	3.7117207	-.083551	-.698119	4.58419	6.7585024*					
	(11.10798)	(3.131395)	(10.50583)	(10.85005)	(18.08417)	(3.920366)					
Poverty					-23.2658						
					(66.64814)						
ln Migrant Stock · Gini						7.838199					
						(5.070308)					
ln Population Density · Gini		4.6237767									
		(4.167362)									
Observations	51	50	51	51	51	50		51	51	51	
R^2	0.7423	0.7451	0.7508	0.7448	0.7429	0.7536		0.7719	0.7793	0.8076	

Note: Robust standard errors in parentheses. Used variance inflation factor (VIF) for diagnosing collinearity in the models. No VIF values regarded as problematic. $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table D 3

Regressions Period 2, 3/31/2020 to 4/19/2020

	Economic							Health			
Model	1	2	3	4	5	6	7	8	9	10	11
ln Economic strength	1.88996	2.35665	7.30399*	4.4326	.69337	2.76108	2.82697				
	(-3.4427)	(3.4515)	(4.3061)	(3.7459)	(3.8317)	(3.5127)	(3.4431)				
ln Life Expectancy								95.8495***	85.4641*	141.616**	108.54**
								(34.962)	(43.903)	(58.769)	(40.177)
$\ln Stringency_{t-1}$							-1.38705				-5.85606
							(8.9493)				(8.7022)
ln Population density	4.95010	4.391899	4.88388	4.78635	4.90617	5.106585	3.4202	4.16367	4.28893	3.8605	3.6211
	(-3.5118)	(3.651066)	(3.5268)	(3.1351)	(3.5296)	(3.81578)	(4.3142)	(3.2939)	(3.3715)	(2.9693)	(4.4016)
ln Migrant Stock	3.5395	3.552146	3.9712	3.59865	4.1449	3.295945	3.15076	6.03911***	5.79035**	7.11972***	6.147**
	(2.5105)	(2.62668)	(2.4018)	(2.4699)	(2.6883)	(3.5343)	(2.8517)	(2.0636)	(2.1434)	(2.4908)	(2.68)
ln Total Population	6.29841**	6.34283**	5.80561**	7.77451**	5.96069**	6.46906**	8.537**	4.24001*	4.64324*	3.42948*	5.43105*
	(2.6564)	(2.69545)	(2.5926)	(2.9258)	(2.7646)	(2.75101)	(3.3835)	(2.1052)	(2.3127)	(1.9476)	(2.7944)
%Urban Population	42.3880**	39.1519*	44.2391**	46.2861**	38.5177*	37.8494*	37.0519*	26.4974	25.544	34.3131*	18.3836
	(19.997)	(19.4783)	(20.512)	(20.651)	(20.572)	(20.1986)	(20.909)	(17.791)	(17.497)	(18.307)	(20.466)
ln Medical Expenditure										-6.20753	
										6.036	
ln Physicians per 1000									1.37781		
									3.7062		
%Population over 65								-9.92597	-11.3823	-4.23608	-4.48277
								(10.595)	(10.982)	(10.718)	(13.465)
ln Tourism				-3.52021							
				(2.2829)							
Governance			-44.6285*								
			(25.255)								
Gini index	-23.215*	-3.91775	-23.1769*	-25.8533**	-18.7657	-5.433893	-27.8377**				
	(12.742)	(4.79192)	(12.113)	(12.6986)	(13.655)	(5.52382)	(13.169)				
Poverty					-15.5002						
					(21.136)						
ln Migrant Stock · Gini						-.7693621					
						(5.27952)					
ln Population Density · Gini		1.4067115									
		(5.218518)									
Observations	42	42	42	42	42	41	39	42	42	42	39
R^2	0.5792	0.5759	0.6054	0.6038	0.5857	0.5335	0.5761	0.5861	0.5879	0.6004	0.5797

Note: Robust standard errors in parentheses. Used variance inflation factor (VIF) for diagnosing collinearity in the models. No VIF values regarded as problematic. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

Table D 4

Regressions Period 3, 4/20/2020 to 5/9/2020

	Economic							Health			
Model	1	2	3	4	5	6	7	8	9	10	11
ln Economic strength	10.0272***	10.2781***	13.1581***	12.6065***	6.98193*	10.3083***	11.1777***				
	(2.9359)	(2.7978)	(2.6091)	(3.459607)	(3.5997)	(2.86832)	(3.9203)				
ln Life Expectancy								75.3072**	35.8389	50.8047	68.6965*
								(32.227)	(39.339)	(45.490)	(36.858)
$lnStringency_{t-1}$							-5.51431				-.247597
							(4.7393)				(4.4989)
ln Population density	1.56406	3.4813681	1.6472	1.31707	1.35405	2.5763487	2.03085	.993394	1.61244	1.61487	.720138
	(2.178)	(2.55627)	(2.1385)	(1.8593)	(2.2476)	(2.62552)	(3.0532)	(2.4261)	(2.4268)	(2.4363)	(3.1152)
ln Migrant Stock	3.096	2.484975	3.4611	3.20299	4.17644	4.039984	2.92904	4.76595**	3.9637	4.39586*	4.27606
	(2.9228)	(3.11803)	(2.9302)	(2.7354)	(3.1430)	(4.01481)	(3.2733)	(2.2435)	(2.521)	(2.5026)	(2.7269)
ln Total Population	4.36459	5.094619	4.5094	5.85653**	3.57834	5.094859	4.57514	2.34197	3.5847	3.0614	2.49204
	(2.9521)	(3.149058)	(2.7959)	(2.245)	(3.0731)	(3.107003)	(3.5649)	(2.4227)	(2.7881)	(2.7371)	(3.6764)
%Urban Population	36.1726***	33.305***	35.382***	38.3546***	32.9971**	36.05324***	33.0425**	48.104***	45.0476***	43.1744**	49.4746***
	(12.463)	(11.6508)	(12.040)	(13.381)	(12.623)	(11.79735)	(14.358)	(13.426)	(14.028)	(16.104)	(14.939)
ln Medical Expenditure										4.20577	
										(5.1435)	
ln Physicians per 1000									4.27699*		
									(2.5089)		
%Population over 65								2.57875	-3.0313	-.742736	3.07909
								(13.874)	(12.246)	(13.102)	(16.986)
ln Tourism				-3.56514							
				(2.5363)							
Governance			-32.7839								
			(22.044)								
Gini index	-7.11573	-7.986**	-6.83783	-5.57438	1.3375	-7.351225**	-3.33165				
	(11.092)	(3.54196)	(10.654)	(10.898)	(13.568)	(3.32359)	(12.737)				
Poverty					-15.5712						
					(10.804)						
ln Migrant Stock · Gini						-3.693744					
						(3.642256)					
ln Population Density · Gini		-5.280335									
		(3.503677)									
Observations	40	40	40	40	40	40	36	40	40	40	36
R^2	0.783	0.7993	0.7966	0.7995	0.7899	0.7975	0.7662	0.7518	0.7649	0.7574	0.7279

Note: Robust standard errors in parentheses. Used variance inflation factor (VIF) for diagnosing collinearity in the models. No VIF values regarded as problematic. *p < 0.1, **p < 0.05, ***p < 0.01

Table D 5

Regressions Period 4, 5/10/2020 to 5/29/2020

	Economic							Health			
Model	1	2	3	4	5	6	7	8	9	10	11
ln Economic strength	5.17297	4.7750481	14.5542**	6.52186	-.828145	3.087053	8.24857				
	(6.0787)	(6.069278)	(6.1341)	(6.1061)	(6.3215)	(6.028458)	(5.7961)				
ln Life Expectancy								98.9127**	39.5248	61.558	70.8414
								(42.885)	(50.107)	(53.800)	(54.2002)
$lnStringency_{t-1}$							-23.4988**				-18.3329*
							(9.800935)				(10.271)
ln Population density	-1.77891	3.800468	-2.50324	-2.13714	-1.64802	-.9062491	-3.93928	-2.8923	-1.8162	-2.77976	-4.84176**
	(2.5275)	(3.110981)	(2.1079)	(2.7505)	(2.260)	(2.375567)	(2.6181)	(2.1304)	(1.9967)	(2.1388)	(2.264)
ln Migrant Stock	-3.00209	-4.036679*	-1.1942	-2.45484	.016740	.9957358	-4.08237*	-.899216	-2.42167	-2.2498	-1.96332
	(2.2539)	(2.322119)	(2.1184)	(2.3181)	(2.4881)	(3.126105)	(2.1978)	(2.363)	(2.4217)	(2.7980)	(2.304)
ln Total Population	12.2101***	12.703***	11.4028***	13.4923***	10.706***	12.5199***	15.596***	10.4552***	13.0682***	11.847***	14.43855***
	(2.7248)	(2.31969)	(2.2855)	(2.7048)	(2.9927)	(2.70526)	(2.9296)	(2.4152)	(2.1925)	(2.4709)	(2.519)
%Urban Population	16.0132	15.76163	9.99893	22.1905	3.69926	26.11636	4.469	19.4182	7.88933	1.83211	15.1831
	(24.670)	(24.2244)	(22.936)	(22.687)	(25.459)	(23.0857)	(22.457)	(13.126)	(13.136)	(18.823)	(12.789)
ln Medical Expenditure										9.02983	
										(7.7436)	
ln Physicians per 1000									8.43259**		
									(3.3666)		
%Population over 65								-22.0406	-26.626	-28.5298	-.465207
								(19.313)	(18.742)	(19.064)	(18.961)
ln Tourism				-4.36265							
				(2.8449)							
Governance			-77.2111***								
			(23.864)								
Gini index	-2.76348	-21.558***	-4.05263	-2.04552	19.1287	-18.3***	.923732				
	(18.538)	(6.421018)	(17.785)	(17.855)	(19.532)	(5.524246)	(19.146)				
Poverty					-45.7146***						
					(16.605)						
ln Migrant Stock · Gini						-9.218651*					
						(5.303079)					
ln Population Density · Gini		-17.38234**									
		(6.444114)									
Observations	40	39	40	40	40	40	37	40	40	40	37
R^2	0.5363	0.6223	0.6279	0.5638	0.6018	0.5811	0.6477	0.5635	0.6175	0.5788	0.6455

Note: Robust standard errors in parentheses. Used variance inflation factor (VIF) for diagnosing collinearity in the models. No VIF values regarded as problematic. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

Table D 6

Regressions Period 5, 5/30/2020 to 6/18/2020

	Economic							Health			
Model	1	2	3	4	5	6	7	8	9	10	11
ln Economic strength	-0.3650	-.5250264	6.98749	1.4831	-2.35769	-1.152035	1.50692				
	(4.151)	(4.283735)	(4.7714)	(4.6767)	(4.706)	(4.200673)	(3.7530)				
ln Life Expectancy								-12.6389	-77.1261*	-23.1147	-29.8314
								(44.827)	(39.271)	(40.159)	(43.564)
$lnStringency_{t-1}$							27.4118***				30.6052***
							(8.9975)				(9.2215)
ln Population density	-0.5424	2.114167	-.193542	-.800833	-.328922	-.1190655	-1.3483	-.91928	.318690	-.685619	-1.86239
	(2.596)	(3.040659)	(2.3611)	(2.7215)	(2.4282)	(2.61661)	(2.5939)	(2.6549)	(2.2915)	(2.7103)	(2.6514)
ln Migrant Stock	1.36925	1.550064	2.67276	.960711	3.31401	3.941381	2.25096	.210558	-.471402	-.097999	1.36338
	(2.6477)	(2.74348)	(2.4961)	(2.5384)	(2.9149)	(3.374195)	(2.5310)	(2.2270)	(2.3702)	(2.6886)	(2.1905)
ln Total Population	6.92271**	6.641239**	6.28449**	8.4473***	5.45614	7.35555**	7.20435**	8.23573***	9.10364***	8.47160***	8.51734***
	(3.0103)	(3.08607)	(2.6979)	(2.951)	(3.2801)	(3.04537)	(2.9177)	(2.6208)	(2.6571)	(2.9771)	(2.5794)
%Urban Population	21.2173	19.08131	19.9497	22.3003	4.59258	26.78941*	12.2023	29.5260**	19.680	26.6395	24.9859**
	(15.222)	(16.1965)	(14.316)	(14.787)	(16.143)	(14.5482)	(14.4971)	(13.089)	(13.696)	(17.136)	(12.157)
ln Medical Expenditure										2.13077	
										(4.9515)	
ln Physicians per 1000									10.4529***		
									(3.3759)		
%Population over 65								-9.01284	-24.1084***	-12.4994	2.63079
								(8.4869)	(7.2011)	(10.174)	(9.671)
ln Tourism				-2.52044							
				(2.1883)							
Governance			-61.2854**								
			(23.138)								
Gini index	27.0835**	-1.059501	23.961**	24.414**	41.8852***	-2.987764	26.0686***				
	(10.508)	(4.106257)	(9.2305)	(10.578)	(8.5419)	(3.86593)	(9.1672)				
Poverty					-36.4609***						
					(13.032)						
ln Migrant Stock · Gini						-7.3221**					
						(3.609121)					
ln Population Density · Gini		-8.789819*									
		(5.09269)									
Observations	54	53	54	54	54	53	51	54	54	54	51
R^2	0.5353	0.5175	0.5984	0.5513	0.5804	0.5275	0.6256	0.4829	0.5685	0.4852	0.5785

Note: Robust standard errors in parentheses. Used variance inflation factor (VIF) for diagnosing collinearity in the models. No VIF values regarded as problematic. *p < 0.1, **p < 0.05, ***p < 0.01

Table D 7

Regressions Period 6, 6/19/2020 to 7/8/2020

	Economic							Health			
Model	1	2	3	4	5	6	7	8	9	10	11
ln Economic strength	1.07938	.238449	8.08049**	.816309	-6.82637*	.3032201	1.86735				
	(3.7601)	(3.79614)	(3.9919)	(4.384)	(3.469)	(3.602268)	(3.5354)				
ln Life Expectancy								46.8621	-1.43808	26.1085	16.4589
								(49.874)	(55.316)	(56.046)	(53.81)
$lnStringency_{t-1}$							19.9385*				20.3035
							(11.039)				(12.564)
ln Population density	2.78343	3.766226	3.6243*	2.82295	3.82923**	3.134166	1.48258	1.162	2.70183	1.08458	.95302
	(2.5559)	(3.330498)	(2.0215)	(2.5848)	(1.6856)	(2.647356)	(2.3475)	(2.1535)	(1.8119)	(2.2257)	(2.1629)
ln Migrant Stock	1.8549	1.716997	3.91979*	1.87837	7.0648***	4.088522	1.92021	1.72552	1.45086	.648039	1.84647
	(2.023)	(2.195938)	(2.1404)	(2.0387)	(2.2377)	(2.961559)	(1.9222)	(2.0755)	(2.0241)	(2.5189)	(1.9819)
ln Total Population	8.82843***	9.220015***	7.47796***	8.59055***	5.56025***	9.20276***	9.08446***	9.45082***	10.5622***	10.220***	9.42017***
	(1.7872)	(1.922498)	(1.7308)	(2.3041)	(1.9987)	(1.890543)	(1.9528)	(1.8162)	(1.7973)	(2.0064)	(2.1749)
%Urban Population	18.4021	19.56269	19.9008*	18.4374	-.728399	22.515386*	14.3939	24.0201**	16.6749	18.6766	20.4916
	(11.731)	(12.9606)	(11.319)	(11.813)	(12.821)	(11.31041)	(11.909)	(11.457)	(11.253)	(12.016)	(12.365)
ln Medical Expenditure										4.72203	
										(5.7275)	
ln Physicians per 1000									7.16462*		
									(3.594)		
%Population over 65								-28.5897**	-35.8977***	-34.466**	-10.8052
								(10.647)	(10.318)	(13.275)	(16.193)
ln Tourism				.423614							
				(2.4172)							
Governance			-72.759***								
			(22.65)								
Gini index	31.2301**	2.156881	27.0119*	31.9268**	55.10449***	-.6776976	22.5902				
	(15.151)	(2.397582)	(14.754)	(14.654)	(11.266)	(3.318513)	(14.629)				
Poverty					-63.4965***						
					(14.218)						
ln Migrant Stock · Gini						-6.330184					
						(4.252103)					
ln Population Density · Gini		-4.844438									
		(5.308929)									
Observations	52	51	52	52	52	51	50	52	52	52	50
R^2	0.6064	0.5813	0.6701	0.6067	0.7419	0.5966	0.6578	0.6051	0.6392	0.6124	0.6345

Note: Robust standard errors in parentheses. Used variance inflation factor (VIF) for diagnosing collinearity in the models. No VIF values regarded as problematic. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

Table D 8

Regressions Period 8, 7/29/2020 to 8/17/2020

	Economic							Health			
Model	1	2	3	4	5	6	7	8	9	10	11
ln Economic strength	0.616524	.6872116	7.88222*	1.53071	-2.41294	.4967328	-.148788				
	(2.9673)	(2.805726)	(4.2359)	(3.4812)	(2.3003)	(2.717847)	(2.697)				
ln Life Expectancy								115.561***	68.8682	283.522***	86.3015**
								(38.531)	(64.288)	(63.926)	(39.369)
$lnStringency_{t-1}$							15.5097*				16.1034**
							(8.6363)				(6.9205)
ln Population density	3.6799*	6.77691***	3.48094**	4.01576*	3.49167**	3.9040797*	2.09374	2.95467*	3.186**	2.25051	2.41895
	(2.111)	(2.363045)	(1.5879)	(2.2411)	(1.6945)	(2.104902)	(1.4652)	(1.570)	(1.3967)	(1.6979)	(1.5979)
ln Migrant Stock	1.14846	2.180442	2.51213	1.05819	3.6248	3.946876	.896585	2.54822	2.87826	5.01731*	1.32786
	(3.1354)	(3.190895)	(3.2152)	(3.200)	(3.0459)	(3.57725)	(3.4252)	(2.9580)	(2.9952)	(2.7606)	(3.3279)
ln Total Population	8.2681**	7.38042**	7.16593**	9.05911**	6.85827**	8.02047**	8.96729***	9.05774***	9.1603***	7.38895***	9.21876***
	(3.1465)	(3.23145)	(3.3391)	(3.7306)	(3.3480)	(3.159448)	(3.1499)	(2.8583)	(2.9631)	(2.6971)	(2.9481)
%Urban Population	48.9848***	44.6877***	48.2126***	49.9907***	36.7212**	48.04***	58.24***	47.7275***	46.9078***	58.6859***	49.437***
	(14.571)	(15.45121)	(13.379)	(14.486)	(15.623)	(14.98091)	(13.159)	(14.731)	(15.262)	(13.243)	(14.860)
ln Medical Expenditure										-18.1283***	
										(5.7542)	
ln Physicians per 1000									5.33889		
									(4.9568)		
%Population over 65								-40.976***	-48.4968***	-22.8895	-23.1736
								(12.045)	(9.7308)	(13.949)	(15.361)
ln Tourism				-1.30344							
				(3.3564)							
Governance			-62.9189**								
			(26.525)								
Gini index	29.4687	-5.493789	28.2946	28.7534	41.6819**	-4.75878	13.5663				
	(18.762)	(4.31407)	(18.048)	(19.334)	(16.247)	(4.313982)	(22.121)				
Poverty					-38.8547**						
					(14.781)						
ln Migrant Stock · Gini						-9.36922*					
						(4.958812)					
ln Population Density · Gini		-16.4909**									
		(6.795744)									
Observations	48	47	48	48	48	47	46	48	48	48	46
R^2	0.6017	0.6274	0.6542	0.6043	0.6512	0.605	0.6792	0.6535	0.6687	0.7175	0.6983

Note: Robust standard errors in parentheses. Used variance inflation factor (VIF) for diagnosing collinearity in the models. No VIF values regarded as problematic. **p* < 0.1, ***p* < 0.05, ****p* < 0.01

Table D 9

Regressions Period 9, 8/18/2020 to 9/6/2020

	Economic							Health			
Model	1	2	3	4	5	6	7	8	9	10	11
ln Economic strength	.916646	2.505344	11.1008**	-.252591	-2.29919	2.8954	1.09155				
	(3.432)	(3.286295)	(4.4922)	(3.490)	(4.0238)	(3.595063)	(3.5352)				
ln Life Expectancy								73.7182	40.114	175.793**	56.881
								(50.534)	(56.252)	(82.417)	(51.866)
$lnStringency_{t-1}$							17.1472**				15.5779**
							(8.2197)				(7.1098)
ln Population density	.15657	4.66659	.330957	.394075	.493499	-.6546798	-.032789	-1.06141	-.103149	-1.42479	-.962973
	(2.505)	(3.035282)	(2.2323)	(2.529)	(2.1896)	(2.673343)	(2.6588)	(2.3842)	(2.3089)	(2.285)	(2.3882)
ln Migrant Stock	-.14887	-.1470572	.141207	-.060192	2.55735	3.259837	.323856	.329483	-.02721	2.68022	.840946
	(2.558)	(2.433066)	(2.2756)	(2.4834)	(3.4439)	(2.202468)	(2.4435)	(2.5194)	(2.5316)	(3.1827)	(2.3765)
ln Total Population	11.4874***	11.5669***	11.0092***	10.2027***	9.52889***	12.4815***	10.4956***	11.5986***	12.3404***	9.81508***	10.8669***
	(2.7517)	(2.663956)	(2.8047)	(3.1575)	(3.1797)	(2.866899)	(3.3448)	(2.4420)	(2.4074)	(2.7633)	(2.7801)
%Urban Population	44.8413***	39.12418**	51.5498***	43.5645***	33.5088**	39.2318**	42.1476***	30.4105*	26.2737	37.4317**	28.2812*
	(13.508)	(15.49571)	(13.549)	(13.167)	(15.972)	(15.08076)	(13.482)	(16.407)	(17.339)	(16.024)	(14.654)
ln Medical Expenditure										-13.203*	
										(7.1526)	
ln Physicians per 1000									7.44644		
									(6.5711)		
%Population over 65								-8.45065	-21.7703	3.56921	4.65967
								(19.108)	(24.217)	(18.732)	(20.202)
ln Tourism				1.76951							
				(3.3718)							
Governance			-79.5489***								
			(26.863)								
Gini index	9.20859	-6.9218128*	7.10108	11.1083	22.774	-7.6482**	-8.13591				
	(17.082)	(3.689152)	(16.057)	(20.113)	(19.092)	(3.330324)	(20.332)				
Poverty					-38.9496						
					(25.074)						
ln Migrant Stock · Gini						-10.0429**					
						(4.073313)					
ln Population Density · Gini		-14.59**									
		(6.073843)									
Observations	46	45	46	46	46	45	44	46	46	46	44
R^2	0.5644	0.5927	0.6489	0.5697	0.5976	0.5918	0.5682	0.5823	0.6019	0.6071	0.593

Note: Robust standard errors in parentheses. Used variance inflation factor (VIF) for diagnosing collinearity in the models. No VIF values regarded as problematic. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

Table D 10

Regressions Period 10, 9/7/2020 to 9/26/2020

	Economic							Health			
Model	1	2	3	4	5	6	7	8	9	10	11
ln Economic strength	-1.54219	-.2962151	.748818	-3.04882	-1.57541	-2.197085	-.71194				
	(3.2501)	(3.312611)	(5.2387)	(3.6594)	(3.3638)	(3.462524)	(3.1570)				
ln Life Expectancy								-17.4071	-42.8398	-66.4736	-14.0487
								(60.295)	(67.661)	(77.499)	(58.502)
$lnStringency_{t-1}$							9.9283				7.36173
							(7.1181)				(7.677)
ln Population density	1.6372	2.325246	1.6112	1.59953	1.63345	2.251742	1.35107	1.54898	2.16325	1.87192	1.27677
	(2.5041)	(2.68742)	(2.4742)	(2.4949)	(2.5069)	(2.48906)	(2.6942)	(2.5861)	(2.615)	(2.5971)	(2.7403)
ln Migrant Stock	-0.639912	-.5286699	-.349267	-.625733	-.609949	-2.581254	-1.24615	-.410665	-1.40729	-1.15098	-.891869
	(2.4753)	(2.444566)	(2.4607)	(2.4479)	(2.5466)	(2.974736)	(2.4489)	(2.5505)	(2.6471)	(2.8214)	(2.6408)
ln Total Population	10.7349***	10.654***	10.27751***	8.55075**	10.7144***	11.13***	11.1227***	9.82836***	11.230***	10.0750***	10.0141***
	(2.5163)	(2.580721)	(2.49617)	(3.2777)	(2.5591)	(2.46033)	(2.5748)	(2.46407)	(2.3868)	(2.5411)	(2.5252)
%Urban Population	52.8999***	49.7258***	52.1580***	50.4900***	52.6878***	56.866***	52.7485***	46.8604***	44.7486**	42.5488**	45.9984***
	(15.197)	(15.67101)	(15.347)	(14.5418)	(16.258)	(16.11086)	(15.789)	(16.246)	(17.836)	(16.672)	(16.713)
ln Medical Expenditure										5.65716	
										(6.3238)	
ln Physicians per 1000									8.36958*		
									(4.1828)		
%Population over 65								9.30196	-5.0366	2.99276	14.5662
								(11.726)	(13.788)	(14.230)	(14.693)
ln Tourism				3.28568							
				(2.8732)							
Governance			-17.224								
			(31.421)								
Gini index	-27.9939**	-6.8793**	-27.476**	-23.2360	-27.6131*	-1.048481	-35.3895**				
	(13.129)	(3.100347)	(13.133)	(15.237)	(15.381)	(4.218867)	(14.779)				
Poverty					-.97122						
					(16.829)						
ln Migrant Stock · Gini						5.484719					
						(4.182623)					
ln Population Density · Gini		-4.486826									
		(5.286829)									
Observations	53	52	53	53	53	52	51	53	53	53	51
R^2	0.6253	0.6366	0.6288	0.6397	0.6254	0.6457	0.6314	0.5993	0.6353	0.6046	0.599

Note: Robust standard errors in parentheses. Used variance inflation factor (VIF) for diagnosing collinearity in the models. No VIF values regarded as problematic. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table D 11

Regressions Period 11, 9/27/2020 to 10/16/2020

	Economic							Health			
Model	1	2	3	4	5	6	7	8	9	10	11
ln Economic strength	4.73702**	4.97322***	7.09998**	1.87484	1.96303	4.724657**	5.76174***				
	(1.7962)	(1.790286)	(3.468)	(1.6743)	(1.7149)	(1.927925)	(1.7111)				
ln Life Expectancy								85.1175***	59.7251**	71.300**	79.0359***
								(25.364)	(25.388)	(33.743)	(24.759)
$lnStringency_{t-1}$							1.29059				3.26315
							(4.491)				(4.1988)
ln Population density	4.1904**	2.3718607*	4.22537**	4.22275**	4.38049**	4.341817**	3.8517*	2.94994*	4.28477**	3.14288*	2.49461
	(2.0049)	(1.255622)	(2.0245)	(1.760)	(1.9851)	(1.866074)	(1.9918)	(1.688)	(1.8516)	(1.6779)	(1.6241)
ln Migrant Stock	-.148848	-1.594915	.104555	-.264327	1.89697	.1363085	-.51288	.811474	.957166	.481069	.501847
	(1.828)	(1.247601)	(1.8380)	(1.6228)	(1.8829)	(2.393664)	(1.8589)	(1.2956)	(1.3499)	(1.4527)	(1.2529)
ln Total Population	8.66422***	9.87422***	8.26348***	6.45908***	6.41826***	8.73644***	9.57895***	7.59093***	7.6008***	7.80177***	8.30827***
	(1.9539)	(1.496944)	(1.9827)	(1.9459)	(1.8646)	(2.027947)	(1.8879)	(1.4169)	(1.3869)	(1.4812)	(1.3461)
%Urban Population	14.4885*	16.8272**	14.0489*	11.6359	5.04683	14.661629*	11.8932	4.53672	1.36201	2.03728	3.39467
	(7.828)	(7.790067)	(7.8905)	(8.3911)	(8.3263)	(8.220064)	(7.5606)	(8.0352)	(7.8993)	(8.9646)	(7.7239)
ln Medical Expenditure										1.95362	
										(2.8511)	
ln Physicians per 1000									5.19245**		
									(2.0887)		
%Population over 65								11.3087*	2.44581	9.22393	17.4882**
								(6.0414)	(7.2694)	(6.2059)	(6.6223)
ln Tourism				4.29886***							
				(1.2724)							
Governance			-17.4559								
			(20.3272)								
Gini index	-14.2335*	-3.83927**	-13.2864	-12.2155	3.20211	-4.060089*	-14.9293*				
	(7.9578)	(1.480495)	(8.3713)	(7.3365)	(8.3193)	(2.235273)	(8.5075)				
Poverty					-37.1795***						
					(10.346)						
ln Migrant Stock · Gini						-.542637					
						(3.091585)					
ln Population Density · Gini		.07852021									
		(2.29945)									
Observations	60	58	60	60	60	59	58	60	60	60	58
R^2	0.6828	0.7153	0.6877	0.7449	0.7456	0.6986	0.7033	0.7405	0.7675	0.7423	0.7636

Note: Robust standard errors in parentheses. Used variance inflation factor (VIF) for diagnosing collinearity in the models. No VIF values regarded as problematic. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

Table D 12

Regressions Period 12, 10/17/2020 to 11/5/2020

	Economic							Health			
Model	1	2	3	4	5	6	7	8	9	10	11
ln Economic strength	8.90263***	8.869235***	13.7506***	5.61691**	5.40871**	9.06463***	10.7599***				
	(2.0348)	(2.177234)	(4.255)	(2.2192)	(2.316)	(2.108224)	(2.0746)				
ln Life Expectancy								99.2176***	40.3077	94.2896**	84.6347***
								(23.016)	(28.083)	(39.045)	23.195
$lnStringency_{t-1}$							13.6166*				15.230**
							(7.4176)				6.2295
ln Population density	(.246786)	.1375616	-.20456	.763403	.080060	.4264365	-.476622	-.069185	1.24423	-.045964	-1.01473
	(1.9793)	(2.490461)	(1.9097)	(1.758)	(1.7435)	(2.058334)	(2.071)	(1.7069)	(1.7258)	(1.7584)	1.5067
ln Migrant Stock	-.104436	.4256054	.289531	-.042506	1.68912	-.1113582	-1.26864	1.74639	1.88124	1.65809	.85435
	(2.0248)	(2.103407)	(2.0498)	(2.0351)	(2.1823)	(2.589853)	(2.0428)	(1.4387)	(1.5242)	(1.6318)	1.5849
ln Total Population	9.23635***	8.902077***	8.86827***	7.00523***	7.86798***	8.775876***	9.42705***	7.60283***	8.02855***	7.67798***	7.4414***
	(1.8847)	(1.95751)	(1.9203)	(2.1851)	(1.9976)	(1.965538)	(2.2345)	(1.3813)	(1.4796)	(1.4861)	1.8064
%Urban Population	5.55902	6.795603	4.59757	2.50525	.760052	4.688187	-2.41651	-2.92062	-6.78879	-3.45704	-9.74481
	(11.522)	(10.86254)	(11.184)	(10.502)	(9.7918)	(12.41017)	(11.219)	(10.086)	(8.7708)	(11.004)	9.1024
ln Medical Expenditure										.557303	
										(3.6259)	
ln Physicians per 1000									6.94223***		
									(2.5491)		
%Population over 65								27.4468***	21.971***	27.0039***	39.8626***
								(6.5086)	(6.8254)	(6.7982)	8.9763
ln Tourism				4.16609**							
				(1.6064)							
Governance			-35.3062								
			(25.311)								
Gini index	-24.0217**	-2.934524	-23.5635**	-19.6375*	-8.65286	-2.548782	-27.9849**				
	(9.4614)	(1.78923)	(8.9262)	(9.9264)	(12.239)	(2.357522)	(10.594)				
Poverty					-35.1112**						
					(13.606)						
ln Migrant Stock · Gini						1.576521					
						(2.939594)					
ln Population Density · Gini		2.006929									
		(3.84497)									
Observations	55	54	55	55	55	54	51	55	55	55	51
R^2	0.7332	0.7319	0.749	0.7704	0.7729	0.7328	0.7306	0.8183	0.855	0.8184	0.8411

Note: Robust standard errors in parentheses. Used variance inflation factor (VIF) for diagnosing collinearity in the models. No VIF values regarded as problematic. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

Table D 13

Regressions Period 13, 11/6/2020 to 11/25/2020

	Economic							Health			
Model	1	2	3	4	5	6	7	8	9	10	11
ln Economic strength	-8.08254***	-7.61448***	-13.7302***	-4.65792**	-3.02161	-8.39514***	-7.76359***				
	(2.4224)	(2.50383)	(4.7342)	(2.2849)	(3.1990)	(2.582685)	(2.4016)				
ln Life Expectancy								-33.4074	-5.17969	-11.7561	-.891503
								(33.138)	(33.854)	(37.205)	(34.382)
$lnStringency_{t-1}$							-5.7592				-10.379**
							(6.5695)				(5.0223)
ln Population density	-7.26178***	-5.815407**	-7.15079***	-7.03482***	-7.35519***	-7.40883***	-7.32511**	-7.25149***	-7.53406***	-7.4384***	-6.63631***
	(2.465)	(2.514356)	(2.40445)	(2.0017)	(2.3569)	(2.210482)	(2.8426)	(2.3609)	(2.2231)	(2.3541)	(2.4204)
ln Migrant Stock	.773685	2.379308	.052317	1.00551	-2.21207	-.7450731	.569363	-.064235	.165434	.660049	.377493
	(1.9349)	(1.650409)	(1.8331)	(1.7530)	(2.1723)	(2.317843)	(1.9479)	(1.7151)	(1.6596)	(1.8869)	(1.716)
ln Total Population	-8.03012***	-8.73873***	-7.40800***	-5.94199***	-5.57098**	-8.23662***	-7.45773***	-7.51928***	-8.25748***	-8.32304***	-7.78065***
	(1.8063)	(1.771473)	(1.6403)	(1.8111)	(2.5772)	(1.810268)	(2.0919)	(1.4889)	(1.4632)	(1.6194)	(1.8008)
%Urban Population	-13.4261	-16.51625	-10.5061	-7.74023	-1.80626	-12.58843	-12.9663	-13.2285	-2.25752	-5.21295	-15.2362
	(11.379)	(11.22697)	(11.512)	(10.029)	(13.134)	(11.54543)	(11.198)	(11.924)	(11.959)	(11.4801)	(11.553)
ln Medical Expenditure										-4.8685*	
										(2.7529)	
ln Physicians per 1000									-6.50055**		
									(3.0156)		
%Population over 65								-34.5091***	-25.7283**	-29.926***	-43.1906***
								(9.7154)	(10.483)	(9.322)	(10.573)
ln Tourism				-5.42739***							
				(1.7831)							
Governance			42.3350								
			(25.468)								
Gini index	13.8197	6.6131505*	16.0786*	16.0057*	-.412233	8.924771**	16.0752*				
	(8.6037)	(3.841214)	(8.2246)	(8.0639)	(9.4513)	(3.912224)	(8.881)				
Poverty					46.0231**						
					(19.397)						
ln Migrant Stock · Gini						4.308057					
						(3.021674)					
ln Population Density · Gini		1.860674									
		(3.794266)									
Observations	51	49	51	51	51	50	50	51	51	51	50
R^2	0.5837	0.5879	0.6167	0.6548	0.6518	0.6114	0.595	0.6714	0.7098	0.6831	0.6943

Note: Robust standard errors in parentheses. Used variance inflation factor (VIF) for diagnosing collinearity in the models. No VIF values regarded as problematic.
**p* < 0.1, ***p* < 0.05, ****p* < 0.01

Table D 14

Regressions Period 14, 11/26/2020 to 12/15/2020

	Economic							Health			
Model	1	2	3	4	5	6	7	8	9	10	11
ln Economic strength	10.1076***	9.81393***	10.0896***	10.0566***	7.51153**	9.755***	10.7875***				
	(2.4549)	(2.426318)	(3.2434)	(2.7326)	(3.0239)	(2.437858)	(2.2121)				
ln Life Expectancy								44.7877	8.17556	3.67652	45.8273
								(30.435)	(37.662)	(29.833)	(31.465)
$lnStringency_{t-1}$							-2.83976				-1.08845
							(6.8603)				(5.1089)
ln Population density	-2.13087	-1.272352	-2.13478*	-2.13247	-1.68518	-2.257647*	-1.99134	-1.62496	-.130983	-1.21387	-1.6566
	(1.2726)	(1.817878)	(1.2594)	(1.2715)	(1.1842)	(1.318467)	(1.4353)	(1.278)	(1.2073)	(1.1957)	(1.2893)
ln Migrant Stock	-2.4066*	-2.190716	-2.41061	-2.40904*	-.73004	-2.861248*	-2.57466**	-.697176	-.830973	-2.2126**	-.697306
	(1.3793)	(1.31988)	(1.4692)	(1.3977)	(1.7872)	(1.460014)	(1.1869)	(1.1008)	(1.2194)	(1.0688)	(1.0909)
ln Total Population	9.75055***	9.73213***	9.75359***	9.71839***	8.50487***	10.2441***	10.0997***	8.4749***	9.12602***	9.40366***	8.78606***
	(1.1948)	(1.112119)	(1.2816)	(1.4926)	(1.4471)	(1.110481)	(1.1711)	(1.0710)	(1.0890)	(1.118)	(1.1870)
%Urban Population	6.33573	6.8402387	6.33408	6.28998	.962469	6.990207	4.96711	14.2803*	6.57199	6.0096	13.0778
	(9.3125)	(9.21113)	(9.4033)	(9.2973)	(8.2059)	(9.603039)	(9.3726)	(8.4447)	(8.5931)	(8.0786)	(8.720)
ln Medical Expenditure										8.02517**	
										(3.3499)	
ln Physicians per 1000									5.9302*		
									(2.9713)		
%Population over 65								29.634***	22.9465**	18.6138*	31.1281***
								(6.5329)	(8.8244)	(9.8235)	(7.1099)
ln Tourism				.072265							
				(1.8819)							
Governance			.163549								
			(16.674)								
Gini index	-9.52615	-4.2165**	-9.52247	-9.53395	-2.44959	-2.544316	-8.82043				
	(9.4182)	(1.881837)	(9.6485)	(9.4481)	(9.1104)	(1.633359)	(10.357)				
Poverty					-19.7803**						
					(9.6771)						
ln Migrant Stock · Gini						1.0300541					
						(1.843256)					
ln Population Density · Gini		-1.812159									
		(3.404439)									
Observations	50	49	50	50	50	49	49	50	50	50	49
R^2	0.8094	0.8248	0.8094	0.8094	0.8272	0.8254	0.8039	0.8099	0.8386	0.8347	0.8044

Note: Robust standard errors in parentheses. Used variance inflation factor (VIF) for diagnosing collinearity in the models. No VIF values regarded as problematic. **p* < 0.1, ***p* < 0.05, ****p* < 0.01

Table D 15

Regressions Period 15, 12/16/2020 to 1/4/2021

	Economic							Health			
Model	1	2	3	4	5	6	7	8	9	10	11
ln Economic strength	7.68991**	8.1262**	9.24307*	8.8330*	7.65207	6.190055	7.32396				
	(3.7727)	(3.94788)	(5.4077)	(5.1179)	(4.7007)	(4.32228)	(4.5879)				
ln Life Expectancy								-11.5215	-50.0527	-79.9866	-78.0419
								(54.439)	(61.813)	(55.887)	(85.949)
$lnStringency_{t-1}$							22.1947				35.0727*
							(14.439)				(17.504)
ln Population density	1.42919	6.2115**	1.37247	1.67838	1.42528	1.461116	2.66599	.98971	1.79457	2.05018	2.66628
	(2.4626)	(2.83272)	(2.4826)	(2.3202)	(2.5182)	(2.6115)	(2.4198)	(2.669)	(2.9523)	(2.8896)	(2.8068)
ln Migrant Stock	0.886566	2.16704	1.08047	.934361	.903075	3.100152	1.79416	2.13023	1.8007	.039052	2.88635
	(2.9389)	(2.76602)	(2.9480)	(3.0251)	(2.9919)	(3.865)	(3.0536)	(2.8536)	(3.0518)	(3.0485)	(2.7983)
ln Total Population	4.33991	3.191899	4.38329	5.35151	4.33087	4.277825	1.91916	3.47469	4.00029	4.9306	1.99318
	(3.5249)	(3.34928)	(3.5345)	(3.7351)	(3.5627)	(3.48884)	(3.7203)	(3.2076)	(3.5721)	(3.5007)	(3.4886)
%Urban Population	-12.0722	-15.7383	-11.5509	-12.9739	-12.1538	-5.324534	-17.1229	-2.44008	-8.60744	-10.1187	11.6783
	(14.955)	(15.2303)	(15.216)	(15.859)	(16.736)	(21.1238)	(17.623)	(17.577)	(17.859)	(16.837)	(22.242)
ln Medical Expenditure										12.3279*	
										(6.5375)	
ln Physicians per 1000									5.48431		
									(5.2349)		
%Population over 65								15.1353	12.4258	-2.33653	13.8753
								(12.125)	(14.396)	(16.616)	(16.425)
ln Tourism				-1.55104							
				(3.5504)							
Governance			-15.2915								
			(31.336)								
Gini index	27.6085**	-4.5047	26.0452**	26.3611**	27.6776**	-1.516207	35.1658**				
	(11.218)	(3.18405)	(10.892)	(11.40)	(12.091)	(5.68215)	(13.234)				
Poverty					-.299378						
					(23.251)						
ln Migrant Stock · Gini						-5.445479					
						(4.79001)					
ln Population Density · Gini		-14.217***									
		(4.41826)									
Observations	44	42	44	44	44	43	41	44	44	44	41
R^2	0.3393	0.4263	0.3431	0.3418	0.3393	0.3315	0.3812	0.2453	0.2727	0.3144	0.2995

Note: Robust standard errors in parentheses. Used variance inflation factor (VIF) for diagnosing collinearity in the models. No VIF values regarded as problematic. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

Table D 16

Regressions Period 16, 1/5/2021 to 1/24/2021

	Economic							Health			
Model	1	2	3	4	5	6	7	8	9	10	11
ln Economic strength	-6.24308**	-6.646269**	-7.16998**	-3.48624	-3.8530	-8.02641***	-7.53658***				
	(2.8383)	(3.23727)	(3.5124)	(3.1470)	(3.8298)	(2.488733)	(2.6557)				
ln Life Expectancy								-125.2124***	-93.3759**	-123.738**	-157.173***
								(29.714)	(37.681)	(56.742)	(50.874)
$lnStringency_{t-1}$							-17.6886**				1.13467
							(7.8463)				(10.455)
ln Population density	0.311919	1.444909	.313669	.790241	.549352	2.313974	1.41926	1.34121	.759629	1.33331	1.98664
	(2.1818)	(2.622676)	(2.1823)	(2.2769)	(2.1182)	(1.986505)	(2.3216)	(1.9956)	(2.3377)	(2.025)	(2.0038)
ln Migrant Stock	3.03044	2.785154	2.84321	3.6446*	1.8973	7.06331***	3.10599	.492359	.907378	.519379	.5250
	(2.0400)	(2.003414)	(2.0890)	(2.0727)	(2.3073)	(2.402799)	(1.8388)	(1.3714)	(1.5219)	(1.7768)	(1.481)
ln Total Population	-9.99937***	-9.65273***	-9.94715***	-8.24155***	-9.45716***	-9.21491***	-7.38712***	-8.07594***	-8.70281***	-8.09099***	-5.60753***
	(2.0408)	(2.171586)	(2.0802)	(2.6747)	(2.0599)	(1.845084)	(2.2454)	(1.5995)	(1.7147)	(1.5875)	(1.6796)
%Urban Population	-36.1587***	-36.58286**	-35.9719***	-35.5869**	-31.8184**	-25.56197**	-16.890	-30.6898**	-27.118**	-30.5529**	-17.980
	(12.642)	(14.23385)	(12.921)	(13.901)	(13.661)	(10.34388)	(11.218)	(11.900)	(11.526)	(13.643)	(11.1005)
ln Medical Expenditure										-.183756	
										(7.0919)	
ln Physicians per 1000									-3.02342		
									(3.0414)		
%Population over 65								8.56448	7.60578	8.70667	10.9351
								(8.6069)	(8.1170)	(11.086)	(10.981)
ln Tourism				-3.71842							
				(2.8857)							
Governance			9.18721								
			(20.097)								
Gini index	9.79068	-2.688671	10.6822	10.078	5.23419	-11.337246*	8.20136				
	(15.553)	(6.87201)	(16.203)	(15.374)	(16.674)	(5.584628)	(15.597)				
Poverty					15.0089						
					(14.732)						
ln Migrant Stock · Gini						-9.647418***					
						(3.433699)					
ln Population Density · Gini		-3.076988									
		(5.221429)									
Observations	40	40	40	40	40	39	35	40	40	40	35
R^2	0.7465	0.7442	0.7477	0.7623	0.7542	0.7689	0.7304	0.8064	0.8116	0.8064	0.7728

Note: Robust standard errors in parentheses. Used variance inflation factor (VIF) for diagnosing collinearity in the models. No VIF values regarded as problematic. *p < 0.1, **p < 0.05, ***p < 0.01

Table D 17

Regressions Period 18, 2/14/2021 to 3/5/2021

	Economic							Health			
Model	1	2	3	4	5	6	7	8	9	10	11
ln Economic strength	.926139	2.178943	10.1993***	-2.52353	-2.90661	1.295441	-1.67894				
	(3.746)	(3.343651)	(2.5034)	(3.8655)	(3.4949)	(3.9211)	(3.5347)				
ln Life Expectancy								15.3401	-30.8434	9.40343	-94.0274
								(38.657)	(38.245)	(83.230)	(63.319)
$lnStringency_{t-1}$							20.4879*				24.5619**
							(10.138)				(11.706)
ln Population density	3.08997	6.059951*	2.20359	2.68922	2.92869	2.783683	2.93765	2.6558	2.9354	2.69366	2.23499
	(3.1425)	(3.070534)	(3.2253)	(2.7357)	(3.1738)	(3.05758)	(3.4516)	(3.094)	(3.1089)	(3.3306)	(3.0681)
ln Migrant Stock	-1.08638	.2529402	-.600855	-1.34643	.934810	1.94174	.43184	-2.22087	-1.69740	-2.36629	-1.58131
	(4.1409)	(4.249644)	(3.9136)	(3.8805)	(4.1115)	(3.46529)	(3.7254)	(3.5692)	(3.5179)	(4.84751)	(3.0362)
ln Total Population	9.26802**	7.73461**	8.60517**	7.27681**	8.10022**	8.2347**	6.28393*	9.94249***	10.3029***	10.1029**	8.35492***
	(3.5422)	(3.685473)	(3.3583)	(2.9972)	(3.5107)	(3.3068)	(3.5857)	(2.8223)	(2.7794)	(3.7882)	(2.6957)
%Urban Population	34.4359*	21.88823	33.2661**	32.3059*	26.5633	27.8147	29.3512**	22.1366*	18.1765	21.1173	23.6795**
	(17.313)	(15.51352)	(14.595)	(16.182)	(18.289)	(17.866)	(11.1003)	(12.486)	(12.4082)	(20.811)	(10.279)
ln Medical Expenditure										.784357	
										(9.6720)	
ln Physicians per 1000									6.21976**		
									(2.7023)		
%Population over 65								18.1687	11.4947	17.4977	33.0221***
								(11.919)	(10.647)	(11.915)	(11.953)
ln Tourism				4.55573**							
				(1.9399)							
Governance			-67.5707***								
			(20.614)								
Gini index	-4.84856	-10.3869***	-12.6842	-2.843	.731371	-9.012***	1.25259				
	(15.356)	(3.285766)	(14.669)	(15.432)	(14.296)	(3.14072)	(13.664)				
Poverty					-43.3070***						
					(11.941)						
ln Migrant Stock · Gini						-7.2587*					
						(3.82237)					
ln Population Density · Gini		-13.61387**									
		(5.274417)									
Observations	42	41	42	42	42	42	39	42	42	42	39
R^2	0.5165	0.5701	0.5921	0.5797	0.5749	0.5504	0.5589	0.5626	0.5954	0.5627	0.6374

Note: Robust standard errors in parentheses. Used variance inflation factor (VIF) for diagnosing collinearity in the models. No VIF values regarded as problematic. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$