Master's thesis

NTNU
Norwegian University of Science and Technology
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Department of Public Health and Nursing

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Examination of Economy- and Health Outcomes Related to Unsuccessful Contact Tracing in South Africa, with Possible Guidelines for Future Implementation of such Technologies

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ABSTRACT

Introduction: The COVID-19 pandemic has disrupted the world economy and health over the past two years, with low- and middle-income countries experiencing the highest toll. South Africa is no exception, spending much money on fiscal support during lockdowns, postpones in treatment of other diseases, lower vaccination rates and increasing debt. The need of successful and effective use of non-pharmaceutical interventions (NPIs) is crucial, with special regards on digital contact tracing technology.

Methods: Time-series analysis of publicly available national data from South Africa, with special regards on defining pandemic patterns in the country. Using time-series analysis, it is possible to describe certain variables, explain the relationship between them and control for how one variable affects another. Our main variables under study are new cases, new deaths, hospital admissions and reproduction rates. Further, the thesis will develop a model for better pandemic surveillance in South Africa, while at the same time tracking effectiveness of digital contact tracing.

Results: The COVID-19 pandemic clearly follows seasonal patterns in South Africa. There are strong relationships between the variables under study, and the reproduction rate controls new cases and new deaths over time. Implementing a proper model surveillance, it is possible for the government to be alert when the pandemic drift out of control. In such case, contact tracing and other NPIs can be effectively implemented in the country, hindering lockdowns and new waves of COVID-19 in South Africa. With more control it is possible to focus on treatment of other diseases, due to more resources and availability in hospitals.

Discussion: Including both negative and positive scenarios of effective contact tracing surveillance, South Africa can implement effectively contact tracing technology to lower the total burden on the national healthcare system. The COVID-19 pandemic experience seasonal spikes forcing the country into lockdowns, and with proper surveillance one can hinder the largest outbreaks. However, it may be difficult to solely analyze contact tracing on its own due to the influence of other NPIs and natural behavior towards increase in cases.

Conclusion: Being alert when the COVID-19 pandemic drifts out of control with Cusum statistics, South Africa can implement necessary measures as effective contact tracing early during outbreaks, possibly ensuring stabilization in treatments of other diseases in the health care system, and at the same time allocating resources to other important health arenas

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ABBREVIATIONS

DPIA: Data Protection Impact Assessment

NPI: Non-Pharmaceutical Interventions

GPS: Global Positioning System

HIC: High Income Countries

LMIC: Lower Middle-Income Countries

WHO: World Health Organization

GBV: Gender-Based Violence

ICU: Intensive Care Units

1.0 INTRODUCTION

The coronavirus outbreak, first registered in Wuhan in December 2019, has disrupted the world economy and health, with more than 500 million confirmed cases and over 6.2 million reported deaths globally as of 29th of April 2022 (WHO, 2022). Over 30 million people have been pushed into extreme poverty by the pandemic, with estimations of nearly 700 million people still living in extreme poverty by 2030 (Bill & Melinda Gates Foundation, 2021). The hardest hit is the most vulnerable, with over 26 millions of those pushed into extreme poverty living in Sub-Saharan Africa. Educational levels are also experiencing growing gaps, with the marginalized groups at most risk (ibid.). While high-income countries have the necessary and available technology to cope with lockdowns and digital lectures, is the situation more difficult in low- and middle-income countries. (Bill & Melinda Gates Foundation, 2021; Kola et al, 2021).

In addition to extreme poverty and educational levels are health systems across the world pushed to their limits, with many countries experiencing the need to postpone important health checkups and services like family planning supplies and services, childhood immunization and treating other communicable diseases as HIV and malaria (Burger & Mchenga, 2021; Hatefi et al, 2020; United Nations, 2020a). In 2020 more than 30 million children missed their routine vaccinations, setting the vaccination rates back to 2005 levels (Bill & Melinda Gates Foundation, 2021). These drawbacks need to be taken into consideration when rapid increase in cases forces countries into lockdowns, focusing more on non-pharmaceutical interventions (NPIs) to prevent the activation of strict measurements, especially in low- and middle-income countries (LMICs) since such measurements have a potential to be long-lasting and devastating for the poor (Kola et al, 2021).

High-income countries (HICs) experience almost fully vaccinated populations when vaccination programs are put to hand, while LMICs fall behind (FHI, 2022; Department of Health – Republic of South Africa, 2022). Vaccine skepticism and availability to vaccines hinder vaccination rates, with the new term "vaccination nationalism" explaining the phenomena (Duke Global Health Innovation Center, 2021; Plus 94 Research, 2021). Economical gaps between HICs and LMICs are also increasing during the pandemic, with LMICs taking up more debt, while decreasing net equity inflows, to give proper fiscal support during lockdowns due to non-symptomatic cases in the community (Dyer, 2021; Murray, 2022; World Bank Group, 2022). These lockdowns lead to increases in deployment rates and income loss, which was steepest for the poorest 40% in the world (Yonzan et al, 2021). Hindering the increasing gaps between HICs and LMICs can be done by using other interventions than vaccination to cope with the pandemic. These interventions are referred to as non-pharmaceutical interventions (NPIs) and have for some years been stated as the most effective public health interventions if there is no effective nor available vaccine (European Centre for Disease Prevention and Control, 2020).

Non-pharmaceutical interventions (NPIs) include measurements as washing of hands, wearing of face masks in public spaces, social distancing, self-isolation, and manual and digital contact tracing. Contact tracing can be defined as the "*systematic process of identification, assessment, and management of people who have been exposed to (..) virus to prevent further transmission of the agent*" (Saurabh & Prateek, 2017, p.226). The systematic process has been effectively and successfully used in LMICs several years before the COVID-19 pandemic (ibid.; WHO, 2015). Manual contact tracing has been the preferred method in tracking close contacts, and usually exists of contact identification, contact listing and contact follow-up of the contacts (Saurabh & Prateek, 2017; WHO, 2015). Identification is done by several interviews to detect possible close contacts to an infected person, and then followed up by the detection of relation to the positive case and the interaction in they might have been infected (ibid.). Contact follow-up is lasting for three weeks, with daily visits from a specified follow-up team on a set location (ibid.). All three stages can however be time-consuming and resource-intensive, and shows limitations related to people´s memory of close contacts (Africa Union, 2020; Hogan et al, 2021).

During the last several years digital contact tracing solutions have slowly phased out manual contact tracing, even though the most common is a hybrid solution (Barrat et al, 2021). Limitations regarding digital contact solutions are related to privacy concerns, availability to technology and user percentage uptake of the solutions. However, the use of Bluetooth technology in most contact tracing applications hinders the need to register personal data and location (Hogan et al, 2021). Due to the vast availability to appropriate technology for most can digital contact tracing solutions fit in both HIC and LMICs (Born et al., 2021; International Telecommunication Union, 2021). Despite some areas of Africa experience less availability to appropriate technology, has South Africa experienced a steep increase in mobile phone subscriptions and availability to technology in last years (Born et al., 2021). On the other hand, the usage and uptake of the available digital contact tracing application, such as COVID Alert

SA app, hinder effectiveness in the country. Recent studies elaborate the need that most of a population must use the digital contact tracing for it to be effective (Ferretti et al, 2020). However, other studies found digital contact tracing to be effective with at least 28% - 30% of the population using it (Wymant et al, 2021; Kinyili et al, 2022). As such, the possibilities for an effective solution in South Africa are present and need monitoring. Therefore, development of a proper model for digital contact tracing effectiveness surveillance is of importance.

Websites such as *Our World in Data* have openly published national daily data from the COVID-19 pandemic in South Africa, including numbers as new cases, new deaths, weekly hospital admissions, reproduction rate and excess mortality (Ritchie et al, 2020). As such, it is possible to detect trends in disease outbreak by doing a time series analysis of the data. Developing a model to track effectiveness of digital contact tracing in South Africa is therefore possible, with special focus on the possibilities of disease outbreak control with effective and successful contact tracing using Cusum statistic charts. Cusum charts may detect timing of pandemic starts, where the average in new cases or deaths naturally shift from a target where the pandemic is under control (Singh et al, 2010). Different models have already been proposed in the literature, however, none solely focuses on outbreaks in South Africa (Ferretti et al, 2020; Saurabh & Prateek, 2017; Vogt et al, 2022). The objective of the thesis is not to find a solution, moreover, to propose a possible model surveillance of digital contact tracing effectiveness in South Africa.

Our main aim is therefore to highlight the economical and health-related outcomes to successful vs. unsuccessful contact tracing in South Africa, with possible guidelines of future implementation of such technology in South Africa.

The rest of the thesis will first focus more on the background literature related to disease burden in South Africa, different available innovation technologies, how to measure the reproduction number and which analysis we will use. Secondly, the paper will focus on developing a model for contact tracing surveillance including limitations to the model. After, results and discussions related to the aim will be given before a conclusion with possible future guidelines will be stated.

2.0 BACKGROUND LITERATURE

High-, middle- and low-income countries face vast challenges related to coping with high fiscal support during the pandemic, and at the same time maintaining proper health care, work environments and educational levels at pre-pandemic values. Since globalization, urbanization and more animal-to-animal interactions can increase the possibility of future pandemics up to a threefold, could these proper challenges be experienced in the future as well (Smith et al, 2007; Marani et al, 2021; European Centre for Disease Prevention and Control, 2020). After focusing on the divergent economic basis these countries have and how if may affect them, the thesis will now focus on the situation in South Africa. Using South Africa as the country of choice its due to the transferable features to other low- and middle-income countries when determining effectiveness of digital contact tracing. Focusing on the total disease burden during the COVID-19 pandemic, and its economic and educational impact, it may be possible to showcase how the situation might be in similar countries.

2.1 DISEASE BURDEN IN SOUTH AFRICA

South Africa is experiencing a toll on the total burden of disease, with an increase in public mental health disorders, with the poor at most risk due to unemployment, lack of access to proper health care services and structural inequality (Nguse & Wassenaar, 2021). Job loss´ impact on mental health and well-being is found to be critical, with adults losing employment showing higher depression scores compared to people who retained their jobs, also at the potential of a long-term impact (Posel et al, 2021). Gender-based violence (GBV) had a dramatic increase in cases during lockdowns according to non-profit organizations, while call centers for GBV experienced a rapid decrease in GBV-related calls, stating that many people lived with GBV without having the opportunity to report (Van Dyk, 2020; Farber, 2020).

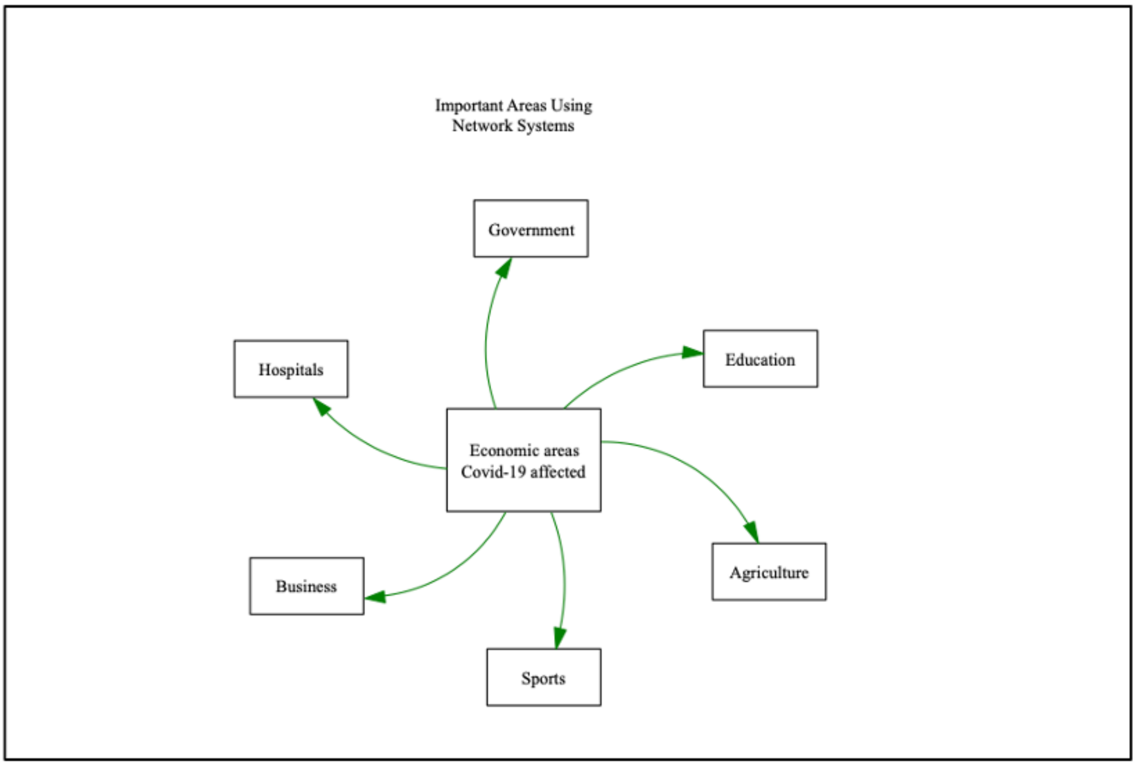


Figure 1: *Important areas using Network Systems.*

Schools are also being shut by the state intervention to avert the diffusion of the COVID-19 epidemic. Thus, the lockdown in South Africa, especially educational institutions, troubled students from level to advance as there was no certainty when to resume. This point of time is difficult for everyone including schools across South Africa. In that period, numerous engagements such as educational administrations, school examinations, intake exams and so forth were hard to hold (The Conversation, 2020). COVID-19 has also affected the utilization of sports, specially related to team sports and events. This could again affect human beings negatively in terms of less physical activity compared to pre-pandemic levels (Hall, 2020). The economic business also experiences serious pandemic effects. Several private and public enterprises closed in this epoch due to accelerated business difficulties due to less revenue, with most of them being in low- and middle-income countries (World Bank Group, 2022). Transition from physical to more digital solutions has also been immaculate in the health sector. As a result of the COVID-19 prevalent, the patient's prognosis was adapted from physical to network medical care (Bora, 2020; Ghosh, 2020; Verma & Mishra, 2020; Webster, 2020).

2.2 DIGITAL CONTACT TRACING

The generalized diagram below (figure 2) demonstrates the mobile technology in several categories, making clear how it is able to communicate with other instances, hopefully getting the user in touch with health-professionals when positive for COVID-19. The outpatient's information can be better stored in a public health archive that subsequently applied for mobile health technology designed to meet the needs of the societal spread of infectious disease that concerns the citizens, say prevailing coronavirus. Some applications work on the exclusive interface and Bluetooth integration, such as digital contact tracing application in South Africa, pinging people messages when being in close contact to contamination.

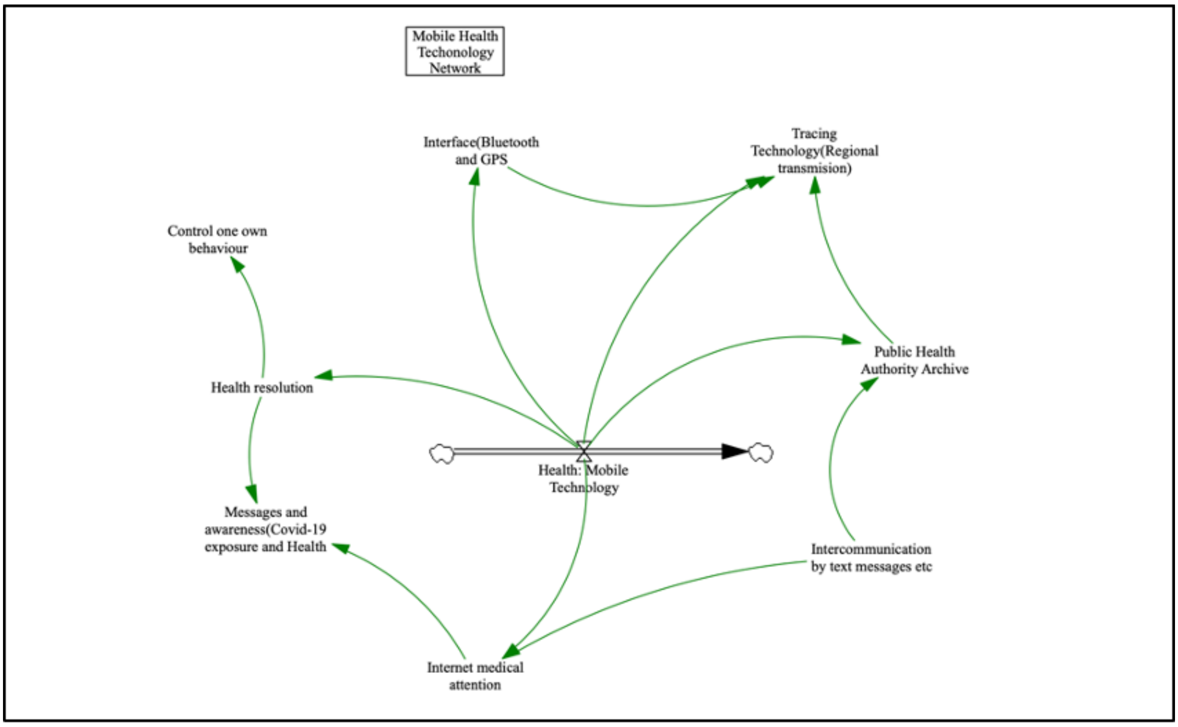


Figure 2: *Mobile Health Technology Network*

Figure 2 explains how an individual can contract the COVID-19 virus from a local outbreak and hope for intensive treatment. The person wants a Medical Centre to have him or her treated, even though the medical Centre is far from the location with bad roads to travel, lack of rail networks with poor weather environments and lack of emergency vehicle facilities are put in place. Here, seeing these setbacks presented above, the patient affected with COVID-19 will get more sick or may even die. However, suppose the patient´s phone has an app installed. In that case, one can obtain speedy medical treatment or advice through a virtual meeting with a health care practitioner in the shortest period (Verhoeven et al., 2020). Digital smartphone contact tracing technology is a feature based on Bluetooth technology to facilitate medical tasks' performance or enhance health development and healthcare operations (Braithwaite et al., 2020; Wang et al., 2020).

Using digital technology to detect communicable disease cases has been introduced in global southern countries for some years, handling transmittable diseases as HIV and Ebola as described earlier (Danquah et al., 2019; Saurabh & Prateek, 2017). The COVID-19 pandemic could bring a considerable backtrack with healthcare management applications to reduce the risk of human outbreaks. WHO (2021) explains that the coronavirus (SARS-CoV-2) primarily advances from close contact transmission. Thus, contact tracing technology is the central countermeasure to control the rise of the virus. The application is designed to identify people who have recently been in close contact with a COVID-19 patient. However, it is difficult for human contact tracing to consistently provide accurate data through direct meetings with health professionals. The patient with the disease encounters unidentified people in the societal daily life, that being in shopping malls, public transport, or church to name a few. Hence, it has become a point of contention for the national or the health authorities to trace human contact. Considering this, Busvine and Rinke (2020) explain that people install the application on their mobile phones and then read the QR codes when getting into a meeting place so that the digital contact tracing can identify the infection status through Bluetooth or a global positioning system (GPS). Jalabneh et al. (2021) demonstrate that the discovery of digital contact tracing can help Apple and Google play with differently designed languages.

Conversely, this approach has great concerns about information, location, and data privacy (Watson & Jeong, 2020; WHO, 2017). However, with support of Apple and Google, the most common protocol in contact tracing technologies is the use of Bluetooth technology which hinders the need of tracking sensitive information from the users (Busvine & Rinke, 2020; Google, 2020). At such, it is possible to ensure users that their private information will not be stored. Without tracking any GPS location nor sensitive information, it is possible to enhance digital contact tracing technology as a counter measurement to stop the COVID-19 chain of infection.

Mentioning the COVID-19 chain of infection and how digital contact tracing can hinder further spread, the focus will now shift towards pandemic variables that are used to describe quantitative features of the pandemic and its spread. Henceforth, highlighting the reproduction number as an important measurement of pandemic spread and time series analysis as an important tool of quantifying disease patterns over time.

2.3 REPRODUCTION NUMBER

The reproduction number (R-number) is the average number of secondary cases produced by a primary case and is well used when determining disease patterns in communicable diseases as COVID-19 (Cori et al, 2013; Arroyo-Marioli et al, 2020). Several factors affect the R-number over time, such as NPIs, temperatures, vaccination and number of susceptible individuals in the society. As standard, a R-number = 1 stabilizes a disease outbreak over time. While R-number < 1 and R-number> 1 decreases and increases, respectively, the disease outbreak. Implementing measurements, both NPIs and pharmaceutical interventions, therefore focuses on decreasing the R-number <1 so a pandemic or a disease outbreak will end. It is common to detect the R_0-number, the basic reproduction number, to determine the average number of secondary cases when all in a population is susceptible. Previous determinations of the R_0-number and R-number have utilized a SIR-model, where one assume that the "*R-number is linearly related to the growth rate of the number of infected individuals*" (Arroyo-Marioli et al, 2020, p.1).

However, Arroyo-Marioli et al. (2020) developed a new real-time estimation of the R-number using the Kalman filter. As such, one is able to include a time-varying growth rate. By using published real data on several values related to the COVID-19 pandemic they construct a time series on infected individuals at given times, and then develop the growth rate using the Kalman filter. Developing the Kalman filter in the time-series made it possible to detect the effectiveness of NPIs such as lockdowns, self-isolation, and social distancing. However, it is of importance to notice that it is almost impossible to include voluntary changes in behavior into the real-time estimation of the R-number, being relevant when analyzing the effectiveness of different NPIs introduced in communicable disease outbreaks (ibid.).

2.4 TIME SERIES ANALYSIS

"*A time series is a collection of observations made sequentially through time*" (Chatfield & Xing, 2019, p.1). The dataset provided by Ritchie et al. (2020) is a continuous discrete time series, since the variables are collected continuously through time (continuous) and the observations are taken daily or weekly (discrete) (Chatfield & Xing, 2019). Our time series data is stochastic, in other words is it only possible to simulate future values with a probability distribution. The future cannot be predicted exactly, despite our variables being real data from South Africa (ibid.). Predicting future values under certain conditions, relying on past data, can be done by using forecasting models in time-series analysis and by implementing the Kalman Filter as described in chapter 2.3.

Time series can have different objectives when used in research, and Chatfield & Xing (2019) classifies those as description, explanation, prediction, and control. In our results we will describe our collected variables through time plots in a set time period in South Africa and explain briefly the variables shown. Describing variables in time plots can for instance be used to show seasonal patterns and development of variables over time, such as describing the pandemic patterns of new cases of COVID-19 in South Africa from early 2020 to late 2021 (Ritchie et al, 2020). Comparing variables in the same time series is also possible, detecting possible interference between them. This can for instance be the relationship between new cases of COVID-19 and the reproduction number (as described in chapter 2.3). Further, following our aim of the thesis a time series can be used to determine a control parameter, for instance digital contact tracing, and detect how the control parameter (or variable) affects the other variables in the time series, for example new cases and/or new deaths (Chatfield & Xing, 2019; Ritchie et al, 2020).

3.0 METHODOLOGY AND MEASUREMENT EFFECT

In this chapter, we will describe our methodological strategy for our research and the development of a model in the prospect for our research questions. This section aims to provide an outline through the research mode. Firstly, data gathering, incorporation, analysis, and detailed account of the sequence of pause effectiveness to accomplish our analysis. This is consequential, in that, in every preferred research question, there are often a diverse approach to carry out. It is indispensable to canvas in an account as to the actions we measured and ushered our study so that it is practical to correctly ascertain the validity of our clarifications of the overall pandemic development (King et al., 1994; Lewis, 2015). Therefore, the locus for this section will not be about discernible features, yet through the outcome of the procedure employed, compassing the study set up for the research (Gerring, 2011). The section design along these lines, in the foremost we demonstrate our preferred study set up, research procedure, the study design, selection technology. Secondly, we introduce the empirical model we have used, study settings, study participants and data. Thirdly, and finally, we will mention some methodological limitations and ethical consideration related to the thesis.

3.1 STUDY DESIGN

The aim of the study thus indicates the cause and effect of contact tracing social interactions between the factors. Nonetheless, to introduce the alliance between them, the study design is decided to see it as the model assigned to address the research questions. Therefore, our approach executes time-series analysis to focus on the high positive coronavirus in South Africa in 2020 and 2021. This follows an area difference in exposure that was pseudo arbitrary, considering secondary data input defect, that permits us to examine the auxiliary effect of contact tracing on the estimation of contingent coronavirus diffusion or speed of its prevalence. We thus pursue the exact and formal time-series statistical method on official, national COVID-19 data for South Africa to evaluate effectiveness of digital contact tracing nationwide.

3.2 STUDY SETTING

In South Africa, clinical laboratories account for positive coronavirus test results to the public health domain in an everyday context. The country assembles all the test outcomes by employing a contact tracing device and other technologies that form a certified reporting of COVID-19 case numbers (Castelyn et al., 2020). Distinctly information on positive cases is expressed by test and trace technology to the national health authorities (Mendelson & Madhi, 2020). All cases examined do not arise from increased exposure spots, such as educational institutions. Instead, the infected person is reached through phone calls or text messages and asked to tell thoroughly their latest neared contacts and spots they have gotten in touch. They could answer virtually through safe internet sites or by phone with a digital contact tracker, COVID Alert South Africa (SA).

Open-source data were used to sample trends in new cases, amount of people tested, mortality rates and vaccination rates for the nation of interest. Full datasets are available from Our World In Data (Ritchie et al, 2020), which were downloaded 3rd of February 2022. Due to lack of some data from the open source was it necessary to implement global research, hence the use of the Kalman filter for tracking the reproduction number (R-number) during the pandemic trends (Arroyo-Marioli et al, 2021). The time frame was set from 7th of February 2020 to 31st of October 2021, due to the available data set of interest (Ritchie et al, 2020). Ending the data set on 31st of October 2021 was done due to a rapid shift in the pandemic trends by the new Omicron variant in November 2021. Omicron led to new policies in South Africa, with governmental actions withdrawing from contact tracing due to less severe illness caused by the virus, as well as herd immunity in the country by either vaccines or previous infections with COVID-19 (Abdullah et al, 2022). Hence, the country experienced an unnatural rapid spike in the number of cases due to removal of measures which could skew the analysis in certain directions. It is therefore natural to focus on data gathered while measurements were still intact.

3.3 SAMPLE SIZE AND SAMPLING TECHNIQUES

In data collected from Our World in Data (Ritchie et al, 2020), the population of South Africa is fixed at 60,041,.996 for the entire time period of interest, from 7th of February 2020 to 31st of October 2021 (ibid.). Our data and methodology depend on simulation of different time periods, hence the need for dynamic data. At first, the equation was tested in a quarter from 7th of February 2020 to 7th of May 2020. In this case, the population had to be dynamic to fit our model. United Nations Department of Economic and Social Affairs predicted the world population in 2019, as was the case for South Africa (United Nations, 2020b). Data provided showed a total population of 59,308,690 in South Africa as of 1st of January 2020 (ibid.). Given the national population growth of 1.28% in 2020, it was possible to formulate the population dynamics from the specific time period (ibid.). Total population growth in 2020 with a percentage growth of 1.28 was 759,151, giving a total population of 60,067,841 at the end of

2020. Dividing the population growth on 365 found a daily average growth of 2079.86, making it possible to find the total population at specific dates in 2020 by the equation (1):

$$y = 59.308.690 + 2079.86x. \qquad (1)$$

For instance, would the total population at baseline, 7th of February, be:

$$y = 59\ 308\ 690 + (2079.86 * 38)$$
$$y = 59\ 308\ 690 + 79034.68$$
$$y = 59\ 387\ 724$$

where x = 1.1.2020 → 07.02.2020, equaling 38 days from baseline. Given the time interval from 7th of February 2020 to 7th of May 2020, the total population at a certain date in the time interval equals too (2):

$$y = 59\ 387\ 724 + (2079.86x), \qquad (2)$$

where x is the number of days since the new baseline 7th of February 2020. These numbers were added into the dataset for more dynamic data related to the population. In addition, was the population density made dynamic by dividing the total area on the new total population from a day-to-day perspective, adding the total land area of 1 221 000 square kilometers into the equation (3):

$$y = ((59\ 387\ 724 + (2079.86x)) / 1\ 221\ 000) \qquad (3)$$

As such, it is possible to implement dynamic population numbers in our analysis. Having a fixed number is not transferable to reality, hence one is closer to real life estimates by implementing dynamic numbers in the formula.

3.4 SELECTION TECHNOLOGY

In our time-series and collection of data, the action has been to collect national surveillance data from South Africa through Our World in Data. Hence, to model our decision-making process by contact tracking technology, it is necessary to have a technology where the residence is free to make an autonomous decision regarding privacy. However, it is important to consider the time during which the technology is introduced. The older the technology to the area, the more difficult it would be to trace network effects in contact tracing decisions than when the technology is relatively new to the area. In this regard, improved technology is likely the candidate due to its predictive development.

3.4.1 STUDY PARTICIPANTS

Since the available dataset is a national set of data, our study participants are the total population of South Africa. In our best-case scenario, regional data would have been preferred in our research model for comparison in the time series. However, due to lack of open access to regional data, national data have been used.

3.5 STATISTICAL ANALYSIS

We choose time series methodology as an observable contender for our Apps technology device systems. This is because the App system's tracking data is derived from the time-series records. In addition to this, time series processes, in opposite to regression analysis, use the interconnection structure of records. That is to say, the data. There are two critical issues associated with this time series process in the current setting. First, we believe that the methods need an early transformation of the time series to meet its condition of 'stationarity'. The second is that our model-fitting process needs autocorrelation functions. Using exponential smoothing is essential for measuring methods for predicting the presence count in the 'stationarity' time series by employing more weight to recent COVID-19 observations, less incline to observations from a distance of time. Thus, the expectation at the time t can be written as,

$$Y_t(s): \ s = 1, \dots, z; \quad t = 1, \dots, q \qquad (4)$$

where s implies the systematic process Area and t implies time. Thus, it is essential to assume that the system processes are monitored constantly in time, say the infection of the outbreak, but uneven in space.

Amorós Salvador (2017), and Chen & Orenstein (2001), demonstrated the development of a notification system for epidemic infections using a time series approach. They closely adapted a seasonal autoregressive integrated moving average (SARIMA) application to record influenza outbreaks. Under this situation, the model predicted, y_{q+1} (s), for each s, by employing above equation 1. Suppose when, we allow $\hat{y}_{q+1}(s)$, implies the expectation value at Area s. Whence, our concerns are in the novelty.

$$E_{q+1}(s) = y_{q+1}(s) - \hat{y}_{q+1}(s), \quad \ldots\ \ldots \qquad (5)$$

For s = 1…, r. Suppose $_{q+1}$ (s) is monitored,

E_{q+1} (s) will be too significant in value at any given Area s; this provides a warning that denotes a situation that should be considered and observed by the authority(s). For this reason, in contact tracing technology, our objective is an optimum expectation in time for every Area against the optimum expectation of unobserved Areas.

3.5.1. DETECTING IRREGULARITY

We believe that the COVID-19 pandemic needs the details of the baseline count and the system to mediates whether the present count significantly surpasses this baseline. So, ideally, the margin value has been selected to meet some criteria of the order:

$$P(X > \varphi \mid \text{endemic}) = \beta \quad \ldots\ldots \quad \ldots\ldots \qquad (6)$$

Where X equals the COVID-19 outbreak count in some fixed interval of time and β is the daily false observation rate, that is to say, the likelihood of starting tracking when no endemic occurs. For this reason, the best we could do is to attempt to meet more vulnerable conditions,

$$P(X > \varphi \mid \text{irregularity}) = \beta \quad \ldots\ldots \quad \ldots\ldots \qquad (7)$$

such that, β is the likelihood of digital contact tracing when no endemic exists in the region. In other words, the likelihood that the margin surpasses by odds.

Again, the timeline at which the coronavirus (SARS-CoV-2) pandemic rises should be examined. For instance, when the digital contact tracing reporting is daily/weeks, should irregularity be announced if the prevalent daily/weekly numbering is within the optimum of the daily or weekly limit. If the false discovery rate is fixed, the result showcases the link between transit time length and limit, since these are indeterminate.

Specifically, when X_p shows the number of incidents score onto p, regular reporting time or also p is matching margin selected such that,

$$P(X_p > \varphi_p \mid \text{irregularity}) = \beta \qquad \ldots\; \ldots\ldots\; \ldots(8)$$

whence, $\varphi_p < k\varphi_1$, then it is relatively feasible to lie under day or weekly margin, for instance, following daily or weekly reporting. Nonetheless, the monthly sum lies beyond the monthly margin. In this fashion, the digital tracking technology centered on weekly scores would skip further spread pandemic happening over more proactive times. We also follow up our baseline values for current time point and the compute from the smoothed baseline corresponding to the same point in previous years. The Marginal φ is criteria-specific and calculated from previous and current observations as the cut-off point for the expected current observation period.

Singh et al (2010) explained a standard cusum statistics that utilised geographical pandemic reports. A cusum chart is used to monitor smaller shifts in the process mean, working as a control chart. We assume that there are spatial scales and that $X = x \times x$ proximity arrays of values x_{mn}, equating proximity of spatial scale m and n, with $0 \le x_{mn} \le 1$, such that,

$$x_{mn} = \exp(-p_{mn}/\theta) \ldots\ldots\ldots\ldots\ldots\; \ldots\ldots\ldots\ldots(9)$$

where p_{mn} represents the space through *m* and *n* and θ is the scale parameter.

$$x_{mn} = \begin{cases} 1 \quad \text{if } p_{mn} \le \theta \\ 0 \text{ otherwise} \end{cases} \ldots\ldots\ldots\ldots\ldots\ldots\ldots(10)$$

Therefore, we allow Z_{mt} to equal the coronavirus (SARS-CoV-2) plaque count in spatial scale *m* at time *t*, with prediction $q_m\gamma$, which describes the pooled outcome.

$$V_{mt} = \sum_{n=1}^{x} x_{mn} o_{nt} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(11)$$

In the same way, the pooled is put forth to explain the baseline values λ_{mt}. A cusum statistics for every geographical location are expressed as,

$$C_{mt} = \max\left\{0, C_{m,t-1} + \left(V_{mt} - \lambda_{mt}\right)\right\} \ldots..(12)$$

This expression cusum statistics will go "pandemic" if the mean rate in the community of scale m skyrockets (Novoa & Varela, 2019; Sibanda & Sibanda, 2007; Unkel et al., 2012).

3.6 METHODOLOGICAL LIMITATION

Data limitation at the start of our project, several values under several variables have not been reported, such as the total number of cases, new cases of infection, new death, and the rest, through the South African national public health pandemic period and not all of these can be sure to have disclosed all referring cases.

Insufficient published data has hindered effective observation of the COVID-19 pandemic and attempts to submit outstanding data reports in society are recurring. Instability through public health or determination of case reporting rates over time will again lead to indeterminate variation structures. The data reference for this thesis is South Africa's national public health, retrieved from 'Our World in Data' (Ritchie, 2020), a daily report case of COVID-19 infection and weekly hospitalized. Problems encountered are recorded by reporting date rather than disease predisposition start date. Then again, the data do not encompass an index for international travel. The data from Ritchie et al (2020) was analyzed in a time series model and shades for the entire country, including 633 observations reported on January 1, 2020, and January 1, 2022. The results below identify each case by date and location of any cases associated with COVID-19 disease infection.

However, with careful consideration of statistical methods, this practice is suitable for the further outbreak of microorganisms. Therefore, developing a structure that can adequately ensure proper disease surveillance on communicable disease outbreaks and pandemics, will be arduous.

3.7 ETHICAL CONSIDERATION

When running a time series analysis, one is not coping with ethical considerations regarding obtaining the data as it is already public available or already used in research. In such case, it is not necessary to worry about informants (as in qualitative research), intervention and control groups in randomized controlled trials, nor any other aspects regarding detection of personal data or localization data as there is no tracking of such data in the Bluetooth technology used in digital contact tracing. However, when implementing new technology in the society the public should democratically decide whether to adopt the technology or not, and the technology must do better than harm on those individuals who adapt it. Furthermore, the digital contact tracing application needs to meet equity criteria in terms of availability and usefulness for all people, independent from sex, socio-economic status, nationality, culture, and ethnicity. Additionally, in positive cases one must cohere to availability to, and effectiveness of, treatment for all groups mentioned, at present and in the future (Ferretti et al, 2020). Moreover, must our results be open and available for all interests, with special regards to sharing of knowledge to low- and middle-income countries.

As known, must all master theses cohere to the ethical guidelines provided by the Faculty of Medicine and Health Science at the Norwegian University of Science and Technology (Norwegian University of Science and Technology, 2020). Having oversight by a supervisor from NTNU further establish a coherent to those guidelines. In addition, the data used must be clarified and given approval by Our World in Data to be used in master theses, which they specifically state on their Coronavirus Pandemic webpage:

> All visualizations, data, and code produced by Our World in Data are completely open access under the Creative Commons BY license. You have the permission to use, distribute, and reproduce these in any medium, provided the source and authors are credited. (Ritchie et al, 2020).

At last, there is no need of running a Data Protection Impact Assessment (DPIA) due to the needed data and aim of our research. Our research data is not "*likely to result in a high risk to the rights and freedoms of natural persons*", as stated in General Data Protection Regulation´s article 35 – Data protection impact assessment (General Data Protection Regulation, 2018, L 119/53).

4.0 FINDINGS AND RESULTS

The Stringency index showcases how strict the measurements for the COVID-19 agenda is in certain countries, with index values from 0 to 100 where 100 is the strictest. Included in the index is measurements such as closure of schools and workplaces, use of mask in public spaces, capacity limitations for public gatherings and so forth (Ritchie et al, 2020). In this case, one can follow how the measurements vary in strictness and track when South Africa implies lockdowns (close to a 100). Adding new cases smoothed per million, one can track the time series of when there is a spike in new cases and comparing that to how strict the measurements are, hence showcasing the importance of stricter measurements when needed (Figure 3). Despite being of uncertain detail, some knowledge about how well the measurements work in decreasing number of new cases could be obtained. However, by showcasing a time series for over two years (as in graph below) there is limitations in withdrawing information about day-to-day and/or weekly patterns. Ritchie et al (2020) is also underlying that these measurements should not be interpreted as a rating of the effectiveness of a nation´s response to battle COVID-19, but more for comparative purposes for showcasing a nation´s measurements over time.

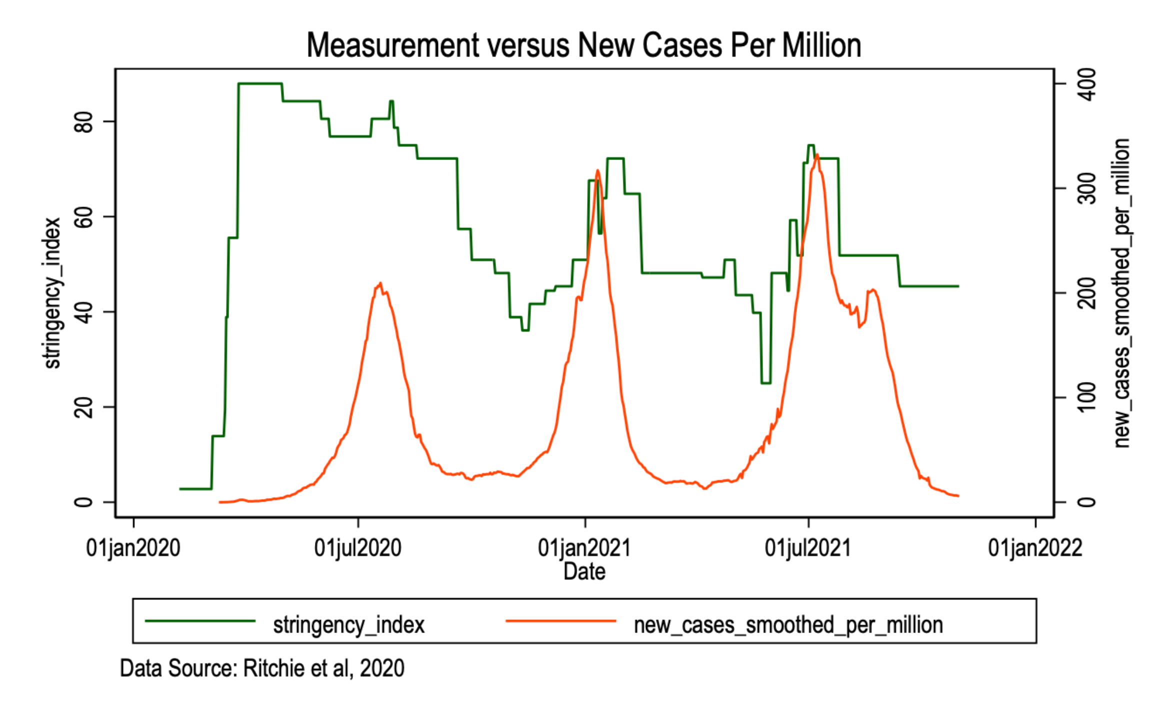


Figure 3: *Stringency Index versus number of new cases smoothed per million.*

After identifying time series based on the first period (2020<= year<= 2021), the figure looks at seasonal patterns of COVID-19. Estimation analysis shows significantly seasonal spikes.

Estimated parameters and summary statistics from fitting a non-stationary Arima (1,1,12) model to the COVID-19 data, new cases smoothed per million in South Africa.

ARIMA regression

Sample: 23mar2020 thru 31oct2021	Number of obs	=	588
	Wald chi2(2)	=	954.69
Log likelihood = 676.7218	Prob > chi2	=	0.0000

DS12. lnew_cases~n	Coefficient	OPG std. err.	z	P>|z|	[95% conf.	interval]
ARMA						
ma						
L1.	.2735636	.0237204	11.53	0.000	.2270725	.3200547
ARMA12						
ma						
L1.	-.7180543	.0247907	-28.96	0.000	-.7666432	-.6694653
/sigma	.0759794	.0010527	72.17	0.000	.0739161	.0780427

Table 1: *Estimated parameters for fitting non-stationary ARIMA Model.*

So, our hypothesis of the seasonal spike of the COVID-19 virus is written as,

$$\Delta\Delta_t \text{lnew\_cases\_smoothed\_pr\_million} = 0.274\varepsilon_{q-1} - 0.76\varepsilon_{q-12} + 0.197\varepsilon_{q-13} + \varepsilon_q$$

$$\text{/Sigma } (\hat{\sigma}) = 0.76$$

The coefficient on ε_{q-13} is the multiplicative of the coefficient on the ε_{q-1} and ε_{q-12} conditions $(0.197 \approx 0.274\text{x-}0.72)$, where the transformation variable indicates that it has used the difference component and progress seasonal difference component Δ_{q-1} to the transformation. In the current case, the critical position is this; it is good enough to believe that these new cases smoothed per million of the population given the contact tracing technology is non-stationary and should not ignore, as it will drift away. On the other hand, if stationary, the system will act out of control (where the mean and variance did not lean on time). Therefore, one is willing to look at non-stationary models, as the rampant moving averages show a significant assessment of the current level of the process.

Checking the dependent variable of new_cases, it is feasible to estimate the possible models to find the R-squared that is suitable for the data. Having checked the possible models of components, the table below (table 2) fit best for the R-squared. Reason being both the Akaike info criterion and Hannan-Quinn criterion being smaller, which fulfill the criteria, and AR(2) and MA(2) are significant. However, the constant C is not significant with a probability > 0.05.

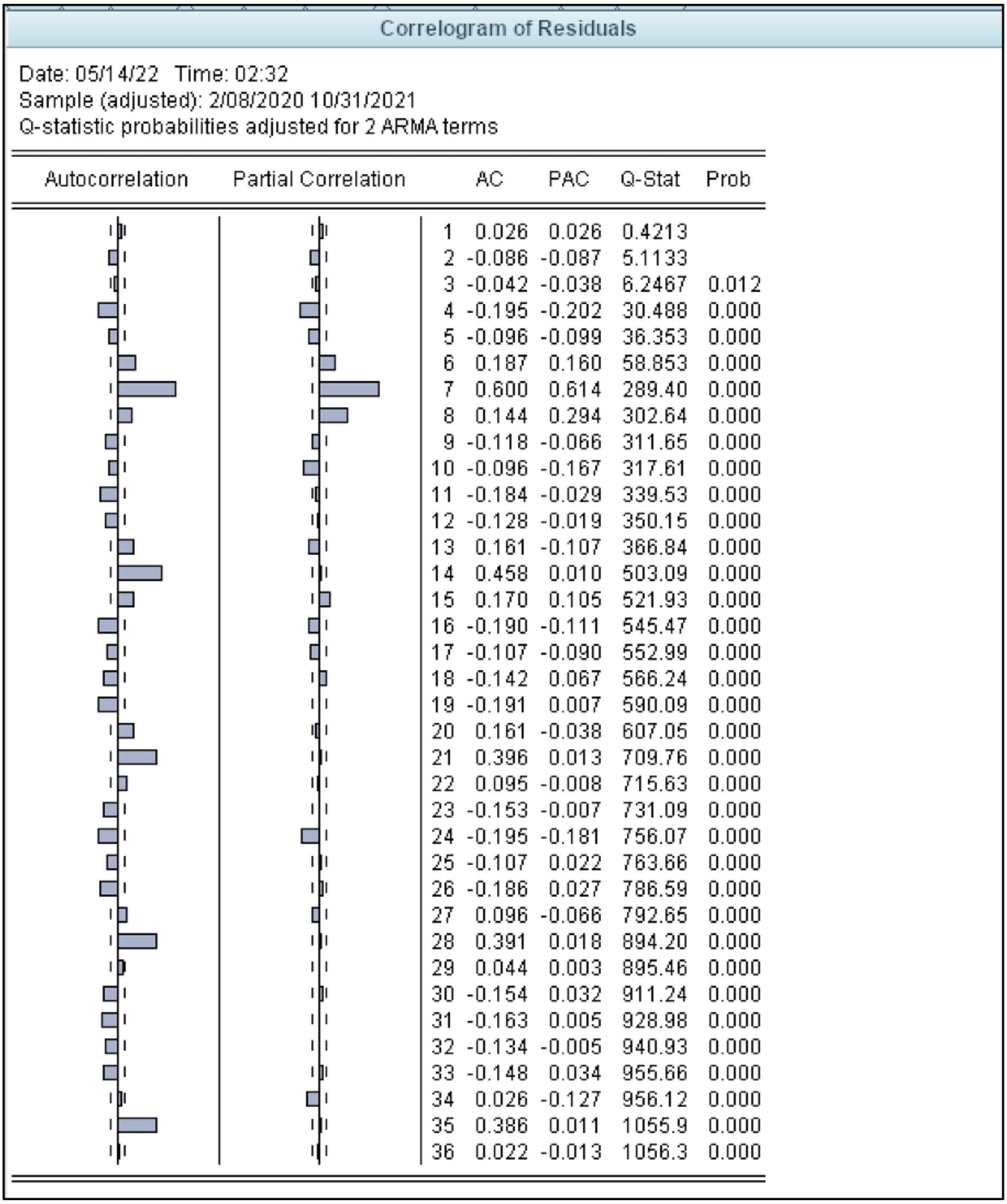
Dependent Variable: D(NEW_CASES)
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 05/14/22 Time: 00:22
Sample: 3/06/2020 10/31/2021
Included observations: 605
Convergence achieved after 37 iterations
Coefficient covariance computed using outer product of gradients
d.f. adjustment for standard errors & covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.521616	39.27995	0.013279	0.9894
AR(2)	0.172528	0.076661	2.250520	0.0248
MA(2)	-0.521392	0.065843	-7.918680	0.0000
SIGMASQ	2576656.	82620.43	31.18667	0.0000

R-squared	0.112131	Mean dependent var	0.378512
Adjusted R-squared	0.107699	S.D. dependent var	1704.956
S.E. of regression	1610.529	Akaike info criterion	17.61363
Sum squared resid	1.56E+09	Schwarz criterion	17.64275
Log likelihood	-5324.123	Hannan-Quinn criter.	17.62496
F-statistic	25.30064	Durbin-Watson stat	2.082280
Prob(F-statistic)	0.000000		

Table 2: *Checking the white noise of new_cases in ARMA Maximum Likelihood.*

Checking for residuals in the correlogram (table 3), one can see values that are crossing the standard error lines in all the correlations (both for autocorrelation and partial correlation). Detecting those patterns, it is possible to understand why the p-values are statistically significant in the correlogram. Henceforth, it is possible to reject the null hypothesis and conclude that the residuals are not white noise. In conclusion, new cases are not stationary as shown in table 2 and 3, and in other explanations in the findings.



Correlogram of Residuals

Date: 05/14/22 Time: 02:32
Sample (adjusted): 2/08/2020 10/31/2021
Q-statistic probabilities adjusted for 2 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.026	0.026	0.4213	
		2	-0.086	-0.087	5.1133	
		3	-0.042	-0.038	6.2467	0.012
		4	-0.195	-0.202	30.488	0.000
		5	-0.096	-0.099	36.353	0.000
		6	0.187	0.160	58.853	0.000
		7	0.600	0.614	289.40	0.000
		8	0.144	0.294	302.64	0.000
		9	-0.118	-0.066	311.65	0.000
		10	-0.096	-0.167	317.61	0.000
		11	-0.184	-0.029	339.53	0.000
		12	-0.128	-0.019	350.15	0.000
		13	0.161	-0.107	366.84	0.000
		14	0.458	0.010	503.09	0.000
		15	0.170	0.105	521.93	0.000
		16	-0.190	-0.111	545.47	0.000
		17	-0.107	-0.090	552.99	0.000
		18	-0.142	0.067	566.24	0.000
		19	-0.191	0.007	590.09	0.000
		20	0.161	-0.038	607.05	0.000
		21	0.396	0.013	709.76	0.000
		22	0.095	-0.008	715.63	0.000
		23	-0.153	-0.007	731.09	0.000
		24	-0.195	-0.181	756.07	0.000
		25	-0.107	0.022	763.66	0.000
		26	-0.186	0.027	786.59	0.000
		27	0.096	-0.066	792.65	0.000
		28	0.391	0.018	894.20	0.000
		29	0.044	0.003	895.46	0.000
		30	-0.154	0.032	911.24	0.000
		31	-0.163	0.005	928.98	0.000
		32	-0.134	-0.005	940.93	0.000
		33	-0.148	0.034	955.66	0.000
		34	0.026	-0.127	956.12	0.000
		35	0.386	0.011	1055.9	0.000
		36	0.022	-0.013	1056.3	0.000

Table 3: *Correlogram of Residuals with Q-statistic probabilities.*

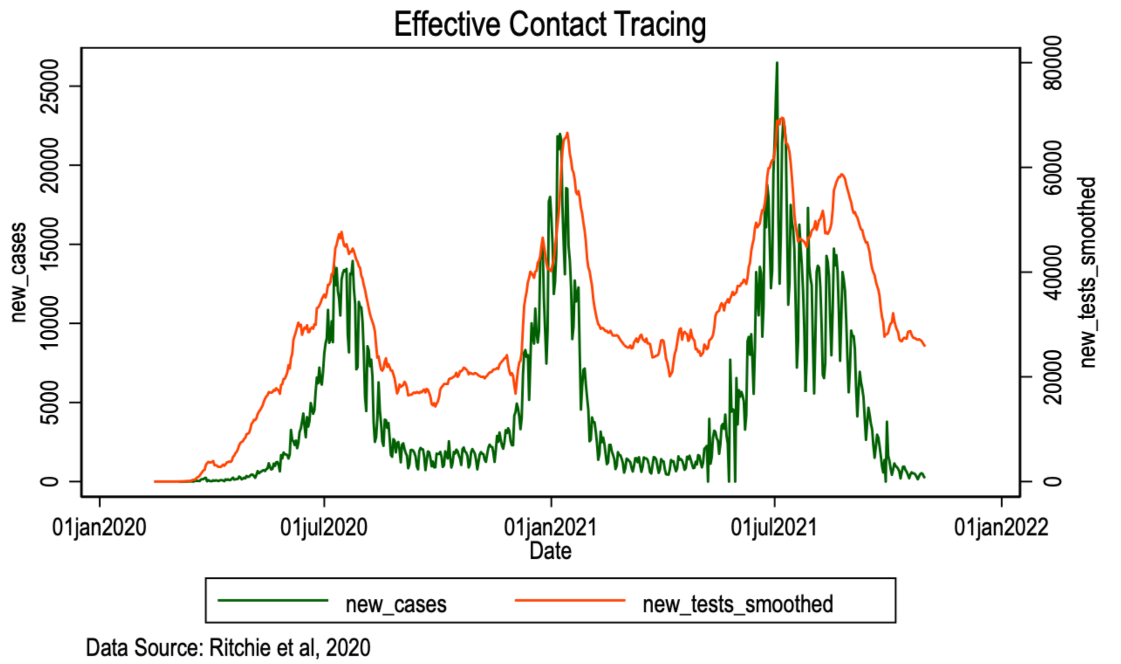


Figure 4: *Relationship between new cases and new tests.*

Figure 4 demonstrates a new test smoothed by examining the rate of COVID-19 disease in the January 2020 test under the auspices of digital contact tracing technology to help decrease the transmission reported to South Africa public health, given the evidence that the actual phenomenon of transmission cannot be exhibited if the government do not implement the test with the help of digital contact tracing technology sufficiently. We find the result of testing of an individual report to the authority methodology effective. The easy assumption is that of invariant mixing that the someone who interacts with someone else is equally presumable to interact with someone else in the given population. Under this situation, the count test of a newly infected person in a community in space $(t, t + \Delta t)$, is relative to the outcome of the infected person in the community, and the count of exposed persons ($Z(t)$) in the population at the period (t), that is to say, $x(t) = Ø*Z(t)$, where the distance is fixed Ø, relative to two other thresholds: the rate at which new interaction is established within two followers in the community per unit space and the likelihood of passing of deadly infection per interaction.

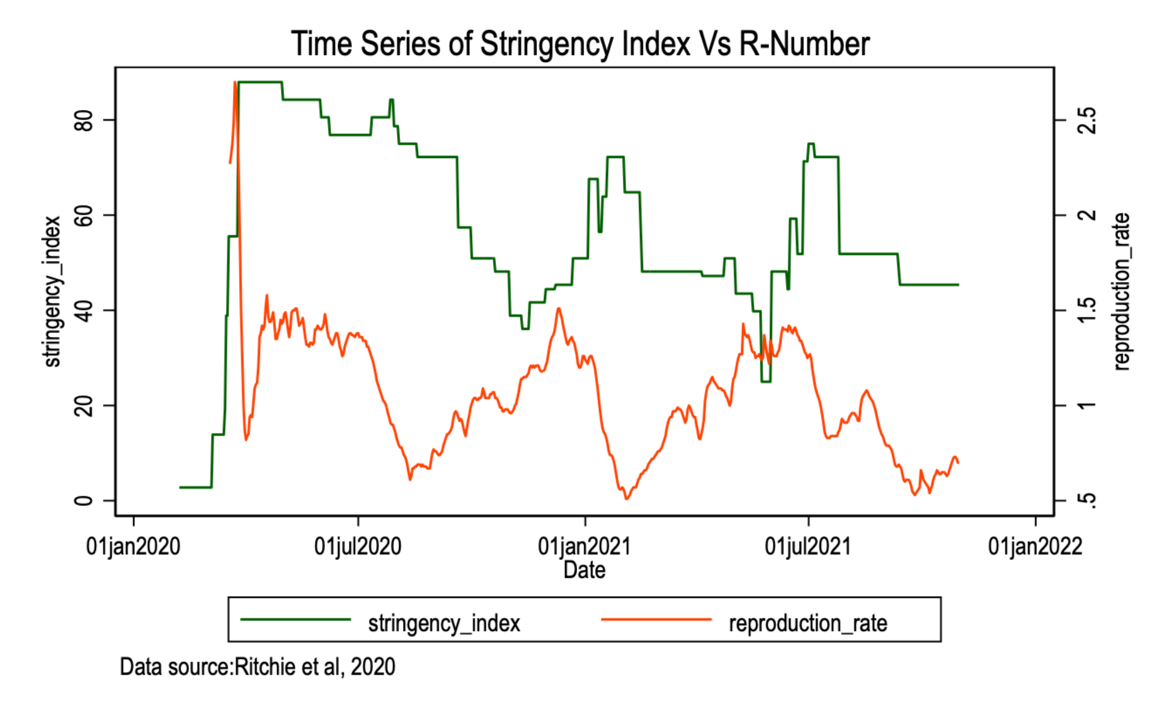


Figure 5: *Relationship between the stringency index and the reproduction number.*

Observed the stringency index and R-number (figure 5). While much has been said about contact tracing and sensor data sharing, the estimated increase in time to infection (t) requires stringent protection measures. Specifically, some events are not the same to overcome the psychological constraints imposed by the community's distrust of the entire data control process. For example, the current incident of COVID-19, its transmission, deadliness, and destruction it is prevailing in the social health domain, the social contact and the economy have accelerated a need for the everyone to report data, with the expectation that it can account the endurance of people. Furthermore, with the accessibility of reporting data from different geographical areas, public health supervisors, government, academics, and participants can launch the exposure and effect of the COVID-19 concerning information factors such as gender, age, health problems, community and others. A clear gap between the stringency index and R-rate is equally moderate throughout the incubation time, but it is relevant to note that there is a strong secular similarity in the control of the spike.

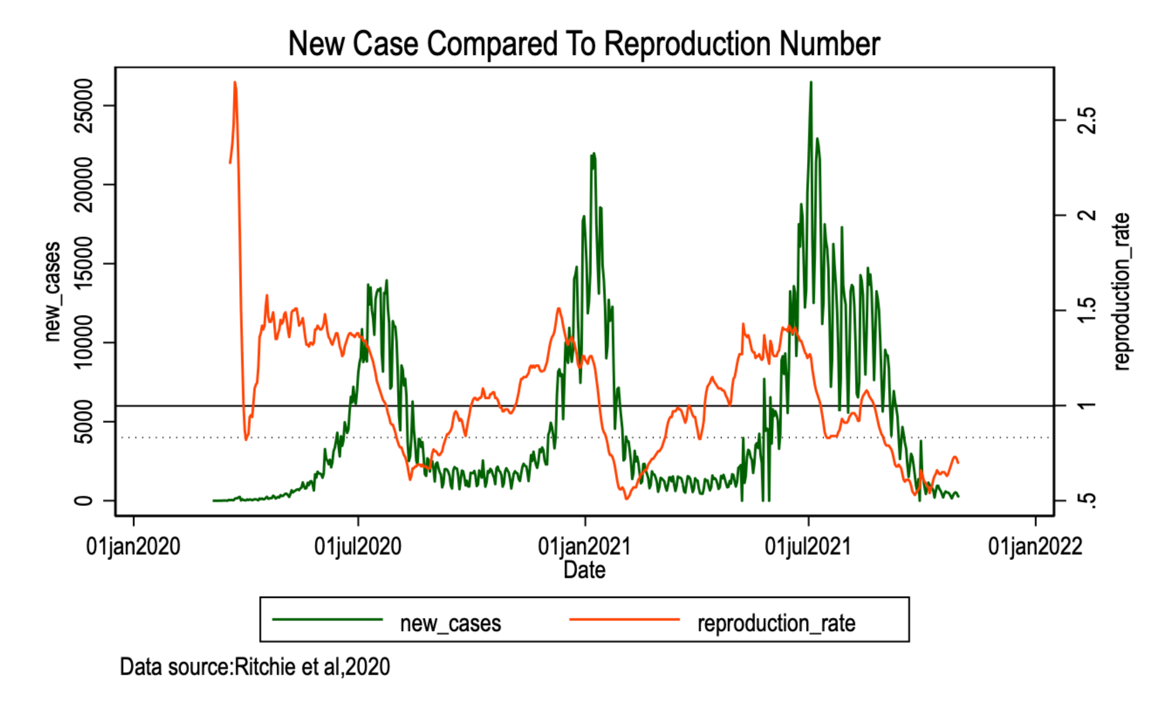


Figure 6: *Relationship between new cases and the reproduction number, with the threshold R-number = 1 as the horizontal line and R-number = 0.8 as the dotted horizontal line.*

This graph (figure 6) counts daily COVID-19 in South Africa from 2020 to late 2021, showing the effect of adjusting the persistence threshold for the current corona pandemic. When running the threshold at a reproduction number of 1, it is possible to detect when the pandemic trends is increasing or decreasing in the number of new cases. As such, the pandemic trend is stable at R-number equaling 1, decreasing with a R-number <1 and increasing with a R-number >1 (Li et al, 2020). Dotted horizontal line is showcasing a R-number equaling to 0.8, showcasing when the outbreak is decreasing by some margin. To notice, there is a certain lag-time between an increase or decrease in the reproduction number and an increase or decrease in the new cases. This could showcase the incubation period and arrival of symptoms before people are testing themselves, providing information on the importance of effective digital contact tracing to reduce the number of unknown cases in the society.

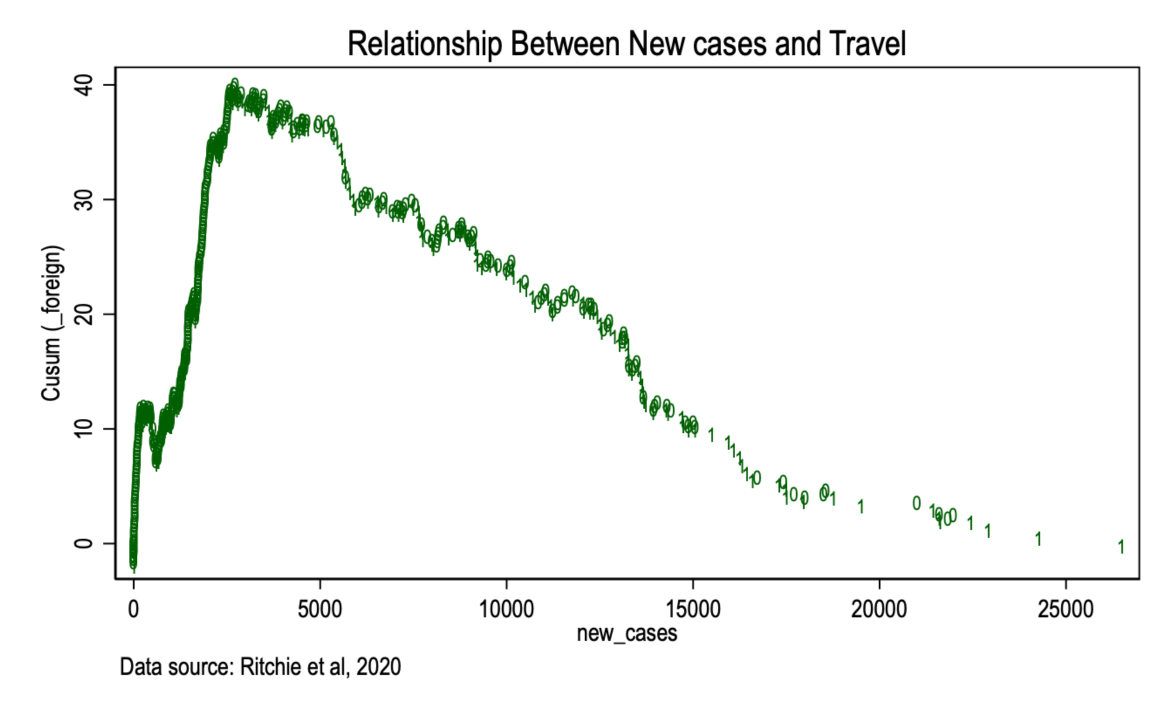


Figure 7: *Travels impact on new cases, domestic and foreign travel.*

Variable	Obs	Pr(1)	CusumL	zL	Pr>zL	CusumQ	zQ	Pr>zQ
_foreign	606	0.3201	40.24	4.740	0.000	20.95	2.706	0.003

.

Table 4: *The estimate of the Cumulative frequency of New Cases.*

The resulting (Figure 7), an inverted u-shape, demonstrates a positive, predictable correlation. In the output above, the trend is adjusted by the significant linear cusum Statistic brand cusumL as shown in table 4. Some 32% carried COVID-19 infections are the entry and exit are all foreign passengers with code 0. As government policy kicks in, the proportion of people traveling abroad has declined with new cases and a drop in infection rates. Domestic travel is more common than foreign travel. Although the quadratic cusum (CusumQ) is not significant, we have no reservations about the possibility of new cases. A sparse view coded with 1, at the end of the x-axis shows the prevalence of declining new cases.

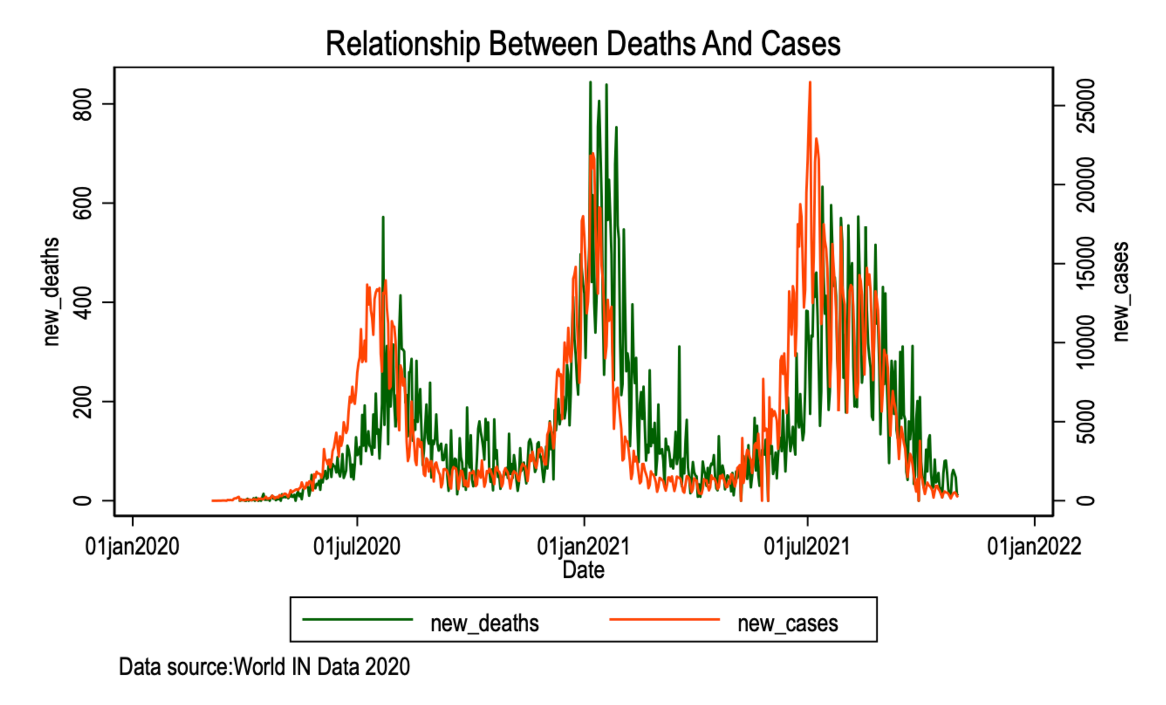


Figure 8: *New cases compared to new deaths.*

Weather conditions at different temperatures, such as minus 10 to 18 degrees Celsius or higher, have eased the reproduction of COVID-19, suggesting that alpine epidemics are more frequent in winter than in summer. Therefore, the expected seasonal difference has been deemed an outbreak (Figure 8). The series from January 2020 onwards shows that three different outbreaks have occurred, accompanied by death. Accordingly, a small event where the rate is projected from other years: January 2020 to 2021. The high point of 2020-2021 has been reported in South African public health, representing extreme peak values, confirming the effectiveness of contact tracing technology in daily and weekly reports. Furthermore, it was associated with virus outbreaks during the period.

The mean range graph, specifically the plot of range versus mean for each seasonal time, points out three epochs in which the virus spreads in different seasons, given the high extreme outliers in the graph below (figure 9).

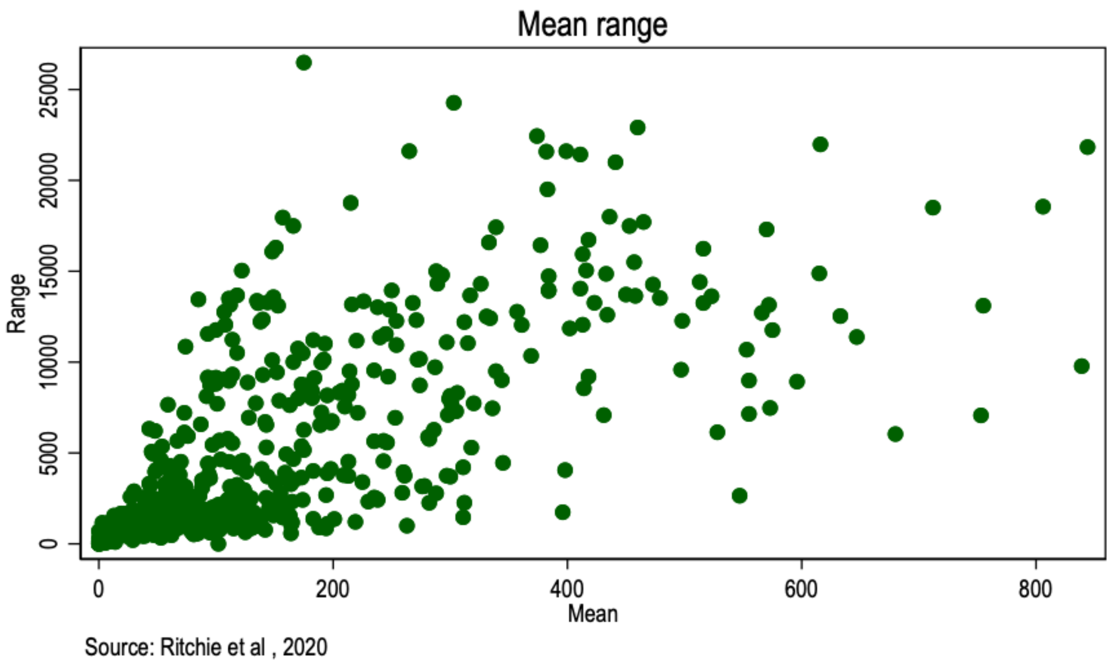


Figure 9: *Cases in the range of mean.*

Control Chart

We assume that the coefficient is steady in stoppage time when the time series is performed. There is the need to run a test based on whether the time series shortly fluctuates in the system. To state, the start sample date is different due to no available recorded data on new deaths before 28th of March 2020 compared to new cases with available data from 6th of March 2020. Cusum is informative and can be used to control the coronavirus (SARS-CoV-2). It allows health authorities or stakeholders to detect on-target changes when the variation outgrowth is generated, providing a surveillance model for epidemics.

The Cusum figure 10 offers the possibility of avoiding the spread of widespread disease. As growing drift time is started, governments can take the necessary steps to curb allowing new cases or new deaths to exceed the shaded upper area of the graph or exceed the confidence interval by implementing necessary measurements. Again, the figure 10 helps understand how digital contact tracing helps track what has happened throughout the reporting period, from March 2020 to October 2021.

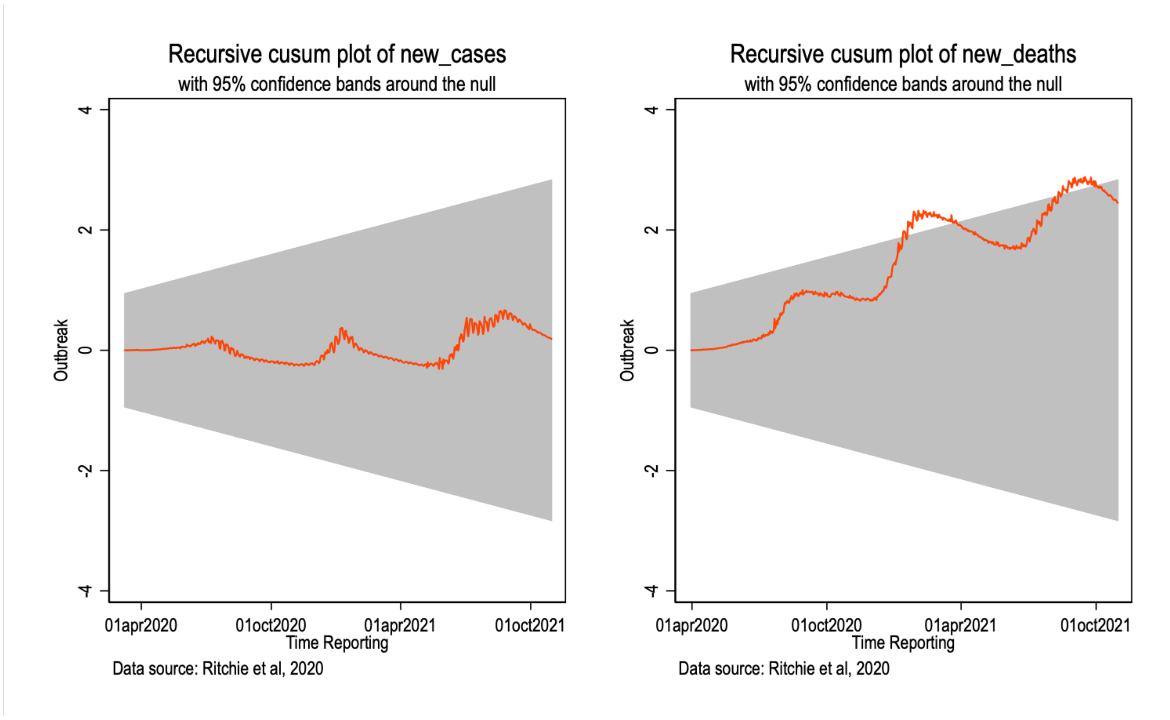


Figure 10: *Control charts look at new deaths and new cases per 1,000 people in 2020 and 2021.*

Control limits are set at 95% risk. The red line shows the view time series (new cases and new deaths on the x-axis). Shaded areas limit, introduce the possibility of death from new infections based on the impact of NPIs including contact tracing technology**.**

However, in order not to affirm to be more formidable on surveillance epidemic issues than any other in authority, there should be a stringency policy measure from around February to May 2020, September to December 2020, January to May 2021 and so forth, in that autumn and spring are the onus for the seasonal infection for the new cases and death. Nevertheless, stringency policies should be put in place throughout the period, given the alarming contact tracing.

Test tables for structural break

Cumulative sum test for parameter stability

Sample: 28mar2020 thru 31oct2021 Number of obs = 583
H0: No structural break

Type	Test statistic	Critical value 1%	5%	10%
Recursive	1.1269	1.1430	0.9479	0.8499

Table 5: *Test for new deaths.*

Cumulative sum test for parameter stability

Sample: 06mar2020 thru 31oct2021 Number of obs = 605

H0: No structural break

Type	Test statistic	Critical value 1%	5%	10%
Recursive	0.2389	1.1430	0.9479	0.8499

Table 6: *Test for new cases.*

In table 5, the analysis of the test results rejects the null hypothesis that there is no structural break since the test statistics > 0.9479 (5%), so the model monitors the data and by figure 10 one can clearly see that the new deaths break the 95% confidence band.

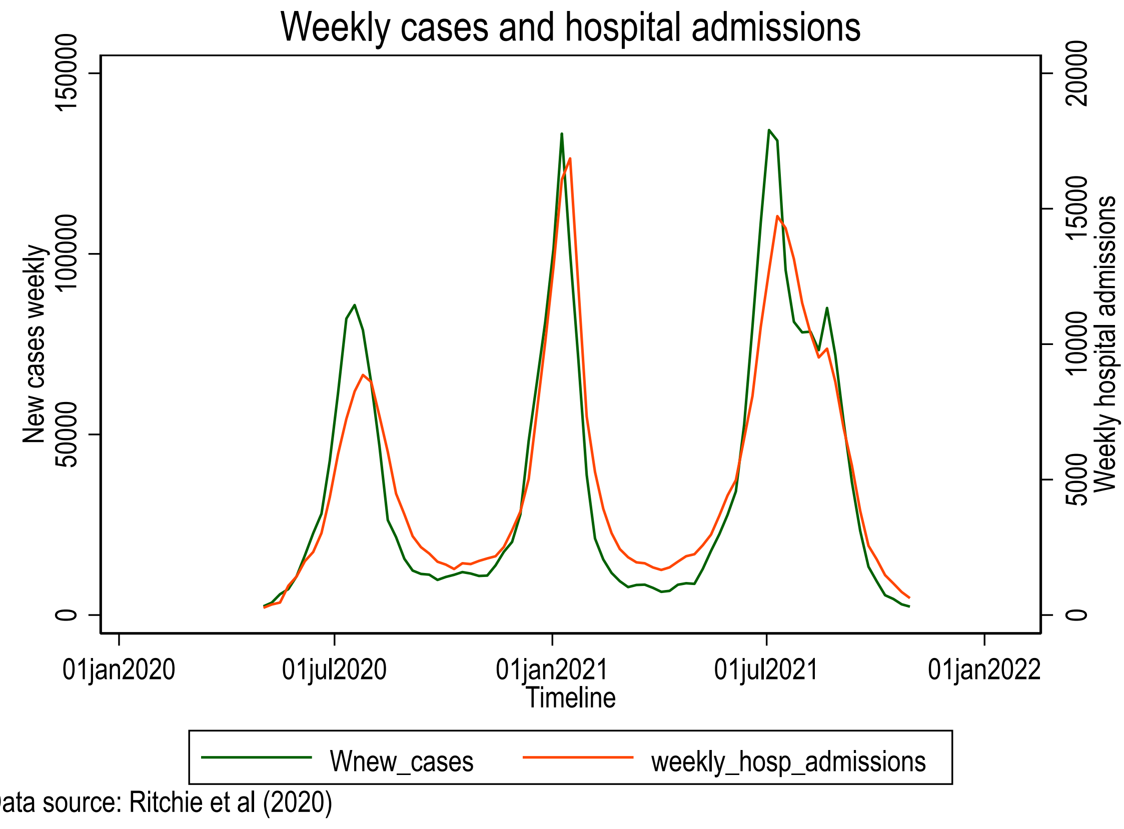


Figure 11: *Relationship between hospital admissions and new cases.*

To get an understanding of the total toll on the health systems, it is wise to determine the relationship between weekly cases and weekly hospital admissions. As such, one gets an overview of the pandemic patterns over time. With no surprise, the more cases the more hospital admissions, and by previous diagrams it follows the seasonal pandemic trends. To get an even better overview of the toll on both health systems and governmental institutions, it should be wise to determine the relationship between weekly new cases, weekly new hospital admissions and the cost range per hospital admissions due to the coronavirus. In figure 12, one could see two different cost scenarios calculated by Edoka et al (2021). Adding those numbers to the already available data on weekly hospital admissions, it is possible to detect the cost patterns.

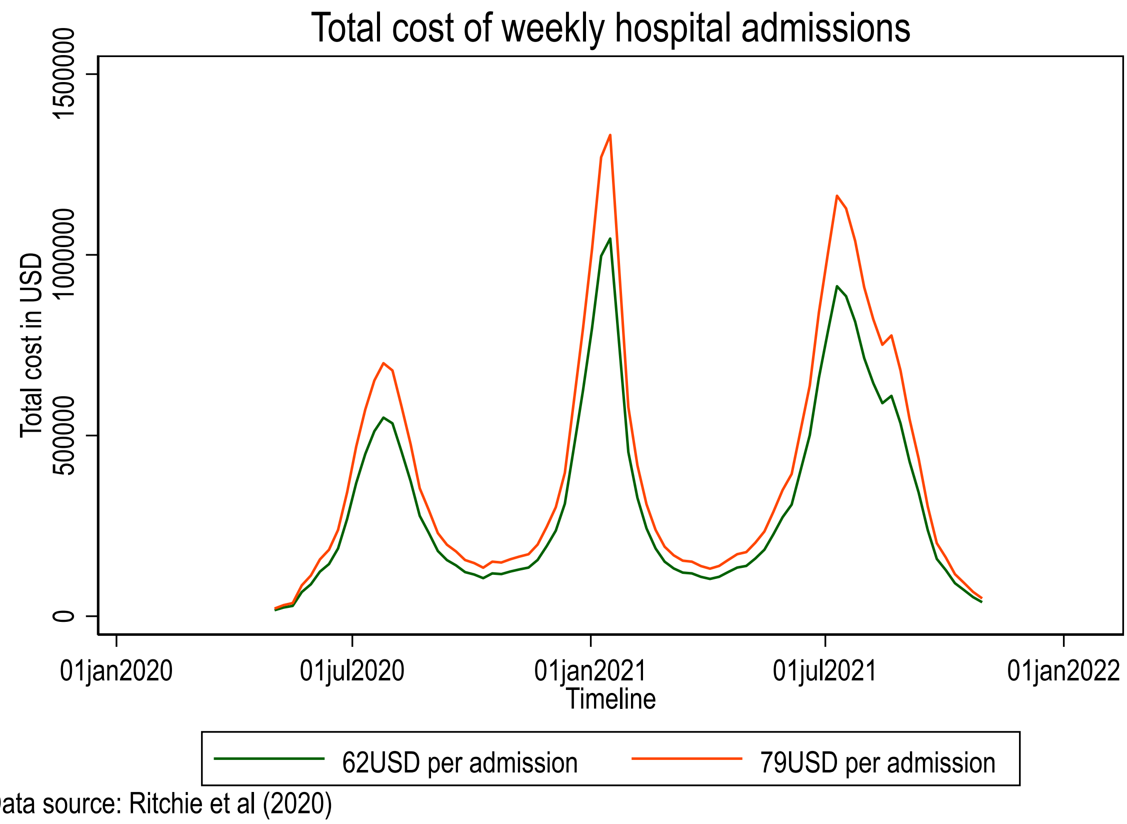
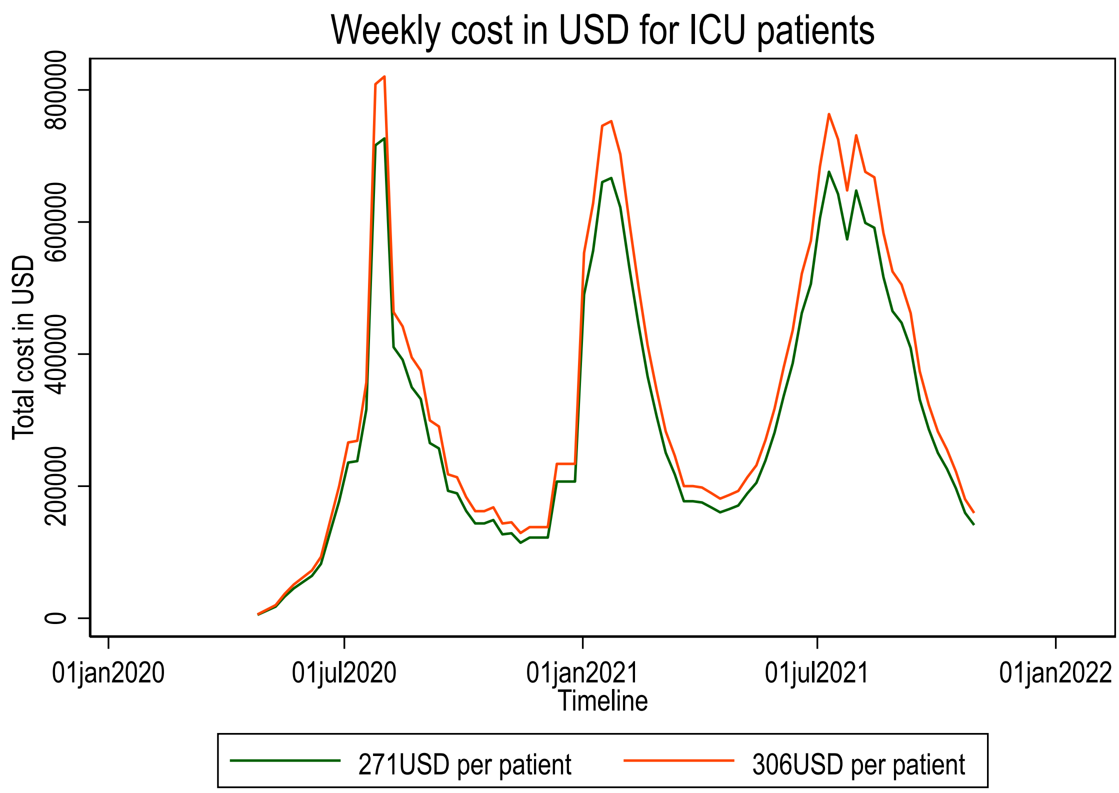


Figure 12: *Two different weekly cost scenarios related to new weekly hospital admissions for patients receiving treatment in general wards.*

However, these numbers are based on care given in general wards. In other words, it is not counting for severe disease occasions in need of care at high care wards or in intensive care units (ICUs). Edoka et al (2021) found the median cost for treatment in high care wards to 156 USD per patient, with the price range for treatment in ICUs ranging from 271USD to 306USD per patient. However, multiplying these numbers with all weekly hospital admissions would overestimate the actual costs due to the percentage of COVID-19 patients in need of such treatments. Implementing weekly data on the number of ICU patients in South African hospitals would get a better estimate on such costs, which can be found in figure 13 including both scenarios of 271USD and 306USD per patient.



Data source: Ritchie et al (2020)

Figure 13: *Two different weekly cost scenarios related to new weekly hospital admissions for patients receiving treatment in intensive care units (ICUs).*

To get an even better understanding on the severity of the disease burden due to COVID-19 one could estimate the excess mortality over the time series under study. Excess mortality is "*defined as the net difference between the number of deaths during the pandemic and the number of deaths that would be expected on the basis of past trends in all-cause mortality*" (Wang et al, 2022, p.1514). As shown in figure 14, the excess mortality floats over time. However, with no surprise, it follows the same patterns as weekly cases and hospital admissions. At most, the excess mortality was 171% 17th of January 2021 as shown in the figure, following the peak in hospital admissions in the same time series. With more successful contact tracing, the pandemic patterns may flatten out over time, decreasing the excess mortality in South Africa.

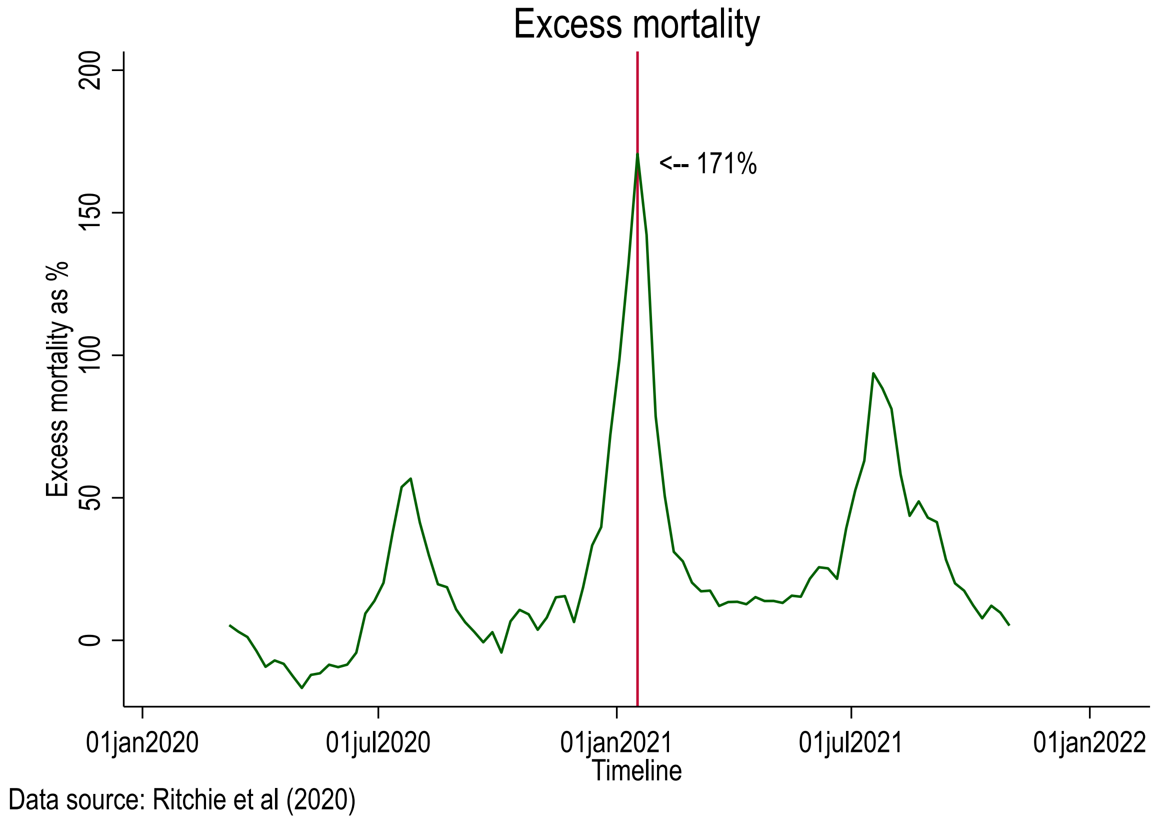


Figure 14: *Excess mortality shown as a percentage of expected deaths in the same period under "normal" conditions.*

Using the available data on new cases in South Africa until 31st of October 2021, it is possible to forecast future values of new cases in 2022. The system uses previous true values to calculate and forecast possible values of new cases. However only possible, from the forecast model it is plausible to assume that new cases of coronavirus will decrease in 2022 due to higher vaccinations rates, previous infections with COVID-19 and general herd immunity in the community. As such, the susceptible class will decrease, and the amount of people alliable for infection is low. Based on the graph (figure 15) it indicates that new cases will decrease over time, and it confirm that the data series is non-stationary.

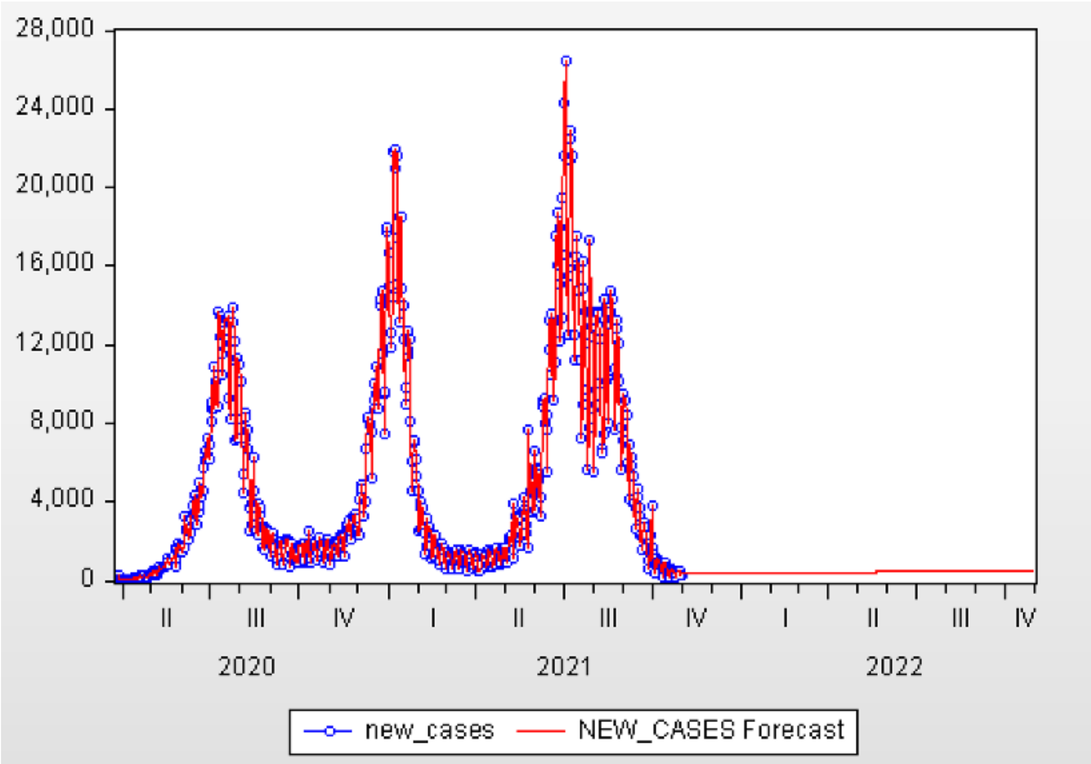


Figure 15: *Forecasting of new values.*

5.0 DISCUSSION

The goal of this project was to highlight the economic and health-related outcomes to successful and/or unsuccessful contact tracing, and to develop a model for proper surveillance of digital contact tracing technology in a communicable disease pandemic. The methodology section has provided the development of a surveillance model using the Cusum statistic approach, while the result section has focused on showcasing important aspects regarding available data and variables, most importantly the seasonal trends on new cases, new deaths, reproduction rate, hospital admissions, costs, and excess mortality. This chapter will focus on discussion of the results, with special regards to the relationship between digital contact tracing technology, and health- and economical outcomes. The section will also strive to provide future guidelines of implementation of digital contact tracing technology and surveillance.

Theoretically, deducing the trends in observing of the reports, warrants by providing details and setting the data for deficient reporting or reportage intervals. The reproduction time of the disease spreading addresses an essential function in classifying the seasonal trend in the coronavirus outbreak (Dash et al., 2021; Gottumukkala et al., 2021). The COVID-19 pandemic drifts in infection rates lag the pandemic drift in disease or exposure. The lag is driven by the spread of disease reproduction time. The surveillance incidence of new cases of infection is exclusively a proportion of the new cases that have been distributed as other incidences might, however, be developing, and that proportion is driven through the reproduction time of spreading in the population (Rocklöv & Sjödin, 2020).

Another attribute of this direction is the description of the overall cumulative sum chart, which is explicitly set up to detect changes in patterns (stoppage time). In our findings and equations 4 and 5, the time variance shows an upward trend. Transient epidemic rises in space show that, over time, changes lead to domestic travel versus foreign travel (local epidemics). Some dynamics between the fitted spatial point and determining factors are noticeable in our results, and the geotemporal link outcome may be understood.

Similar studies found a significant longitudinal upward trend in the study (Arroyo-Marioli et al., 2021; Singh, 2010), in chorus with detection dissimilarity in sequence. Here, prevalence spikes or jumps in a long-term rise, and the linked report shows an epidemic inflexion point.

However, other studies by Moultrie et al. (2021) found a positive secular tendency for the coronavirus (SARS-CoV-2) research in South Africa.

The decisive efficiency margins for the digital contact tracing for family cases of coronavirus are guidance to follow how well the process is carried out and what needs to be encouraged, from the community to the state (Kleinman & Merkel, 2020). The results show that the margins should show the digital contact tracing trends' changing actions in figures 4 and 6. Furthermore, the reference lines shown (figure 10) during the grace period can inform the authorities of the proposed action by investigating the effectiveness of the contact tracing system, thereby driving its capacity to further outbreaks.

One main finding was that responsibility, between government, local stakeholders, non-governmental organizations, and the people, is required to deliver effective digital contact tracing with public health management support, understanding the importance of using the contact tracing in the country. Understand the uses of contact tracing apps, controlling network structure, and technical expertise to construct a guide and put the app to work throughout the pandemic (Jalabneh et al.,2021; Danquah et al., 2019). Results were aimed at health-related outcomes of unsuccessful contact tracing technology. New cases are estimated based on new tests going well, reproduction numbers, infected people tracing, and infected people control during quarantine to stop the additional household spread of coronavirus. Hence, digital contact tracing app success has recourse to how many people in the population are contacted by the virus and how urgent new cases are tested. At the same time, how successful quarantine thwarted additional outbreaks. Once all these are accessed, the simulation track how infected people are traced.

Conversely, past studies comparing human contact tracing have shown that face-to-face contact tracing for data collection has successfully monitored several outbreaks of Ebola (Kleinman & Merkel, 2020). Our research shows that the effectiveness of digital contact-tracing technology relative to human contact-tracing methods covers a truly rapid attack on the virus when the available data is confirmed at any rate. In contrast, the information is often exposed to publishing lags through which the mass outbreak is the least to have been published (Unkel et al., 2012). Therefore, clear awareness of the reporting process for digital contact tracing and the delays in mapping a successful SARS-CoV-2 pandemic detection system is helpful.

Furthermore, the result shows that the recursive Cusum plot observes and controls infection outbreaks in the health protection system by utilizing recent data collected reports. Therefore, a 95% confidence prediction interval for the present rate may be computed from the average value and standard error of the reference line monitoring, while the observed over the proportion is confirmed epidemic abnormal if it lives outside the control warning interval (Novoa & Varela, 2019; Sibanda & Sibanda, 2007).

Implementing surveillance modelling via Cusum statistics could give an upper hand for South African government in deciding when stricter measurements are needed when new cases or new deaths drift outside of the control limits. When the pandemic drifts outside the control limits, it is reasonable to expect a higher toll on the national healthcare system. This again can cause disruptions on treatment and surveillance on other diseases in South Africa, as have been the case for Aids and malaria the previous years (Burger & Mchenga, 2021; Hatefi et al, 2020). Contributing to better pandemic surveillance via modelling strategics can lead to more effective digital contact tracing and implementation of other NPIs in early phases of possible outbreaks, hindering the need of postponing routine health check-ups and treatment in the South African healthcare system. Additionally, could better surveillance and more effective contact tracing cause a decrease in mortality rates, and hospital admissions in both the general wards and the intensive care units (ICUs) (Edoka et al, 2021). As shown in figure 12 and 13 is the costs related to such treatments high, especially for patients needing treatment in the ICU. Weekly costs for those patients are somewhere between 6 – 800.000USD during COVID-19 waves in July 2020, January 2021, and July 2021. Lowering the number of patients needing treatment by decreasing number of new cases could spare South Africa for money in direct treatment costs and infection control in the hospitals, with possibilities of using the same money in treatment for other diseases in South Africa, providing an opportunity of financial and educational growth in the country due to a lower total disease burden (Hatefi et al, 2020).

However, these are the results from the positive scenarios simulated in chapter 4, and it is of importance to state that it may not be the case in a real-life scenario. That said, other research related to digital contact tracing highlights the positive opportunities even with lower numbers of users (Kinyili et al, 2020; Wymant et al, 2021). As such, it may be realistic to base discussion on the positive scenarios in South Africa and how it could affect the pandemic trends in the country. Either way, it is important to mention the decreased trust in the government of South Africa in the early phase of the pandemic, with almost half of the population worrying that the government used the pandemic to increase their power and authority in the country (Plus 94 Research, 2021). Additionally, over half of the population found it (very) difficult to comply with lockdowns and national measurements to deal with the seasonal patterns of the pandemic, further hindering the proper use of measurements to decrease the new number of cases over time (ibid.). Mentioning such, it could underline the possibilities of how much successful and effective contact tracing could decrease the seasonal patterns of the pandemic. Using public trusted and inflectional people when showcasing the importance of downloading and using the digital contact tracing application may lead to an increase in usage percent uptake, and again may lead to a more successful and effective contact tracing in South Africa. By doing so, it may lead to a decrease in new cases flattening out the steep rises in the seasonal spikes as seen in the provided figures 8-11, preventing the need of lockdowns and high fiscal support to cope with strict measurements.

5.1 LIMITATIONS AND STRENGTHS OF THE STUDY

Our main research limitation is the available data set, since the data is national and not regional. Regional data would have been preferred, due to the possibilities of comparing different regions in South Africa and the effect digital contact tracing has on the pandemic in those regions. Most research on effectiveness of different measurements towards COVID-19 compare data from different countries, and then run comparative analysis on the different effectiveness of measurements as digital contact tracing. Due to our research solely focusing on South Africa, would regional data inside the country made our research even more contributing to new knowledge. However, that have not been the case and it is not possible to run comparative analysis from one region to another.

Further on is analysis done on digital contact tracing a limitation since it is somehow impossible to withdraw other influential measurements and natural behavior towards pandemic outbreaks. Natural behaviors could be decreasing social contact, staying more at home, decreased limit to testing and so forth voluntarily. Henceforth, when the government implement strict measurements as staying at home and working from home, many may already voluntary adapted daily life accordingly. In that case, the number of new cases may decrease either way because of changes in natural behavior towards rapid increases in cases. However, with that in mind could effectiveness of digital contact tracing be analyzed when new cases are low, medium, and high to decrease the impact from natural behavior as much as possible. Despite taking care of natural behavior would there still be a limitation related to the implementation of other non-pharmaceutical interventions as washing of hands and use of face masks, often implemented at the same time as contact tracing (or even before). One way of dealing with this drawback however would be to compare regional effectiveness of measurements with and without digital contact tracing implemented.

Another limitation is also related to the data collected, since one may experience serious lag in reported cases and a vast number of unknown cases in the society. However, it is plausible to assume that with proper and effective digital contact tracing almost all close contacts would be traced. This is in the most positive scenarios, and more realistic scenarios may still have unknown cases. How large this proportion is however difficult to detect, and it may be even more difficult to calculate the impact these numbers have on the findings. Either way will the susceptible class decrease over pandemic time, lowering the amount of possible unknown cases in the society.

This thesis has an array of successes. To the author's awareness, this can be of early discourse on the success of digital contact tracing performance and suggest measures for digital tracing, considering the coronavirus. The statisticians should barely develop the mathematical concepts. Nonetheless, if irregular counts are practical and warrant more research, they should be more involved in implementing the system and expanding access to timely data and controls. The transmission systems used by mobile apps, including the observation of regional data, have sparked discussions about confidentiality and may interfere with data protection by making end-users insecure from destructive intrusions. In addition, the Bluetooth communication path has social, economic, and technological biases because such a society requires cell phones. However, as stated earlier can these biases possibly be conquered due to the rapid increase in cell phone availability in low- and middle income-countries.

6.0 CONCLUSION

Highlighting the vast impact lockdowns and increase in cases of COVID-19 has on national economy and disease burden, it is necessary to evaluate the importance of measurements who can limit the disease burden of COVID-19 in South Africa. Digital contact tracing technology is one of many, but the impact the technology can have on keeping the pandemic under some control is vast. Effective and proper tracing of contacts, without any limitations related to human memory, time, or resources, could give South Africa an upper hand in dealing with pandemics as COVID-19, successively isolate and test known close contacts, breaking the chain of transmission. Implementing a Cusum statistic modelling for pandemic surveillance in new cases and new deaths could further help reducing the reproduction number, rapidly knowing when more intensive contact tracing should be implemented. As such, one is not only reducing the national costs related to rigorous fiscal support, but also ensuring continuation of other important treatment and check-ups in the healthcare institutions. Further research should focus on solutions where it is possible to solely analyze the effect on digital contact tracing technology alone, finding proper analysis techniques to evaporate the infiltration of natural behavior and other NPIs on the research results. The promotion of digital contact tracing techniques in data collection, especially the accessibility of geographic data points and a robust digital rapid counting system, is suitable for avoiding disease exposure. In conclusion, digital contact tracing in South Africa can go beyond a single community to encompass regions. The outbreak does not consider state borderland, and therefore, the extension of the state's timely detection process for information in global settings is relevant.

With that in mind is our research not a solution, but more a proposed model for effective contact tracing and pandemic surveillance in South Africa and in similar countries.

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APPENDIX: STATA CODE

```

** CREATE AND STRUCTURE FUND DATA FILE
4 use "/Users/awuahasamoah/Desktop/NTNU M THESIS/**Thesis-data-per-27th-of-April-Stata.dta"
gen date2 = date(År, "DMY")
format date2 %td
gen year = year(date2)
format year %ty
gen month = month(date2)
drop År
///The Authors Stata Command file for Figures and Tables
///Figure3:t
twoway (tsline stringency_index) (tsline new_cases_smoothed_per_million, yaxis(2))
///Figure4:
twoway (tsline new_cases) (tsline new_tests_smoothed, yaxis(2))
 ///Figure5:
twoway (tsline stringency_index) (tsline reproduction_rate, yaxis(2))
///Figure6:
twoway (tsline stringency_index, yaxis(2)) (tsline new_cases_smoothed_per_million )
///Figure7:
twoway (tsline new_tests_smoothed) (tsline new_cases, yaxis(2))
///Figure8:
twoway (tsline new_deaths) (tsline new_cases, yaxis(2))
///Figure9:
twoway (tsline new_cases) (tsline reproduction_rate, yaxis(2))
///Figure10:
twoway (tsline new_tests_smoothed) (tsline reproduction_rate, yaxis(2)), title("Effective Contact Tracing")
///Figure11
twoway (tsline Wnew_cases) (tsline weekly_hosp_admissions, yaxis(2))
///Figure12
twoway (tsline GWcost1) (tsline GWcost2)
///Figure13
twoway (tsline ICUcost1) (tsline ICUcost2)
///Figure14
tsline excess_mortality, tline(17jan2021)

///Prediction Graph New Cases
twoway (line lnew_cases   t) (line llnew_casesh1 t)
/// log transformation
generate logdelay = ln(new_cases)
reg logdelay t L.new_cases
/// We need to run three cases against R-rate to see the pattern

estat sbcusum, name(new_deaths, replace)
/// Here we can add time to the model to see what happens to the drift
regress new_cases t L.new_cases
estat sbcusum, name(new_cases, replace)
regress new_deaths t L.new_deaths
estat sbcusum, name(new_deaths, replace)
/// We need to run three cases against R-rate to see the pattern and compare them
reg new_deaths L.new_deaths
estat sbcusum, name(new_deaths, replace)
cusum _foreign new_cases, s(none) recast(scatter) mlabel(_foreign) mlabp(0)
///Tables
twoway scatter new_cases new_deaths, mstyle(p1 p10) title("Mean range")
reg new_deaths L.new_deaths
estat sbcusum, name(new_deaths, replace)


********************************************************************************
```

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