University College Cork, Ireland
Coláiste na hOllscoile Corcaigh

Title: "Analysing the Impact of the COVID-19 Pandemic on Human Mobility Nationally and Internationally using Data Generated from ICTs"

Student Name and Number: Grainne Donegan (117312963)

Supervisor: Dr. Marguerite Nyhan

Date: 20/04/2021

Declaration of Authenticity

I hereby certify that this Final Year Project is solely based on my own work, that no one has written for me and that has not been previously submitted for another degree, either at University College Cork or elsewhere. All sources have been properly cited, clearly documented and fairly used. I have read and understood the regulations of University College Cork concerning plagiarism.

Signature: Gráinne Donegan Date: 17/04/2021

Acknowledgements

Firstly, I would like to thank my research supervisor, Dr. Marguerite Nyhan for her help throughout the year with my Final Year Project (FYP), initially offering me the chance to work with her as one of her MaREI interns last Summer during the early stages of the pandemic, and also for providing guidance whenever I had any queries along with giving extremely helpful feedback, which were pivotal to completing the project. I would also like to thank Dr. Ken Bruton for his feedback on my FYP Presentation. I would also like to thank Anna O'Regan for providing advice with regards to my data preprocessing. Finally, I would also like to thank both Mike Donegan and Saskia Scholze for proofreading my FYP report prior to submission.

Abstract

COVID-19 has disrupted life as we know it, influencing everything in our lives from our commute to work to our weekly shopping trips. Alterations in mobility patterns have been created as a result of travel restrictions imposed by governments to stop the spread of COVID-19. These changes have been noted by tech giants Apple, Facebook and Google, which has prompted them to release datasets containing information on these physical mobility changes.

These datasets will be analysed to establish the relationship between mobility patterns and COVID-19 cases in a variety of countries, by creating python programming scripts to analyse both the Apple & Google derived mobility datasets along with COVID-19 case & death counts from Our World In Data, as well as meteorological data, government announcement and national holidays. This methodology will be repeated for Ireland, Brazil, New Zealand, Sweden, South Korea and Germany and all results will be presented in both tabular and graphical form to ensure that a comparative analysis is conducted.

Many noteworthy findings were obtained from his methodology, such as the fact that there is a strong association between COVID-19 cases and mobility patterns evident in society. It was also evident that COVID-19 case values had very little influence on the number of people visiting parks. New Zealand's repressive actions to curb the spread of the disease also garnered praise as New Zealand had extremely low transmission levels when compared to a country with similar population size, i.e. Ireland.

These findings reinforce the use of lockdowns to mitigate the spread of the virus along with encouraging an increase in land use allocated for parks. This research can, therefore, be used by departments of health and the government to determine the needs of a society during a pandemic and when to introduce travel restrictions if mobility patterns increase a substantial amount.

Executive Summary

COVID-19, a disease caused by the coronavirus SARS-CoV-2, has had a significant impact on daily life. It dictates the media we consume, the conversations that we have and the new ways in which we work. As a result of its contagious nature, travel restrictions have been imposed on the majority of the global population, which vary from social distancing campaigns to harsh lockdowns with the closure of borders. Such restrictive measures have had an impact on the mobility patterns of society, which have been well-documented by big tech companies such as Google, Facebook and Apple. Therefore, they have released datasets documenting the fluctuations in visits to certain places in the midst of the ever-changing pandemic. This report details the methodology adopted to analyse these datasets along with its implementation to determine the association between COVID-19 cases and mobility patterns both nationally and internationally.

The relationship between locational occupancy and daily COVID-19 case values became the focal point of this report, when initially analysing the impact of COVID-19. Society, healthcare systems and economies were severely impacted by the rise of cases and the spread of the pandemic globally. Upon completion of the research, it became apparent that COVID-19 cases and travel restrictions were not mutually exclusive, as often governments would intervene with social distancing measures or lockdowns to mitigate the spread of the disease as cases rose. Therefore, Google and Apple-derived mobility datasets were analysed in order to determine the association between mobility patterns and reported COVID-19 case incident rates for numerous countries, along with documenting any interesting findings that could be used by public health officials and governments to curb the spread of COVID-19.

The following aims were adopted for this research paper:

(i) Process publicly available Google and Apple mobility datasets at a national level in Ireland and for various countries around the world, using a number of custom built Python programming scripts.

(ii) Conduct an exploratory data analysis and graphical/visual analysis of the mobility datasets. This will include examining variations in mobility patterns for different categories in relation to influential factors.

(iii) Quantify observed alterations in mobility patterns in response to fluctuating numbers of COVID-19 cases, government announcements, public holidays and meteorological data and determine all contributing factors.

(iv) Examine the associations between the Google-derived mobility categories (Retail & Recreation, Grocery & Pharmacy Stores, Parks, Transit Stations, Workplaces and Residential) and COVID-19 case rates, incorporating a 14 day lag period, applying regression analyses - Ordinary Least Squares (OLS) single and multiple linear regression models.

(v) Discuss the implications of the analyses on the development of public health policies related to COVID-19 and in the design of liveable cities for the future.

A python programme was created to analyse the Google & Apple mobility datasets in tandem with COVID-19 case & death values, as well as meteorological data and to determine the relationship between mobility patterns and reported COVID-19 case rates for numerous countries. The influence of factors such as government intervention and public holidays were also investigated alongside the mobility datasets. In-depth statistical analyses in graphical and tabular form provided a series of results, which can be replicated in a scalable manner using the programming scripts.

Based on the results, a number of interesting findings were acquired. Overall, a strong association between COVID-19 cases and mobility patterns evident in society became apparent, as the rise of visits outside of the home led to an increase in COVID-19 cases two weeks later. The analysis also proved that COVID-19 case counts had a negligible to weak influence on visits to greenspaces, as unlike the other Google mobility categories (i.e. Retail & Recreation, Grocery & Pharmacy Stores, Transit Stations, Workplaces and Residential) a weak correlation constant and coefficient of determination (R^2) was obtained when analysing the relationship between COVID-19 cases and park visits. A similarly weak relationship can be seen between meteorological data and both COVID-19 case & death values, as well as mobility data. Upon completion of an international analysis, New Zealand's harsh lockdowns and border closure proved to be the most effective method of quashing the disease in a country, as many elements of everyday have resumed as normal.

Therefore, based on these findings, it can be concluded that this research can be utilised in order to influence public health decisions, promote the need to allocate urban area space to parks and reinforce the use of travel restrictions as effective measures to curb the spread of COVID-19.

Table of Contents

List of Figures

List of Tables

Abbreviations

Abbreviations	
AIC	Akaike Information Criterion
API	Application Programming Interface
CSO	Central Statitstics Office
ECDC	European Centre for Disease Control
GPS	Global Positioning System
ICT	Information and Communication Technology
IFR	Infection Fatality Rate
NPI	Non-Pharmaceutical Intervention
OECD	Organisation for Economic Co-operation and Development
OLS	Ordinary Least Squares
OWID	Our World in Data
UN	United Nations
WHO	World Health Organisation

Nomenclature

Nomenclature	
y	Box-Cox & Yeo-Johnson Transformation Input Value
λ	Box-Cox & Yeo-Johnson Transformation Parameter
w	Box-Cox & Yeo-Johnson Transformed Value
k	AIC Model Parameter
L	Highest Value of the Likelihood Function for an AIC Model
Y_{it}	OLS Regression Analysis Dependent Variable for Country i at Time t
X_{it}	OLS Regression Analysis Independent Variable for Country i at Time t
$X_{i(t-14)}$	OLS Regression Analysis Independent Variable for Country i at Time t-14 Includes 14 Day COVID-19 Case
α	OLS Regression Analysis Line Intercept
β	OLS Regression Analysis Line Slope

1.0 Introduction

As a result of the COVID-19 pandemic, everyday life as we know it has been disrupted. As currently over half of the world has been told to minimise their movement or has been asked to remain at home (Sandford, 2020) due to the COVID-19 pandemic, this has caused a sharp rise in questions being asked with regards to our open spaces (Honey-Rosés et al. 2020) and other factors in society. The decline in mobility has been documented by many big tech companies, such as Google, Apple and Facebook, which utilised the data of their own users who have either opted in or allowed the company to access their location history.

The mobility of a population is determined by numerous factors, which include transport usage, people remaining at home and workplace visits. Throughout the timeline of the pandemic, many countries have implemented various policies in order to reduce the impact of COVID-19 on society, which can also heavily influence mobility patterns in the form of grocery store and retail outlet visits. Early impacts of COVID-19 can already be seen in the form of traffic reductions (Chandran, 2020), but many factors are still to be investigated. Hence, mobility datasets have been produced by Google, Apple and Facebook in order to aid public health authorities in determining suitable measures to aid the population, ensuring they are anonymous, devoid of personal information.

In this FYP, the impact of COVID-19 on society will be determined and the use of the data in the future decision making will be investigated, using the readily available Google and Apple mobility data sets. This will enable the determination of mobility patterns and the alteration of society's actions amid the pandemic. The data is vital, as it allows future planners and health officials to determine the needs of the population and can integrate them into the design of cities and policies in the future.

2.0 Literature Review

The COVID-19 pandemic has pervaded every element of daily life and has changed the way we think and behave in a manner that has not been seen in recent times. Over half of the world's population has been told to minimise their movement or has been asked to remain at home (Sandford, 2020) during the pandemic and this has had huge impacts on society. Specifically, our usual mobility patterns have been impacted as a result of the nature of the virus and how it spreads.

In this literature review, the effect of COVID-19 on health, society and the economy will be examined. Following that, the impact of COVID-19 restrictions and governmental interventions on society will be discussed. The latter half of the literature review will include a discussion into movement, locations and mobility patterns of societies, along with potential areas of investigation for this FYP. The following approach will be adopted for the literature review:

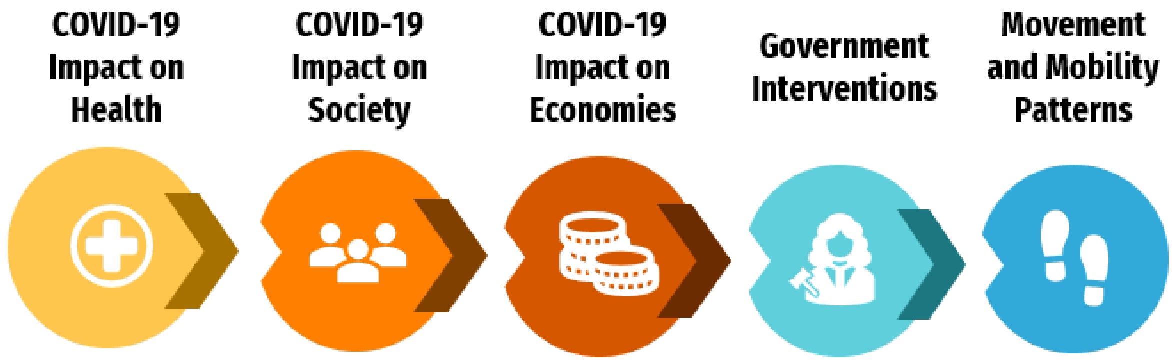


Figure 2.1: Literature Review approach initially analysing the impact of COVID-19 on health, society and economies, resulting government interventions and the impact of these of movement, locational occupancy and mobility patterns

2.1 COVID-19 Impact on Health

COVID-19 is a disease caused by a recently detected Severe Acute Respiratory Syndrome Coronavirus (ECDC, 2020a), which was previously not identified in humans until the latter half of 2019. Its quick transmission through society has had a significant impact on health as there have been over 55 million cases globally (Johns Hopkins University, 2020).

As the global death toll surpasses 1,300,000 (WHO, 2020a) at the time of writing[1], the health of the population and its prominence amidst a pandemic have never been so pivotal. Along with clear health impacts from COVID-19, the virus has also had a drastic secondary impact on both physical and mental health. In a survey carried out by the WHO, 93% of

[1] 1,338,769 deaths globally at 10:29am CET, 19 November 2020 according to WHO

countries claim that the pandemic has postponed or even halted mental health services (WHO, 2020b), even though there is a significant increase in demand for these mental health services (UN, 2020).

COVID-19 has also led to an increase in physical deaths related to cancer, as a result of postponed treatments, diagnosis, additional stresses etc., which is reflected for example in an estimated 5.8 – 6.0% increase in oesophageal cancer deaths up to 5 years after diagnosis as a result of the pandemic (Maringe, et al, 2020). The significant death toll is noticed when compared to other notable death causes for the US, as COVID-19 in less than 10 months, has killed more people in the US than car crashes, suicides and strokes do in a full year (CNN, 2020a).

2.2 COVID-19 Impact on Society

COVID-19's rampant contagious nature has forced many countries to impose measures to reduce human interactions, having a clear social impact on society. As many countries impose some form of lockdown, social isolation, of older people in particular, has led to heightened levels of loneliness evident in society (Groarke et al., 2020).

Young people have also been disproportionally affected during the pandemic, as employees under 25 years of age were ≈ 2.5 times as likely to work in an industry that has had to shut down as a result of the pandemic, as other employees (Joyce & Xu, 2020). Many young children and adolescents have had their education briefly halted as a result of the pandemic, where all 46 OECD and partner countries had closed some or all of their schools by the end of March 2020 (Schleicher, 2020). This also has potentially led to the increasing inequalities in education amongst children with different socioeconomic backgrounds (Doyle, 2020), as a lack of resources could inhibit a child's educational development.

2.3 COVID-19 Impact on Economies

Undoubtedly COVID-19 has had a significant impact on the economy in both developed and developing societies. For example, people with higher disposable incomes are more likely to "Work From Home" in the countryside (Tanguay & Lachapelle, 2020), but many jobs in manufacturing or secondary industries within cities cannot be carried out from home

(Nicola et al., 2020) and therefore, this creates a greater social divide between people living in the countryside and in cities (Sánchez-Páramo, 2020).

Many industries have been subjected to a stark drop in demand and as a result, are close to bankruptcy. This is especially true in the case for industries that depend on tourism, such as the airline industry, which is estimated to lose $84 billion in 2020 (Klein, 2020), as a result of many flight cancellations from lockdowns and border closures. The retail industry, specifically stores which depend on brick and mortar outlets, have been impacted. This is evident for major retail companies, such as JC Penney in the US, who filed for bankruptcy in May (Chutchian, 2020). The EU had also estimated a 7.5% contraction of the EU GDP in 2020 (European Commission, 2020) with the IMF predicting the worst recession since the Great Depression (Reuters, 2020).

2.4 Government Interventions

In order to mitigate the spread of the virus, many governments have adopted various approaches to limit the spread of COVID-19. Some countries have implemented a series of non-pharmaceutical interventions (NPIs), in order to reduce the reproductive number of COVID-19 (Ferguson et al., 2020). Currently there are no pharmaceutical interventions in the form of a vaccine readily available and at the time of writing (19/11/20), but there are 54 vaccines being tested in clinical trials on humans (New York Times, 2020). Some NPIs, such as physical distancing, require between 2 to 5 weeks to register an impact on the virus spread (Cacciapaglia et al., 2020) resulting in many countries having negative infection rates as a result of social restrain, whether a policy was implemented or not.

NPIs are a common method used to supress diseases. They include, but are not limited to self-isolation, public building closures and social distancing measures. They have varying degrees of restriction, but all have a common goal to quash the spread of COVID-19. Wellenius et al. (2020) discovered that the most effective NPI during the first wave of the pandemic from a government was the limitation of restaurant and bar operation, with closures leading to 25.8% increase in residential visits. It also became evident that emergency measures had minimal impact on park visits, but this is due to the fact that their research was carried out in the Summer and is compared to the Winter, when people are more reluctant to go to the park.

Globally, many governments have utilised various responses to stop the spread of the virus, with countries such as Sweden (BBC, 2020) and South Korea (TIME, 2020) opting not to implement a countrywide lockdowns, instead relying on the obedience of their population to adhere to the physical distancing policies created. The complete antithesis occurred in both Croatia (The Dubrovnik Times, 2020) and New Zealand (Cousins, 2020), which utilised stringent lockdown procedures to try to quickly mitigate the spread of COVID-19. NPIs were not possible to adopt or reinforce in every country, which is reflected in a government's reduced influence in developing countries. Due to their poor fiscal capacity, many people working in informal markets or living in extreme poverty would return to work against the recommendations of the government, as a lockdown would be deemed financially infeasible. Alon et al. (2020) suggested that a blanket lockdown would not be effective in developing countries and that their unique characteristics would deem the closure of schools a successful mitigating action to stop the spread of COVID-19 in intergenerational households.

The Irish government implemented a series of NPIs, which resembled the approach utilised by many of its European counterparts. Ireland initially closed all educational and childcare facilities on the 12th of March (The Irish Times, 2020), but subsequently imposed a full lockdown on the 27th of March, implementing a "Stay at Home" order (Gov.ie, 2020), which led to the closure of many retail and recreational outlets. Following two extensions to the lockdown, Ireland entered "Phase 1", easing the restrictions, where people could now meet with up to four people within 5km of their home and people working outdoors could return to work (MerrionStreet.ie, 2020). This was followed by "Phase 2", where people could travel within their county or 20km of their homes if they are crossing county boundaries, meet up with up to six people outside your household and all retail can open. "Phase 3" was the final reduction in restrictions, where people could now travel anywhere across Ireland, outdoor gatherings of up to 200 people were permitted and restaurants, indoor gyms and places of worship can open. As the 2nd wave of COVID-19 has impacted Ireland, a brand new five tier system with varying degrees of restrictions has been introduced, with Ireland undergoing a 2nd lockdown on October 21st, 2020 (RTÉ, 2020) in the hopes of supressing the spread of the virus again.

Not many pharmaceutical interventions have been utilised throughout the pandemic, as there was no previously-known vaccine to COVID-19. One attempt is Remdesivir, an antiviral drug produced by Gilead, which came to prominence when Donald Trump took the drug after he contracted the virus in October 2020 (CNN, 2020b). The drug was never widely used, as it showed adverse effects after use (Wang et al. 2020). Yet, due to the mass spread of misinformation, people ingested chemicals such as bleach in the hope of eradicating the virus (Islam S. et al., 2020), yet no claim has been made to support its use. Currently the pharmaceutical intervention that governments globally are waiting on is a finalised vaccine in the hopes of curbing the spread of the virus. This reinforces the importance of implementing suitable physical distancing policies and mitigating actions to aid the public health officials in preventing further spread of COVID-19 (Delen et al., 2020).

2.5 The Movement, Locational Occupancy and Mobility Patterns of Societies

Mobility is the ease of movement from one point to another with mobility patterns referring to the frequency and the sequence in which certain locations are visited or occupied. A distinguishable characteristic between societies is the mobility patterns a society might exhibit along with its general form of movement between locations. COVID-19 has clearly had an impact, with many people restricting their own movement or governments imposing policies to reduce the general movement of society.

Due to the spread of the virus and a high number of asymptomatic cases, every individual has greatly restricted their movement, which has significantly altered the existing mobility patterns engrained in our daily lives. This is partially as a result of imposed “Work From Home” orders and lockdowns, which allow the population to travel within a certain radius from their home. As an individual’s mobility is extremely relevant to the transmission of the virus, the infection fatality ratio (IFR) is a frequently mentioned parameter (Cecconello et al., 2020) when discussing the congregation of people and their mobility patterns on a daily basis. It is the ratio of deaths to the cases of COVID-19 (Condit, 2020) and it is utilised in the prediction of the impact of the pandemic and its spread in society.

With the fear of catching COVID-19 out in public, there has been a sharp decline in the use of public transport. This is reflected in studies, such as one from the Hubei Province in China, which revealed that COVID-19 spread from one person to nine people during a long distance bus journey (Null & Smith, 2020). The decline in public transport usage could lead to a possible collapse of transport systems in countries where it might be underfunded. This would inevitably lead to an increase in car use, which is an antithetical impact of the implementation of public transport in the first place. This could also potentially force the alteration of existing transport infrastructure, based on established mobility patterns. This is already evident in Milan, which has added an extra 35km of bicycle lanes to the city, removing lanes for vehicles and widening the footpaths (Laker, 2020), as a result of an increased use of green space and roads by humans rather than vehicles.

In order to notice any changes in mobility patterns or the movement of an individual from one location to another, the change in movement must be detected and monitored to ensure that there is a shift in the mobility pattern originally displayed. Before technology could accurately determine these changes, mobility was monitored using crude methods. One such example is a household travel survey issued by the Central Statistics Office (CSO) in Ireland (CSO, 2020), which asks households about their travel both domestically and abroad, in order to determine any significant changes in locations visited or modes of transport utilised. In recent years with the rise of social media use, its prevalence has led to an increase in determining movement and mobility patterns of society. Liu et al. (2018) is an example of a study which utilises geo-tagged social media data from twitter to determine the mobility patterns of people in a given location. Studies like this enable a large scale comparison of movement, but the lack of real time data highlights the importance of Information and Communication Technologies (ICTs) and how mobility data can actively be monitored with a high degree of accuracy.

Mobility patterns are increasingly monitored using ICTs (Cohen-Blankshtain, & Rotem-Mindali, 2016). The ever-increasing desire for attaining movement data has fuelled the development of technologies and the adaptation of current software or applications to monitor a user's mobility pattern. An example of ICT data is Global Positioning System (GPS) data, which can be gathered from humans wearing sensors (Zheng et al. 2008) or enabling the location of a mobile device to be shared at all times.

ICT data gathered using wearable sensors was very common in the 2000s and early 2010s, due to only a few smartphones in circulation. Studies, such as Rhee et al. (2011), which observes human walk patterns in five different outdoor sites, utilised handheld GPS devices when monitoring the movement of the volunteers. ICT data also can be monitored using call records, which is examined in Kang et al. (2010), where the raw mobile call records for a major Chinese city were compiled and used to derive mobility patterns for people based on various demographics.

ICT data is fundamental in the future design of amenities, as they enable the creation of complex and accurate smart mobility systems in a seamless manor and therefore, can harbour much more mobility data across a much broader area (Benevolo et al. 2016). ICT data is now a well-integrated aspect of any urban area where it is used to monitor traffic in the form of traffic light sensors (Rapid Flow, 2020) or vehicle mobility using vehicle-to-vehicle (V2V), and vehicle-to-infrastructure (V2I) technology (Chandra Dey et al. 2016). This was particularly useful in monitoring the mobility patterns in Italy throughout the pandemic, where movement between Italian provinces was studied using ICT data (Pepe et al., 2020), based on a user's radius of gyration, which measures the spatial range of an individual's mobility patterns (Gonzalez et al., 2008).

The overall decline in mobility as a result of COVID-19 has also been documented by many big tech companies, due to the bank of data at their disposal. Companies such as Google (Google, 2020), Apple (Apple, 2020) and Facebook (Facebook, 2020), have released datasets monitoring the change of mobility as a result of the pandemic.

2.6 Conclusion

In conclusion, COVID-19 has had a drastic impact on our lives, and in tandem with government interventions to mitigate its spread, it has led to a significant alteration of mobility patterns. In an emerging field of study based on COVID-19's influence of society, the mobility datasets provided by big tech companies highlighted the importance of interventions, such as social distancing and emphasised how various factors dictate the mobility patterns we adopt.

They have the ability to enable public health officials to not only create better policies, which cater to the needs of a population, but to monitor the spread of the virus, investigating the impact of mitigating actions on the reproduction of COVID-19 (Wellenius et al., 2020). The Google COVID-19 and Apple Mobility datasets in particular have proven to be vital resources in the investigation into the impact of COVID-19 on countries. They not only enable a broad investigation into how policies have impacted mobility patterns, but how these mobility factors have an impact on other areas of society.

This reinforces the importance of utilising the datasets to fill in statistical gaps that might not be apparent at initial glance when observing the effects affiliated with the virus and creates a novel field of investigation into mobility patterns. Without the datasets, the spread of the virus could not be as closely monitored and mitigating actions would not be implemented in time to prevent further spread of the disease. Therefore, the datasets provided by the big tech companies are clearly invaluable assets that not only help slow the spread of COVID-19 but could also potentially save lives. They provide the ability to carry out urgent and necessary research on the new and emerging field of research i.e. the association between COVID-19 and mobility patterns, which will be investigated in this FYP.

3.0 Aims & Objectives

The overarching aim of this research is to increase the knowledge based on the impact of COVID-19 on human behaviour during the pandemic through the analyses of human mobility patterns. Google and Apple mobility data will be utilised in order to determine the relationships and to examine the association between mobility patterns and reported COVID-19 case incident rates for numerous countries. The study intends to use a number of custom-built programming scripts to ensure that the data can be analysed quickly and in a scalable manner for multiple countries. The results will have implications for both public health and the development of future liveable cities.

The specific aims include the following:

(i) Process publicly available Google and Apple mobility datasets at a national level in Ireland and for various countries around the world, using a number of custom built Python programming scripts.

(ii) Conduct an exploratory data analyses and graphical/visual analyses of the mobility datasets. This will include examining variations in mobility patterns for different categories in relation to influential factors.

(iii) Quantify observed alterations in mobility patterns in response to fluctuating numbers of COVID-19 cases, government announcements, public holidays and meteorological data and determine all contributing factors.

(iv) Examine the associations between the Google-derived mobility categories (Retail & Recreation, Grocery & Pharmacy Stores, Parks, Transit Stations, Workplaces and Residential) and COVID-19 case rates, incorporating a 14 day lag period, applying regression analyses - Ordinary Least Squares (OLS) single and multiple linear regression models.

(v) Discuss the implications of the analyses on the development of public health policies related to COVID-19 and in the design of liveable cities for the future.

4.0 Methodology

This chapter details the methodology utilised, the datasets examined and the statistical analyses carried out in order to formulate an analysis of human mobility patterns nationally in Ireland and internationally during the COVID-19 pandemic, which commenced in the year 2020. In order to carry out this project, numerous steps had to be followed in order to ensure that a consistent analysis for the various countries occurred. This was pivotal for reducing bias, as well as ensuring useful and accurate deductions could be made from the research. In order to obtain the final analysis, Google and Apple mobility datasets, as well as COVID-19 datasets were examined. The foundations of this FYP consist of the initial wave analysis, examining the Google and Apple mobility data in graphical form along with the COVID-19 case and death counts and announcement of government interventions. This report will breakdown the association between human mobility and COVID-19 cases for Ireland, Brazil, New Zealand, Sweden, South Korea and Germany, as detailed in the following sections.

4.1 Google Mobility Data

The Google COVID-19 mobility dataset, which was created in response to the pandemic, was employed in this study. The Google mobility data were used as an indicator of location, movement and human mobility patterns in the analyses. The Google mobility metrics were generated based on "Location History" data gathered from Google accounts on devices while also considering the privacy and anonymity of Google users (Aktay et al., 2020).

"Location History" is determined by past activity on the Google website or apps as well as real-time signals (Google Privacy & Terms, 2020). Real-time signals are either obtained from the IP address of the internet connection, which will determine the general area that an individual is in or real-time signals are acquired from the device's Global Positioning System (GPS) location. Activity can determine your location if you are searching for certain amenities in an area, which insinuates that you are either in the area or intend on visiting the area, or when completing your Google profile you can include locations of importance, such as work or home, which further aid in identifying your location. Google has also introduced an Application Programming Interface (API) called Google Location Services, which allows Google to determine your location more accurately by also determining the availability of nearby WiFi access points and cellular towers (Gonzalez, 2019).

Google's COVID-19 mobility data is broken down into national and regional datasets for over 130 countries and is split into 6 different mobility categories: "Retail & Recreation", "Grocery & Pharmacy Stores", "Residential", "Transport", "Parks", and "Workplaces". The values obtained are relative to a baseline i.e. the median values of each of the categories throughout the first 5 weeks of the year spanning 3rd of January – 6th of February 2020. The following figure provides a breakdown of the 6 categories:

Figure 4.1: The 6 Google Mobility Categories (Retail & Recreation, Grocery & Pharmacy Stores, Residential, Transport, Parks and Workplaces) between the 17/02/20 and 15/01/21 relative to a 5 week baseline values from 03/01/20 to 06/02/20

In order to maintain user data privacy and to ensure consistency of the anonymous nature of the data, information for all regions less than 3km^2 or regions that has less than 100 contributing users after introducing noise, were not included in these pre-processed datasets. Information was not published by Google if a confidence interval of 97.5% was created from the ratio of the current mobility data values to the baseline and there was a 10% or greater disparity between the obtained value and that of the maximum or minimum values for the ratio (Aktay et al., 2020). This has enabled Google to produce pre-processed datasets, which can be found on Google's COVID-19 Community Mobility Report website (Google, 2020).

When pre-processing the information, data wrangling, which is the process of collecting, choosing and transforming the data to be used, was a vital element of preparing the data for statistical analyses. Python programmes, using Anaconda and Jupyter notebooks, were created (Appendix B), which would collect the data for a specific country or region, filling any gaps found in the datasets and utilised to form graphs for the various mobility characteristics mentioned above. Graphs for Ireland and 20 other countries were created from the Google COVID-19 Mobility dataset. These countries were selected due to their notable approaches to the pandemic, or the lack thereof, and the prevalence of the virus among the population.

4.2. Apple Mobility Data

Apple Mobility data was used in tandem with the Google Mobility data to further investigate human mobility patterns during the COVID-19 pandemic. Apple have specifically set up a website (Apple, 2020) dedicated to exhibiting their findings for both major cities and countries. Unlike the Google Mobility data, the Apple Mobility data is broken down into various forms of transport rather than mobility categories. These were "Transit", "Driving" and "Walking" for a city, region or country, highlighting the change in various forms of transport in focal cities and countries across the globe. This can be seen in the Figure 4.2 adjacent to this paragraph.

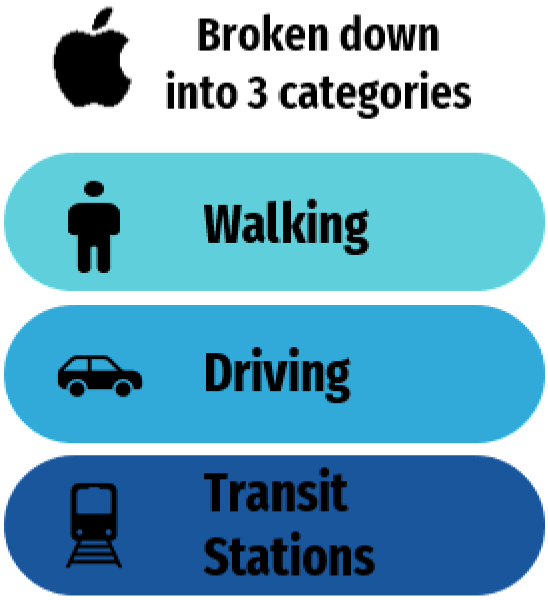


Figure 4.2: The 3 Apple derived mobility categories with values ascertained being compared to the value obtained on the same day in 2019

The Apple Mobility dataset varies from the Google Mobility dataset in terms of data collection methods employed and the geographical coverage also as it is obtained by the variation on the number of searches for a destination on the Apple Maps app compared to the same time last year (Cacciapaglia et al., 2020). It only monitors data in cities or countries where there is a high prevalence in Apple device ownership, compared to the Google Mobility data, which investigates the mobility categories in over 130 countries (Forbes, 2020) and multiple regions within these countries.

Various parameters characterise the Apple dataset (Apple, 2020), which includes the fact that a day constitutes the 24 hours between midnight to the following midnight Pacific time (GMT – 8:00). If daily breakdowns became available, the mobility for the day would vary between countries, as the beginning of the day compared to the baseline day, would be out of sync. The cities are also measured based on the greater metropolitan area, but Apple Maps uses random, rotating identifiers to ensure anonymity in the gathered data. This is further reinforced by the fact that Apple Maps doesn't gather demographic details, reducing the ability to identify individuals and increases the impartiality of the data and its associated uses. Similar to the Google Mobility data, the Apple dataset is cleaned and the 3 mobility categories for a particular country or region are selected and are merged with the Google data in line with the dates of analysis between 17/02/20 and 15/01/21. This is to ensure that the analysis can be automated for all countries that will be investigated.

4.3. COVID-19 Data

In order to investigate the impact of the pandemic, COVID-19 data must be critically analysed with the mobility data to detail any potential influential factors affiliated with the fluctuating number of cases and deaths. National COVID-19 case and deaths count values were obtained for countries globally from Our World In Data (OWID) (OWID, 2020/2021; Hasell, Mathieu, Beltekian, et al., 2020). The specific death and case count was based on the daily reported values announced by a countries own health department and gathered by Johns Hopkins University.

OWID analyses 111 countries with the majority of the data originating from the Department of Health in each country who release their own official figures daily or weekly. For example, Irish data is sourced from the Irish government's COVID-19 Data Hub (Government of Ireland, 2020). Some countries might not release testing or case values in an adequate manner e.g. Slovakia , hence OWID utilises reliable sources such as Johns Hopkins University's Coronavirus Resource Centre (John's Hopkins University, 2020). Initially OWID utilised data from the European Centre for Disease Prevention and Control (ECDC), but in November 2020, the ECDC opted to report values weekly rather than daily (ECDC, 2020b).

OWID analyses COVID-19 and its real-time impact using varying metrics. Metrics, such as confirmed cases, confirmed deaths, case fatality rate, tests, tests per confirmed case and share of positive tests are shown in graphical form or can be downloaded in tabular form as a comma separated values (csv) file. These elements enable a more accurate comparison between countries and how successful they have been in combatting the disease, as OWID provides extra functions, such as utilising a seven day rolling average or allowing graphical data per country to be shown "per million people". This enables the creation of graphs, which highlight the temporal variability of COVID-19 case and deaths rates. Therefore, the data can be examined in a standardised way between countries and regions, aligning with government legislation, to determine the impact of COVID-19.

4.4. Influential Factors

Various factors influenced the datasets provided by the big tech companies, as governments applied mitigating legislation and societies altered their behaviour to counter COVID-19's contagious nature. In order to develop a more in-depth understanding of how mobility patterns changed as a result of COVID-19, governmental announcements, national holidays and influential events throughout 2020 were analysed to determine their individual impact. Therefore, milestones of a country's lockdown were noted and any holidays or changes in the state of the pandemic in a given country were examined, in the event that they altered the mobility pattern of the population. This aided the determination of any sources resulting in peaks or troughs in the accumulated datasets when in their graphical form. These graphs will highlight the temporal variability of the dataset parameters from 17/02/20 to 15/01/20, which enable a visual comparison of the ICT-derived mobility categories, COVID-19 cases and influential factors.

Several sources were examined throughout the course of the project when analysing the varying degrees of influence of national holidays on a country's behaviour during the pandemic. NPIs implemented by a government also were investigated in case they had a pivotal impact on mobility and then the degree of successful implementation of each individual intervention could be determined. At the time of writing, European governments are currently grappling with a second wave of the virus, which enables the further examination of the NPIs and how they vary between the two waves and if there is a potential reduction in their influence.

National holidays can be quite influential, but the stark contrast in Summer and Winter weather conditions could lead to the creation of drastic changes in mobility. Certain mobility categories can be impacted by the seasonal weather, whether it is warmer or cooler, depending on the location of a country in the northern or southern hemisphere. Sources, such as the meteorological service for various countries e.g. Ireland (Met Éireann, 2020), were utilised, with the weather for certain days were checked if there was an unexplained peak in the data not affiliated with any national holiday or governmental intervention.

Overall, many potential influential factors of the mobility datasets were explored and many possible initial biases of the data were also looked into in order to mitigate the possibility of skewing obtained results and conclusions made, which would inaccurately represent the impact of COVID-19 on a country. These will be discussed at length in the latter half of this report. Credible sources from governments and their departments of health, along with meteorological services, will be utilised to ensure the integrity of the project. The sources for all the influential factors for the countries that were analysed can be found in Figure 4.3 below.

	Ireland	Brazil	New Zealand	Sweden	Germany	South Korea
Government Announcements	gov.ie	gov.br	Ministry of Health, NZ	Public Health Agency of Sweden	Deutschland.de	Center for Strategic & International Studies
Mobility Data	Google, Apple	Google	Google	Google	Google	Google

Figure 4.3: Government announcement and mobility data sources for Ireland, Brazil, New Zealand, Sweden, Germany and South Korea

4.5 Preprocessing Data

To accurately obtain conclusions from the data, the dataset needed to be preprocessed in order to conduct any statistical analyses. The first step carried out in preprocessing the data consist of transforming the raw data. The following transformations were investigated and applied to data to determine the most suitable transformation method to apply. P-values were obtained in tandem with the transformation to determine if the data's normality increased as a result:

Feature Scaling:

Feature scaling refers to obtaining the range of values from a dataset and scaling them down to a value between 0 and 1. It is a useful in order to translate all negative values in the raw dataset to the positive axis and avoids the use of manipulating data with negative values, which could cause a lot of issues when carrying out certain arithmetic on the values. The feature scaling function from the Scikit-learn library i.e. sklearn.preprocessing.MinMaxScaler() was used to minimise the range between the maximum and minimum values in the dataset.

Natural Log:

Log transformations are commonly used in data analytics to determine the relative change between different data points. The natural log was obtained for both the raw and scaled data to determine which data was more appropriate to use, which can be seen in Appendix I and J respectively. Another variation of the transformation conducted included adding 1 to each value in the dataset. The natural log of 0 is not possible to obtain as a discrete or continuous value and therefore, if the number 1 was not added to the dataset, the number 0 was dropped in the other variation of the natural log transformation. The latter variation was not favoured due to the fact that the data was biased as the lowest value was dropped skewing the data towards higher values.

Quantile Transformation:

A quantile distribution is often used to normalise a distribution with reference to another distribution. The reference distribution for this transformation was a Gaussian distribution. In this transformation, the highest value of the raw data is mapped to the highest value of the Gaussian distribution and the values decrease, while mapping with the relevant number in the other distribution. A p-value can be obtained as a result to determine if the raw data follows a normal distribution. The quantile transformer function in the Scikit-learn learn library was used to apply this method i.e. sklearn.preprocessing.QuantileTransformer().

Box-Cox Transformation:

A Box-Cox transformation is a common transformation used to transform non-normal data into a normal or Gaussian distribution. It applies the following formulae to the values in the dataset to transform them:

$$w(\lambda) = \begin{cases} (y^{\lambda} - 1)/_{\lambda} \ if \ \lambda \neq 0; & \text{(Equation 1.)} \\ log(y) \ if \ \lambda = 0. & \text{(Equation 2.)} \end{cases}$$

Where *w* refers to the transformed value, *y* is the input value and λ is the transformation parameter. Equation 1 is applied to the raw value if the resultant λ is not equal to 0, otherwise equation 2 is used. λ is automatically calculated when using the SciPy library function scipy.stats.boxcox() and the closer it is the 1, the more normally distributed the data is. As the Box-Cox transformation requires all values to be positive, it can only be used on the scaled data + 1. Therefore, the Yeo-Johnson transformation must also be examined.

Yeo-Johnson Transformation:

A Yeo-Johnson Transformation is quite similar to the Box-Cox transformation but has varying equations for negative and zero values in the dataset. The following equations were applied to the values:

$$w(\lambda) = \begin{cases} ((y+1)^{\lambda} - 1)/\lambda \quad if\ \lambda \neq 0,\ y \geq 0; & \text{(Equation 3.)} \\ log(y+1) \quad if\ \lambda = 0, y \geq 0; & \text{(Equation 4.)} \\ -[(-y+1)^{(2-\lambda)} - 1]/(2-\lambda) \quad if\ \lambda \neq 2,\ y < 0; & \text{(Equation 5.)} \\ -log(-y+1) \quad if\ \lambda = 2, y < 0. & \text{(Equation 6.)} \end{cases}$$

Where w refers to the transformed value, y is the input value and λ is the transformation parameter. The various boundary conditions that deduce which equation is most suitable to use can be found adjacent to the equation itself. In order to conduct a Yeo-Johnson transformation, the SciPy library function scipy.stats.yeojohnson() can be used to apply the transformation method to the values.

Once a suitable transformation method has been selected, the skewness of the transformed dataset can be obtained. A test for skewness determines how asymmetrical the data is and therefore can be used to determine which dataset is most normal. It should be noted that if a skewness value greater than 1 or less than -1 is obtained, the data distribution is highly skewed. If the range is between 0.5 to 1 or -1 to -0.5, the distribution is moderately skewed and if the skewness is between -0.5 and 0.5, the distribution is approximately symmetric. The SciPy library function scipy.stats.skewtest() was applied to the transformed dataset to determine the skewness.

The Akaike Information Criterion or AIC is the final step of preprocessing carried out to prepare the dataset for statical analyses. The AIC is a mathematical model used to determine the quality of the dataset, by assessing the error relative to other models and estimating how well a model fits data it was produced from. The lower the AIC, the better the data generated from the model fits the model itself. Since there is no sole AIC function in a python library, the following formula was applied to the data to determine the best fit:

$$AIC = 2k - 2\ln(L) \qquad \text{(Equation 7.)}$$

Where k refers to the number of parameters in the model and L is the highest value of the likelihood function for that model. Applying the transformations, the skewness test and the AIC check, the optimum dataset is created and can be used for statistical analyses.

4.6. Statistical Analyses

In order to carry out statistical analyses, the datasets previously mentioned had to be manipulated and merged together to form a singular csv file to work with. The Google and Apple Mobility datasets were initially examined by creating time series graphs stratified by mode of transport or the mobility characteristics and their alteration throughout the pandemic between 17th February 2020 until 15th January 2021. These time series were compared with COVID-19 and weather data to critically analyse the change in transport use and the alterations in mobility patterns.

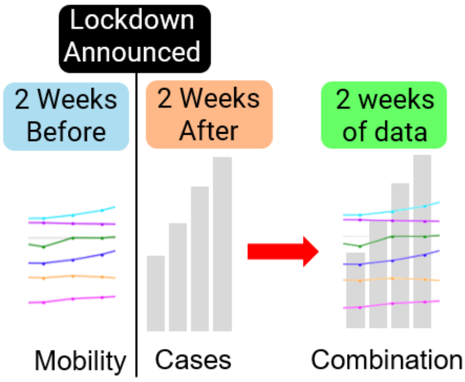


Figure 4.4: The creation of the Lockdown Datasets formed by aligning the data, incorporating a 14 day lag period between live data (mobility and weather) and the reporting of COVID-19 cases.

Ireland was selected as the first country to analyse and therefore, the Ireland dataset was further broken into subsets, which accounted for the various lockdowns. These subsets consisted of the 2 weeks of mobility data before the announcement of a lockdown with the 2 weeks of COVID-19 case and death data to account for the 14 day lag period between live data and the reporting of COVID-19 data (WHO, 2021). This led to the creation of the following data subsets, which includes the date range for the mobility data and the aligned COVID-19 case and death data:

(i) School Closures (First Closure of Schools on 12/03/2020):
Mobility Data: 27/02/2020 – 12/03/2020
COVID-19 Data: 12/03/2020 – 26/03/2020

(ii) Lockdown1 (First Lockdown on 27/03/2020):
Mobility Data: 13/03/2020 – 27/03/2020
COVID-19 Data: 27/03/2020 – 10/04/2020

(iii) Lockdown2 (Second Lockdown on 21/10/2020):
Mobility Data: 07/10/2020 – 21/10/2020
COVID-19 Data: 21/10/2020 – 04/11/2020

(iv) Lockdown3 (Third Lockdown on 22/12/2020):
Mobility Data: 08/12/2020 – 22/12/2020
COVID-19 Data: 22/12/2020 – 05/01/2021

From these subsets and the overall Ireland dataset, the mean, standard deviation, minimum and maximum values relative to the baseline were calculated.

For the Ireland dataset, graphs were created for the various mobility categories over the time period of the analysis. These graphs were created in tandem with incorporating notable dates and governmental announcements, which would create the basis for the statistical analysis. Any peaks or troughs, which coincided with national holidays or the implementation of mitigating actions by the government, were further investigated to determine the correlation between the announcement or holiday and the decline or rise in location visits or transport usage. The graphs also highlighted any outliers in the data so they could potentially be removed in case they skewed the results of the statistical analysis.

In order to determine the relationship between the various categories in the datasets, correlation matrices were initially created to determine the strength of the correlation between the categories and if the correlation was positive or negative. The method of correlation utilised was Spearman's rank correlation to obtain Spearman's rho, which is used to determine the association between characteristics in the dataset. The closer the value is to 1 or -1, the stronger the correlation between both categories. The method was also adopted ahead of other correlation methods, such as Pearson since it makes no assumptions about the distribution of the data. These matrices provided a quick glance at the association between categories and enabled further examination to determine the legitimacy of the correlation coefficient values obtained.

Linear regression analyses were carried out using Jupyter notebooks and Python in order to establish the association between COVID-19 and mobility patterns. An Ordinary Least Squares (OLS) single linear regression model was first utilised to determine the association between the COVID-19 case and mobility category data. Firstly, the mobility and COVID-19 case data were plotted, a line of best fit was applied and then OLS linear regression analyses was conducted. in case they skewed the results. An OLS single linear regression model takes on the following equations:

$$Y_{it} = \alpha + \beta X_{it} \qquad \text{(Equation 8.)}$$

$$Y_{it} = \alpha + \beta X_{i(t-14)} \qquad \text{(Equation 9.)}$$

Where i represents the country analysed, t is the number of days since the mobility dataset started (i.e. number of days since 17/02/2020), Y_{it} is the dependent variable for country i at time t and represents the COVID-19 case numbers, X_{it} is the independent variable, which represents the mobility category value for country i at a time t in Equation 8, α represents the intercept of the graphs created and β represents the coefficient or slope of the straight line, which determines if the categories are negatively or positively associated. The mobility category data values for the 2 weeks before the lockdown were used and aligned with the case values when the lockdown began to incorporate the 14 day lag period between infection and the reporting of the cases. Equation 9 incorporates the lag between COVID-19 cases and mobility data, hence $X_{i(t-14)}$ is used when analysing the 14 day lag Ireland datasets and all the subsets. This was due to the WHO announcing that there was up to a 14 day delay between becoming infected with COVID-19 and showing symptoms (WHO, 2021).

Similarly, an OLS multiple linear regression model was adopted to determine the relationship between cases, mobility categories and the weather data, to determine the influence of weather on mobility patterns throughout the pandemic. It takes on a form similar to its singular equivalent, but consists of extra coefficients and independent variables for the weather data:

$$Y_{it} = \alpha + \beta_1 X_{1it} + \beta_2 X_{2it} \qquad \text{(Equation 10.)}$$

$$Y_{it} = \alpha + \beta_1 X_{1i(t-14)} + \beta_2 X_{2i(t-14)} \qquad \text{(Equation 11.)}$$

Where i represents the country analysed, t is the number of days since the mobility dataset started (i.e. number of days since 17/02/2020), Y_{it} is the dependent variable from country i at time t and represents the COVID-19 case numbers, X_{1it} and X_{2it} in Equation 10 are the independent variables, which represent different mobility category values for the same date as the cases, but $X_{1i(t-14)}$ and $X_{2i(t-14)}$ in Equation 4 represent the mobility category values 14 days before the dependent value, α represents the intercept of the graphs created and β_1 and β_2 represent the coefficient or slope of the straight line graphs of the mobility categories, which determines if the categories are negatively or positively associated. Due to the large number of graphs to be outputted in this section, the R^2 and β values will be printed in tabular form to indicate if the association is strong between various categories.

These statistical methods enable the creation of a detailed analytical breakdown of a country's mobility patterns during the pandemic and its relationship with the COVID-19 case and death values nationally. This scalable and replicable analysis, which can be seen in Appendix B, can be adopted for other countries, in order to automate the process and in tandem with COVID-19 case incidence rates, enable the comparison of a country's performance during the pandemic with other countries.

A basic first wave analysis was carried out for 20 countries and states, which can be found in Appendix A, served as a basis for selecting countries for the full method detailed above. Therefore, the countries further analysed, along with Ireland, will be Brazil, New Zealand, Sweden, South Korea and Germany, enabling the comparison between different countries and highlighting the varying impacts of government interventions, public holidays, weather and cultural differences. This provides a thorough investigation into the new and novel area of research based on deducing the association between COVID-19 case & death counts and mobility patterns sourced from ICT datasets.

5.0 Results

The methodology, as outlined in section 4.0, was utilised to produce a detailed analysis for Ireland, Brazil, New Zealand, Sweden, South Korea and Germany. These countries were selected based on a first wave analysis, found in Appendix A. Ireland was selected as there is a lack of literature and research in this specific area in Ireland and it is of interest to the readership of this project report and to the scientific community in Ireland and internationally. Brazil and Sweden were selected due to their alternative approach in the pandemic, where government intervention was minimal. New Zealand, South Korea and Germany were selected, due to the praise they obtained for their ability to minimise the impact of COVID-19 on their countries, compared to their neighbouring countries on the different continents. These countries were also selected to ensure geographical global distribution of national COVID-19 mitigation approaches.

5.1. Detailed Analyses for Ireland

5.1.1 *Ireland Dataset*

Following the methodology, a dataset, which merged the Google and Apple mobility data, OWID cases and deaths data, as well as weather data from Met Éireann, was initially created. The top 10 rows of the dataset can be seen in Table 5.1, which has the following column headings: Date, Retail & Recreation (%), Grocery & Pharmacy Stores (%), Parks (%), Transit Stations (%), Workplaces (%), Residential (%), New Cases, New Deaths, Driving (%), Transit (%), Walking (%), Max. Temp. (^{o}C), Min Temp. (^{o}C) and Precipitation (mm).

Meteorological data was selected to analyse the impact of a heatwave or cold weather on the increase or decrease of COVID-19 cases.

Table 5.1: Dataset of Ireland (n=333) based on COVID-19 case and death count values from OWID, Google & Apple mobility data and Met Éireann meteorological data ranging from the 17/02/2020 to 15/01/2021

Ireland Dataset based on Mobility, COVID-19 and Meteorological Data during the COVID-19 Pandemic														
Source	Google	Google	Google	Google	Google	Google	OWID	OWID	Apple	Apple	Apple	Met.ie	Met.ie	Met.ie
Date	Retail & Recreation (%)	Grocery & Pharmacy Stores (%)	Parks (%)	Transit Stations (%)	Workplaces (%)	Residential (%)	New Cases	New Deaths	Driving (%)	Transit (%)	Walking (%)	Max Temp (°C)	Min Temp (°C)	Precipitation (mm)
17/02/2020	-3.0	-4.0	-17.7	-6.0	-4.3	2.3	0.0	0.0	29.5	26.5	51.2	8.3	4.8	5.0
18/02/2020	-0.8	-3.5	-10.3	-4.5	-5.0	2.0	0.0	0.0	33.3	25.8	51.3	8.9	5.1	7.8
19/02/2020	-0.2	-3.4	-9.2	-4.0	-5.8	2.0	0.0	0.0	37.5	29.9	48.3	10.8	6.9	13.7
20/02/2020	1.2	-3.0	-5.7	-3.5	-6.8	2.0	0.0	0.0	42.7	28.8	58.6	10.3	4.7	7.1
21/02/2020	1.1	-3.0	-5.0	-3.1	-7.7	2.1	0.0	0.0	57.0	46.8	83.1	11.4	8.5	11.3
22/02/2020	2.4	-2.1	-0.4	-1.6	-7.3	1.7	0.0	0.0	42.0	27.8	87.9	12.0	7.5	11.3
23/02/2020	2.9	-1.4	3.9	-0.6	-7.1	1.4	0.0	0.0	20.7	11.7	22.8	12.2	5.9	6.9
24/02/2020	1.9	-1.1	2.6	-0.4	-5.9	1.1	0.0	0.0	14.0	14.4	13.0	11.7	5.4	11.0
25/02/2020	0.7	-0.4	1.7	-0.4	-4.4	1.0	0.0	0.0	14.2	12.1	11.9	7.7	2.8	5.8
26/02/2020	0.3	0.0	3.7	0.0	-2.9	0.7	0.0	0.0	20.7	14.1	24.6	7.7	3.5	2.6

In order to analyse a 14 day lag in the case and death count data, another dataset was created, which offset the recorded case and death data by 14 days. This additional dataset, where the first 10 rows can be seen in Table 5.2, was created in order to compare the correlation and regression analyses values obtained for the raw Ireland dataset. The 14 day lag Ireland dataset will be used at a later point in the analysis.

Table 5.2: Dataset of Ireland (n=333) based on COVID-19 case and death count values from OWID, Google & Apple mobility data and Met Éireann meteorological data. The mobility and weather data ranges from the 17/02/2020 to 15/01/2021, whereas the case and death data begins 14 days later to account for the 14 day reporting lag.

Ireland Dataset based on Mobility, COVID-19 and Meteorological Data during the COVID-19 Pandemic with a 14 Day Lag on Case and Death Values														
Source	Google	Google	Google	Google	Google	Google	OWID	OWID	Apple	Apple	Apple	Met.ie	Met.ie	Met.ie
Date	Retail & Recreation (%)	Grocery & Pharmacy Stores (%)	Parks (%)	Transit Stations (%)	Workplaces (%)	Residential (%)	New Cases	New Deaths	Driving (%)	Transit (%)	Walking (%)	Max Temp (°C)	Min Temp (°C)	Precipitation (mm)
17/02/2020	-3.0	-4.0	-17.7	-6.0	-4.3	2.3	0.0	0.0	29.5	26.5	51.2	8.3	4.8	5.0
18/02/2020	-0.8	-3.5	-10.3	-4.5	-5.0	2.0	0.0	0.0	33.3	25.8	51.3	8.9	5.1	7.8
19/02/2020	-0.2	-3.4	-9.2	-4.0	-5.8	2.0	0.0	0.0	37.5	29.9	48.3	10.8	6.9	13.7
20/02/2020	1.2	-3.0	-5.7	-3.5	-6.8	2.0	0.0	0.0	42.7	28.8	58.6	10.3	4.7	7.1
21/02/2020	1.1	-3.0	-5.0	-3.1	-7.7	2.1	0.0	0.0	57.0	46.8	83.1	11.4	8.5	11.3
22/02/2020	2.4	-2.1	-0.4	-1.6	-7.3	1.7	0.0	0.0	42.0	27.8	87.9	12.0	7.5	11.3
23/02/2020	2.9	-1.4	3.9	-0.6	-7.1	1.4	0.0	0.0	20.7	11.7	22.8	12.2	5.9	6.9
24/02/2020	1.9	-1.1	2.6	-0.4	-5.9	1.1	0.0	0.0	14.0	14.4	13.0	11.7	5.4	11.0
25/02/2020	0.7	-0.4	1.7	-0.4	-4.4	1.0	0.0	0.0	14.2	12.1	11.9	7.7	2.8	5.8
26/02/2020	0.3	0.0	3.7	0.0	-2.9	0.7	0.0	0.0	20.7	14.1	24.6	7.7	3.5	2.6

5.1.2 *Preprocessing of Ireland Data*

In order to successfully analyse the data for Ireland, it had to be preprocessed before any statistical analysis could be conducted. This was to ensure that the cleaned data could provide legitimate results upon analysing the Ireland dataset.

Transformation

Multiple forms of transformation were initially used to alter the data's structure in order to increase its normality, as normally distributed data is a common assumption in statistical analyses. Normalisation in the form of scaling the data and translating the data to the positive axis, natural log of data by adding 1 to all values, natural log of data removing all 0 values, quantile transformation, Box-Cox transformation and Yeo-Johnson transformation were the various forms of transformations carried out on the Ireland data. These can be seen in Figure 5.1, where the Retail & Recreational Data for Ireland is transformed and graphically plotted using a histogram.

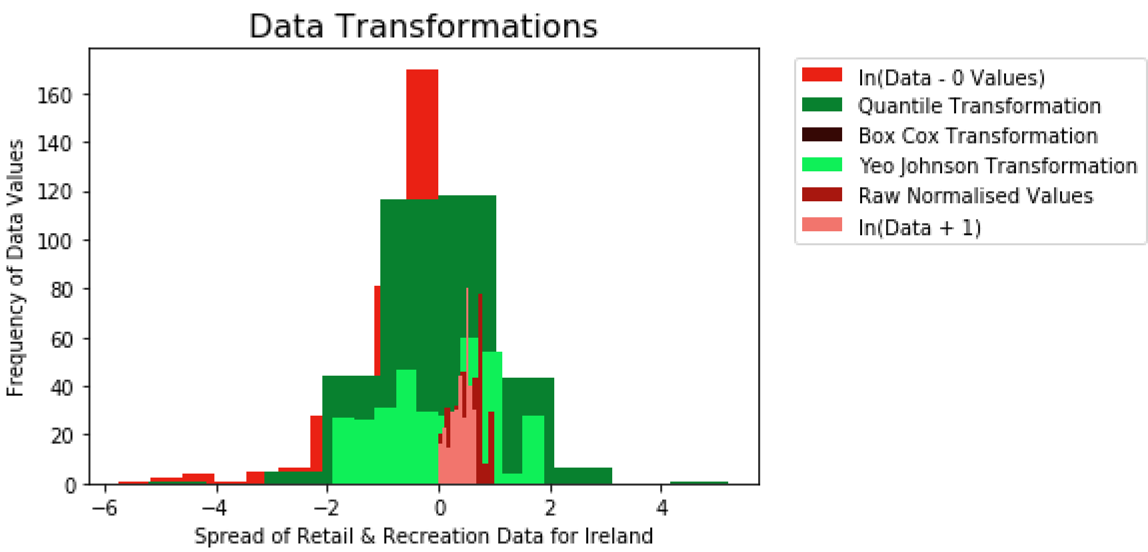


Figure 5.1: Histograms of all the Data Transformations performed (Normalisation and Translating to positive axis, Natural Log of Data by adding 1 to all values, Natural Log of Data removing all 0 values, Quantile Transformation, Box Cox Transformation and Yeo Johnson Transformation) on the Retail & Recreation Mobility Category from the Ireland Dataset.

Figure 5.1 graphically highlights the various forms of transformations undergone, in order to determine the most suitable transformation to use for the data overall. A P-value for each transformation was obtained in order to finalise the transformation that was going to be utilised. Table 5.3 consists of these P-values and if they are greater than 0.05, they can be deemed normally distributed.

Table 5.3: P-Values obtained for the Data Transformations performed (Normalisation and Translating to positive axis, Natural Log of Data by adding 1 to all values, Natural Log of Data removing all 0 values, Quantile Transformation, Box Cox Transformation and Yeo Johnson Transformation) on the Retail & Recreation Mobility Category from the Ireland Dataset

Transformation	P-Value
ln(Data - 0 Values)	1.66E-77
Quantile	0
Box-Cox	0
Yeo-Johnson	0
Raw Normalised	9.75E-78
ln(Data + 1)	9.75E-78

None of the values satisfied this criteria, with the Quantile transformation, Box-Cox transformation and Yeo-Johnson transformation all returning 0 values and therefore, were not deemed suitable. The transformation where the natural log of the raw data was obtained and all 0 values were removed, was not considered suitable, as only data of a certain value was removed, which would make the transformed data biased. Therefore, both the normalised, translated data and the transformation where the natural log of the raw data + 1 were examined on the entire Ireland dataset, as well as a separate scaled dataset. These figures can be found in Appendix I and J.

Skewness Test

A skewness test was conducted to establish which specific transformation should be used, as it determines how skewed the data is. If a skewness value less than -1 or greater than 1 is acquired, the category distribution is deemed highly skewed. If it ranges between -1 & -0.5 or 0.5 & 1, the distribution is said to be moderately skewed and if the skewness ranges from -0.5 to 0.5, the distribution is regarded as approximately symmetrical.

The skewness test was conducted on both the raw data and the transformational data where the natural log of the raw data + 1 is ascertained for the entire Ireland dataset, as well as a separate scaled dataset.

Table 5.4: Skewness value of the different Google & Apple-derived mobility categories, COVID-19 case & death count data and meteorological data for the Ireland Dataset and the Normalised + Translated raw data and the natural log of the data values + 1

Skewness of Ireland Dataset		
	Raw Data Translated	Ln(Data +1)
Retail	-1.67	-10.05
Grocery	-4.30	-10.81
Parks	5.94	-9.87
Transit Stations	3.54	-9.58
Workplaces	0.69	-9.31
Residential	1.94	-8.95
Cases	15.42	-4.43
Deaths	18.47	6.84
Driving	2.17	-6.87
Transit	7.56	-5.87
Walking	7.67	-4.40
Max. Temp	1.61	-1.12
Min. Temp	-0.56	-7.99
Precipitation	12.43	2.59

Table 5.5: Skewness value of the different Google & Apple-derived mobility categories, COVID-19 case & death count data and meteorological data for the Scaled Ireland Dataset and the Normalised + Translated raw data and the natural log of the data values + 1

Skewness of Scaled Ireland Dataset		
	Raw Data Translated	Ln(Data +1)
Retail	-1.67	-3.65
Grocery	-4.30	6.28
Parks	5.94	3.92
Transit Stations	3.54	0.20
Workplaces	0.69	-2.46
Residential	1.94	-0.63
Cases	15.42	14.59
Deaths	18.47	16.30
Driving	2.17	0.59
Transit	7.56	5.29
Walking	7.67	5.76
Max. Temp	1.61	-0.75
Min. Temp	-0.56	-2.52
Precipitation	12.43	10.73

When comparing the Table 5.4 and Table 5.5 to determine whether the scaled or non-scaled dataset should be used to conduct the statistical analysis of Ireland, it became apparent that the scaled values for the natural log of the data values + 1, as seen in Table 5.5, were in a more suitable range than the non-scaled data and therefore, were selected for further analyses.

Similarly, the same process was carried out for the 14 day lag Ireland and scaled datasets and the same decision was arrived upon i.e. to further analyse the scaled 14 day lag data for Ireland. This is evident from Table 5.6 and Table 5.7.

Table 5.6: Skewness value of the different Google & Apple-derived mobility categories, COVID-19 case & death count data and meteorological data for the Ireland Dataset with a 14 day lag and the Normalised + Translated raw data and the natural log of the data values + 1

Skewness of Ireland(w/ 14 day lag)		
	Raw Data Translated	Ln(Data +1)
Retail	-1.67	-10.05
Grocery	-4.30	-10.81
Parks	5.94	-9.87
Transit Stations	3.54	-9.58
Workplaces	0.69	-9.31
Residential	1.94	-8.95
Cases	9.56	-5.51
Deaths	19.12	7.42
Driving	2.17	-6.87
Transit	7.56	-5.87
Walking	7.67	-4.40
Max. Temp	1.61	-1.12
Min. Temp	-0.56	-7.99
Precipitation	12.43	2.59

Table 5.7: Skewness value of the different Google & Apple-derived mobility categories, COVID-19 case & death count data and meteorological data for the Scaled Ireland Dataset with a 14 day lag and the Normalised + Translated raw data and the natural log of the data values + 1

Skewness of Scaled Ireland(w/ 14 day lag)		
	Raw Data Translated	Ln(Data +1)
Retail	-1.67	-3.65
Grocery	-4.30	6.28
Parks	5.94	3.92
Transit Stations	3.54	0.20
Workplaces	0.69	-2.46
Residential	1.94	-0.63
Cases	9.56	8.12
Deaths	19.12	17.02
Driving	2.17	0.59
Transit	7.56	5.29
Walking	7.67	5.76
Max. Temp	1.61	-0.75
Min. Temp	-0.56	-2.52
Precipitation	12.43	10.73

Akaike Information Criterion (AIC)

The AIC for the datasets was obtained in order to determine which model is most suitable for the statistical analysis. The AIC determines the quality of the dataset, by estimating the error relative to the other models. For the initial examination, the quality of the individual mobility categories, COVID-19 case and death values and the meteorological data of the scaled Ireland dataset were compared to a normal distribution. This was done in order to determine the quality of each individual category.

Table 5.8: AIC value of the different Google & Apple-derived mobility categories, COVID-19 case & death count data and meteorological data for the Scaled Ireland Dataset and the Normalised + Translated raw data and the natural log of the data values + 1

AIC of Scaled Ireland Dataset		
	Raw Data Translated	Ln(Data +1)
Retail	56.44	-197.05
Grocery	-254.71	-458.73
Parks	-89.15	-340.51
Transit Stations	-25.94	-265.32
Workplaces	-15.17	-253.36
Residential	53.23	-208.89
Cases	-395.89	-580.44
Deaths	-799.78	-954.57
Driving	68.16	-182.28
Transit	-119.11	-322.04
Walking	-191.90	-394.23
Max. Temp	-133.33	-367.71
Min. Temp	-104.65	-376.92
Precipitation	-334.33	-488.56

Table 5.9: AIC value of the different Google & Apple-derived mobility categories, COVID-19 case & death count data and meteorological data for the Scaled Ireland Dataset with a 14 day lag and the Normalised + Translated raw data and the natural log of the data values + 1

AIC of Scaled Ireland(w/ 14 day lag)		
	Raw Data Translated	Ln(Data +1)
Retail	56.44	-197.05
Grocery	-254.71	-458.73
Parks	-89.15	-340.51
Transit Stations	-25.94	-265.32
Workplaces	-15.17	-253.36
Residential	53.23	-208.89
Cases	-141.31	-312.46
Deaths	-824.27	-984.92
Driving	68.16	-182.28
Transit	-119.11	-322.04
Walking	-191.90	-394.23
Max. Temp	-133.33	-367.71
Min. Temp	-104.65	-376.92
Precipitation	-334.33	-488.56

AIC values can be compared by the fact that the lower the AIC value, the better the model fits the data it was created from. When comparing Table 5.8 and Table 5.9, it is apparent in both instances that the data which is formed by obtaining the natural log of the data values + 1 is more suitable for the statistical analyses. Therefore, the Ireland dataset will be translated to the positive axis, 1 will be added to each number and the natural log of this value will be taken. This transformed dataset will now be referred to as the "Ireland dataset" for the remainder of this report and can be seen in Table 5.10.

Table 5.10: Resultant Dataset of Ireland (n=333) based on COVID-19 case and death count values from OWID, Google & Apple mobility data and meteorological data from Met Éireann ranging from the 17/02/2020 to 15/01/2021

Ireland Dataset based on Mobility, COVID-19 and Meteorological Data during the COVID-19 Pandemic															
Source	Google	Google	Google	Google	Google	Google	OWID	OWID	Apple	Apple	Apple	Met.ie	Met.ie	Met.ie
Date	Retail & Recreation (%)	Grocery & Pharmacy Stores (%)	Parks (%)	Transit Stations (%)	Workplaces (%)	Residential (%)	New Cases	New Deaths	Driving (%)	Transit (%)	Walking (%)	Max Temp (°C)	Min Temp (°C)	Precipitation (mm)
17/02/2020	0.655996	0.359518	0.1882	0.6438	0.6509	0.0789	0	0.022	0.559	0.617	0.56	0.0927	0.2849	0.0878
18/02/2020	0.669156	0.365827	0.2258	0.654	0.6458	0.068	0	0.022	0.574	0.614	0.561	0.1235	0.2973	0.1338
19/02/2020	0.672346	0.367084	0.231	0.6573	0.6398	0.068	0	0.022	0.59	0.63	0.551	0.2151	0.3681	0.2242
20/02/2020	0.680233	0.372097	0.2484	0.6607	0.6319	0.068	0	0.022	0.609	0.626	0.584	0.1918	0.2808	0.1225
21/02/2020	0.680095	0.372097	0.2516	0.6631	0.6252	0.0727	0	0.022	0.661	0.693	0.656	0.2424	0.4272	0.1884
22/02/2020	0.687458	0.382752	0.2735	0.6735	0.6285	0.0585	0	0.022	0.606	0.622	0.67	0.2689	0.3907	0.1884
23/02/2020	0.689897	0.391544	0.2937	0.6801	0.6296	0.049	0	0.022	0.524	0.557	0.467	0.2776	0.3294	0.1192
24/02/2020	0.68419	0.395044	0.2877	0.681	0.6394	0.0394	0	0.022	0.497	0.568	0.432	0.2557	0.3094	0.1838
25/02/2020	0.677626	0.403729	0.2837	0.681	0.6501	0.0346	0	0.022	0.497	0.559	0.428	0.061	0.1987	0.1011
26/02/2020	0.675157	0.408911	0.293	0.6838	0.6619	0.0248	0	0.022	0.524	0.567	0.473	0.061	0.2297	0.0466

Similarly, Table 5.11 was created for the new Ireland graph with a 14 day lag.

Table 5.11: Resultant Dataset of Ireland (n=333) with a 14 day lag based on COVID-19 case and death count values from OWID, Google & Apple mobility data and meteorological data from Met Éireann ranging from the 17/02/2020 to 15/01/2021

Ireland Dataset based on Mobility, COVID-19 and Meteorological Data during the COVID-19 Pandemic with a 14 Day Lag on Case and Death Values														
Source	Google	Google	Google	Google	Google	Google	OWID	OWID	Apple	Apple	Apple	Met.ie	Met.ie	Met.ie
Date	Retail & Recreation (%)	Grocery & Pharmacy Stores (%)	Parks (%)	Transit Stations (%)	Workplaces (%)	Residential (%)	New Cases	New Deaths	Driving (%)	Transit (%)	Walking (%)	Max Temp (°C)	Min Temp (°C)	Precipitation (mm)
17/02/2020	0.655996	0.359518	0.1882	0.6438	0.6509	0.0789	0	0.022	0.559	0.617	0.56	0.0927	0.2849	0.0878
18/02/2020	0.669156	0.365827	0.2258	0.654	0.6458	0.068	0	0.022	0.574	0.614	0.561	0.1235	0.2973	0.1338
19/02/2020	0.672346	0.367084	0.231	0.6573	0.6398	0.068	0	0.022	0.59	0.63	0.551	0.2151	0.3681	0.2242
20/02/2020	0.680233	0.372097	0.2484	0.6607	0.6319	0.068	0	0.022	0.609	0.626	0.584	0.1918	0.2808	0.1225
21/02/2020	0.680095	0.372097	0.2516	0.6631	0.6252	0.0727	0	0.022	0.661	0.693	0.656	0.2424	0.4272	0.1884
22/02/2020	0.687458	0.382752	0.2735	0.6735	0.6285	0.0585	0	0.022	0.606	0.622	0.67	0.2689	0.3907	0.1884
23/02/2020	0.689897	0.391544	0.2937	0.6801	0.6296	0.049	0	0.022	0.524	0.557	0.467	0.2776	0.3294	0.1192
24/02/2020	0.68419	0.395044	0.2877	0.681	0.6394	0.0394	0	0.022	0.497	0.568	0.432	0.2557	0.3094	0.1838
25/02/2020	0.677626	0.403729	0.2837	0.681	0.6501	0.0346	0	0.022	0.497	0.559	0.428	0.061	0.1987	0.1011
26/02/2020	0.675157	0.408911	0.293	0.6838	0.6619	0.0248	0	0.022	0.524	0.567	0.473	0.061	0.2297	0.0466

5.1.3 *Descriptive Statistics*

The Ireland dataset was initially used to monitor the fluctuations in the Retail & Recreation (%), Grocery & Pharmacy Stores (%), Parks (%), Transit Stations (%), Workplaces (%) and Residential (%) graphs in relation to COVID-19 cases and deaths between the 17th February 2020 and 15th January 2021 relative to the baseline. Correlation matrices were also formed for the overall datasets and the lockdowns mentioned in the "Methodology" section to monitor the association between COVID-19 cases and the mobility categories.

The descriptive statistics for the overall dataset were obtained after the creation of the Ireland dataset. The statistics can be found in Table 5.12:

Table 5.12: Descriptive Statistics (Mean, Standard Deviation, Minimum & Maximum Values and Source) of the Ireland Dataset Categories (n=333) from the 17/02/2020 to 15/01/2020 with data sourced from Google, Apple, OWID and Met Éireann

Detailed Statistics for Ireland Dataset					
	Mean	Standard Deviation	Min. Value	Max. Value	Data Source
Retail	0.41	0.18	0.00	0.69	Google
Grocery	0.35	0.12	0.00	0.69	Google
Parks	0.32	0.14	0.00	0.69	Google
Transit Stations	0.34	0.16	0.00	0.69	Google
Workplaces	0.37	0.16	0.00	0.69	Google
Residential	0.38	0.18	0.00	0.69	Google
Cases	0.05	0.10	0.00	0.69	OWID
Deaths	0.05	0.06	0.00	0.69	OWID
Driving	0.35	0.18	0.00	0.69	Apple
Transit	0.23	0.15	0.00	0.69	Apple
Walking	0.23	0.13	0.00	0.69	Apple
Max. Temp	0.35	0.14	0.00	0.69	Met Éireann
Min. Temp	0.42	0.14	0.00	0.69	Met Éireann
Precipitation	0.09	0.12	0.00	0.69	Met Éireann

Similarly, descriptive statistics of the Ireland dataset with a 14 day lag on COVID-19 case and death data were also produced in Table 5.13.

Table 5.13: Descriptive Statistics (Mean, Standard Deviation, Minimum & Maximum Values and Source) of the Ireland Dataset Categories (n=333) with a 14 day lag on COVID-19 case & death data, from the 17/02/2020 to 15/01/2020 with data sourced from Google, Apple, OWID and Met Éireann

Detailed Statistics for Ireland Dataset with a 14 day lag					
	Mean	Standard Deviation	Min. Value	Max. Value	Data Source
Retail	0.41	0.18	0.00	0.69	Google
Grocery	0.35	0.12	0.00	0.69	Google
Parks	0.32	0.14	0.00	0.69	Google
Transit Stations	0.34	0.16	0.00	0.69	Google
Workplaces	0.37	0.16	0.00	0.69	Google
Residential	0.38	0.18	0.00	0.69	Google
Cases	0.14	0.15	0.00	0.69	OWID
Deaths	0.05	0.06	0.00	0.69	OWID
Driving	0.35	0.18	0.00	0.69	Apple
Transit	0.23	0.15	0.00	0.69	Apple
Walking	0.23	0.13	0.00	0.69	Apple
Max. Temp	0.35	0.14	0.00	0.69	Met Éireann
Min. Temp	0.42	0.14	0.00	0.69	Met Éireann
Precipitation	0.09	0.12	0.00	0.69	Met Éireann

5.1.4 *Google Mobility Graphs*

Graphs for Ireland over the course of the pandemic were produced with the overall oscillations in the mobility category data around the baseline evident in the upcoming figures. The raw unprocessed data is used to represent the real and live impact of COVID-19 on mobility rather than the preprocessed data, which is used in subsequent sections. Figure 5.2 on the following page provides a quick synopsis of all the mobility pattern changes between 17th February 2020 to 15th January 2021. From Figure 5.2, it quickly becomes apparent that the closure of schools on the 12th of March 2020 had a significant impact on mobility patterns, as up until then, the mobility category graphs were hovering about the baseline, but after the 12/03/2020, the graphs begin to greatly diverge from the baseline.

The Residential, Retail & Recreation, Grocery & Pharmacy Store, Workplaces and Transit Station graphs mirror the rise and fall of the daily COVID-19 case values. The Residential graph follows the shape of COVID-19 cases, which occurs approximately 14 days before it is evident in the COVID-19 case graph. The Parks graph is unlike the other mobility category graph as it doesn't follow the highs and lows evident in the COVID-19 case graph. The various graphs appear to gradually converge with the baseline, but at a glance, when a lockdown is announced or a "stay-at-home" order is issued, the graphs drastically alter direction away from the baseline, which is often followed by a stark rise in COVID-19 cases reported.

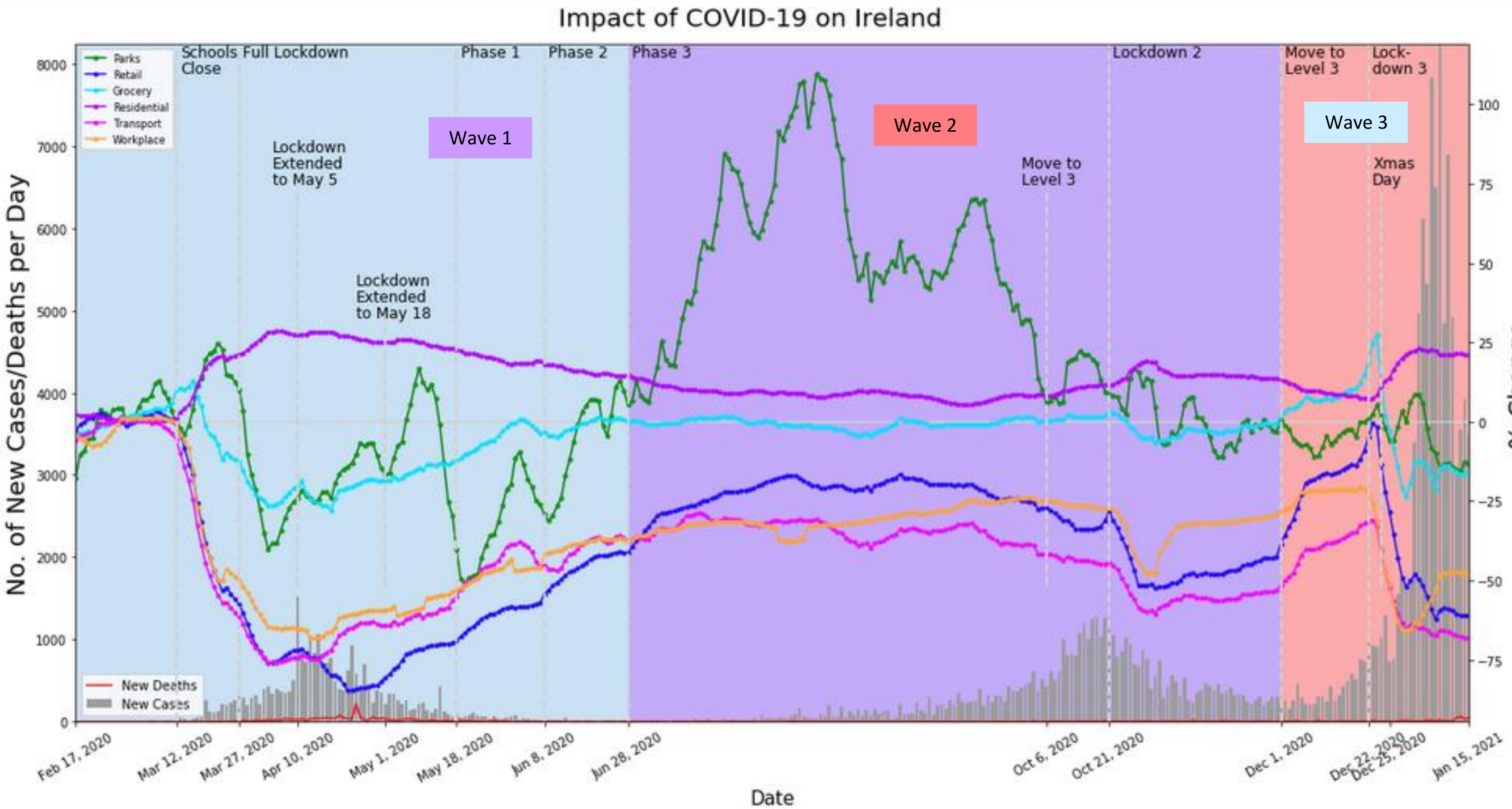


Figure 5.2: Graph of the temporal variability of the daily Google-derived mobility categories, the daily COVID-19 cases & death rates from OWID for Ireland (n=333) in relation to government announcements, including travel restrictions and lockdowns/stay-at-home orders, national holidays and meteorological conditions from 17/02/2020 to 15/01/2021. The data used is the raw unprocessed Ireland data. The Google-derived mobility categories are Retail & Recreation, Grocery & Pharmacy Stores, Parks, Transit Stations, Workplaces and Residential, and they are represented as the % change in relation to a 5 week baseline ranging from 03/01/2020 to 06/02/2020. The 3 waves of COVID-19 in Ireland are identifiable by the colour blocks, which end at the completion of a lockdown period. Wave 1 ranges between 17/02/2020 and 28/06/2020, wave 2 ranges between 28/06/2020 and 01/12/2020 and wave 3 ranges between 01/12/2020 and 15/01/2021.

The mobility category graphs are shown individually on the following pages, so the peaks and troughs of the graphs are shown relative to their overall change over the course of the pandemic timeline used in this report.

Retail & Recreational

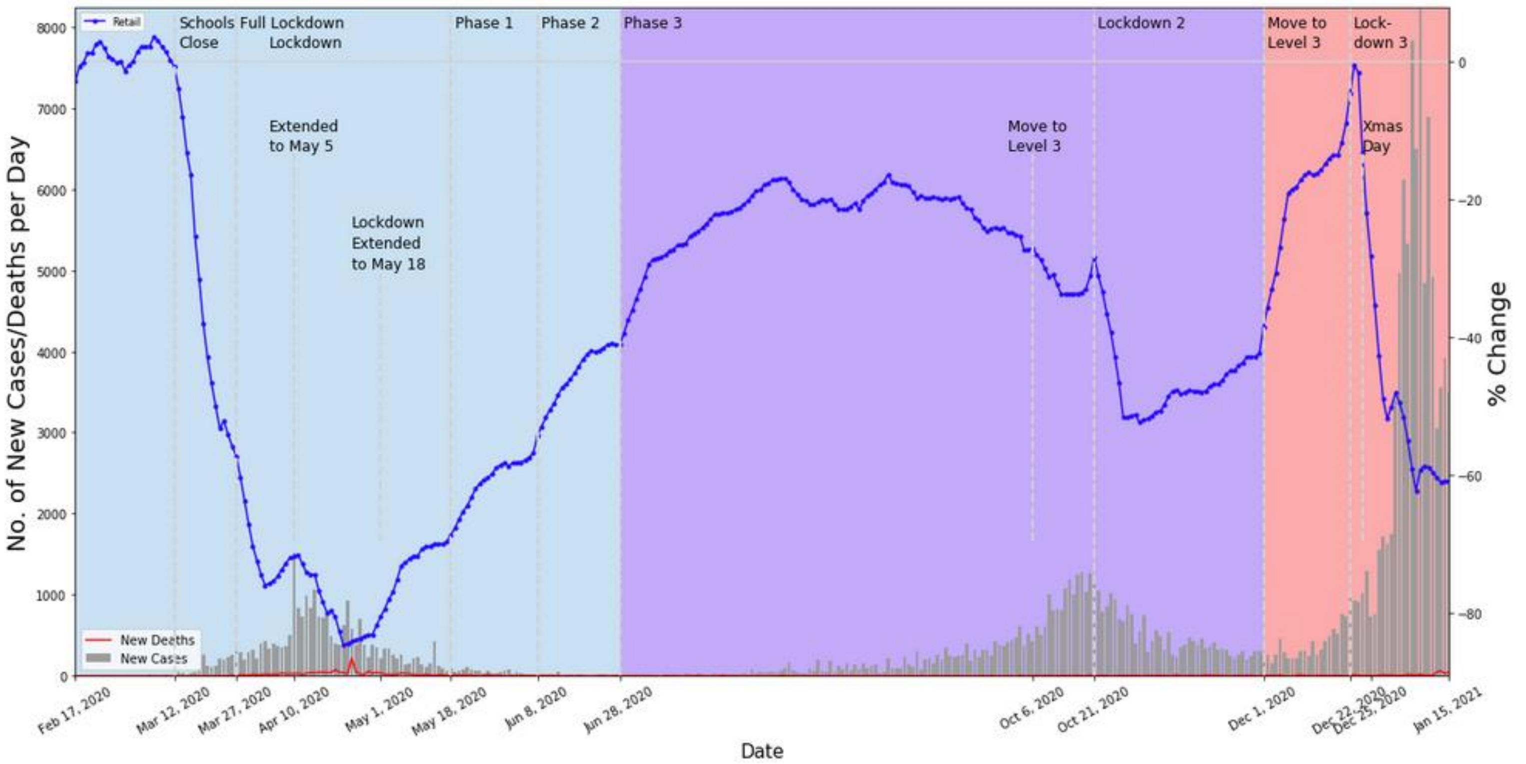


Figure 5.3: Graph of the temporal variability of the daily Google-derived mobility data for Retail & Recreation Place Visits and the daily COVID-19 cases & death rates from OWID for Ireland (n=333) in relation to significant dates between 17/02/2020 and 15/01/2021. The data used is the raw unprocessed Ireland data. The % change of the graph is in relation to a 5 week baseline and the 3 waves of COVID-19 in Ireland are identifiable by the colour blocks, which end at the completion of a lockdown period.

Figure 5.3 reinforces the observations initially seen in Figure 5.2, where the Retail & Recreation graph mimics the opposite shape of the COVID-19 case graph. Significant decreases in the graph occur after the announcements of lockdowns or closure of education facilities. As the mobility restrictions are eased in the form of a phased reopening in May and June 2020 or a move to level 3 on the 1st December 2021, the Retail and Recreation graph rises at a slower pace than it fell, but only once reaches the baseline before Christmas day, when people would normally be heading home anyway to enjoy Christmas with their families.

Workplaces

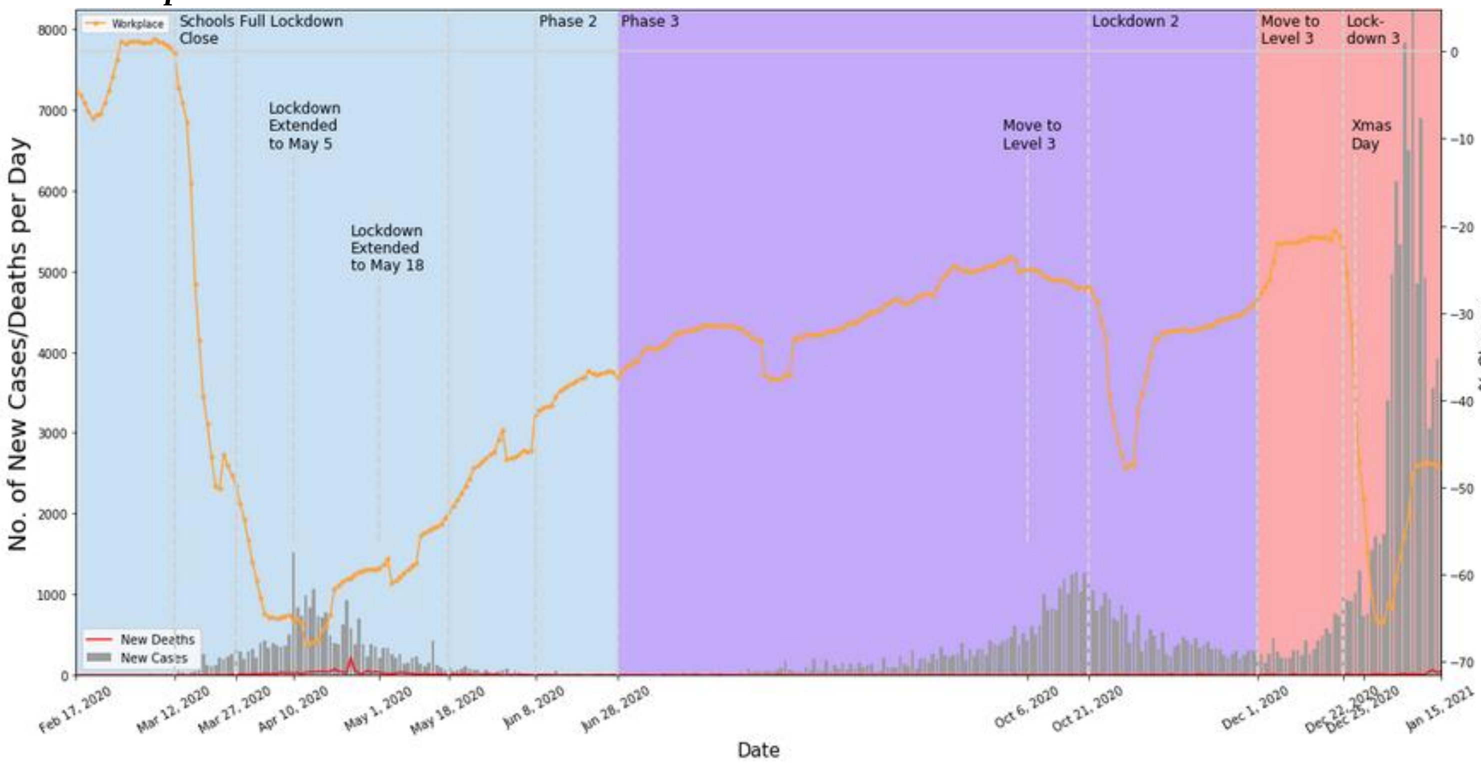


Figure 5.4: Graph of the temporal variability of the daily Google-derived mobility data for Workplace Visits and the daily COVID-19 cases & death rates from OWID for Ireland (n=333) in relation to significant dates between 17/02/2020 and 15/01/2021. The data used is the raw unprocessed Ireland data. The % change of the graph is in relation to a 5 week baseline and the 3 waves of COVID-19 in Ireland are identifiable by the colour blocks, which end at the completion of a lockdown period.

Figure 5.4 follows a similar shape to Figure 5.3, but is more sensitive, when compared to the other five Google mobility categories, to national holidays, as the graph appears stagnant around national holidays, such as Bank Holiday Mondays, Easter, Christmas and Halloween.

Parks

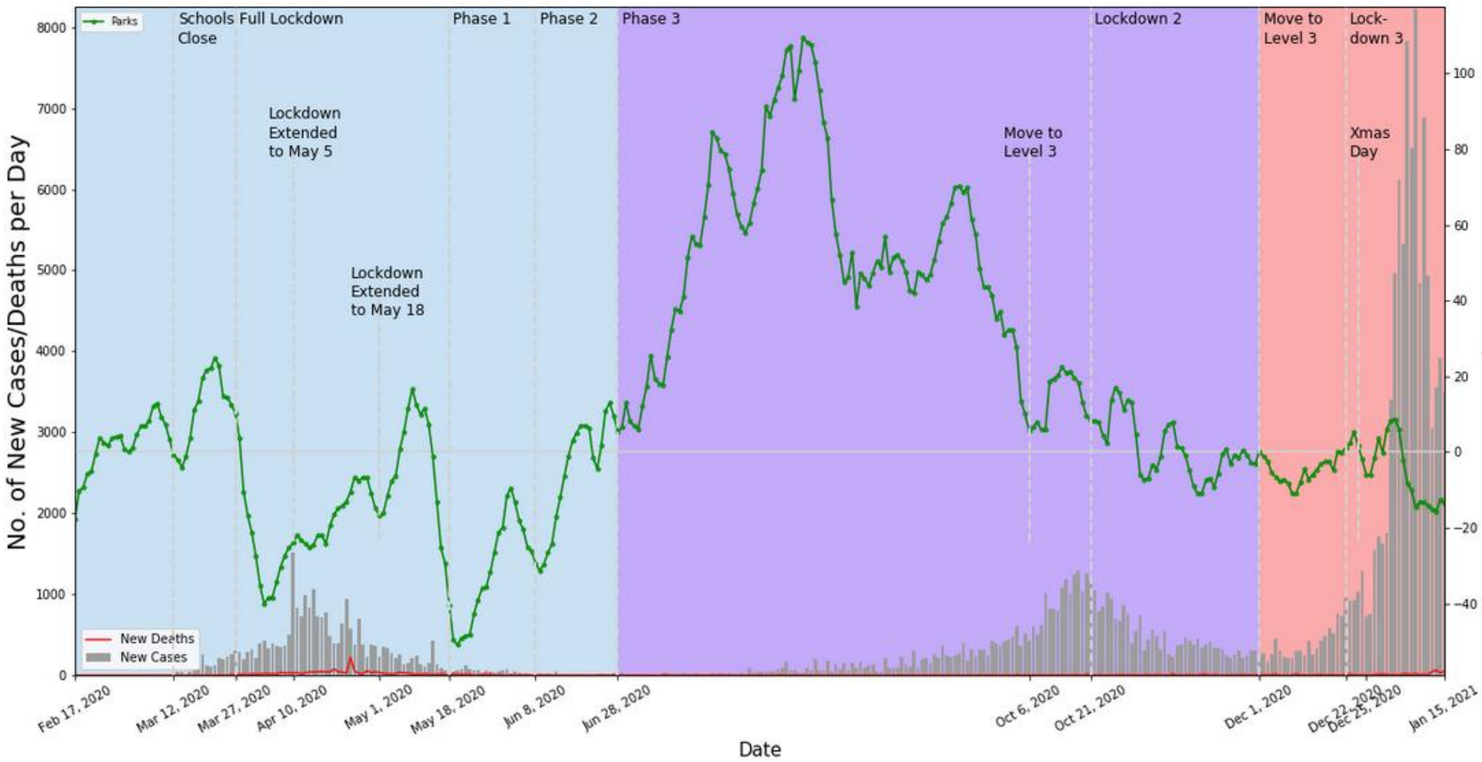


Figure 5.5: Graph of the temporal variability of the daily Google-derived mobility data for Park Visits and the daily COVID-19 cases & death rates from OWID for Ireland (n=333) in relation to significant dates between 17/02/2020 and 15/01/2021. The data used is the raw unprocessed Ireland data. The % change of the graph is in relation to a 5 week baseline and the 3 waves of COVID-19 in Ireland are identifiable by the colour blocks, which end at the completion of a lockdown period.

Figure 5.5 follows a different shape when compared to the other mobility category graphs as mentioned previously. People were not under house arrest during the pandemic but were limited in their movement. This still enabled many people in Ireland to visit parks or greenspaces in their vicinity even if retail stores and workplaces were closed. Localised peaks can often be seen around national holidays, but the fact that the graph doesn't resemble the shape of the COVID-19 case graph merits a closer investigation into the association between the two categories.

Transit Stations

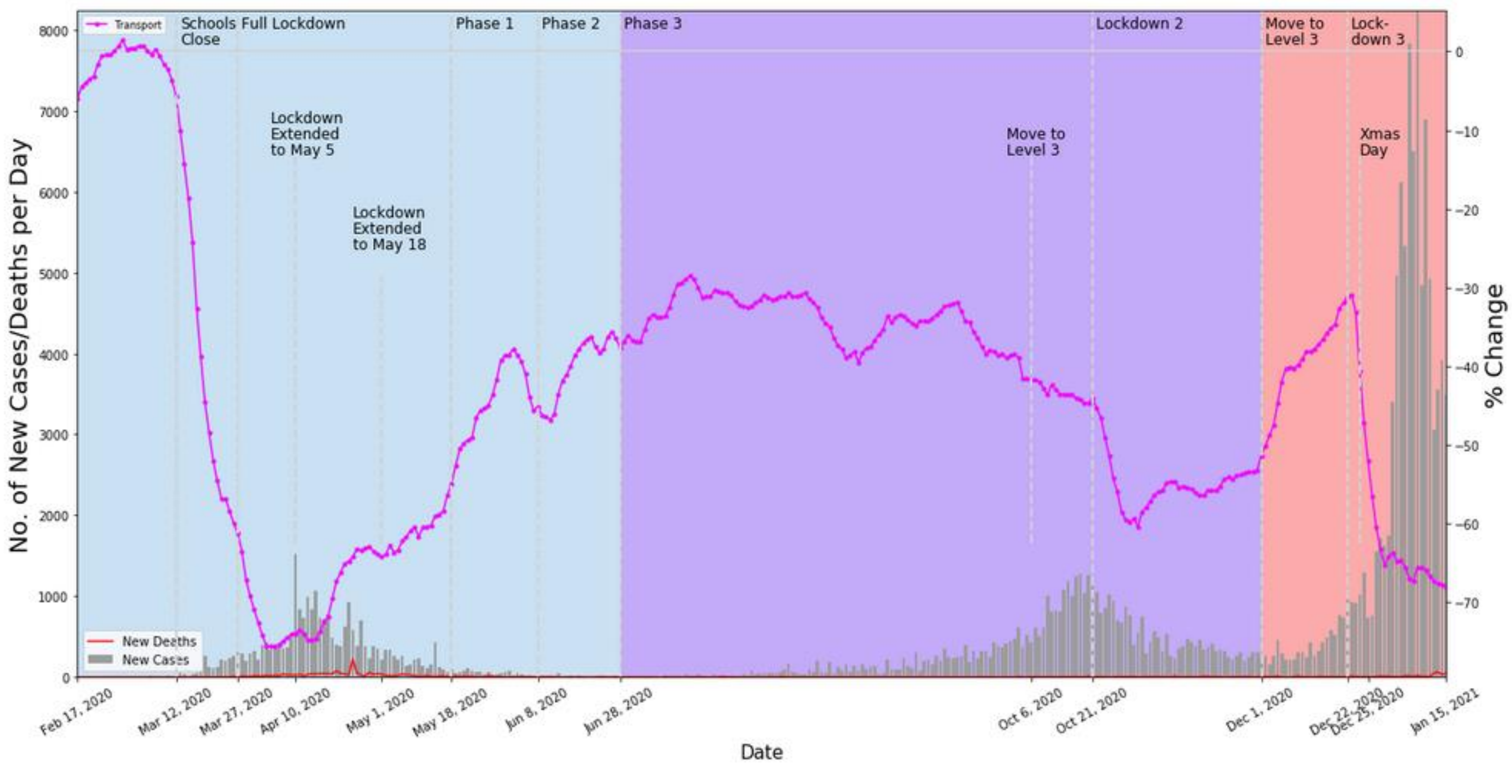


Figure 5.6: Graph of the temporal variability of the daily Google-derived mobility data for Transit Station Visits and the daily COVID-19 cases & death rates from OWID for Ireland (n=333) in relation to significant dates between 17/02/2020 and 15/01/2021. The data used is the raw unprocessed Ireland data. The % change of the graph is in relation to a 5 week baseline and the 3 waves of COVID-19 in Ireland are identifiable by the colour blocks, which end at the completion of a lockdown period.

Figure 5.6 follows a similar pattern to Figure 5.3, with the graph's peaks and troughs roughly aligning with COVID-19 case graph. The graph never recovers to its pre-COVID-19 baseline values, hovering often at about a -30% change in transit station visits throughout the period of mobility pattern monitoring.

Grocery & Pharmacy Stores

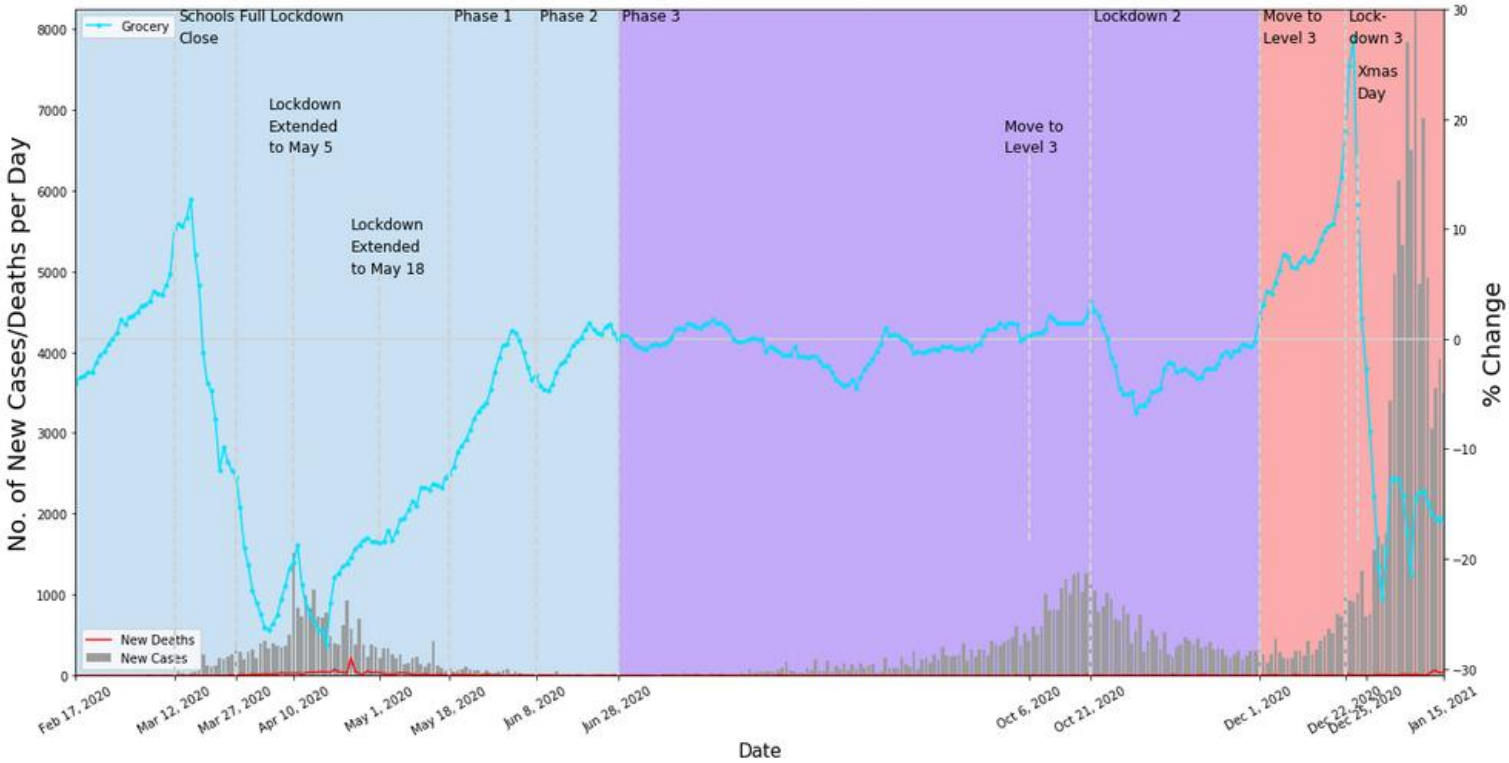


Figure 5.7: Graph of the temporal variability of the daily Google-derived mobility data for Grocery & Pharmacy Store Visits and the daily COVID-19 cases & death rates from OWID for Ireland (n=333) in relation to significant dates between 17/02/2020 and 15/01/2021. The data used is the raw unprocessed Ireland data. The % change of the graph is in relation to a 5 week baseline and the 3 waves of COVID-19 in Ireland are identifiable by the colour blocks, which end at the completion of a lockdown period.

Figure 5.7 experiences a similar dip in the first wave to Figure 5.6, but initially rises when schools were closed and eventually recovers to its baseline values in June. The graph oscillates around the baseline for the majority of the 2nd wave and begins to drastically climb when approaching Christmas and Lockdown 3, as people visit shops to buy holiday foods.

Residential

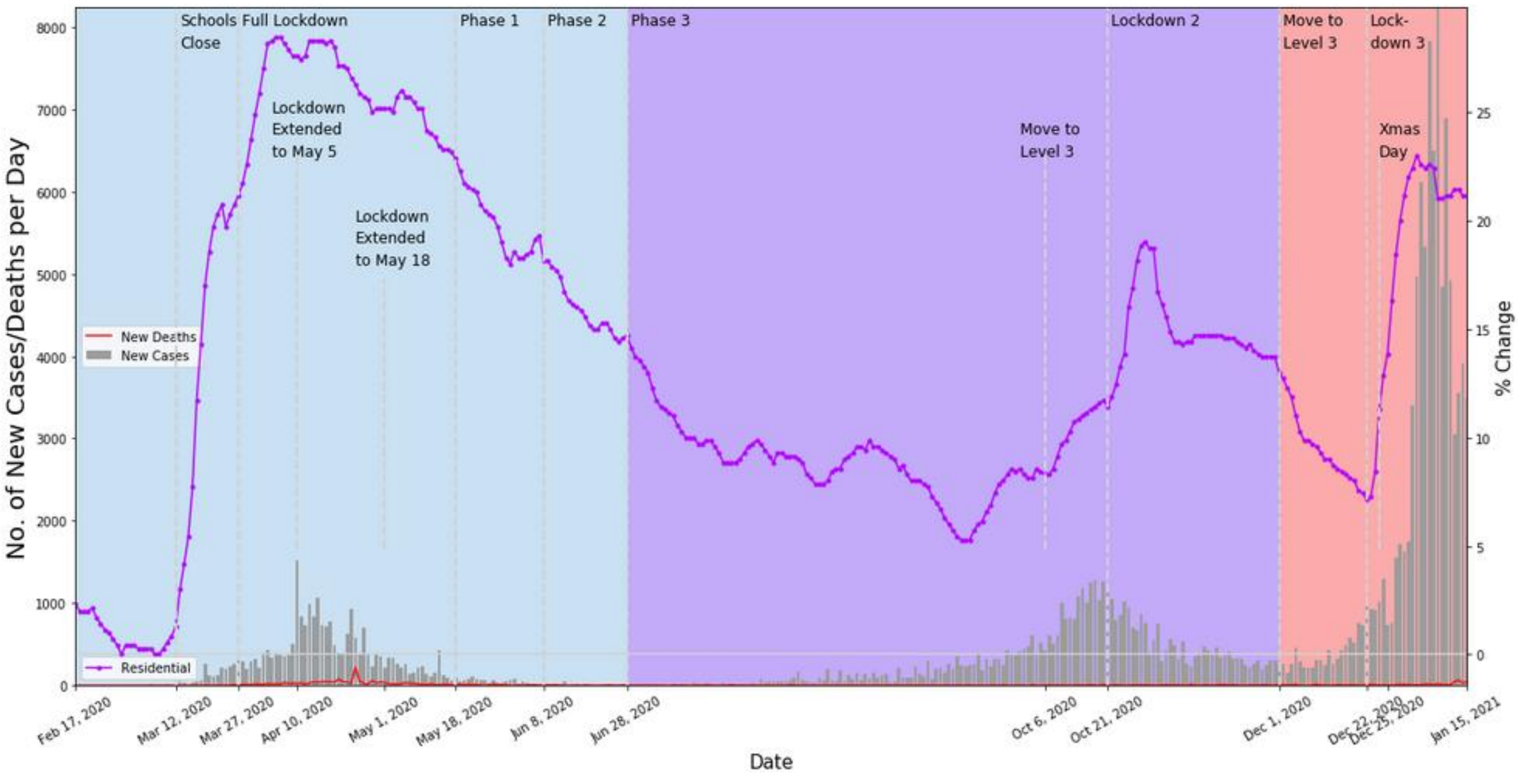


Figure 5.8: Graph of the temporal variability of the daily Google-derived mobility data for Residential Visits and the daily COVID-19 cases & death rates from OWID for Ireland (n=333) in relation to significant dates between 17/02/2020 and 15/01/2021. The data used is the raw unprocessed Ireland data. The % change of the graph is in relation to a 5 week baseline and the 3 waves of COVID-19 in Ireland are identifiable by the colour blocks, which end at the completion of a lockdown period.

Figure 5.8 follows a unique shape as a result of government interventions compared to the majority of the other mobility categories. As schools close, a sharp rise in people remaining at home is evident, which is expected if a "stay-at-home" order is issued. The graph reaches a peak of 28.43% above the baseline during the first wave, referring to an increase of 28.43% more people are remaining at home, but this value is not seen in the subsequent waves.

Mobility Types – Walking, Transit & Driving

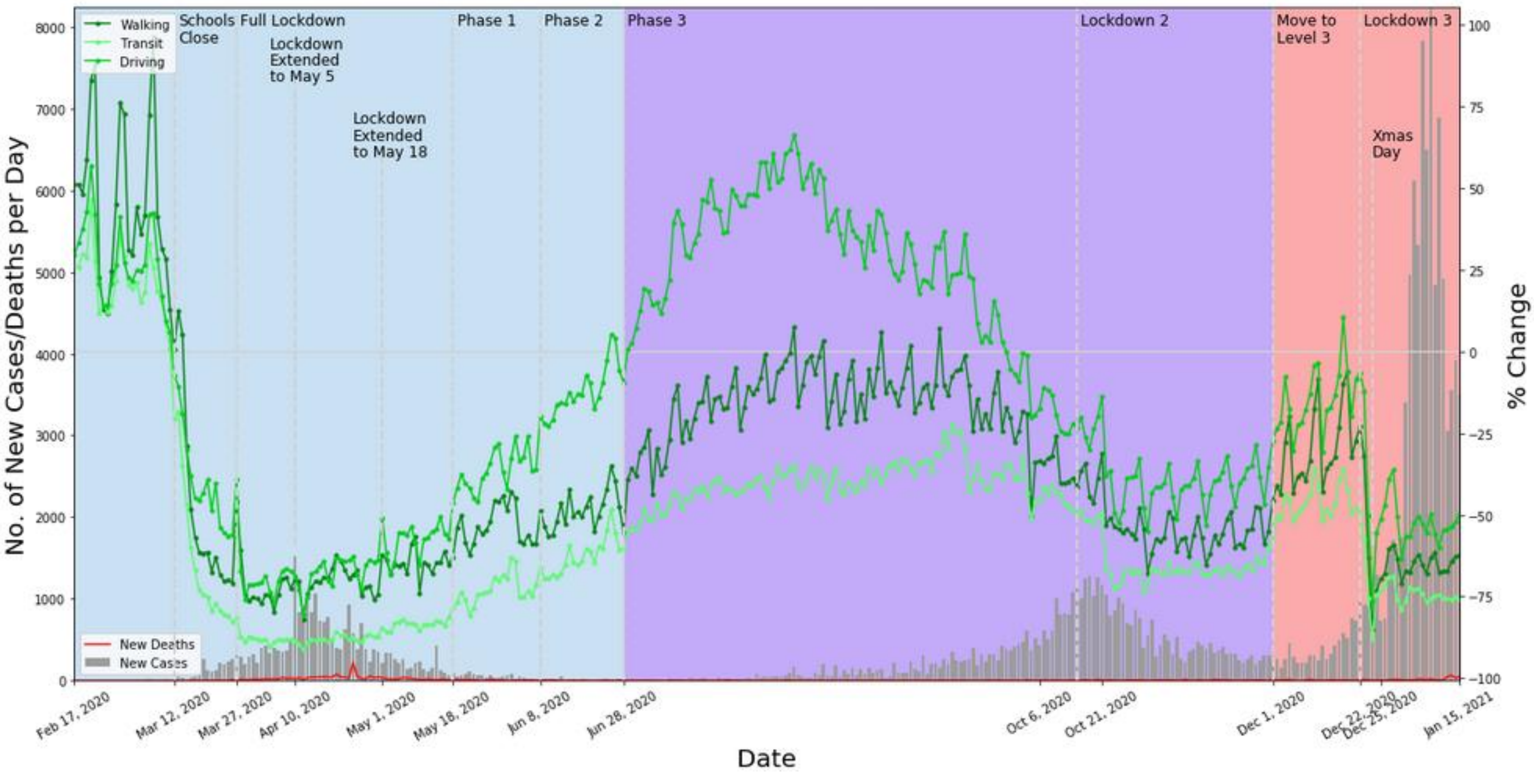


Figure 5.9: Graph of the temporal variability of the daily Apple-derived mobility categories and the daily COVID-19 cases & death rates from OWID for Ireland (n=333) in relation to government announcements, including travel restrictions and lockdowns/stay-at-home orders, national holidays and meteorological conditions from 17/02/2020 to 15/01/2021. The Apple-derived mobility categories are Walking, Transit and Driving, and they are represented as the % change in relation to the same day in 2019. The data used is the raw unprocessed Ireland data.

Figure 5.9 represents the change in the usage of the different transportation modes during the pandemic. The Transit Station Apple graph exhibits a similar pattern to that of its Google counterpart (Figure 5.6), but both the Walking and Driving graphs appear to recover or exceed their 2019 values, which is evident during the 2nd wave. The graphs tend to fall when a lockdown is announced. The graphs are also more visually erratic when compared to the Google graphs, as they are compared to the number of searches for a location on that specific day in 2019, whereas the Google data is compared to a baseline based on 5 week average values for the mobility categories.

5.1.5 *Lockdown Datasets and Accompanying Detailed Statistics*

A lockdown refers to "a temporary condition imposed by governmental authorities (as during the outbreak of an epidemic disease) in which people are required to stay in their homes and refrain from or limit activities outside the home involving public contact (such as dining out or attending large gatherings)" (Merriam Webster, 2020). Ireland was subjected to three lockdowns in the form of "stay-at-home" orders issued by the government along with additional measures during the three waves of COVID-19. These lockdown datasets, which are formed from the overall Ireland dataset, whose values have been translated to the positive axis, 1 added to each number and the natural log of this value is used, were analysed to gain the individual statistics for Lockdown 1, Lockdown 2, Lockdown 3 and initial school closures. The statistics can be seen in tabular form below and a table which synopsises the mean and standard deviation for the various graphs is included at the end of this section.

School Closures

Table 5.14: Descriptive Statistics (Mean, Standard Deviation, Minimum & Maximum Values and Source) of the School Closures (n=14) Dataset with a 14 day lag in case & death values(Mobility Data: 27/02/2020 – 12/03/2020 and COVID-19 Data: 12/03/2020 – 26/03/2020) with data sourced from Google, Apple, OWID and Met Éireann

Detailed Statistics for School Closure Dataset					
	Mean	Standard Deviation	Min. Value	Max. Value	Data Source
Retail	0.68	0.01	0.67	0.69	Google
Grocery	0.44	0.02	0.42	0.48	Google
Parks	0.30	0.02	0.28	0.33	Google
Transit	0.68	0.01	0.66	0.69	Google
Workplaces	0.69	0.00	0.68	0.69	Google
Residential	0.01	0.01	0.00	0.03	Google
Cases	0.01	0.01	0.00	0.03	OWID
Deaths	0.02	0.00	0.02	0.03	OWID
Max. Temp	0.17	0.08	0.05	0.30	Met Éireann
Min. Temp	0.26	0.10	0.08	0.42	Met Éireann
Precipitation	0.09	0.08	0.02	0.31	Met Éireann

When looking at the statistical values obtained in Table 5.14, for the School Closure dataset, it quickly becomes apparent that a comparatively low standard deviation is evident for the six Google-derived mobility categories, which suggests that a lot of values are clustered around the mean. This is anticipated, as the mobility category values are based on the 2 weeks before the school closures, when COVID-19 was still considered novel and the WHO hadn't deemed it a pandemic until the 11/03/2020 (Cucinotta & Vanelli, 2020). No restrictions or alternative measures had been implemented by the government at this point.

Lockdown 1

Table 5.15: Descriptive Statistics (Mean, Standard Deviation, Minimum & Maximum Values and Source) of the Lockdown 1 (n=14) Dataset with a 14 day lag in case & death values (Mobility Data: 13/03/2020 – 27/03/2020 and COVID-19 Data: 27/03/2020 – 10/04/2020) with data sourced from Google, Apple, OWID and Met Éireann

Detailed Statistics for Lockdown 1 Dataset					
	Mean	Standard Deviation	Min. Value	Max. Value	Data Source
Retail	0.47	0.14	0.30	0.67	Google
Grocery	0.42	0.11	0.25	0.55	Google
Parks	0.33	0.05	0.26	0.39	Google
Transit	0.40	0.16	0.20	0.65	Google
Workplaces	0.43	0.17	0.23	0.68	Google
Residential	0.36	0.19	0.04	0.55	Google
Cases	0.04	0.01	0.02	0.05	OWID
Deaths	0.09	0.03	0.03	0.17	OWID
Max. Temp	0.18	0.08	0.06	0.31	Met Éireann
Min. Temp	0.30	0.09	0.13	0.45	Met Éireann
Precipitation	0.08	0.07	0.00	0.23	Met Éireann

Unlike the Table 5.14, the six Google-derived mobility graphs in Table 5.15 have much larger standard deviations, which suggests the spread of data is much larger. This represents the initial panic buying stage after the schools were closed. When compared to Table 5.14, the COVID-19 case and death statistics have significantly risen, even though there is only a 15 day difference between the start of both Lockdown 1 and school closures.

Lockdown 2

Table 5.16: Descriptive Statistics (Mean, Standard Deviation, Minimum & Maximum Values and Source) of the Lockdown 2 (n=14) Dataset with a 14 day lag in case & death values (Mobility Data: 07/10/2020 – 21/10/2020 and COVID-19 Data: 21/10/2020 – 04/11/2020) with data sourced from Google, Apple, OWID and Met Éireann

Detailed Statistics for Lockdown 2 Dataset					
	Mean	Standard Deviation	Min. Value	Max. Value	Data Source
Retail	0.47	0.01	0.46	0.50	Google
Grocery	0.42	0.01	0.41	0.43	Google
Parks	0.34	0.03	0.30	0.38	Google
Transit	0.35	0.01	0.34	0.37	Google
Workplaces	0.47	0.01	0.46	0.48	Google
Residential	0.31	0.03	0.26	0.35	Google
Cases	0.09	0.03	0.04	0.13	OWID
Deaths	0.04	0.01	0.02	0.05	OWID
Max. Temp	0.36	0.04	0.29	0.42	Met Éireann
Min. Temp	0.45	0.09	0.23	0.59	Met Éireann
Precipitation	0.09	0.18	0.00	0.64	Met Éireann

Unlike the first lockdown (Table 5.15) the standard deviation is smaller, highlighting the impact of the school closures 15 days prior to the first lockdown. The impact of Lockdown 2, as seen in Table 5.16 isn't as drastic, due to the smaller spread of mobility data. The higher mean COVID-19 case and death count also highlights the recorded spread of the coronavirus is much higher than the values in Lockdown 1, which triggered the initial restrictive measures.

Lockdown 3

Table 5.17: Descriptive Statistics (Mean, Standard Deviation, Minimum & Maximum Values and Source) of the Lockdown 3 (n=14) Dataset with a 14 day lag in case & death values (Mobility Data: 08/12/2020 – 22/12/2020 and COVID-19 Data: 22/12/2020 – 05/01/2021) with data sourced from Google, Apple, OWID and Met Éireann

Detailed Statistics for Lockdown 3 Dataset					
	Mean	Standard Deviation	Min. Value	Max. Value	Data Source
Retail	0.58	0.02	0.56	0.62	Google
Grocery	0.51	0.03	0.48	0.57	Google
Parks	0.25	0.02	0.22	0.28	Google
Transit	0.41	0.02	0.38	0.45	Google
Workplaces	0.51	0.00	0.51	0.52	Google
Residential	0.27	0.02	0.23	0.30	Google
Cases	0.20	0.15	0.09	0.56	OWID
Deaths	0.05	0.02	0.03	0.08	OWID
Max. Temp	0.22	0.05	0.14	0.29	Met Éireann
Min. Temp	0.33	0.10	0.02	0.45	Met Éireann
Precipitation	0.17	0.10	0.05	0.40	Met Éireann

The sharp rise in COVID-19 cases towards the end of 2020, which can be seen in the mobility graphs earlier, is evident in Table 5.17, as a high standard deviation and maximum value for COVID-19 cases is obtained over the 2 week period.

Summary of Detailed Statistics for Ireland

Table 5.18 provides a quick synopsis of the mean and standard deviation of each category in the Ireland dataset and its subsets for School Closures, Lockdown 1, Lockdown 2 and Lockdown 3. By comparing these values, it highlights the various stages of the spread of COVID-19 and provides an insight into the mobility categories prior to the announcement of a lockdown or the initial school closures.

Table 5.18: Summary of the Detailed Statistics consisting of the Mean and Standard Deviation (std) for the Google-derived mobility data, OWID COVID-19 case & death count and Met Éireann meteorological data for the entire Ireland datasets and its subsets: School Closures, Lockdown 1, Lockdown 2 and Lockdown 3

Summary of the Mean (Standard Deviation) for each Mobility Category during the Stages of Ireland's COVID-19 Timeline																						
	Retail		Grocery		Parks		Transit Stations		Workplaces		Residential		Cases		Deaths		Max. Temp		Min. Temp		Precipitation	
	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std	Mean	Std
Ireland	0.41	0.18	0.35	0.12	0.32	0.14	0.34	0.16	0.37	0.16	0.38	0.18	0.05	0.10	0.05	0.06	0.35	0.14	0.42	0.14	0.09	0.12
School Closures	0.68	0.01	0.44	0.02	0.30	0.02	0.68	0.01	0.69	0.00	0.01	0.01	0.01	0.01	0.02	0.00	0.17	0.08	0.26	0.10	0.09	0.08
Lockdown 1	0.47	0.14	0.42	0.11	0.33	0.05	0.40	0.16	0.43	0.17	0.36	0.19	0.04	0.01	0.09	0.03	0.18	0.08	0.30	0.09	0.08	0.07
Lockdown 2	0.47	0.01	0.42	0.01	0.34	0.03	0.35	0.01	0.47	0.01	0.31	0.03	0.09	0.03	0.04	0.01	0.36	0.04	0.45	0.09	0.09	0.18
Lockdown 3	0.58	0.02	0.51	0.03	0.25	0.02	0.41	0.02	0.51	0.00	0.27	0.02	0.20	0.15	0.05	0.02	0.22	0.05	0.33	0.10	0.17	0.10

Many results can be acquired from Table 5.18. For example, it is apparent that the mean of the majority of the mobility categories in Lockdown 1 and Lockdown 2 are similar, but the much larger standard deviation obtained in Lockdown 1 highlights the volatile nature of the mobility category graphs at the first lockdown compared to the second lockdown.

5.1.6 *Correlation Matrices*

Correlation matrices were formulated to provide a quick overview into the relationship between the various characteristics of the datasets. They allow the reader to quickly interpret the results and to further investigate the relationship between the characteristics. Spearman's ρ was obtained to determine the association between the Google & Apple mobility categories, COVID-19 case & death values and meteorological data.

Ireland

The correlation matrix for the Ireland data, which has been translated to the positive axis, 1 added to each number and the natural log of each value is used, in Figure 5.10 exhibits many strong associations between categories. The Apple mobility categories of Driving (%), Transit (%) and Walking (%) are quite closely correlated, which is evident by the high correlation coefficient value and a deep shade of red in the squares. This suggests as more people walk, drive or use public transport, it leads to an increase in all the Apple-derived mobility graph data.

Similarly, a moderate to high positive correlation can be seen between five of the Google-derived mobility graphs: Retail & Recreation, Grocery & Pharmacy Stores, Parks, Transit Stations and Workplaces, which indicates that as more people visit a certain locations that is associated with the mobility categories, the more likely that people will visit other locations with different functions. The Residential category has a contrasting relationship with the other mobility categories, which is evident in the form of a negative correlation between itself and the rest of the Google and Apple mobility categories. This is represented by a square with a blue background containing a negative value. The Residential data appears to have a relatively moderate to strong association with the new_deaths data, which needs to be further examined in the report.

The meteorological categories appear to have a relatively weak to no correlation with many of the mobility categories. The only noticeable strong correlation found in these categories is the one between Minimum and Maximum Temperatures, which is expected, because as the days become warmer the maximum and minimum temperatures experienced will rise.

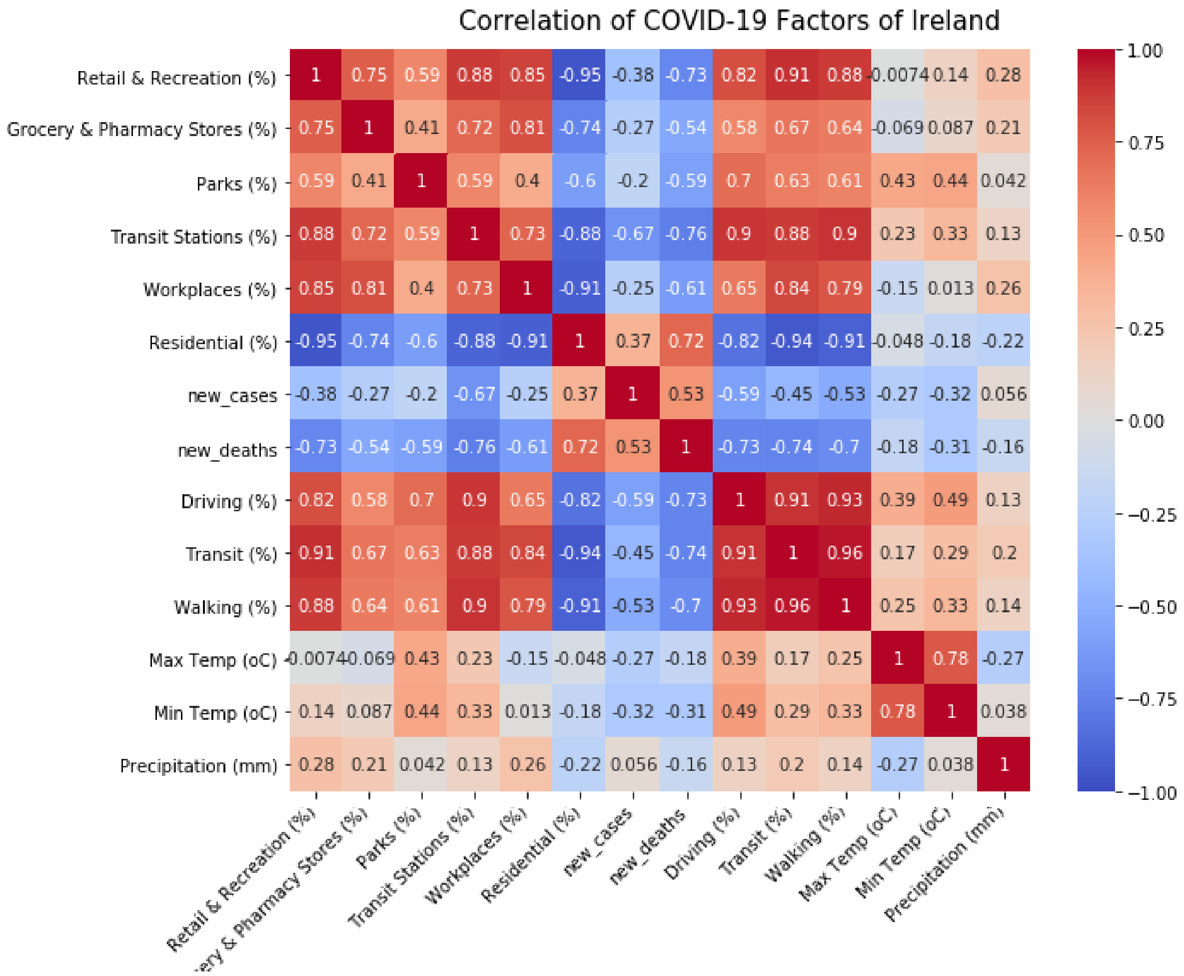


Figure 5.10: Correlation Matrix of the Ireland Dataset consisting of the Google & Apple-derived mobility category data, COVID-19 case and death values from OWID and meteorological data from Met Éireann, using Spearman's method to determine association between the categories

This was compared to the 14 day lag dataset categories to determine if there would be any drastic changes in the strength of the relationships and if the relationships had become negative or positively correlated with the delay in case and death data. As seen in Figure 5.11, only the values for both the case and death relationship with the other categories had changed. The lag evidently leads to a stronger correlation with COVID-19 case data, but a weaker one with COVID-19 deaths.

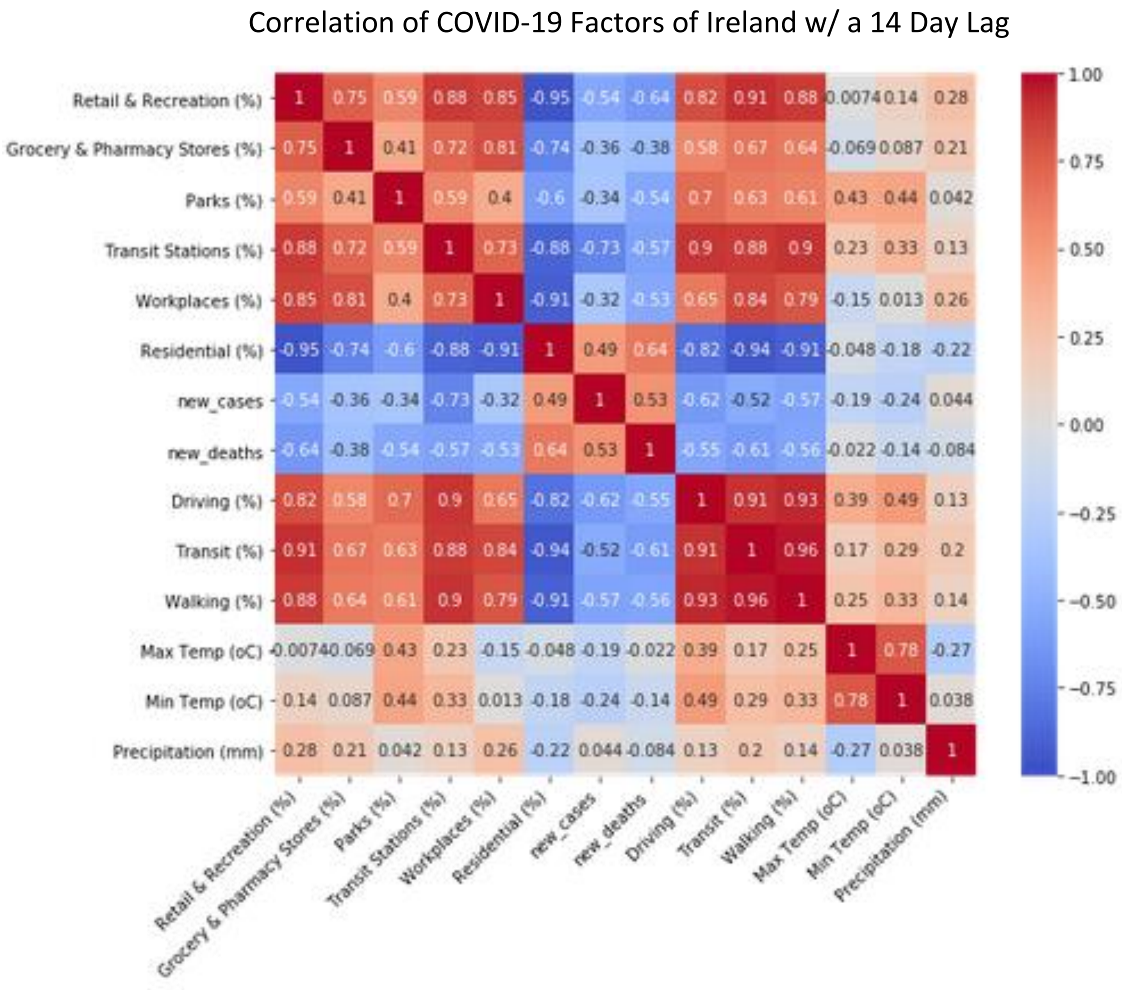


Figure 5.11: Correlation Matrix of the Ireland Dataset w/ a 14 day lag consisting of the Google & Apple-derived mobility category data, COVID-19 case and death values from OWID and meteorological data from Met Éireann, using Spearman's method to determine association between the categories

School Closures

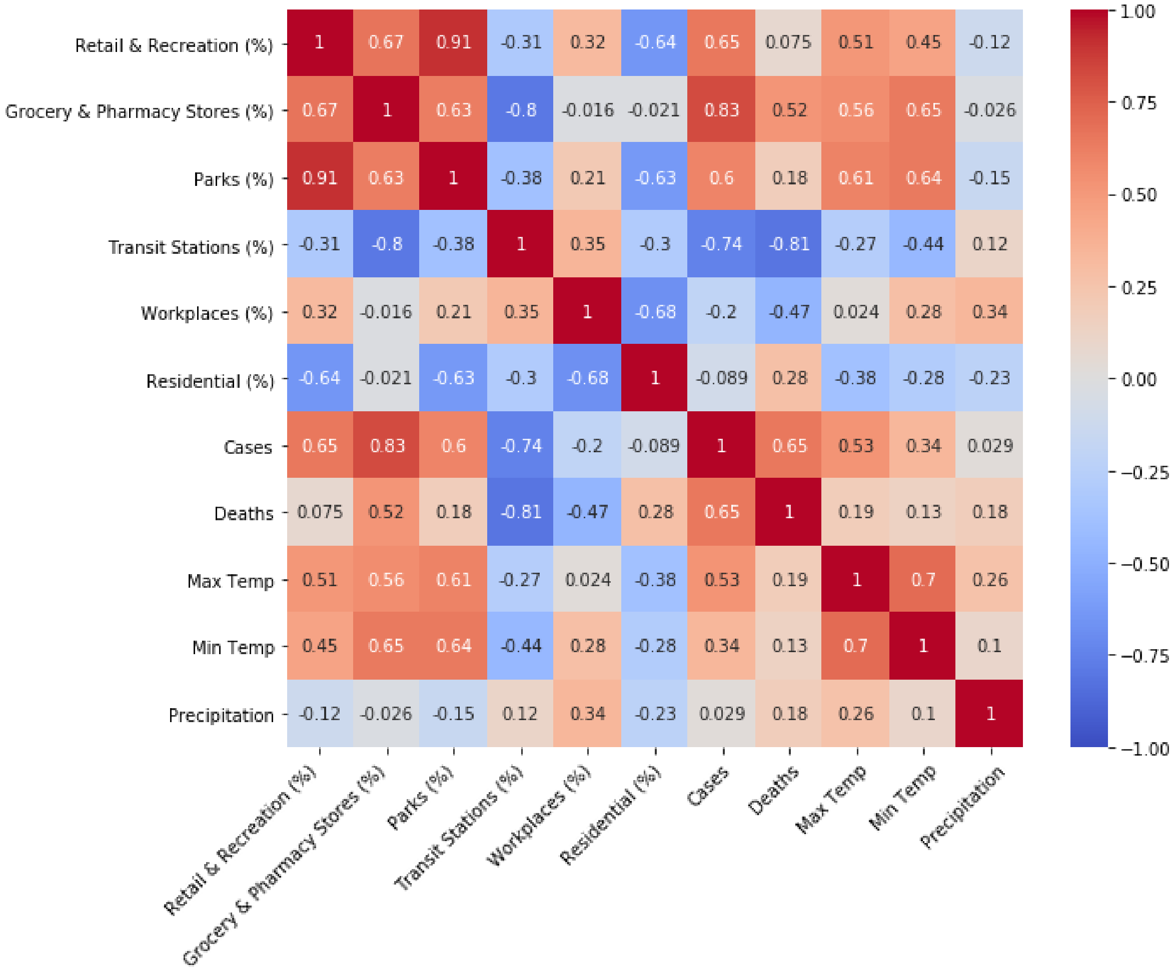


Figure 5.12: Correlation Matrix of the School Closure Dataset consisting of the Google-derived mobility category data, COVID-19 case and death values from OWID w/ a 14 day lag and meteorological data from Met Éireann, using Spearman's method to determine association between the categories. (Mobility Data: 27/02/2020 – 12/03/2020 and COVID-19 Data: 12/03/2020 – 26/03/2020)

Figure 5.12 appears to have a greater range of correlation values which are less clustered when compared to Figure 5.10. Many of the relationships evident in Figure 5.10 still hold for the Google mobility categories, but the Transit Station values appear to be negatively correlated to the majority of the School Closure dataset categories. The meteorological data association with the other dataset categories also seems to slightly increase, but this is expected, as this dataset only looks at 2 weeks of COVID-19 case & deaths data along with 2 weeks of mobility and meteorological data.

Lockdown 1

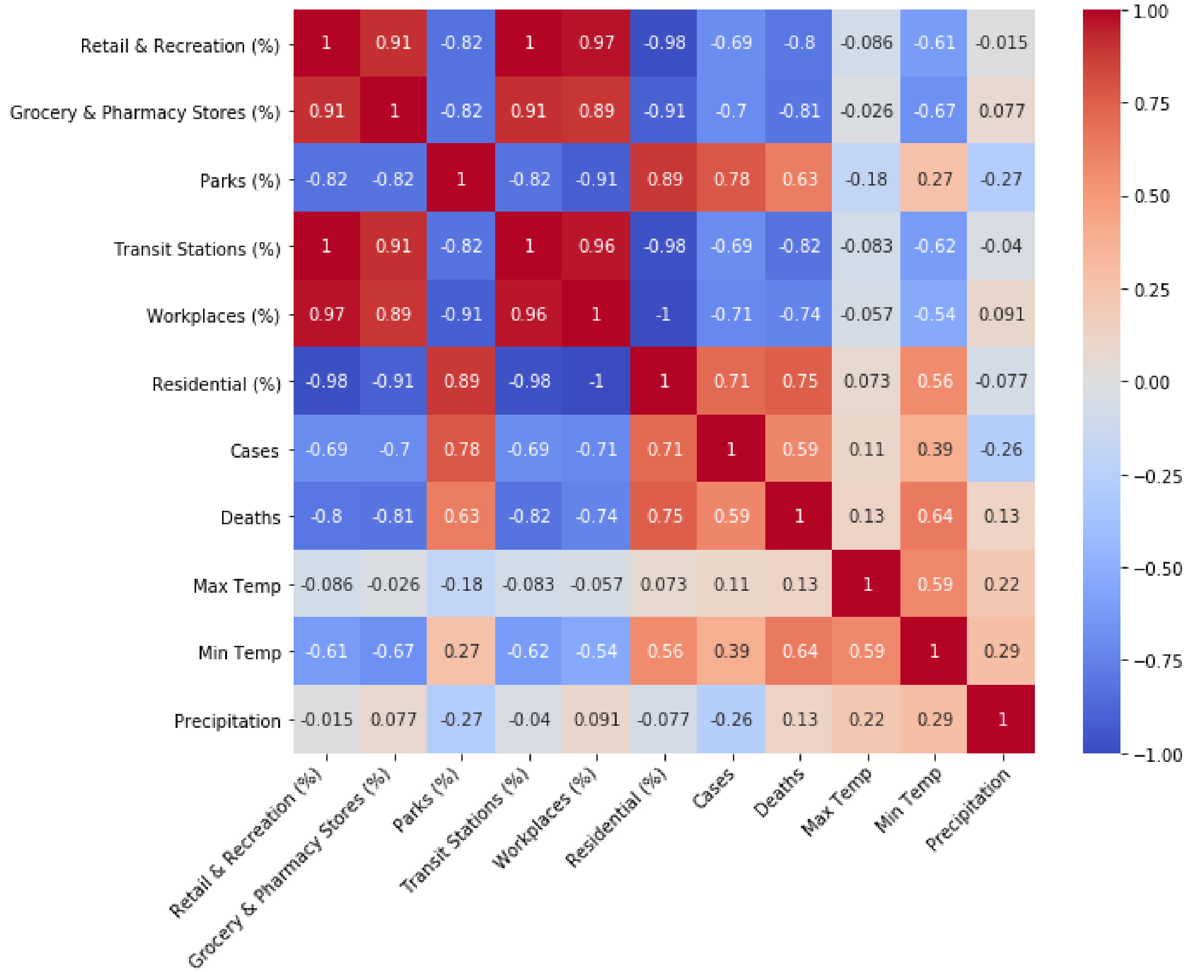


Figure 5.13: Correlation Matrix of the Lockdown 1 Dataset consisting of the Google-derived mobility category data, COVID-19 case and death values from OWID w/ a 14 day lag and meteorological data from Met Éireann, using Spearman's method to determine association between the categories. (Mobility Data: 13/03/2020 – 27/03/2020 and COVID-19 Data: 27/03/2020 – 10/04/2020)

Figure 5.13's categories tend to be more clustered than Figure 5.12. Some of the values obtained are different to the ones exhibited in previous correlation matrices, such as the moderate to strong association between Deaths and Residential. This suggests that as people stay home and the Residential (%) values increase, deaths increase 2 weeks later, as many people were infected prior to staying home. Similar instances can be seen between other categories such as the moderate negative correlation between the Minimum Temperature and Grocery & Pharmacy Stores. As these relationship have not been evident in Figure 5.10 and Figure 5.12, they warrant a further investigation when examining the regression models.

Lockdown 2

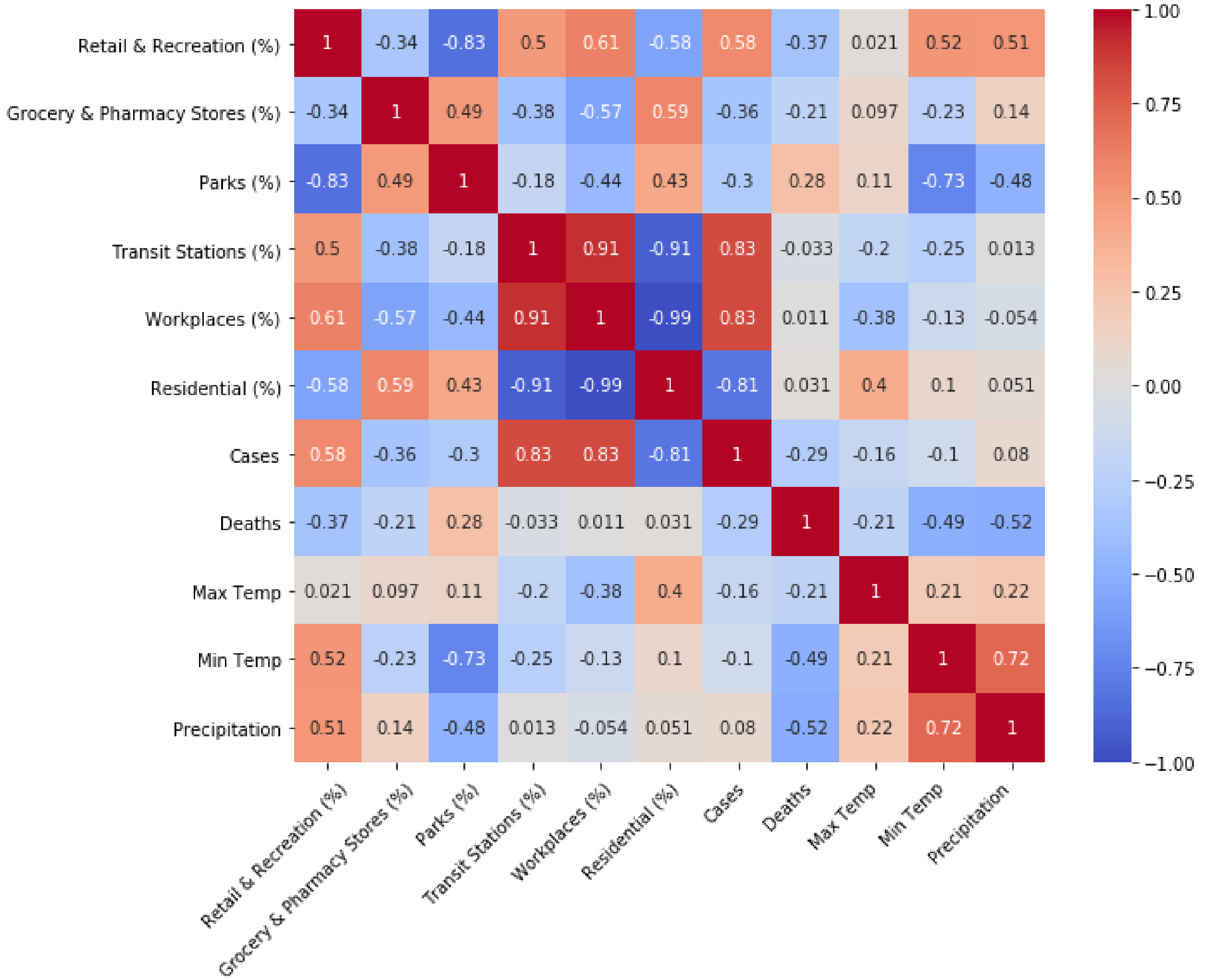


Figure 5.14: Correlation Matrix of the Lockdown 2 Dataset consisting of the Google-derived mobility category data, COVID-19 case and death values from OWID w/ a 14 day lag and meteorological data from Met Éireann, using Spearman's method to determine association between the categories. (Mobility Data: 07/10/2020 – 21/10/2020 and COVID-19 Data: 21/10/2020 – 04/11/2020)

Figure 5.14 is similar to the nature of Figure 5.12, which appears to have a greater range of correlation values that are less clustered overall. The centre of the correlation matrix contains the strongest associations, such as the one negative strong correlation between the Residential and Workplaces data. This suggests that as less people attend their normal workplaces, more people remain home, which is expected if a lockdown is put into place. Similarly, there is a strong negative association between Parks and Retail & Recreation, which suggests that as retail stores and recreational facilities close, more people will visit parks or greenspaces in their locality.

Lockdown 3

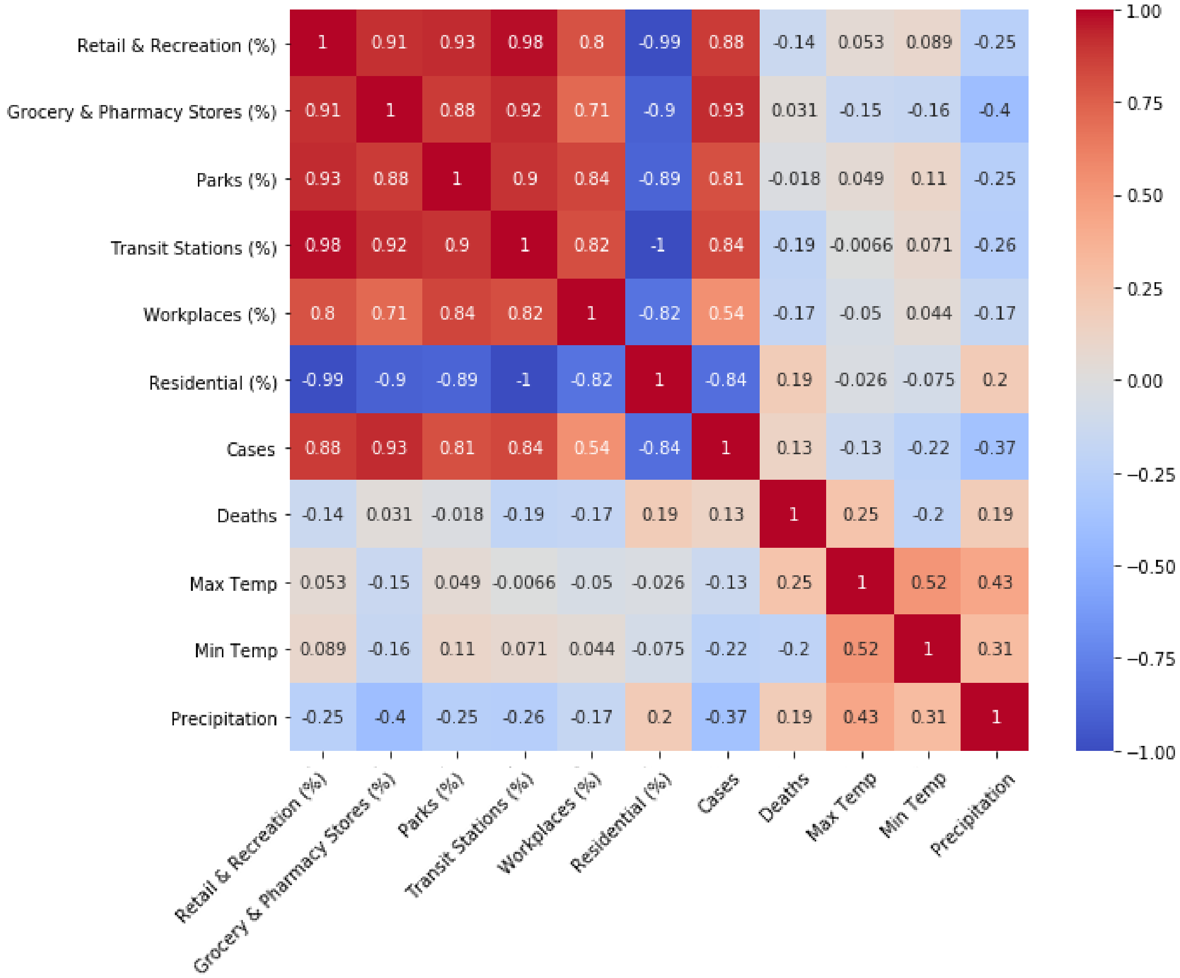


Figure 5.15: Correlation Matrix of the Lockdown 3 Dataset consisting of the Google-derived mobility category data, COVID-19 case and death values from OWID w/ a 14 day lag and meteorological data from Met Éireann, using Spearman's method to determine association between the categories. (Mobility Data: 08/12/2020 – 22/12/2020 and COVID-19 Data: 22/12/2020 – 05/01/2021)

Figure 5.15 is graphically similar to Figure 5.10, where there is a strong positive association between the majority of the Google mobility categories. The COVID-19 case data is also strongly associated with the mobility categories, with the Residential data being the only one that is negatively correlated with the COVID-19 case values. The meteorological data appears to have a weak or non-existent association with many of the mobility categories, which emphasises the fact that it is not influential in the alteration of the mobility category data.

P-Values

A P-value is often used to verify an obtained result for a model in order to determine if it is statistically significant. A P-value was obtained for the correlation values, in order to determine if the resultant correlation coefficient accurately represents the relationship between the dataset categories for Ireland.

Table 5.19: P-values for the correlation between the Google & Apple-derived mobility category data, COVID-19 case & death values from OWID and Meteorological Data for Ireland from Met Éireann, where the yellow values represent the P-values greater than 0.05 and are therefore, considered statistically insignificant. The remaining values(white squares) are valid results, which reinforce that the correlation values obtained in the matrices are accurate.

P-values for the correlation between Mobility data, COVID-19 Cases and Meteorological Data for Ireland														
	Retail	Grocery	Parks	Transit Stations	Workplaces	Residential	Cases	Deaths	Driving	Transit	Walking	Max. Temp	Min. Temp	Precipitation
Retail	0	5.20E-62	2.30E-32	8.10E-111	1.82E-95	1.82E-95	4.34E-13	6.36E-56	4.57E-82	4.95E-128	1.54E-108	8.93E-01	9.36E-03	2.52E-07
Grocery	5.20E-62	0	2.86E-15	1.49E-55	3.76E-78	2.36E-59	4.07E-07	1.05E-26	1.05E-31	1.97E-44	9.05E-40	2.11E-01	1.14E-01	9.12E-05
Parks	2.30E-32	2.86E-15	0	6.23E-33	2.10E-14	1.07E-34	2.34E-04	9.11E-33	1.18E-50	1.61E-38	4.55E-35	3.60E-16	2.29E-17	4.49E-01
Transit Stations	8.10E-111	1.49E-55	6.23E-33	0	5.02E-57	1.82E-111	6.08E-45	9.63E-64	2.76E-119	3.84E-108	1.98E-123	3.11E-05	7.69E-10	2.03E-02
Workplaces	1.82E-95	3.76E-78	2.10E-14	5.02E-57	0	2.29E-128	3.06E-06	2.22E-35	3.73E-41	1.44E-91	2.08E-71	7.73E-03	8.07E-01	1.20E-06
Residential	6.13E-175	2.36E-59	1.07E-34	1.82E-111	2.29E-128	0	4.50E-12	1.12E-54	3.14E-84	1.41E-161	1.36E-125	3.87E-01	1.11E-03	4.36E-05
Cases	4.34E-13	4.07E-07	2.34E-04	6.08E-45	3.06E-06	4.50E-12	0	2.04E-25	3.54E-32	3.67E-18	2.29E-25	7.13E-07	2.88E-09	3.07E-01
Deaths	6.36E-56	1.05E-26	9.11E-33	9.63E-64	2.22E-35	1.12E-54	2.04E-25	0	2.34E-57	9.85E-59	4.82E-51	1.05E-03	4.05E-09	4.43E-03
Driving	4.57E-82	1.05E-31	1.18E-50	2.76E-119	3.73E-41	3.14E-84	3.54E-32	2.34E-57	0	2.64E-125	4.14E-148	7.56E-14	1.35E-21	1.45E-02
Transit	4.95E-128	1.97E-44	1.61E-38	3.84E-108	1.44E-91	1.41E-161	3.67E-18	9.85E-59	2.64E-125	0	2.57E-187	1.45E-03	7.62E-08	1.62E-04
Walking	1.54E-108	9.05E-40	4.55E-35	1.98E-123	2.08E-71	1.36E-125	2.29E-25	4.82E-51	4.14E-148	2.57E-187	0	2.78E-06	4.19E-10	1.12E-02
Max. Temp	8.93E-01	2.11E-01	3.60E-16	3.11E-05	7.73E-03	3.87E-01	7.13E-07	1.05E-03	7.56E-14	1.45E-03	2.78E-06	0	9.37E-69	4.27E-07
Min. Temp	9.36E-03	1.14E-01	2.29E-17	7.69E-10	8.07E-01	1.11E-03	2.88E-09	4.05E-09	1.35E-21	7.62E-08	4.19E-10	9.37E-69	0	4.83E-01
Precipitation	2.52E-07	9.12E-05	4.49E-01	2.03E-02	1.20E-06	4.36E-05	3.07E-01	4.43E-03	1.45E-02	1.62E-04	1.12E-02	4.27E-07	4.83E-01	0

Table 5.19 highlights the P-values obtained for the correlation values between the Ireland dataset categories. The yellow values represent the P-values that are greater than 0.05 and therefore are deemed not statistically significant. Therefore, some of the relationships between meteorological data and mobility category data cannot be critically analysed, as this would compromise the accuracy of the report.

Table 5.20, which represents the P-values obtained for the correlation values between the Ireland dataset categories with a 14 day lag on the COVID-19 case and death cases, is similar to Table 5.19, where a lot of the meteorological data exhibits a statistically insignificant relationship with many of the mobility categories. This is represented in the form of yellow squares where the P-value is greater than 0.05 and a few additional ones can be seen between the relationships of the meteorological data with the COVID-19 case and death data.

Table 5.20: P-values for the correlation between the Google & Apple-derived mobility category data, COVID-19 case & death values from OWID and Meteorological Data for Ireland from Met Éireann, with a 14 day lag on COVID-19 case & death data, where the yellow values represent the P-values greater than 0.05 and are therefore, considered statistically insignificant. The remaining values(white squares) are valid results, which reinforce that the correlation values obtained in the matrices are accurate.

P-values for the correlation between Mobility data, COVID-19 Cases and Meteorological Data for Ireland, where there is a 14 day lag in Case Data														
	Retail	Grocery	Parks	Transit Stations	Workplaces	Residential	Cases	Deaths	Driving	Transit	Walking	Max. Temp	Min. Temp	Precipitation
Retail	0	5.20E-62	2.30E-32	8.10E-111	1.82E-95	1.82E-95	1.21E-26	3.96E-39	4.57E-82	4.95E-128	1.54E-108	8.93E-01	9.36E-03	2.52E-07
Grocery	5.20E-62	0	2.86E-15	1.49E-55	3.76E-78	2.36E-59	2.17E-11	3.60E-13	1.05E-31	1.97E-44	9.05E-40	2.11E-01	1.14E-01	9.12E-05
Parks	2.30E-32	2.86E-15	0	6.23E-33	2.10E-14	1.07E-34	1.98E-10	5.62E-27	1.18E-50	1.61E-38	4.55E-35	3.60E-16	2.29E-17	4.49E-01
Transit Stations	8.10E-111	1.49E-55	6.23E-33	0	5.02E-57	1.82E-111	2.01E-56	3.11E-30	2.76E-119	3.84E-108	1.98E-123	3.11E-05	7.69E-10	2.03E-02
Workplaces	1.82E-95	3.76E-78	2.10E-14	5.02E-57	0	2.29E-128	1.34E-09	4.30E-26	3.73E-41	1.44E-91	2.08E-71	7.73E-03	8.07E-01	1.20E-06
Residential	6.13E-175	2.36E-59	1.07E-34	1.82E-111	2.29E-128	0	1.55E-21	1.98E-40	3.14E-84	1.41E-161	1.36E-125	3.87E-01	1.11E-03	4.36E-05
Cases	1.21E-26	2.17E-11	1.98E-10	2.01E-56	1.34E-09	1.55E-21	0	1.32E-25	1.24E-36	1.69E-24	3.32E-30	6.78E-04	1.21E-05	4.26E-01
Deaths	3.96E-39	3.60E-13	5.62E-27	3.11E-30	4.30E-26	1.98E-40	1.32E-25	0	3.45E-28	5.36E-36	7.94E-29	6.89E-01	1.24E-02	1.26E-01
Driving	4.57E-82	1.05E-31	1.18E-50	2.76E-119	3.73E-41	3.14E-84	1.24E-36	3.45E-28	0	2.64E-125	4.14E-148	7.56E-14	1.35E-21	1.45E-02
Transit	4.95E-128	1.97E-44	1.61E-38	3.84E-108	1.44E-91	1.41E-161	1.69E-24	5.36E-36	2.64E-125	0	2.57E-187	1.45E-03	7.62E-08	1.62E-04
Walking	1.54E-108	9.05E-40	4.55E-35	1.98E-123	2.08E-71	1.36E-125	3.32E-30	7.94E-29	4.14E-148	2.57E-187	0	2.78E-06	4.19E-10	1.12E-02
Max. Temp	8.93E-01	2.11E-01	3.60E-16	3.11E-05	7.73E-03	3.87E-01	6.78E-04	6.89E-01	7.56E-14	1.45E-03	2.78E-06	0	9.37E-69	4.27E-07
Min. Temp	9.36E-03	1.14E-01	2.29E-17	7.69E-10	8.07E-01	1.11E-03	1.21E-05	1.24E-02	1.35E-21	7.62E-08	4.19E-10	9.37E-69	0	4.83E-01
Precipitation	2.52E-07	9.12E-05	4.49E-01	2.03E-02	1.20E-06	4.36E-05	4.26E-01	1.26E-01	1.45E-02	1.62E-04	1.12E-02	4.27E-07	4.83E-01	0

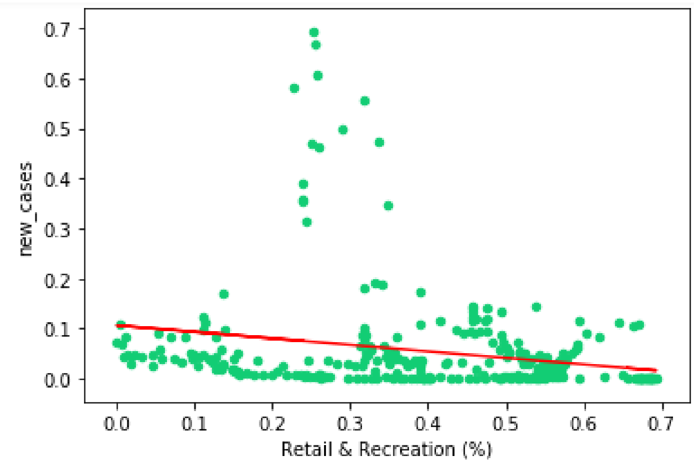
5.1.7 *Regression Analysis*

The regression analyses carried out – both OLS single and multiple linear regression models, are shown in both graphical and tabular form to synopsise the relationship between the different categories in the dataset and its lockdown subsets. The examination based on the results will be discussed at length throughout the report.

5.1.7.1 *Single Linear Regression*

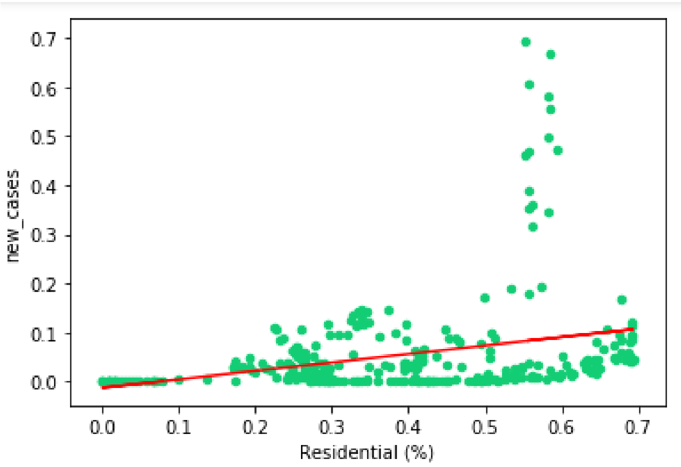
An OLS single linear regression model was used in this section to further analyse the association between the characteristics related to mobility and case values. This was done to reinforce the close affiliation noted in the correlation matrices between certain factors and to look at the data even closer to determine any influential data points.

Ireland




```
R-squared: 0.053
α constant (intercept): 0.106
β coefficient (slope): -0.130
```

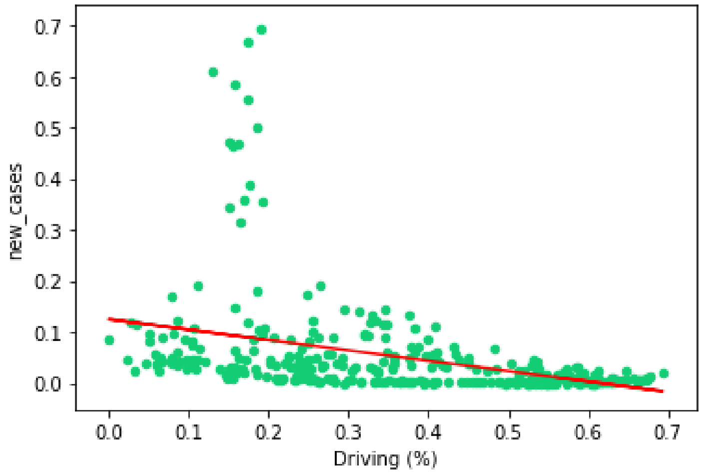
Figure 5.16: Relationship between Case Numbers from OWID and Retail & Recreational Visits data from Google between 17/02/2020 and 15/01/2021 in Ireland (n=333)




```
R-squared: 0.090
α constant (intercept): -0.013
β coefficient (slope): 0.172
```

Figure 5.17: Relationship between Case Numbers from OWID and Residential Store Visits data from Google between 17/02/2020 and 15/01/2021 in Ireland (n=333)

To analyse the relationship between COVID-19 cases and the Google-derived mobility data for the Ireland dataset, OLS regression was conducted and a graphical output was obtained. Note that the Ireland data refers to the raw Ireland data, which has been translated to the positive axis, 1 added to each number and the natural log has been taken for each value is then used. Following on from the correlation matrices, the specific relationship can be determined based on the slope of line and the axis labels. Five out of six of the Google mobility category data graphs (Retail & Recreation, Grocery & Pharmacy Stores, Parks, Transit Stations and Workplaces) follow the same shape as Figure 5.16. This suggests that as COVID-19 cases drop, more people are inclined to visit retail stores and recreational facilities. Figure 5.17 from the mobility categories, as the graph tentatively implies that as COVID-19 cases rise, the number of people staying at home increases, due to the various government interventions introduced to restrict movement and mitigate the spread of COVID-19. The low R^2 values ascertained reinforce that these observations need to be further examined, which will be conducted using the aligned subsets.

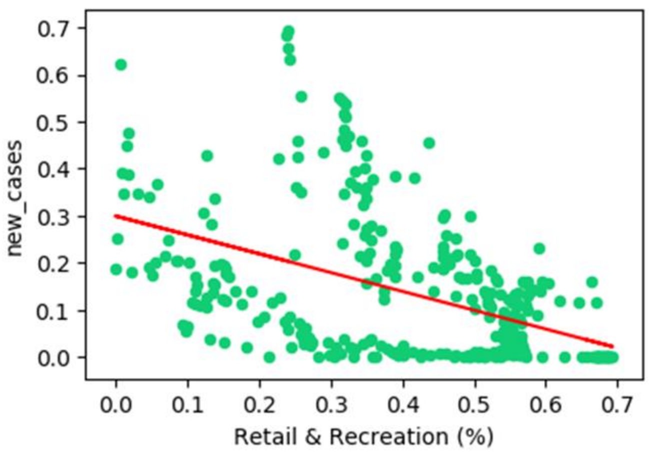


R-squared: 0.136
α constant (intercept): 0.125
β coefficient (slope): -0.203

Figure 5.18: Relationship between Case Numbers from OWID and % Driving data from Apple between 17/02/2020 and 15/01/2021 in Ireland (n=333)

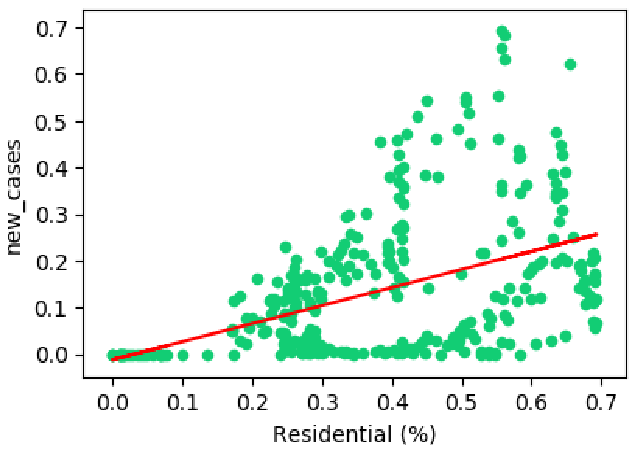
The Apple Mobility data also have a similar relationship with the COVID-19 case data when compared with Figure 5.16. Figure 5.18 and the remaining Apple graphs (Walking (%) and Transit(%)) tend to highlight that as cases drop, people are more prone to drive somewhere, which is evident in the fact that travel restrictions were removed once cases were brought down to manageable levels at the end of Lockdown 1. The entire OLS single linear regression model graphs can be seen in Appendix C, which have a similar relationship to the graphs mentioned in this section. Due to obtaining some graphs with counterintuitive results, this supports the need to break down the Ireland graph into subsets i.e. School Closures, Lockdown 1, Lockdown 2 and Lockdown 3.

Ireland with a 14 Day Lag in COVID-19 Case and Death Data



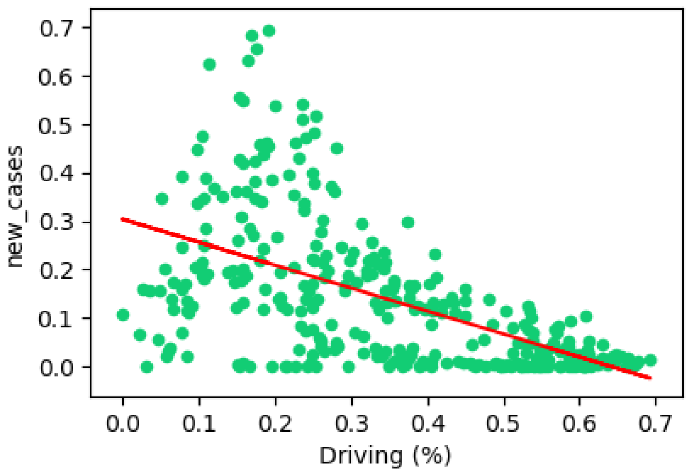
R-squared: 0.226
α constant (intercept): 0.300
β coefficient (slope): -0.400

Figure 5.19: Relationship between Case Numbers from OWID and Retail & Recreational Visits data from Google between 17/02/2020 and 15/01/2021 in Ireland (n=333) with a 14 day lag in COVID-19 Case Values



R-squared: 0.204
α constant (intercept): -0.012
β coefficient (slope): 0.387

Figure 5.20: Relationship between Case Numbers from OWID and Residential Visits data from Google between 17/02/2020 and 15/01/2021 in Ireland (n=333) with a 14 day lag in COVID-19 Case Values

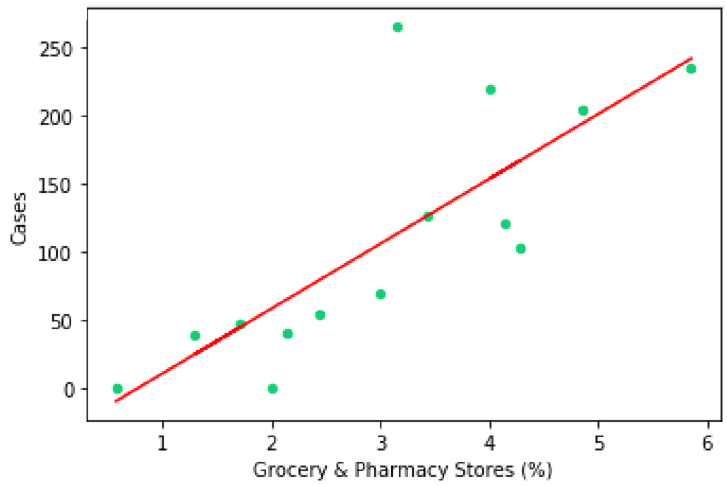



```
R-squared: 0.331
α constant (intercept): 0.304
β coefficient (slope): -0.473
```

Figure 5.21: Relationship between Case Numbers from OWID and % Driving data from Apple between 17/02/2020 and 15/01/2021 in Ireland (n=333) with a 14 day lag in COVID-19 Case Values

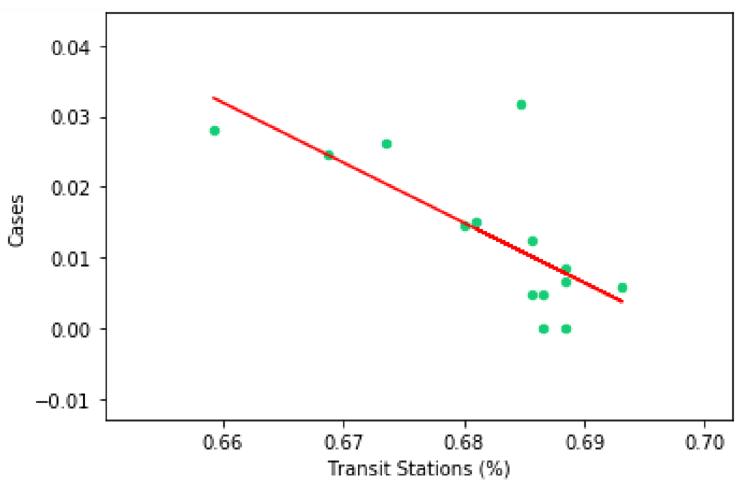
When comparing the same figures obtain for the Ireland dataset with and without a 14 day lag in COVID-19 case & death values, the R^2 values are significantly higher. This is evident between Figure 16 and Figure 19, as Figure 5.19 has an R^2 value which is over 4 times larger than the non-14 day lag counterpart. This is similarly evident in Figure 5.20 for the Residential data and Figure 5.21 for Driving data. The remaining graphs can be seen in Appendix D. Overall, this suggests that there is a stronger relationship between the mobility data and COVID-19 cases when a 14 day lag is applied.

School Closures




```
R-squared: 0.617
α constant (intercept): -36.980
β coefficient (slope): 47.569
```

Figure 5.22: Relationship between Case Numbers from OWID and Grocery & Pharmacy Store Visits data from Google around School Closures in Ireland (n=14) w/ a 14 day lag in COVID-19 case data

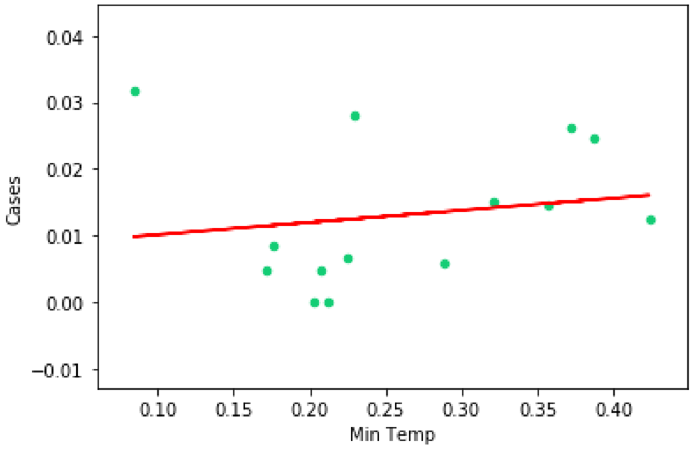



```
R-squared: 0.533
α constant (intercept): 0.592
β coefficient (slope): -0.849
```

Figure 5.23: Relationship between Case Numbers from OWID and Transit Station Visits data from Google around School Closures in Ireland (n=14) w/ a 14 day lag in COVID-19 case data

As the closure of schools on the 12th March 2020 was the first governmental intervention introduced, an OLS regression model was adopted to determine the relationship between the 2 weeks of Google mobility data prior to the announcement and the resultant cases

2 weeks after the intervention was announced. Figure 5.22 highlights as Grocery & Pharmacy store visits increased 2 weeks prior to the school closures, COVID-19 cases increased the 2 weeks after the announcement. This was evident for five out of six of the Google mobility category data graphs apart from Transit Stations, which can be seen in Figure 5.23. The negative slope tentatively implies that as people reduce their use of public transport 2 weeks prior to the lockdown, there is a rise in reported COVID-19 cases. Much higher R^2 values were acquired, which reinforces the close association between COVID-19 case values and the Google mobility categories.

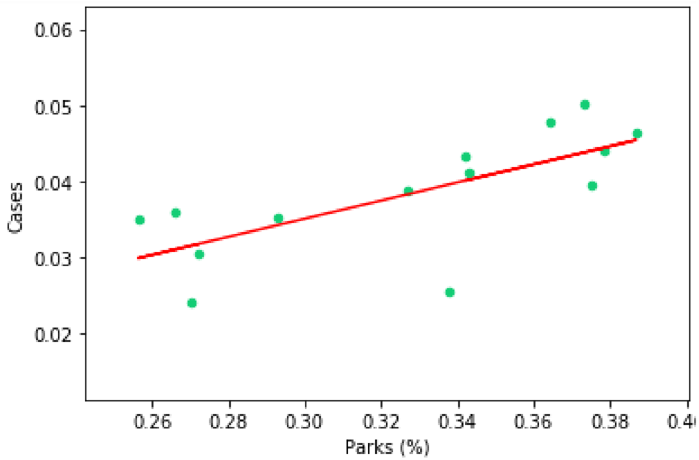


R-squared: 0.028
α constant (intercept): 0.008
β coefficient (slope): 0.018

Figure 5.24: Relationship between Case Numbers from OWID and Min. Temperature from Met Éireann around School Closures in Ireland (n=14) w/ a 14 day lag in COVID-19 case data

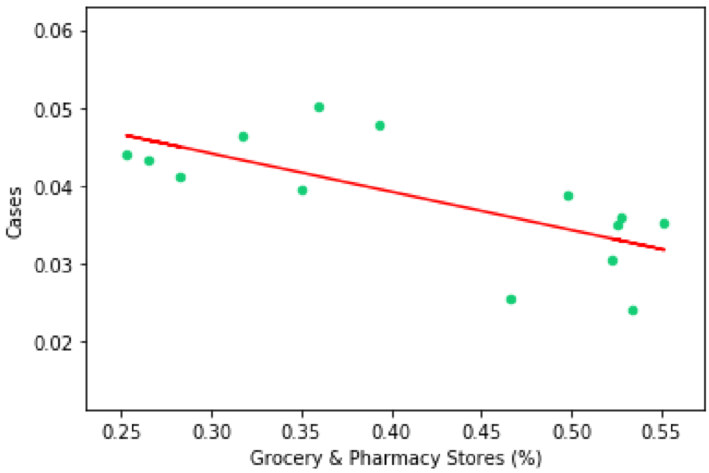
The meteorological categories had a relatively weak correlation in the matrix, which is reinforced by a low R^2 value for the graphs, such as Figure 5.24, depicting the relationship between COVID-19 cases and minimum temperature. This suggests that the temperature didn't have an influential impact into the rise or fall of COVID-19 cases and that the mitigating actions of the government had a much greater impact on curbing the spread of COVID-19. The remaining School Closure graphs can be seen in Appendix E for individual examination.

Lockdown 1



R-squared: 0.497
α constant (intercept): -0.001
β coefficient (slope): 0.119

Figure 5.25: Relationship between Case Numbers from OWID and Park Visits data from Google during Lockdown 1 in Ireland (n=14) w/ a 14 day lag in COVID-19 case data

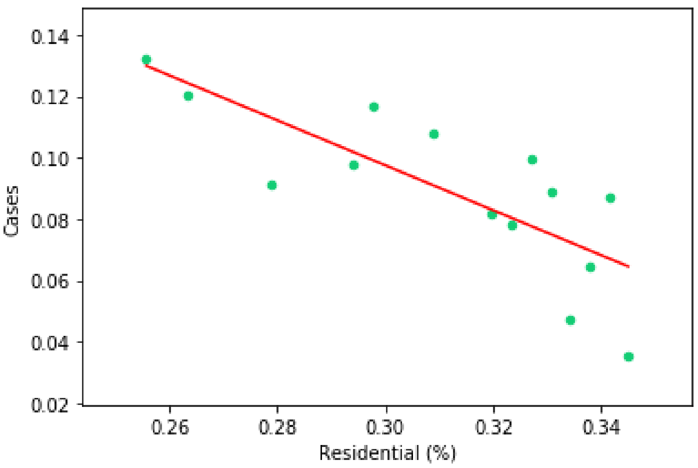


R-squared: 0.477
α constant (intercept): 0.059
β coefficient (slope): -0.049

Figure 5.26: Relationship between Case Numbers from OWID and Grocery & Pharmacy Stores Visits data from Google during Lockdown 1 in Ireland (n=14) w/ a 14 day lag in COVID-19 case data

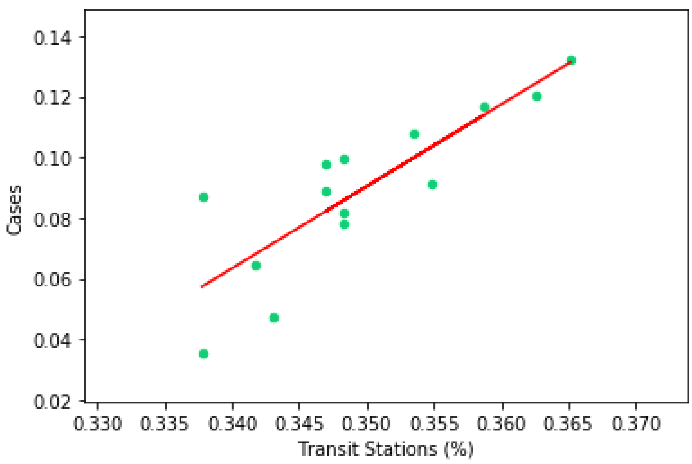
As mentioned previously in the correlation matrix section, the Lockdown 1 data acquired is the complete antithesis of the School Closures graphs. Figure 5.25 is the only graph which maintains its shape, because, as previously mentioned, due to the closure of schools, workplaces and many tertiary industry facilities, parks and greenspaces were open for all. Grocery & Pharmacy store visits decreased 2 weeks prior to Lockdown 1, as observed in Figure 5.26, while COVID-19 cases increased the 2 weeks after the announcement, as many people remained indoors and restricted their movements. Similar to the School Closure graphs, moderate to high R^2 values were obtained, which highlights the close association between the Lockdown 1 subset mobility categories at localised points. No association between the rise in COVID-19 cases and meteorological data was evident as mentioned previously and all the Lockdown 1 OLS single linear regression model graphs can be found in Appendix F for further analysis.

Lockdown 2




```
R-squared: 0.616
α constant (intercept): 0.317
β coefficient (slope): -0.733
```

Figure 5.27: Relationship between Case Numbers from OWID and Residential Visits data from Google during Lockdown 2 in Ireland (n=14) w/ a 14 day lag in COVID-19 case data

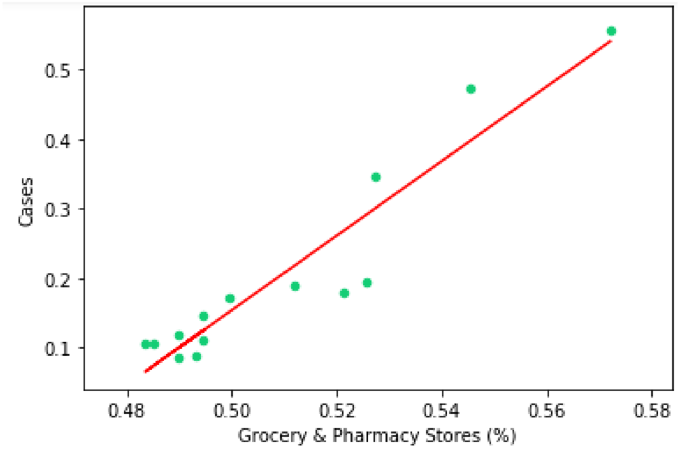



```
R-squared: 0.712
α constant (intercept): -0.856
β coefficient (slope): 2.705
```

Figure 5.28: Relationship between Case Numbers from OWID and Transit Station Visits data from Google during Lockdown 2 in Ireland (n=14) w/ a 14 day lag in COVID-19 case data

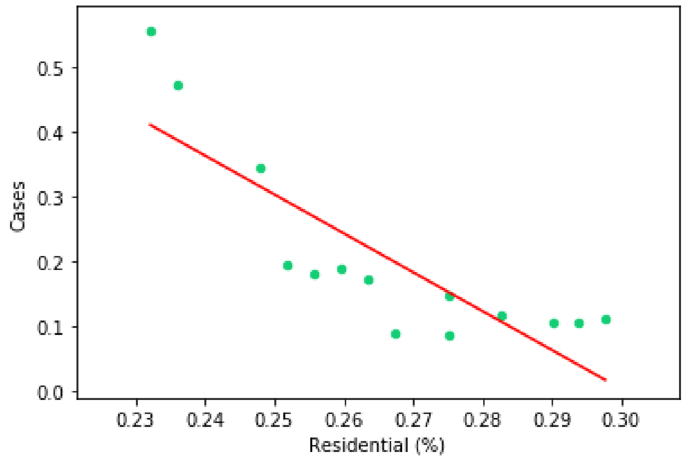
Many of the Lockdown 2 graphs revert back to a similar shape to the School Closure graphs (Figure 5.22 and 5.23), but Figure 5.28, the Transit Stations graph exhibits a strong positive association between visits to transit stations and a rise in COVID-19 cases reported. Figure 5.27 represents the impact of the "stay-at-home" order or "Level 5" restrictions imposed on the population, as when people opted to stay at home, COVID-19 case rates began to decline. This decline is also evident in the Grocery & Pharmacy Stores graph. Moderate coefficients of determination were apparent amongst the OLS single linear regression models for the Google mobility categories and COVID-19 cases, enabling a strong association between them. As mentioned for the Lockdown 1 graphs, no apparent association can be found between the rise in COVID-19 cases and meteorological data. Similar to the other dataset regression results, all the Lockdown 2 OLS single linear regression model graphs can be found in Appendix G.

Lockdown 3




```
R-squared: 0.890
α constant (intercept): -2.524
β coefficient (slope): 5.355
```

Figure 5.29: Relationship between Case Numbers from OWID and Grocery & Pharmacy Store Visits data from Google during Lockdown 3 in Ireland (n=14) w/ a 14 day lag in COVID-19 case data

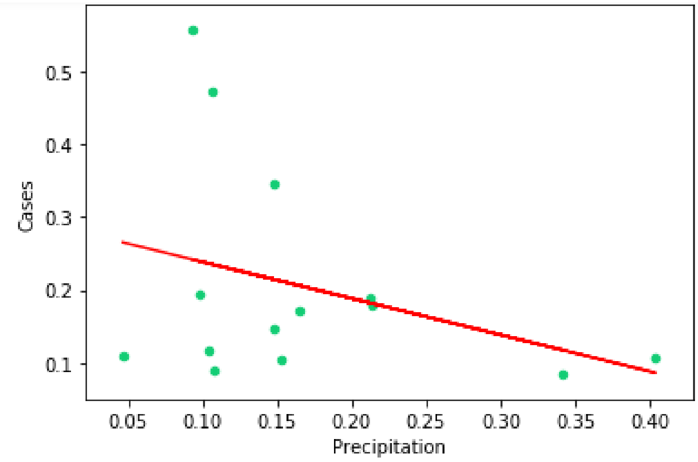



```
R-squared: 0.702
α constant (intercept): 1.802
β coefficient (slope): -5.998
```

Figure 5.30: Relationship between Case Numbers from OWID and Residential Visits data from Google during Lockdown 3 in Ireland (n=14) w/ a 14 day lag in COVID-19 case data

Lockdown 3 graphs, which can all be found in Appendix H, reveal the strongest association between the mobility and meteorological data and the COVID-19 cases. Five out of six of the Google mobility category data graphs (Retail & Recreation, Grocery & Pharmacy Stores, Parks, Transit Stations and Workplaces) all follow the same shape, which was evident in the Ireland dataset graphs and can be seen in Figure 5.29. This suggests that as more people go out and visit grocery & pharmacy stores, COVID-19 cases will rise 2 weeks later. The opposite can be seen in Figure 5.30, which highlights that as more people stay at home, the COVID-19 case rates will drop.

The highest R^2 value for meteorological data obtained occurred in Lockdown 3 when a coefficient of determination value of 0.113 between the COVID-19 cases and Precipitation was




```
R-squared: 0.113
α constant (intercept): 0.288
β coefficient (slope): -0.500
```

Figure 5.31: Relationship between Case Numbers from OWID and Precipitation from Met Éireann during Lockdown 3 in Ireland (n=14) w/ a 14 day lag in COVID-19 case data

obtained (Figure 5.31). This highlights that the weather evident throughout 2020 had a minimal impact on daily human mobility.

The R^2 values obtained for the various datasets (Ireland, School Closures, Lockdown 1, Lockdown 2 and Lockdown 3) can be synopsised into Table 21.

Table 5.21 highlights the variety of associations between the dataset categories analysed throughout and the colour of the boxes indicates the strength of the association between the categories and COVID-19 cases. They range from dark red, meaning no association, to dark green signifying a strong relationship between the 2 factors for a certain time period. The meteorological data had an insignificant impact on the COVID-19 case values throughout, whereas the mobility categories, especially during the 3rd lockdown, were quite strongly associated with the COVID-19 cases following the 2 weeks after the announcement of a significant measure.

Table 5.21: Association between Cases and Google & Apple-derived mobility data, COVID-19 case & death count from OWID and meteorological data for the entire Ireland dataset from Met Éireann and subsets(School Closures, Lockdown 1, Lockdown 2 and Lockdown 3)

Synopsis of the association(R^2 value) between dataset categories and reported COVID-19 Cases for Ireland, the Lockdowns and School Closures														
Dataset	Retail	Grocery	Parks	TransitG	Workplaces	Residential	Deaths	Driving	TransitA	Walking	Max. Temp	Min. Temp.	Precipitation	Cases
Ireland	0.05	0.10	0.03	0.19	0.09	0.09	0.06	0.14	0.08	0.11	-	-	-	
School Closures	0.22	0.62	0.20	0.53	0.01	0.06	0.58	-	-	-	0.23	0.03	0.00	
Lockdown1	0.44	0.48	0.50	0.44	0.48	0.45	0.24	-	-	-	0.05	0.15	0.02	
Lockdown2	0.30	0.20	0.06	0.71	0.63	0.62	0.13	-	-	-	0.01	0.01	0.00	
Lockdown3	0.83	0.89	0.54	0.81	0.42	0.70	0.01	-	-	-	0.05	0.01	0.11	

The related p-values for the Ireland dataset and the Ireland with a 14 day lag in COVID-19 cases dataset were obtained and can be seen in Table 5.22. Since the P-values are less than 0.05, there is strong evidence of linear association between most of the variables for the 2 datasets. Further breakdown of the data into subsets was conducted to strengthen the associations.

Table 5.22: P-values for the OLS single linear regression between the Google & Apple-derived mobility category data and COVID-19 case & death values from OWID.

P-Values for the OLS Single Linear Regression of the Ireland and Ireland w/a 14 day lag in COVID-19 case value datasets											
Dataset	Retail	Grocery	Parks	TransitG	Workplaces	Residential	Deaths	Driving	TransitA	Walking	Cases
Ireland	0.000	0.000	0.001	0.000	0.000	0.306	0.000	0.000	0.000	0.000	
Ireland (w/ lag)	0.000	0.000	0.000	0.000	0.000	0.497	0.000	0.000	0.000	0.000	

5.1.7.2 *Multiple Linear Regression*

An OLS multiple linear regression model was used in this section to determine the relationship between case data and two characteristics of the data that are not closely correlated. From the correlation matrices, a clear strong relationship between the various mobility categories is apparent, but the minimum temperature, maximum temperature and the precipitation have a weak or non-existent correlation with the mobility categories. This section explores the association between the weather categories and the mobility categories along with case numbers to determine more intricate relationships between the data in tabular form.

Table 5.23: Relationship between Meteorological Data from Met Éireann, COVID-19 Cases from OWID and Google Mobility Categories for the Ireland (n=333) Dataset between 17/02/2020 and 15/01/2021

Synopsis of the association[R^2 value(β_1,β_2)] between Mobility data, COVID-19 Cases and Meteorological Data for Ireland							
	Retail	Grocery	Parks	Transit	Workplaces	Residential	Cases
Max. Temp.	0.15(-0.14,-0.23)***	0.19(-0.26, -0.22)***	0.09(-0.04, -0.2)***	0.26(-0.26, -0.2)***	0.21(-0.21, -0.25)***	0.19(0.18, -0.23)***	
Min. Temp.	0.1(-0.11 -0.16)***	0.14(-0.23, -0.15)***	0.07(-0.06, -0.15)***	0.21(-0.25, -0.12)***	0.14(-0.18, -0.17)***	0.14(0.16, -0.16)***	
Precipitation	0.07 (-0.15, 0.12)	0.12(-0.28, 0.13)	0.04(-0.13, 0.09)	0.2(-0.278, 0.12)	0.11(-0.2, 0.13)	0.11(0.18, 0.12)	
*P-value < 0.05; **P-value < 0.01; ***P-value < 0.001							

When analysing the relationship between COVID-19 cases, the Google-derived mobility data and the weather data, Table 5.23 highlights that there is an extremely weak or non-existent relationship between these factors over the entire dataset ranging from 17/02/2020 to 15/01/2021. This is anticipated as the temporal variability in these characteristics, throughout the 333 days included in the Ireland dataset, reduces the predictability overall. This creates a need to look at the milestone dates in Ireland's COVID-19 timeline to deduce if they have a stronger localised association.

An OLS multiple linear regression model was also obtained for the Ireland dataset which includes the 14 day lag period.

Table 5.24: Relationship between Meteorological Data from Met Éireann, COVID-19 Cases from OWID and Google Mobility Categories for the Ireland (n=333) Dataset between 17/02/2020 and 15/01/2021 with a 14 day lag for the COVID-19 case and death data

Synopsis of the association[R^2 value(β_1,β_2)] between Mobility data, COVID-19 Cases and Meteorological Data for Ireland 14 day lag							
	Retail	Grocery	Parks	Transit	Workplaces	Residential	Cases
Max. Temp.	0.31(-0.41, -0.31)***	0.19(-0.44, -0.28)***	0.11(-0.26, -0.15)***	0.41(-0.55, -0.24)***	0.22(-0.36, -0.33)***	0.28(0.4, -0.3)***	
Min. Temp.	0.27(-0.38, -0.23)***	0.17(-0.39, -0.24)***	0.12(-0.25, -0.18)***	0.39(-0.53, -0.17)***	0.19(-0.32, -0.27)***	0.25(0.37, -0.25)***	
Precipitation	0.26(-0.43, 0.26)	0.14(-0.46, 0.21)	0.11(-0.33, 0.16)	0.39(-0.57, 0.21)	0.16(-0.35, 0.21)	0.23(0.41, 0.22)	
*P-value < 0.05; **P-value < 0.01; ***P-value < 0.001							

The values in Table 5.24 are comparatively higher than the ones in Table 5.23, where the lag is not accounted for in the Irish data. This suggests the alignment of the case lag has led to the creation of a stronger relationship between COVID-19 case data, meteorological data and Google-derived mobility data. The P-values were obtained for the Ireland dataset and the Ireland with a 14 day lag dataset. Similarly, β values for a 95% confidence interval were ascertained when controlled for the weather variable. Positive β values suggest that there is a positive association between characteristics. The majority of the P-values were below 0.05, implying that the results are statistically significant. This additional information was not obtained for the subsets, as n = 14, but the R^2 values were important to acquire in order to analyse the localised relationship between the categories.

Table 5.25: Relationship between Meteorological Data from Met Éireann, COVID-19 Cases from OWID and Google Mobility Categories for the School Closure (n=14) Dataset w/ a 14 day lag in COVID-19 case data (Mobility & Meteorological Data: 27/02/2020 – 12/03/2020 and COVID-19 Data: 12/03/2020 – 26/03/2020)

Synopsis of the association(R^2 value) between Mobility data, COVID-19 Cases and Meteorological Data for School Closures							
	Retail	Grocery	Parks	Transit	Workplaces	Residential	Cases
Max. Temp.	0.31	0.62	0.28	0.57	0.23	0.34	
Min. Temp.	0.23	0.69	0.23	0.54	0.03	0.12	
Precipitation	0.22	0.62	0.2	0.55	0.01	0.06	

Table 5.25 focuses on the 2 weeks of mobility and weather data prior to the initial closure of schools and the 2 weeks of case date following the closure. Examining the OLS multiple linear regression model for this time period enables the accruement of moderate R^2 values. This is evident in the case of Minimum Temperature, Grocery & Pharmacy Stores and COVID-19 cases, which have a moderate coefficient of determination at 0.69.

Table 5.26: Relationship between Meteorological Data from Met Éireann, COVID-19 Cases from OWID and Google Mobility Categories for the Lockdown 1 (n=14) Dataset w/ a 14 day lag in COVID-19 case data (Mobility & Meteorological Data: 13/03/2020 – 27/03/2020 and COVID-19 Data: 27/03/2020 – 10/04/2020)

Synopsis of the association(R^2 value) between Mobility data, COVID-19 Cases and Meteorological Data for Lockdown 1							
	Retail	Grocery	Parks	Transit	Workplaces	Residential	
Max. Temp.	0.48	0.51	0.6	0.48	0.53	0.51	Cases
Min. Temp.	0.45	0.48	0.55	0.45	0.49	0.47	
Precipitation	0.47	0.5	0.5	0.47	0.49	0.46	

The spread of R^2 values obtained in Table 5.26 is quite narrow, ranging between 0.45 to 0.6. The consistency overall suggests that the weather had an influence on people's movement during the first lockdown, which was not blatant from the OLS single linear regression models or the correlation matrix.

Table 5.27: Relationship between Meteorological Data from Met Éireann, COVID-19 Cases from OWID and Google Mobility Categories for the Lockdown 2 (n=14) Dataset w/ a 14 day lag in COVID-19 case data (Mobility & Meteorological Data: 07/10/2020 – 21/10/2020 and COVID-19 Data: 21/10/2020 – 04/11/2020)

Synopsis of the association(R^2 value) between Mobility data, COVID-19 Cases and Meteorological Data for Lockdown 2							
	Retail	Grocery	Parks	Transit	Workplaces	Residential	
Max. Temp.	0.31	0.21	0.06	0.71	0.64	0.62	Cases
Min. Temp.	0.39	0.23	0.12	0.71	0.63	0.64	
Precipitation	0.31	0.2	0.07	0.76	0.67	0.63	

Quite a weak association between park visits, COVID-19 cases and meteorological data is noticeable in Table 5.27, which contrasts the strong correlation between transit station visits, cases and weather data. As the pandemic progresses there appears to be a slow convergence towards a strong association or R^2 value, which highlights how the different categories are increasing in their influence in one another.

Table 5.28: Relationship between Meteorological Data from Met Éireann, COVID-19 Cases from OWID and Google Mobility Categories for the Lockdown 3 (n=14) Dataset w/ a 14 day lag in COVID-19 case data (Mobility & Meteorological Data: 08/12/2020 – 22/12/2020 and COVID-19 Data: 22/12/2020 – 05/01/2021)

Synopsis of the association(R^2 value) between Mobility data, COVID-19 Cases and Meteorological Data for Lockdown 3							
	Retail	Grocery	Parks	Transit	Workplaces	Residential	
Max. Temp.	0.9	0.92	0.58	0.84	0.42	0.75	Cases
Min. Temp.	0.91	0.89	0.57	0.87	0.43	0.81	
Precipitation	0.83	0.89	0.55	0.81	0.45	0.71	

Table 5.28, which represents the 3rd lockdown, exhibits the strongest associations between meteorological data, COVID-19 cases and the Google mobility categories. This is anticipated, as during the Winter, most people will stay indoors as it is quite cold, whereas in the Summer, people remain indoors for work etc., but also are more inclined to visit parks and greenspaces.

5.1.8 *Ireland Results Conclusion*

Overall, the association between many factors increase when analysed in a smaller timeframe. The initial correlation can be observed in a correlation matrix, but the use for OLS single linear regression models, enabled the visualisation of this data and how the various factors are related. The outcomes will be discussed at length in the Discussion session to account for any facts that can be deduced from the results acquired. The in-depth investigation will also be carried out for the following countries: Brazil, New Zealand, Sweden, South Korea and Germany.

5.2. International Analyses

In order to examine the association between COVID-19 and mobility patterns, the investigation had to be broadened internationally to determine if a similar impact to mobility in Ireland was seen in other continents. Many countries were analysed as part of a first wave analysis, which can be graphically seen in Appendix A. The difference in policy or mitigating actions implemented, along with case rates dictated which countries were selected for a further analysis.

Countries, such as Sweden and South Korea opted not to implement a countrywide lockdown, instead relying on the obedience of their population to adhere to the social distancing policies created. The complete antithesis occurred in New Zealand, which utilised stringent lockdown procedures to quickly curb the spread of COVID-19. This section consists of a brief analysis and overview of Brazil, New Zealand, Sweden South Korea and Germany, with some accompanying graphs to help illustrate the relationship between COVID-19 cases and mobility patterns.

5.2.1 *Analysis of Brazil*

Brazil was selected as a country of interest with regards to the spread of the disease and the president, Jair Bolsonaro's response amid rising case numbers. Brazil garnered a lot of media attention due to Bolsonaro's infamous opposition to the implementation of a lockdown or restrictions to stop COVID-19 spreading amongst the population (Phillips, 2020). Therefore, no official lockdown occurred in the South American country, with only some individual states and cities imparting preventative restrictions on the public.

Unlike Ireland, Brazil has not been subjected to 3 different waves, but rather 2 larger waves, which have lasted much longer. Initially the lockdown introduced in São Paulo had a significant impact on the mobility patterns in Brazil as many states and cities followed suit by implementing restrictive measures (Gov.br, 2021). Even though Bolsonaro tested positive for COVID-19 on the 7th of July, it still didn't influence his decision to impose a potential lockdown.

Yet as cases have increased over time, the mobility category graphs, as seen in Figure 5.32, have continued to converge towards the baseline. This can be seen in the Residential graph, as it slowly moves towards the baseline, but only ever reaches about 10% above the baseline, which represents the average values for each mobility category for a 5 week period between the 3rd of January and 6th of February 2020. Also as many lockdown restrictions were removed in order to save the economy, many people were encouraged to return to work. Therefore, it is also worth noting that the Workplace graph similarly approaches the baseline, but eventually crosses it in December, suggesting that more people went to work during the Christmas season than the five week baseline period at the beginning of 2020, when more people might have gone on holiday, as the five weeks coincided with the Summer months.

The sharp rise in cases and the fact that Manaus, in North West Brazil, was declared a COVID-19 hotspot, highlights the high infectious nature of the P.1 COVID-19 variant found there. The overall shape of the graphs suggest that the fluctuating COVID-19 case values had very little impact on the mobility of the population. This also highlights the impact of the informal economy in developing countries, as many people do not have the option to "work from home", compared to their counterparts in first world countries.

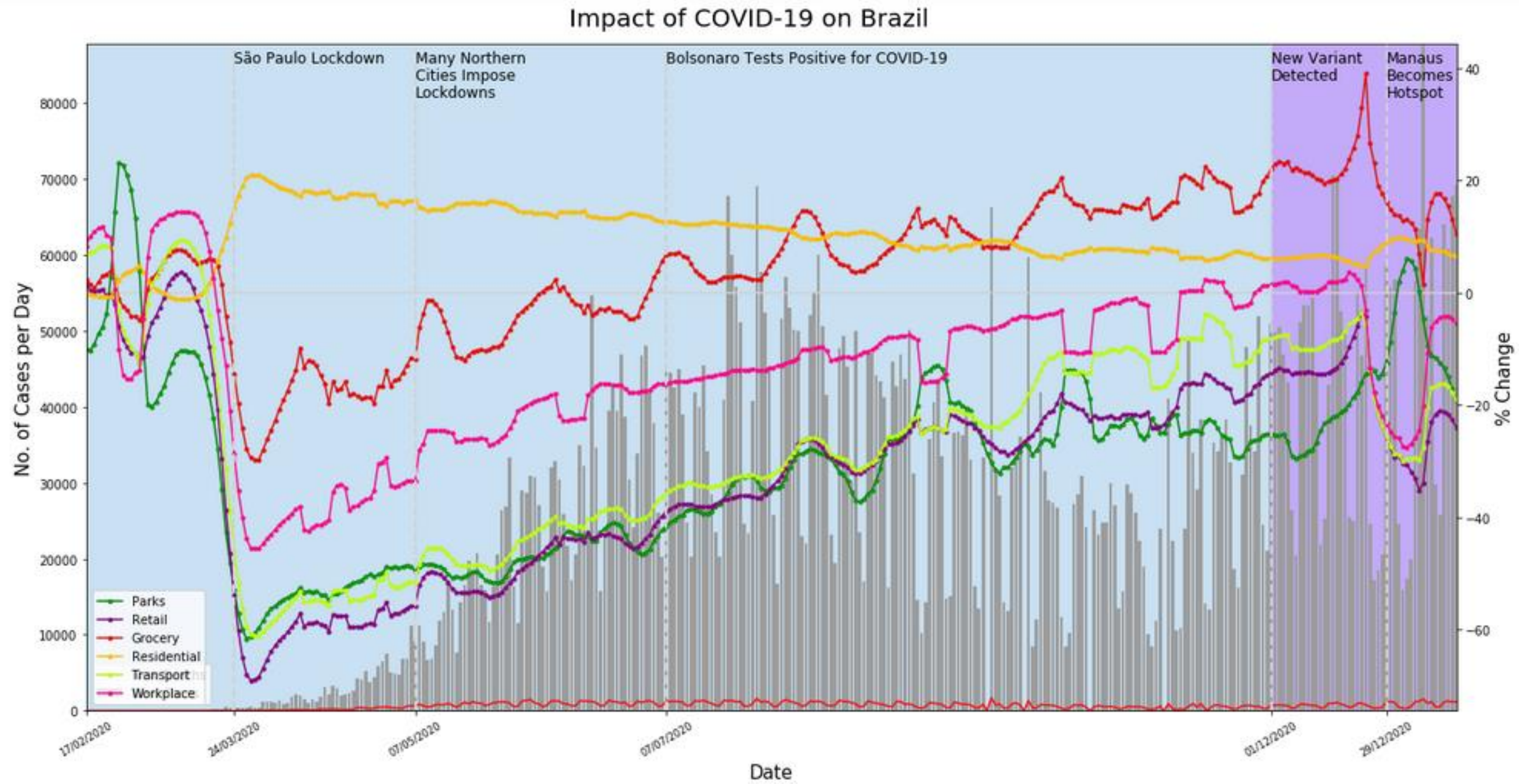


Figure 5.32: Graph of the temporal variability of the daily Google-derived mobility categories and the daily COVID-19 cases & death rates from OWID for Brazil (n=333) in relation to government announcements, notable milestones from 17/02/2020 to 15/01/2021. The data used is the raw unprocessed Brazil data. The Google-derived mobility categories are Retail & Recreation, Grocery & Pharmacy Stores, Parks, Transit Stations, Workplaces and Residential, and they are represented as the % change in relation to a 5 week baseline ranging from 03/01/2020 to 06/02/2020. The 2 waves of COVID-19 in Brazil are identifiable by the colour blocks, which end at the completion of a lockdown period. Wave 1 ranges between 17/02/2020 and 01/12/2020 and wave 2 ranges between 01/12/2020 and 15/01/2021 in this figure.

5.2.2 *Analysis of New Zealand*

Unlike Brazil, New Zealand's approach to the pandemic earned Jacinda Ardern, the Prime Minister of New Zealand, a lot of praise and therefore, New Zealand was selected as a country of interest with regards to the impact of COVID-19 on the nation. New Zealand adopted harsh lockdowns and restrictions in order to quash the spread of COVID-19 (Ministry of Health NZ, 2021). A four tier "Alert Level" system was adopted, with Alert Level 1 consisting of the elimination of physical distancing and any lockdown restrictions and Alert Level 4 consisting of a harsh lockdown with closed borders. Due to the swift actions of the government, community transmission has remained low and scenes of an alternative reality that resemble pre-COVID-19 times are abundant (Ng, 2021).

Lockdown occurred at the end of March and similar to many countries, people remained at home, which is highlighted in the decline of workplace visits and the rise in the Residential graph, which was observed in Figure 5.33. The change of the mobility category graphs is not as drastic as other countries, due to the short lived extreme lockdown when COVID-19 first

University College Cork, Ireland
Coláiste na hOllscoile Corcaigh

appeared in New Zealand. Even though the alert level within the country and cities, such as Auckland, alternates, most graphs converge to the baseline, as some sense of normalcy returns to daily life.

One of the noticeable differences when compared to countries in the Northern Hemisphere, is that the Parks graph remains much lower than the baseline throughout the majority of the year. This could potentially be a result of the fact that the five week baseline is during the Summer, and the first waves of the pandemic occurred during the Winter in New Zealand. Evidently, there are no large deviances in the mobility category visits as a result of COVID-19 cases being relatively low, which has resulted in public holidays, such as Christmas, having a significant impact on the number of people at work or in parks.

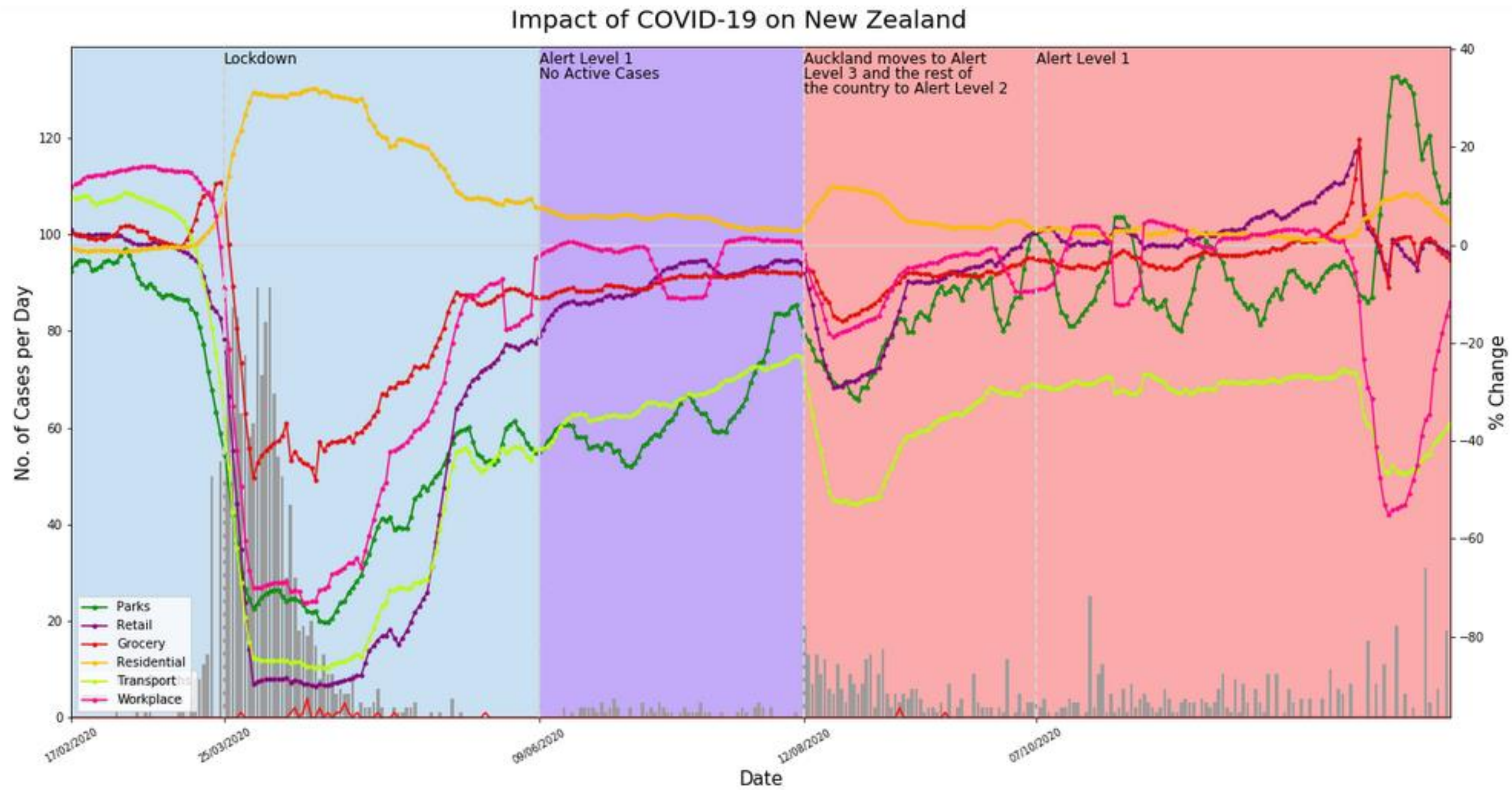


Figure 5.33: Graph of the temporal variability of the daily Google-derived mobility categories and the daily COVID-19 cases & death rates from OWID for New Zealand (n=333) in relation to government announcements, notable milestones from 17/02/2020 to 15/01/2021. The data used is the raw unprocessed New Zealand data. The Google-derived mobility categories are Retail & Recreation, Grocery & Pharmacy Stores, Parks, Transit Stations, Workplaces and Residential, and they are represented as the % change in relation to a 5 week baseline ranging from 03/01/2020 to 06/02/2020. The 3 waves of COVID-19 in New Zealand are identifiable by the colour blocks, which end at the completion of a lockdown period. Wave 1 ranges between 17/02/2020 and 08/06/2020, wave 2 ranges between 08/06/2020 and 12/08/2020 and wave 3 ranges between 12/08/2020 and 15/01/2021 in this figure.

5.2.3 *Analysis of Sweden*

Sweden adopted a more lenient approach to preventing the spread of COVID-19, implementing social distancing policies rather than a lockdown. Sweden's alternative approach has been well-documented, as it varied significantly to the methods utilised in other European countries along with its Scandinavian counterparts.

Measures such as social distancing, working from home and avoiding unnecessary travel where possible were initially encouraged (Public Health Agency of Sweden, 2021), but due to a stark rise in COVID-19 cases, stricter restriction has to be introduced on the 18th of December. This roughly coincided with the release of a report from an independent commission that highlighted how Sweden's governmental actions had led to a large rise in COVID-19 deaths among people in nursing homes, supporting the motion of introducing a lockdown (Coronakommissionen, 2020).

Due to a lack of stringent COVID-19 mitigating actions, the mobility category graphs were not influenced by many announcements during the first 11 months of the pandemic, which can be seen in Figure 5.34 below. At first glance, it quickly becomes apparent that the Park visits graph increases during the Summer at a much more significant rate than any other graph, which could be a result of the lack of restrictions imposed on gatherings and movement on the population. The Retail, Residential and Grocery graphs all hover around the baseline as many non-essential stores remained open during the pandemic in Sweden. The biggest impact of government imposed restrictions can be seen on the 18th of December 2020, when limitations increased. These measures were introduced due to the rising number of COVID-19 cases and led to the largest drop in many of the mobility category graphs, such as Workplaces, which almost reached 60% below the baseline.

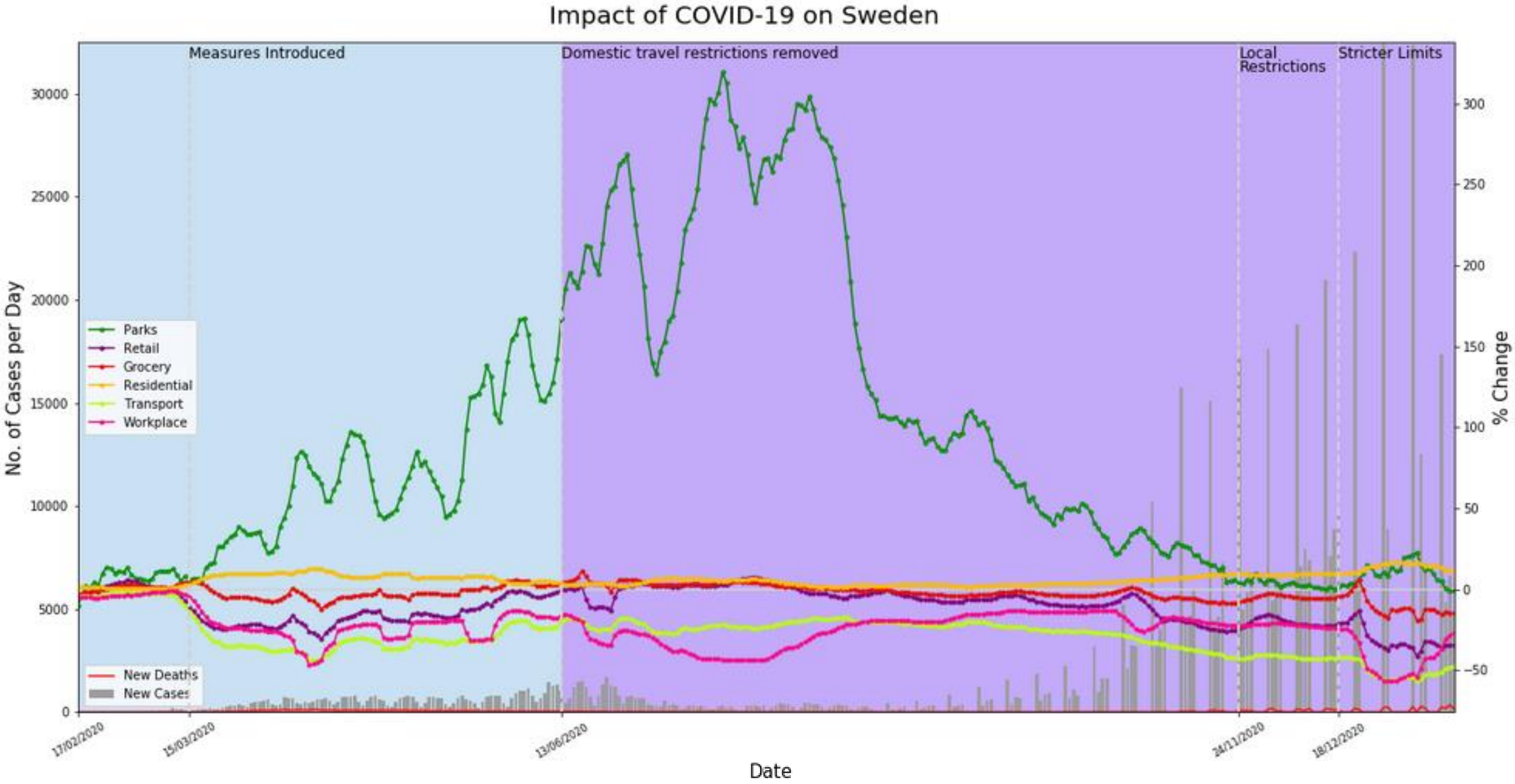


Figure 5.34: Graph of the temporal variability of the daily Google-derived mobility categories and the daily COVID-19 cases & death rates from OWID for Sweden (n=333) in relation to government announcements, notable milestones from 17/02/2020 to 15/01/2021. The data used is the raw unprocessed Sweden data. The Google-derived mobility categories are Retail & Recreation, Grocery & Pharmacy Stores, Parks, Transit Stations, Workplaces and Residential, and they are represented as the % change in relation to a 5 week baseline ranging from 03/01/2020 to 06/02/2020. The 2 waves of COVID-19 in Sweden are identifiable by the colour blocks, which end at the completion of a lockdown period. Wave 1 ranges between 17/02/2020 and 13/06/2020 and wave 2 ranges between 13/06/2020 and 15/01/2021 in this figure.

5.2.4 *Analysis of South Korea*

Similar to Sweden, South Korea took a more liberal approach when applying restrictive measure during the pandemic and put trust in its own population to maintain social distancing measures. Instead of applying a lockdown nationally or in any of its cities, South Korea promoted an "Enhanced Social Distancing" campaign (Cha & Kim, 2020), where everyone would wear masks and an extensive and efficient trace, test and treat system was set up to quickly prevent the spread of COVID-19 (Bicker, 2020). The unique approach utilised by South Korea merited a further investigation into the relationship between COVID-19 cases and mobility patterns in the country.

The Google mobility category graphs seen in Figure 5.35 follow different shapes to Figure 5.33 for New Zealand and 5.32 for Brazil, as they initially took a dip when many cities were declared "Special Disaster Zones". They quickly rose to baseline levels, where they hovered about throughout latter half of the first wave and early part of the second wave, insinuating that life was quite normal and no drastic measures had influenced the movement of the population. The only exception was the Parks graph, but this could be due to the increase in temperature and improved weather compared to the baseline Winter conditions. Even though numbers remain low, a third wave triggered stricter limits initially in Seoul on the 22nd of November 2020 and then countrywide on the 18th of December 2020, where social distancing measures were introduced to encourage the public to stay 1.5m away from one another. These measures led to a significant drop in the Retail & Recreational, Transport, Parks and Workplace visit graphs, as people followed guidelines and opted to stay home, rather than go outside and break the guideline. This is reflected in the rise of the Residential graph from the 22nd of November 2020 onwards.

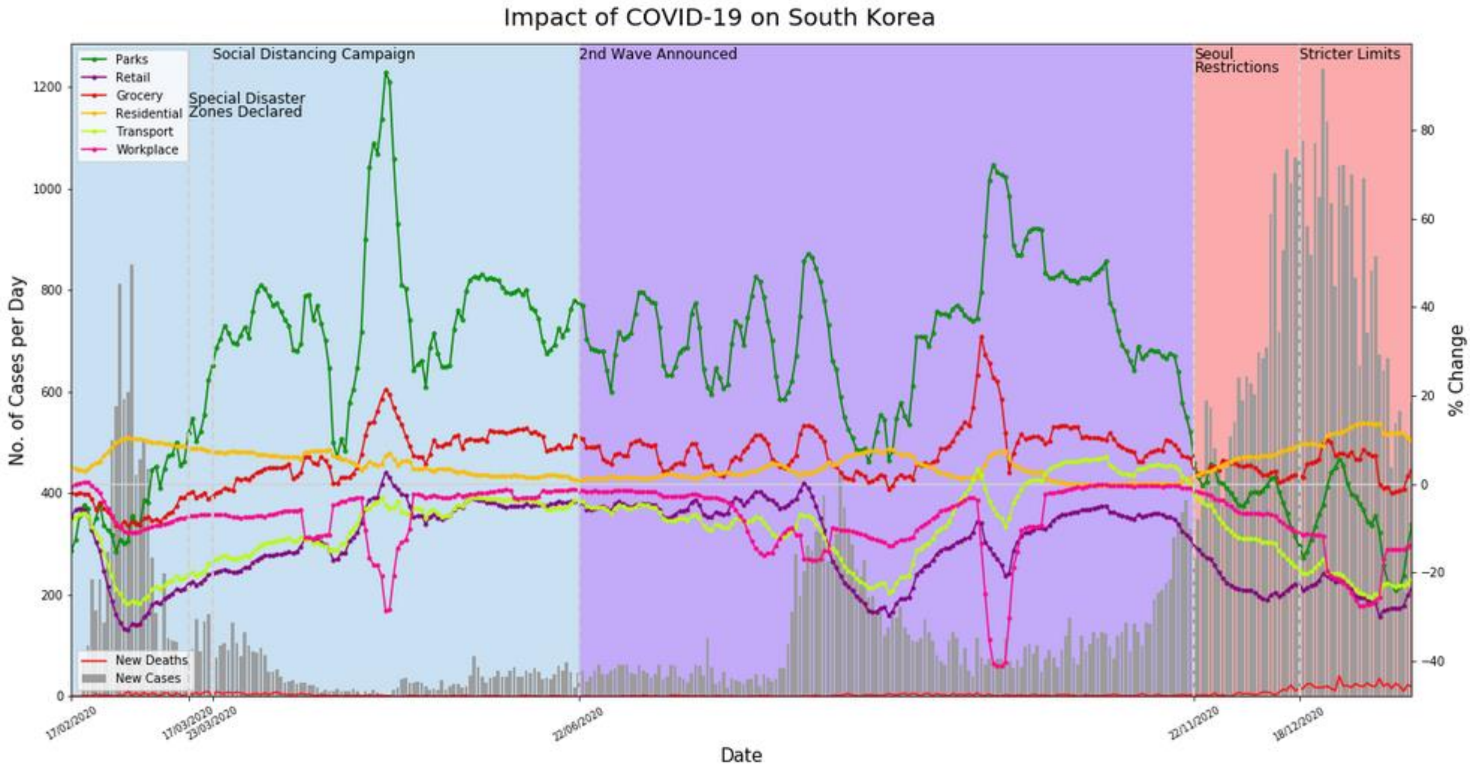


Figure 5.35: Graph of the temporal variability of the daily Google-derived mobility categories and the daily COVID-19 cases & death rates from OWID for South Korea (n=333) in relation to government announcements, notable milestones from 17/02/2020 to 15/01/2021. The data used is the raw unprocessed South Korea data. The Google-derived mobility categories are Retail & Recreation, Grocery & Pharmacy Stores, Parks, Transit Stations, Workplaces and Residential, and they are represented as the % change in relation to a 5 week baseline ranging from 03/01/2020 to 06/02/2020. The 3 waves of COVID-19 in South Korea are identifiable by the colour blocks, which end at the completion of a lockdown period. Wave 1 ranges between 17/02/2020 and 22/06/2020, wave 2 ranges between 22/06/2020 and 22/11/2020 and wave 3 ranges between 22/11/2020 and 15/01/2021 in this figure.

5.2.5 *Analysis of Germany*

Germany is the last country that will be analysed to determine the relationship between its mobility patterns and COVID-19. Germany was selected for this investigation as it was praised for its ability to keep transmission levels low. This was partially due to an existing National Pandemic Plan, which was altered, allowing for immediate and drastic action to stop the spread of COVID-19 (Robert Koch Institut, 2020). As a country with many manufacturing and industrial links, Germany also became well known as one of the areas where COVID-19 spikes would occur in industrial plants, such as the one at a meat plant in Coesfeld in North Rhine-Westphalia, where 260 cases were confirmed (Lütticke, 2020).

The rise and fall of COVID-19 cases can be seen in Figure 5.36, in tandem with the volatility in the Google mobility graphs. Dramatic changes in the mobility category graphs occurred with the initial rise in COVID-19 cases. They slowly began to move towards the baseline until a third wave hit Germany and a 30 day "Wave Break" was introduced. This was essentially a 30 day lockdown to prevent the further spread of COVID-19. A further dip in all the graphs, apart from the Residential one is seen on the 16th of December 2020, as a stricter lockdown is introduced to mitigate the spread of the disease. Throughout the early stages of the pandemic, the Parks graph is subjected to many localised peaks and troughs, potentially due to public holidays and the baseline consisting of 5 weeks during the Winter. Overall Germany has gone through 3 waves of COVID-19 like many other European countries, but due to its decisive actions throughout, the majority of its mobility patterns returned to normal baseline levels or exceeded them.

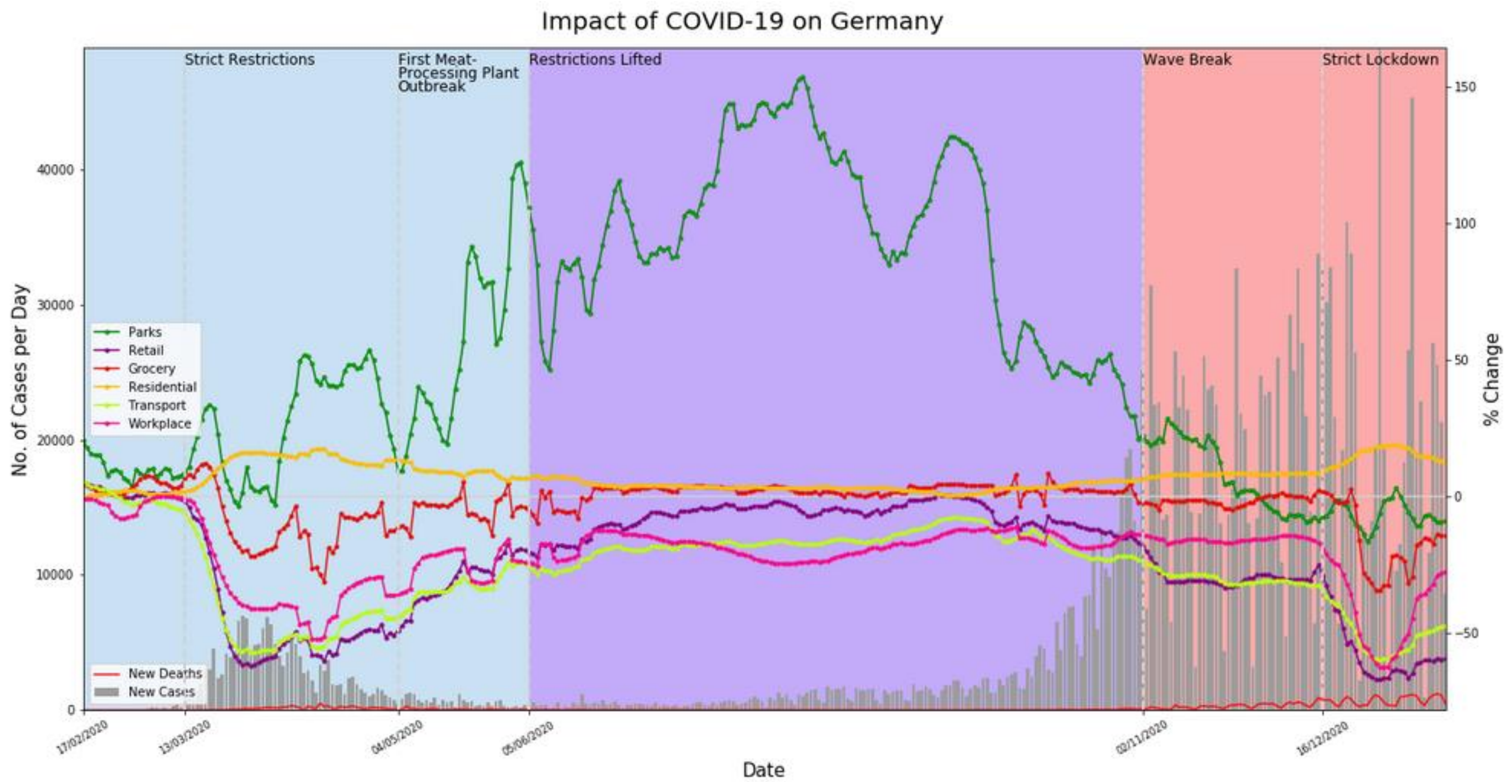


Figure 5.36: Graph of the temporal variability of the daily Google-derived mobility categories and the daily COVID-19 cases & death rates from OWID for Germany (n=333) in relation to government announcements, notable milestones from 17/02/2020 to 15/01/2021. The data used is the raw unprocessed Germany data. The Google-derived mobility categories are Retail & Recreation, Grocery & Pharmacy Stores, Parks, Transit Stations, Workplaces and Residential, and they are represented as the % change in relation to a 5 week baseline ranging from 03/01/2020 to 06/02/2020. The 3 waves of COVID-19 in Germany are identifiable by the colour blocks, which end at the completion of a lockdown period. Wave 1 ranges between 17/02/2020 and 05/06/2020, wave 2 ranges between 05/06/2020 and 02/11/2020 and wave 3 ranges between 02/11/2020 and 15/01/2021 in this figure.

6.0 Discussion

This report constitutes part of a new and novel area of research that has emerged from the recent COVID-19 pandemic. Due to constant changes in lockdown measures and various COVID-19 variants creating new waves, the research in this field is everchanging, with new possible fields of research created daily. Conducting an extensive investigation into a potential relationship between COVID-19 and mobility patterns evident in society by preprocessing large, freely accessible data followed by applying statistical analyses, leads to many new findings. Quantifying these findings and highlighting them in both graphical and tabular form as outlined in the methodology, provide a greater insight into the association between COVID-19 cases and mobility patterns within a country, which can be compared internationally.

6.1 Research Findings

Based on the methodology used, four key findings have emerged from the investigation. They will be discussed in the following section and can be identified as:

1. COVID-19 cases are strongly associated with mobility patterns.
2. New Zealand's lockdown measures proved to be most effective internationally.
3. COVID-19 had the least influence on park visits during the pandemic.
4. Weather does not have a large influence solely on COVID-19 case & death values and mobility patterns.

Finding 1: COVID-19 Cases are Strongly Associated with Mobility Patterns

In the midst of the pandemic, one apparent finding is the strong association between COVID-19 cases and mobility patterns of a population. This is evident throughout the investigation in both graphical and tabular form, especially if a government intervened to curb the spread of the disease. These mitigating actions, which resulted from a rise in COVID-19 cases, led to the divergence of mobility patterns when compared to a baseline for both the Apple and Google mobility data.

As seen in the investigation into the impact of COVID-19 in Ireland and the population's mobility, equal and opposite shapes in the Google and Apple mobility graphs emerged when compared to the COVID-19 cases. This prompted the creation of another dataset, where COVID-19 case and death values were translated by 14 days in order to statistically verify the strong association between COVID-19 cases and mobility patterns. Obtaining a correlation coefficient for the relationship between the COVID-19 case and death values along with the mobility category values would signify if there was a relationship between any two factors in the Ireland dataset. This can be seen in Figure 5.10, which highlights both the strong and negative correlation values obtained that were deemed statistically significant as suitable P-values were acquired. The 14 day lag reinforces the relationship between mobility and COVID-19 cases, tentatively implying that changes in mobility patterns impact COVID-19 case rates.

In the Ireland dataset, the constant fluctuation in COVID-19 cases and the numerous lockdown measures introduced had clearly impacted the dataset and its ability to produce accurate outcomes in the OLS single linear regression model. This led to the creation of four subsets (i.e. School Closures, Lockdown 1 , Lockdown 2 and Lockdown 3), as smaller datasets focused on a 2 week period surrounding a lockdown, proved to be a better indicator of the influence of rising mobility category data on an increase in COVID-19 cases two weeks later. This is apparent in the Lockdown 3 OLS single linear regression graphs obtained, as can be seen in Appendix H. In the Retail & Recreation, Grocery & Pharmacy Stores, Parks, Transit Stations and Workplaces graphs relative to COVID-19 cases, as visits to these locations increase, COVID-19 cases increase 14 days later, which led to a third COVID-19 wave in Ireland. The Residential graph varies for the same time period, because as the percentage of people remaining home and the Residential graph values increase, the COVID-19 cases drop. This supports the use of lockdowns as a mitigating action to curb the spread of COVID-19.

The strong relationship between the mobility patterns of a population and COVID-19 cases is also noticeable internationally through the graphical representation of the transient state of the pandemic. Fluctuations in daily COVID-19 cases seen in New Zealand (Figure 5.33), South Korea (Figure 5.35) and Germany (Figure 5.36) mirrored the mobility category graphs. These countries constantly adopted preventative measure to stop the spread of COVID-19 and therefore, gained many admirers for their swift strategies to suppress the disease. Their success highlights the importance of analysing mobility patterns as they can be utilised to determine an incoming wave of COVID-19. This is as a result of the strong relationship between COVID-19 cases and mobility patterns.

Finding 2: New Zealand's Lockdown Measures Proved to be Most Effective Internationally out of All Countries Analysed

As part of a first wave analysis and a further investigation into some countries of interest, New Zealand stood out as the leading country for preventing the spread of COVID-19. An accurate population comparison can be made with Ireland as both countries have a population of about 4.9 million on their islands. New Zealand's peak daily COVID-19 case value is 89 compared to Ireland's at 7832 (OWID, 2021) over the same 11 month time period. New Zealand's lockdowns are comparatively much harsher than many countries, as even though they are in "Alert Level 1", which is their "Prepare" stage, where society is functioning similar to pre-COVID-19 times, borders remain closed for all international travel apart from those who are normally resident in New Zealand.

Figure 5.33 highlights the effectiveness of the four alert levels, as even though the country only moved to "Alert Level 2" with Auckland on "Alert Level 3", there was almost a 40% drop in the use of transportation, followed by the quashing of the disease and a return to "Alert Level 1" on the 7th of October 2020. The scenes of normalcy exhibited in New Zealand emphasises the effectiveness of their preventative measures that enabled the country to maintain an extremely low incidence rate of 3.73 in 1,000,000 (OWID, 2021) when compared to Brazil (318.77 in 1,000,000) and Sweden (651.53 in 1,000,000) on the 14th of January 2021. New Zealand's ability to maintain extremely low COVID-19 case and death values relative to the other countries investigated, reinforces its status as one of the best countries internationally to impose preventative measures on its population and to halt the spread of the disease.

Finding 3: COVID-19 had the Least Influence on Park Visits During the Pandemic

After conducting the investigation it became apparent that the Parks mobility category was the least influenced by COVID-19 case values. Unlike the rest of the mobility categories, when analysing the figures, the Parks graph rarely followed the shape of the COVID-19 case values. This was initially evident in Figure 5.2 where the Parks graph trended upwards during the Summer months, whereas the percentage change relative to the baseline for the other mobility graphs was much smaller. The unique shape of the Parks graph is also evident in the Sweden investigation where the Parks graph in Figure 5.34 almost reached 300% above the baseline. The baseline represents a 5 week period between the 3rd of January and 6th of February 2020 in the Google mobility data, which occurs during the Winter for Ireland, Germany, Sweden and South Korea. This could have influenced the Park visits for these countries, as people are less inclined to visit parks during Winter months when the weather might be more downcast and snowfall might occur.

When further investigations were carried out for Ireland, correlation and regression analyses for the relationship between Parks and COVID-19 cases enabled an additional examination into the legitimacy of their neutrality. The correlation constant and R^2 values were ascertained to determine the strength of the relationship in Figure 5.10 and Table 5.21, respectively. Both values were low, which suggests little to no association between the two factors. Meteorological factors such as minimum and maximum temperatures exhibited a moderate correlation with park visits, but overall, this indicates that potentially due to restrictions in place closing schools and workplaces, people spent their free time visiting local parks that were within their travelable catchment area, especially during public holidays.

Finding 4: Weather does not have a Large Influence solely on COVID-19 Case & Death Values and Mobility Patterns

When analysing the impact of meteorological data on both COVID-19 cases & deaths as well as the Google & Apple mobility data, utilising the graphical format wasn't deemed suitable and therefore, it was investigated as part of the extensive Ireland examination. Initially, poor correlation values overall were discovered in Figure 5.10, but due to some of the meteorological P-values having no statistical significance, as seen in Table 5.19, analysis on the smaller subsets to determine the immediate impact around the focal point moments during Ireland's COVID-19 timeline, had to be conducted.

When analysing the individual subsets for the different lockdowns and school closures, maximum and minimum temperatures along with precipitation values appeared to have a moderate relationship with other categories. Examples include a moderate correlation value of 0.65 between Minimum Temperature and Grocery & Pharmacy Store visits during school closures (Figure 5.12), as well as a strong negative correlation value of -0.73 between Minimum Temperature and Park visits during Lockdown 2 (Figure 5.14). Overall weak correlation constants in tandem with poor R^2 values obtained in the single mobility categories, as seen in Table 5.21, reinforce that weather alone has no significant impact on any dataset factor. Therefore, this suggests that if a country is subjected to a heatwave, COVID-19 cases will not decrease without any government interventions. The antithesis is true if a country is exposed to colder weather, as cases will not increase solely due to the presence of below average meteorological conditions.

When coupled with mobility data as part of OLS multiple linear regression analysis, which is used to predict COVID-19 cases, it had an impact on some factors, especially those during Lockdown 3, where an R^2 value of 0.91 was obtained for the relationship between Retail & Recreational visits, Minimum Temperature and cases 14 days later in Table 5.28. Apart from the rare influence as seen in Lockdown 3, meteorological data has very little influence solely on mobility patterns and COVID-19 case & death values and therefore, is not an appropriate form of data to use when measuring the spread of the disease or the alterations in mobility within society.

6.2 Comparative Analysis with Other Studies

Due to the new and novel area of research created by the pandemic, not many existing studies can be analysed to determine the association between COVID-19 and mobility patterns within a society. This investigation was conducted as there was an existing need to determine the relationship between the mobility patterns exhibited by society and if it led to a change in COVID-19 cases, as well as a need to determine if a change in COVID-19 cases reported would encourage or discourage a population to travel.

Research papers, such as Wellenius et al. (2020), which examines the impact of government interventions on COVID-19 case numbers, often analyse one factor, such as government interventions or one Google mobility category and its impact with COVID-19 cases. Similarly during COVID-19 press conferences, state epidemiologists and scientists provide figures and graphs, which indicate that there is a relationship between COVID-19 and mobility but many have not written research papers, as they are focused on the real time data and how it can be used to determine if a new wave is coming. Once the COVID-19 pandemic is under control, with the vast majority of the global population vaccinated, a plethora of papers will be published to analyse the overall timeline of COVID-19 and its subsequent relationship with mobility to determine their relationship and how it can be used to prevent future pandemics.

6.3 Strengths and Limitations of the Research

As with any research, strengths and limitations can dictate its use and effectiveness. Many strengths in this research can be found due to the topical nature of COVID-19 and the alteration of the population's mobility as a result of the pandemic.

Strengths

A strength of this research is the scalable methodology used to conduct the investigation between COVID-19 case & death values and mobility patterns. The method used to perform the in depth analysis for Ireland is easily adaptable for any country that has readily available Google & Apple mobility data, as well as COVID-19 case & death data, either from an independent source such as the ECDC or directly from a national source, such as a country's department of health. If these datasets are in csv form, they can be transformed to a certain format if they are not sourced from OWID, Google and Apple. They can then be run to produce a graph of the transient nature of mobility and COVID-19 cases, along with correlation matrices and regression analysis graphs to analyse the association between COVID-19 cases and the various Google & Apple mobility categories. This can be seen in Appendix B, which consists of the python programme used to conduct the international analysis in a quick and thorough manner.

Another strength consists of utilising the research carried out to determine if a future wave is on the horizon based on the mobility patterns exhibited by society at a given moment. As seen in figure 5.15, two weeks before the third lockdown was implemented in Ireland, high mobility category rates relative to those exhibited in previous weeks were evident, which led to a stark rise in COVID-19 cases, two weeks following the lockdown. This suggests that if the government or the National Public Health Emergency Team (NPHET) analysed the mobility data, they could have implemented a lockdown sooner and therefore, greatly reduced the number of COVID-19 cases and deaths on the island of Ireland. Due to plenty of open mobility data, that is updated daily, available to many countries, governments can utilise this research to intervene earlier and reduce the impact of the pandemic on its population.

Limitations

Similar to the strengths, numerous limitations also exist in the research. Due to the everchanging state of pandemic, the work conducted is almost obsolete by the time it is ready to publish and therefore, needs to be constantly updated in order to ensure it is accurate and of use to the reader at the time of reading. This research was updated at four various points throughout its 11 months in order to ensure an accurate representation of the initial stages of the pandemic were analysed. If the investigation timeline was extended, the influence of vaccinations would have to be further incorporated into the analysis as an increasing number of people in Western countries are being vaccinated.

Another restriction consists of the limited regional data available, as Google provides its own documents on states or counties within a country, yet it does not publicise this information. Providing this information would potentially limit the number of national lockdowns, focusing on localised measures to mitigate the spread of COVID-19 within a county. Google and Apple's control of these datasets allow them to only publish data they deem suitable. Therefore, no individual state analysis can be conducted unless its large enough that the big tech company merits the investigation by publishing the data in csv file format.

Due to the information being produced by a finite number of companies, they have control of the frequency of the data and how often it is published. Therefore, research, such as the work undergone in this report, is limited by the data it is provided. Even though the datasets are rich in up-to-date information, companies such as Google and Apple have the ability to halt the creation of these datasets and therefore, this research is bound by the time that these companies will publish the datasets.

6.4 Recommendations for Future Work

Due to the transient state of the pandemic and ever-changing scenarios presented with COVID-19, the scope for future work is extremely broad. In order to carry out even further work, more people would be required to build upon this investigation, as more and more datasets and variables are becoming intertwined with the research. The increasing number of COVID-19 variants with altering degrees of contagiousness and fatality merit their own graphs to determine which has a greater impact on mobility patterns. Similarly, an increasing number of vaccinations available also influence the COVID-19 case count and mobility pattern values, yet not all vaccines work in the same way, are as preventative as one another and are as readily available in any country. Therefore, an even broader investigation incorporating these features could be performed in the future.

Machine learning techniques could also be applied to verify if COVID-19 cases can be predicted by changes in mobility. This is possible due to available data from numerous lockdowns and if the existing data is segregated into test and train data, an accurate model can be created to determine COVID-19 case rises early based on changes in mobility. Research can also be expanded to more countries and after 1 year, identical time periods one year apart can be mapped onto each other to determine the strength of a lockdown measure and to determine if factors such as "lockdown fatigue" can be quantified based on the effectiveness of a preventative measure.

6.5 Implications of Research

The research conducted in this report has many implications for both governmental and health policies, as well as future COVID-19 and pandemic research. Therefore, this section is split into "Policy" and "Future Research" in order to incorporate the impact of the research found in this report.

Policy

This research evidently has implications for public health strategy and the creation of government policy. With regards to planning policy, many measures can be introduced to ensure cities are more liveable in a potential future age of pandemics. This includes increasing certain dimensions within a building to ensure people can pass through areas while maintaining social distancing if a future pandemic were to occur or ensuring a set ventilation requirement for buildings with high capacity in order to prevent COVID-19 from lingering in the air within a space for too long. Based on the surge in park visits during the pandemic, the importance of allocating or converting areas to greenspace within an urban area are vital, as people would frequently visit them during a lockdown.

Similarly, public health strategies could be thoroughly developed based on this research, incorporating COVID-19 and hypothetical viruses or diseases in the future with varying degrees of contagiousness and lethality. This would ensure that all countries are well equipped for any future pandemic and can meet the mobility requirements of the public, based on the graphical and tabular results produced in this report.

Research

This research could influence other existing analyses in determining the relationship between COVID-19, mobility and other contributing factors. Similarly, it could be further developed and merged with existing research. As outlined in section 6.4, a myriad of research avenues are created with the research found in the report, as it highlights the strong association between mobility patterns and COVID-19 cases. This creates scope to analyse other contributing factors and to apply machine learning techniques to determine how accurately certain lockdown measures and mobility categories can alter the number of COVID-19 cases 14 days later.

7.0 Conclusion

Overall, COVID-19 has had a drastic impact on daily life, disrupting the norm and altering the way we live. Therefore, the well-documented cyclical nature of lockdowns and reopenings has distorted the mobility patterns exhibited by society. Based on readily available datasets, it can be deduced that COVID-19 cases are strongly associated with mobility patterns, which can be determined in graphical or tabular form.

The results reinforce the importance of parks and greenspace within cities during the pandemic and highlight that meteorological data has a negligible influence on COVID-19 case rates without incorporating the mobility of a population. This research also highlights how New Zealand proves to be the most effective country at suppressing the disease, which has led to a restoration in its mobility patterns, aligning with pre-COVID-19 mobility data. This in depth research reinforces the fact that COVID-19 has had a substantial impact on mobility patterns and therefore, must be embedded in all new areas of government policy and health strategy to optimise societal movement, without compromising the health of the population.

8.0 References

Aktay, Bavadekar, Cossoul, Davis, Desfontaines, Fabrikant, Gabrilovich, Gadepalli, Gipson, Guevara, Kamath, Kansal, Lange, Mandayam, Oplinger, Pluntke, Roessler, Schlosberg, Shekel, Vispute, Vu, Wellenius, Williams, Wilson (2020). *Google COVID-19 Community Mobility Reports: Anonymization Process Description (version 1.0)* https://arxiv.org/abs/2004.04145

Alon, Kim, Lagakos, Van Vuren (2020). *How Should Policy Responses to the COVID-19 Pandemic Differ in the Developing World?* CEGA Working Paper Series No. WPS-131. Center for Effective Global Action. University of California, Berkeley. Text. https://doi.org/10.26085/C3F59F

Apple (2020). *Apple maps Mobility Trends Reports*. https://www.apple.com/covid19/mobility

BBC (2020). *Did Sweden's coronavirus strategy succeed or fail?* https://www.bbc.com/news/world-europe-53498133

Benevolo, Dameri, D'Auria (2016). *Smart mobility in smart city: Action taxonomy, ICT intensity and public benefits*. In T. Torre, A. M. Braccini, & R. Spinelli (Eds.), Empowering organizations: Enabling platforms and artefacts (pp. 13–28). Cham: Springer.

Bicker, (2020). *Coronavirus in South Korea: How 'trace, test and treat' may be saving lives*. https://www.bbc.com/news/world-asia-51836898

Cacciapaglia, Cot, Sannino (2020). *Mining Google and Apple mobility data: Twenty-one shades of European social distancing measures for COVID-19.* arXiv:2008.02117v1 [physics.soc-ph]

Cecconello, Diniz, Silva (2020). *Using the infection fatality rate to predict the evolution of Covid-19 in Brazil*. medRxiv 2020.07.01.20144279; doi: https://doi.org/10.1101/2020.07.01.20144279

Cha & Kim, (2020). *A Timeline of South Korea's Response to COVID-19*. https://www.csis.org/analysis/timeline-south-koreas-response-covid-19

Chandra Dey, Rayamajhi, Chowdhury, Bhavsar, Martin (2016). *Vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication in a heterogeneous wireless network –* Performance evaluation, Transportation Research Part C: Emerging Technologies, Volume 68, 2016, Pages 168-184, ISSN 0968-090X, https://doi.org/10.1016/j.trc.2016.03.008

Chutchian (2020). *Iconic US retailer JC Penney rescued from collapse amid Covid hit.* https://www.irishexaminer.com/business/companies/arid-40079402.html

CNN (2020a). *Covid-19 has killed 250,000 people in the US. That's 10 times the deaths from car crashes in a year*. https://edition.cnn.com/2020/11/18/health/covid-19-deaths-us-250k-trnd/index.html

CNN (2020b). *To treat Covid-19, President Trump is taking Remdesivir, dexamethasone and more*. https://edition.cnn.com/2020/10/04/health/covid-trump-drugs-remdesivir-dexamethasone-explainer/index.html

Cohen-Blankshtain & Rotem-Mindali (2016). *Key research themes on ICT and sustainable urban mobility*. International Journal of Sustainable Transportation, 10, 17 - 9.

Condit (2020). *Infection Fatality Rate – A Critical Missing Piece for Managing Covid-19.* Virology Blog. https://www.virology.ws/2020/04/05/infection-fatality-rate-a-critical-missing-piece-for-managing-covid-19/

Coronakommissionen, (2020). *Coronakommissionen*. https://coronakommissionen.com/

CSO (2020). *Household Travel Survey*. https://www.cso.ie/en/methods/tourismandtravel/householdtravelsurvey/

Cucinotta & Vanelli (2020). *WHO Declares COVID-19 a Pandemic*. Acta Biomed. 2020 Mar 19;91(1):157-160. doi: 10.23750/abm.v91i1.9397. PMID: 32191675; PMCID: PMC7569573.

Delen, Eryarsoy, Davazdahemami (2020). *No Place Like Home: Cross-National Data Analysis of the Efficacy of Social Distancing During the COVID-19 Pandemic.* JMIR Public Health Surveillance 2020; 6(2): e19862 URL: https://publichealth.jmir.org/2020/2/e19862 DOI: 10.2196/19862

Doyle (2020). *COVID-19: Exacerbating Educational Inequalities?* http://publicpolicy.ie/papers/covid-19-exacerbating-educational-inequalities/

ECDC (2020a). *European Centre for Disease Prevention and Control Q & A on COVID-19: Basic facts*. https://www.ecdc.europa.eu/en/covid-19/facts/questions-answers-basic-facts

ECDC (2020b). *Download the daily number of new reported cases of COVID-19 by country worldwide*. https://www.ecdc.europa.eu/en/publications-data/download-todays-data-geographic-distribution-covid-19-cases-worldwide

European Commission (2020). *European Economic Forecast Spring 2020*. doi:10.2765/788367 https://ec.europa.eu/info/publications/european-economic-forecast-spring-2020_en

Facebook (2020). *COVID-19 Mobility Data Network.* https://visualization.covid19mobility.org/?date=2020-07-09&dates=2020-04-09_2020-07-09&region=GBR

Ferguson, Laydon, Nedjati-Gilani, Imai, Ainslie, Baguelin, Bhatia, Boonyasiri, Cucunubá, Cuomo-Dannenburg, Dighe, Dorigatti, Fu, Gaythorpe, Green, Hamlet, Hinsley, Okell, van Elsland, Thompson, Verity, Volz, H Wang, Y Wang, Walker, Walters, Winskill, Whittaker, Donnelly, Riley, Ghani (2020). *Impact of non-pharmaceutical interventions (NPIs) to reduce COVID-19 mortality and healthcare demand* (Report 9). https://www.imperial.ac.uk/mrc-global-infectious-disease-analysis/covid-19/report-9-impact-of-npis-on-covid-19/

Forbes (2020). *Google Publishes Location Data Across 130 Countries To Show How Coronavirus Lockdowns Are Working. https://www.forbes.com/sites/isabeltogoh/2020/04/03/google-publishes-location-data-across-130-countries-to-show-how-coronavirus-lockdowns-are-working/?sh=146598526562*

Groarke, Berry, Graham-Wisener, McKenna-Plumley, McGlinchey, Armour (2020). *Loneliness in the UK during the COVID-19 pandemic: Cross-sectional results from the*

COVID-19 Psychological Wellbeing Study. PLOS ONE, 2020; 15 (9): e0239698 DOI: 10.1371/journal.pone.0239698

Gonzalez (2019). *Android Developer's Guide to the Google Location Services API.* https://www.toptal.com/android/android-developers-guide-to-google-location-services-api

Gonzalez, Hidalgo, Barabasi (2008). *Understanding individual human mobility patterns.* Nature 453, 779–782 (2008).

Google LLC (2020*). Google COVID-19 Community Mobility Reports*. https://www.google.com/covid19/mobility/

Google Privacy & Terms (2020). *How Google uses location information.* https://policies.google.com/technologies/location-data?hl=en-US

Government of Ireland (2020). *Ireland's COVID-19 Data Hub.* https://covid19ireland-geohive.hub.arcgis.com/

Gov.ie (2020). *Public Health Measures in place until 12 April to prevent spreading COVID-19.* https://www.gov.ie/en/publication/cf9b0d-new-public-health-measures-effective-now-to-prevent-further-spread-o/?referrer=/en/publication/539d23-stay-at-home-the-latest-public-health-measures-to-prevent-the-spread/

Gov.br, (2021). *Coronavírus: o que você precisa saber e como prevenir o contágio*. https://coronavirus.saude.gov.br.

Hasell, Mathieu, Beltekian, et al (2020). *A cross-country database of COVID-19 testing*. Sci Data 7, 345 (2020). https://doi.org/10.1038/s41597-020-00688-8

Islam S, Sarkar, Khan, Mostofa, Hasan, Kabir, Yeasmin, Islam M, Amin, Anwar, Chughtai, Seale (2020). *COVID-19–related infodemic and its impact on public health: a global social media analysis*. Am J Trop Med Hyg. 2020; https://doi.org/10.4269/ajtmh.20-0812

Johns Hopkins University (2020). *COVID-19 Dashboard by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University*. https://coronavirus.jhu.edu/map.html

Joyce & Xu (2020*): Sector shutdowns during the coronavirus crisis: which workers are most exposed?*, IFS Briefing Note, No. BN278, Institute for Fiscal Studies, London.

Kang, Gao, Lin, Xiao, Yuan, Liu, Ma, (2010). *Analyzing and geo-visualizing individual human mobility patterns using mobile call records*. 2010 18th International Conference on Geoinformatics, Geoinformatics 2010. 1 - 7. 10.1109/GEOINFORMATICS.2010.5567857.

Klein (2020). *These Industries Were Hardest Hit in the First 100 Days of the Pandemic. Where They Are Headed Next.* https://www.barrons.com/articles/covids-first-100-days-hit-these-industries-hardest-heres-how-they-could-recover-51592643600

Laker (2018). *What would a truly walkable city look like?* https://www.theguardian.com/cities/2018/sep/19/what-would-a-truly-walkable-city-look-like

Liu, Wang, Ye (2018). *Comparing mobility patterns between residents and visitors using geo-tagged social media data.* Transactions in GIS. 2018; 22: 1372– 1389. https://doi.org/10.1111/tgis.12478

Lütticke, (2020). *Germany agrees stricter meat industry regulations following coronavirus outbreaks.* https://www.dw.com/en/germany-agrees-stricter-meat-industry-regulations-following-coronavirus-outbreaks/a-53510078

Maringe, Spicer, Morris, et al, (2020). *The impact of the COVID-19 pandemic on cancer deaths due to delays in diagnosis in England, UK: a national, population-based, modelling study*. Lancet Oncol2020;21:1023-34. doi:10.1016/S1470-2045(20)30388-0 pmid:32702310

Merriam-Webster (2020). *Definition of Lockdown.* https://www.merriam-webster.com/dictionary/lockdown

MerrionStreet.ie (2020). *Government approves moving to Phase 1 of easing Covid 19 restrictions*. https://merrionstreet.ie/en/News-Room/News/Government_approves_moving_to_Phase_1_of_easing_Covid_19_restrictions.html

Met Éireann (2020). *Monthly Data - Cork Airport.* https://www.met.ie/climate/available-data/monthly-data

Ministry of Health NZ, (2021). *COVID-19 (novel coronavirus).* https://www.health.govt.nz/our-work/diseases-and-conditions/covid-19-novel-coronavirus

New York Times (2020*). Coronavirus Vaccine Tracker* https://www.nytimes.com/interactive/2020/science/coronavirus-vaccine-tracker.html

Nicola, Alsafi, Sohrabi, Kerwan, Al-Jabir, Iosifidis, Agha M., Agha R., (2020). *The socio-economic implications of the coronavirus pandemic (COVID-19): A review*. International Journal of Surgery. 78:185–193. doi: 10.1016/j.ijsu.2020.04.018.

Ng, (2021). *A Portal Into a Universe Without Covid*. https://www.nytimes.com/2021/03/03/magazine/a-portal-into-a-universe-without-covid.html

Null & Smith, (2020). *COVID-19 Could Affect Cities for Years. Here Are 4 Ways They're Coping Now.* TheCityFix: World Resource Institute (WRI) https://thecityfix.com/blog/covid-19-affect-cities-years-4-ways-theyre-coping-now-schuyler-null-hillary-smith/

Our World in Data (2020). *Our World in Data COVID-19 database*. https://github.com/owid/covid-19-data/tree/master/public/data

Pepe, Bajardi, Gauvin, Privitera, Lake, Cattuto, Tizzoni (2020). *COVID-19 outbreak response, a dataset to assess mobility changes in Italy following a national lockdown.* https://www.nature.com/articles/s41597-020-00575-2 https://doi.org/10.1038/s41597-020-00575-2

Phillips, (2020). *Bolsonaro says he 'wouldn't feel anything' if infected with Covid-19 and attacks state lockdowns*. https://www.theguardian.com/world/2020/mar/25/bolsonaro-brazil-wouldnt-feel-anything-covid-19-attack-state-lockdowns.

Public Health Agency of Sweden, (2021). *The Public Health Agency of Sweden* https://www.folkhalsomyndigheten.se/the-public-health-agency-of-sweden

Rapid Flow (2020). *Surtrac Smart Traffic Signals.* https://www.rapidflowtech.com/

Rhee, Shin, Hong, Lee, Kim, Chong (2011) *On the Levy-walk nature of human mobility*, IEEE/ACM Trans. Netw., vol. 19, no. 3, pp. 630-643, Jun. 2011.

Reuters (2020). *IMF chief says pandemic will unleash worst recession since Great Depression.* https://www.reuters.com/article/us-health-coronavirus-imf/imf-chief-says-pandemic-will-unleash-worst-recession-since-great-depression-idUSKCN21R1SM

Robert Koch Institut, (2020). *Ergänzung zum Nationalen Pandemieplan – COVID-19 – neuartige Coronaviruserkrankung*. https://www.rki.de/DE/Content/InfAZ/N/Neuartiges_Coronavirus/Ergaenzung_Pandemieplan_Covid.pdf?__blob=publicationFile

RTÉ (2020). *Will Ireland's new lockdown beat the second Covid-19 wave?* https://www.rte.ie/brainstorm/2020/1105/1176080-ireland-second-wave-covid-19-lockdown-autumn-winter/

Sánchez-Páramo (2020). *COVID-19 will hit the poor hardest. Here's what we can do about it.* https://blogs.worldbank.org/voices/covid-19-will-hit-poor-hardest-heres-what-we-can-do-about-it

Sandford (2020). *Coronavirus: Half of humanity now on lockdown as 90 countries call for confinement.* https://www.euronews.com/2020/04/08/coronavirus-in-europe-eu-science-chief-quits-slamming-response-to-pandemic

Schleicher (2020). *The Impact Of Covid-19 On Education - Insights From Education At A Glance 2020*, https://www.oecd.org/education/the-impact-of-covid-19-on-education-insights-education-at-a-glance-2020.pdf

Tanguay, Lachapelle (2020). *Remote work worsens inequality by mostly helping high-income earners*. https://theconversation.com/remote-work-worsens-inequality-by-mostly-helping-high-income-earners-136160

The Dubrovnik Times (2020). *Lockdown or curfew for Covid-19 looks unlikely for Croatia.* https://www.thedubrovniktimes.com/news/croatia/item/10203-lockdown-or-curfew-for-covid-19-looks-unlikely-for-croatia

The Irish Times (2020). *Coronavirus: Schools, colleges and childcare facilities in Ireland to shut.* https://www.irishtimes.com/news/health/coronavirus-schools-colleges-and-childcare-facilities-in-ireland-to-shut-1.4200977

Cousins (2020). *New Zealand eliminates COVID-19.* Lancet. 2020 May 9;395(10235):1474. doi: 10.1016/S0140-6736(20)31097-7. PMID: 32386582; PMCID: PMC7252131.

TIME (2020). *South Korea's Health Minister on How His Country Is Beating Coronavirus Without a Lockdown.* https://time.com/5830594/south-korea-covid19-coronavirus/

UN (2020). *COVID-19 sparks increased demand for mental health services: UNFPA.* https://news.un.org/en/story/2020/10/1075122

Wang Y, Zhang D, Du G, Du R, Zhao J, Jin Y, Fu S, Gao L, Cheng Z, Lu Q, Hu Y, Luo G, Wang K, Lu Y, Li H, Wang S, Ruan S, Yang C, Mei C, Wang Y, Ding D, Wu F, Tang X, Ye X, Ye Y, Liu B, Yang J, Yin W, Wang A, Fan G, Zhou F, Liu Z, Gu X, Xu J, Shang L, Zhang Y, Cao L, Guo T, Wan Y, Qin H, Jiang Y, Jaki T, Hayden FG, Horby PW, Cao B, Wang C. (2020). *Remdesivir in adults with severe COVID-19: a randomised, double-blind, placebo-controlled, multicentre trial*. Lancet. 2020 May 16;395(10236):1569-1578. doi: 10.1016/S0140-6736(20)31022-9. Epub 2020 Apr 29. Erratum in: Lancet. 2020 May 30;395(10238):1694. PMID: 32423584; PMCID: PMC7190303.

Wellenius, Vispute, Espinosa, Fabrikant, Tsai, Hennessy, Williams, Gadepalli, Boulange, Pearce, Kamath, Schlosberg, Bendebury, Stanton, Bavadekar, Pluntke, Desfontaines, Jacobson, Armstrong, Gabrilovich (2020). *Impacts of State-Level Policies on Social Distancing in the United States Using Aggregated Mobility Data during the COVID-19 Pandemic Impacts of State-Level Policies on Social Distancing in the United States Using Aggregated Mobility Data during the COVID-19 Pandemic*. arXiv:2004.10172 https://arxiv.org/abs/2004.10172

WHO (2021). *Questions and Answers.* https://www.who.int/emergencies/diseases/novel-coronavirus-2019/question-and-answers-hub/q-a-detail/coronavirus-disease-covid-19

WHO (2020a): *WHO Coronavirus Disease (COVID-19) Dashboard.* https://covid19.who.int/

WHO (2020b*): World Mental Health Day on 10 October to highlight urgent need to increase investment in chronically underfunded sector*. https://www.who.int/news/item/05-10-2020-covid-19-disrupting-mental-health-services-in-most-countries-who-survey

Zheng, Li, Chen, Xie, Ma (2008). *Understanding mobility based on GPS data*. In Proc. Ubicomp'08, ACM Press: 312-321

Appendices

Appendix A: First Wave Analysis Graphs

Appendix B: Python Programming Script

Appendix C: Ireland OLS Regression Analysis Graphs

Appendix D: Ireland with a 14 Day Lag OLS Regression Analysis Graphs

Appendix E: School Closures OLS Regression Analysis Graphs

Appendix F: Lockdown 1 OLS Regression Analysis Graphs

Appendix G: Lockdown 2 OLS Regression Analysis Graphs

Appendix H: Lockdown 3 OLS Regression Analysis Graphs

Appendix I: Raw Ireland Natural Log Transformation Histograms

Appendix J: Scaled Ireland Natural Log Transformation Histograms

Appendix K: FYP Logbook

Appendix A

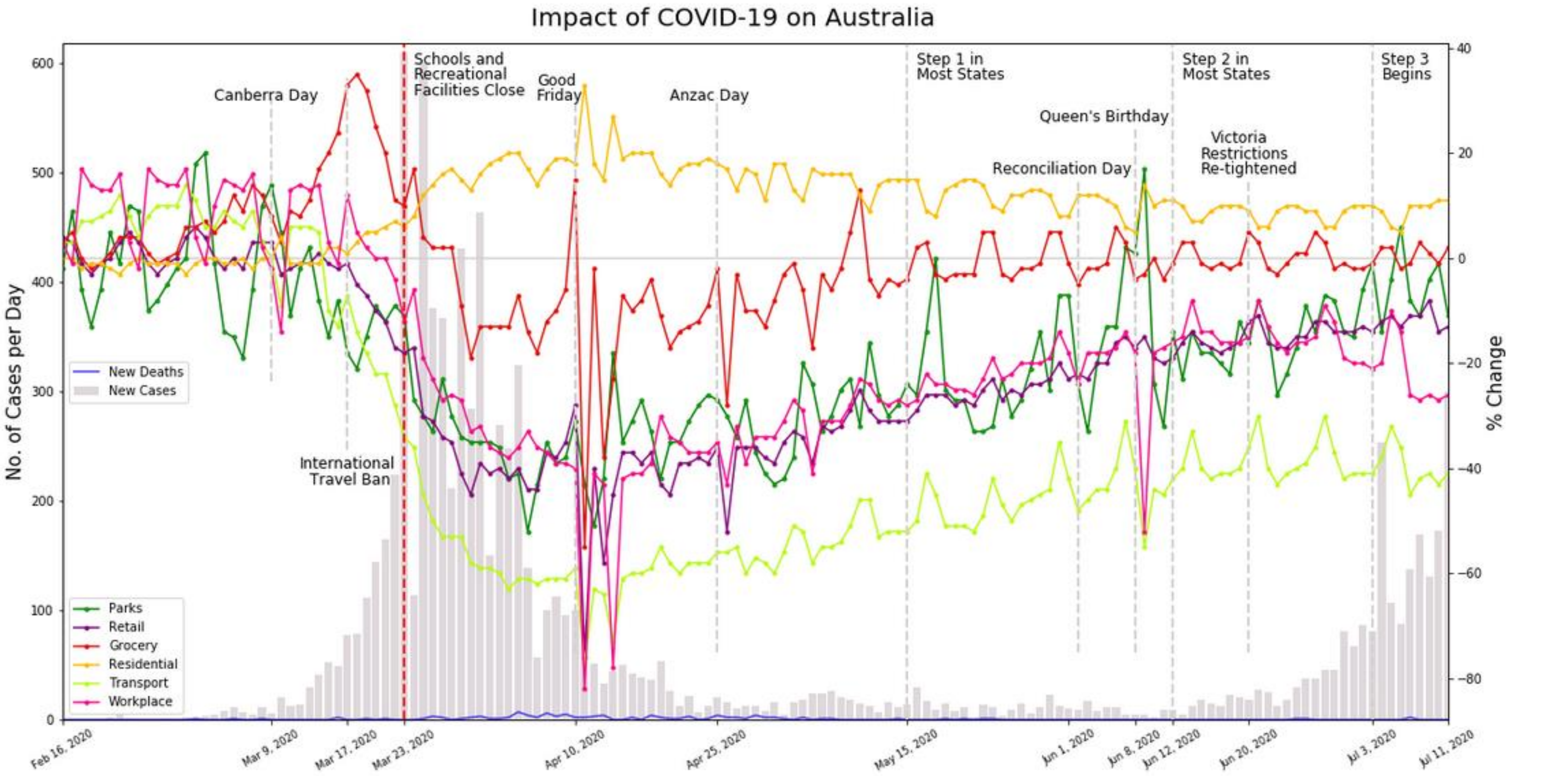


Figure A.1: Graph of the temporal variability of the daily Google-derived mobility categories, the daily COVID-19 cases & death rates from OWID for Australia (n=145) in relation to government announcements, including travel restrictions and lockdowns/stay-at-home orders and national holidays from 16/02/2020 to 11/07/2020. The data used is the raw unprocessed Australia data. The Google-derived mobility categories are Retail & Recreation, Grocery & Pharmacy Stores, Parks, Transit Stations, Workplaces and Residential, and they are represented as the % change in relation to a 5 week baseline ranging from 03/01/2020 to 06/02/2020.

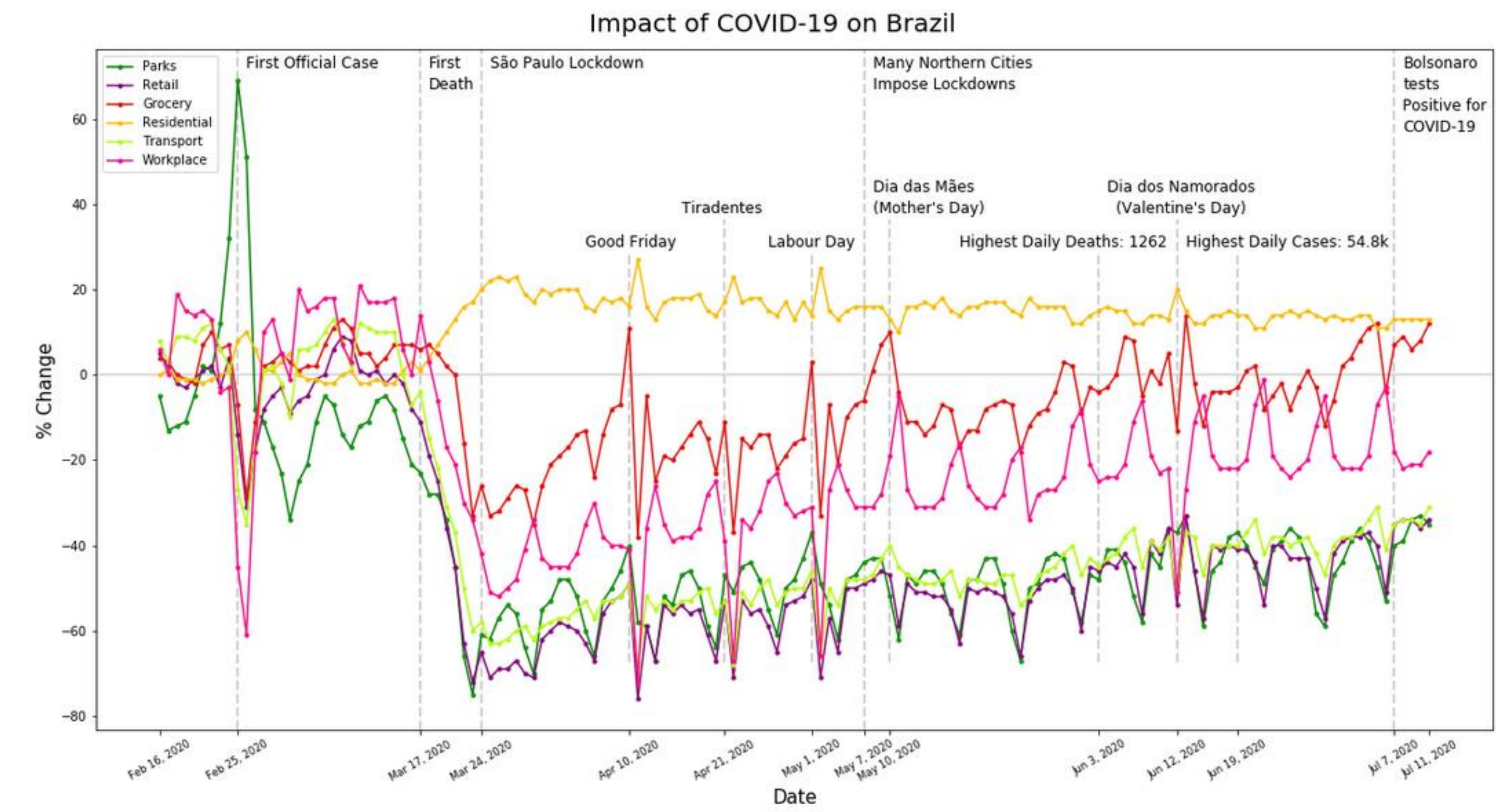


Figure A.2: Graph of the temporal variability of the daily Google-derived mobility categories, the daily COVID-19 cases & death rates from OWID for Brazil (n=145) in relation to government announcements, including travel restrictions and lockdowns/stay-at-home orders and national holidays from 16/02/2020 to 11/07/2020. The data used is the raw unprocessed Brazil data. The Google-derived mobility categories are Retail & Recreation, Grocery & Pharmacy Stores, Parks, Transit Stations, Workplaces and Residential, and they are represented as the % change in relation to a 5 week baseline ranging from 03/01/2020 to 06/02/2020.

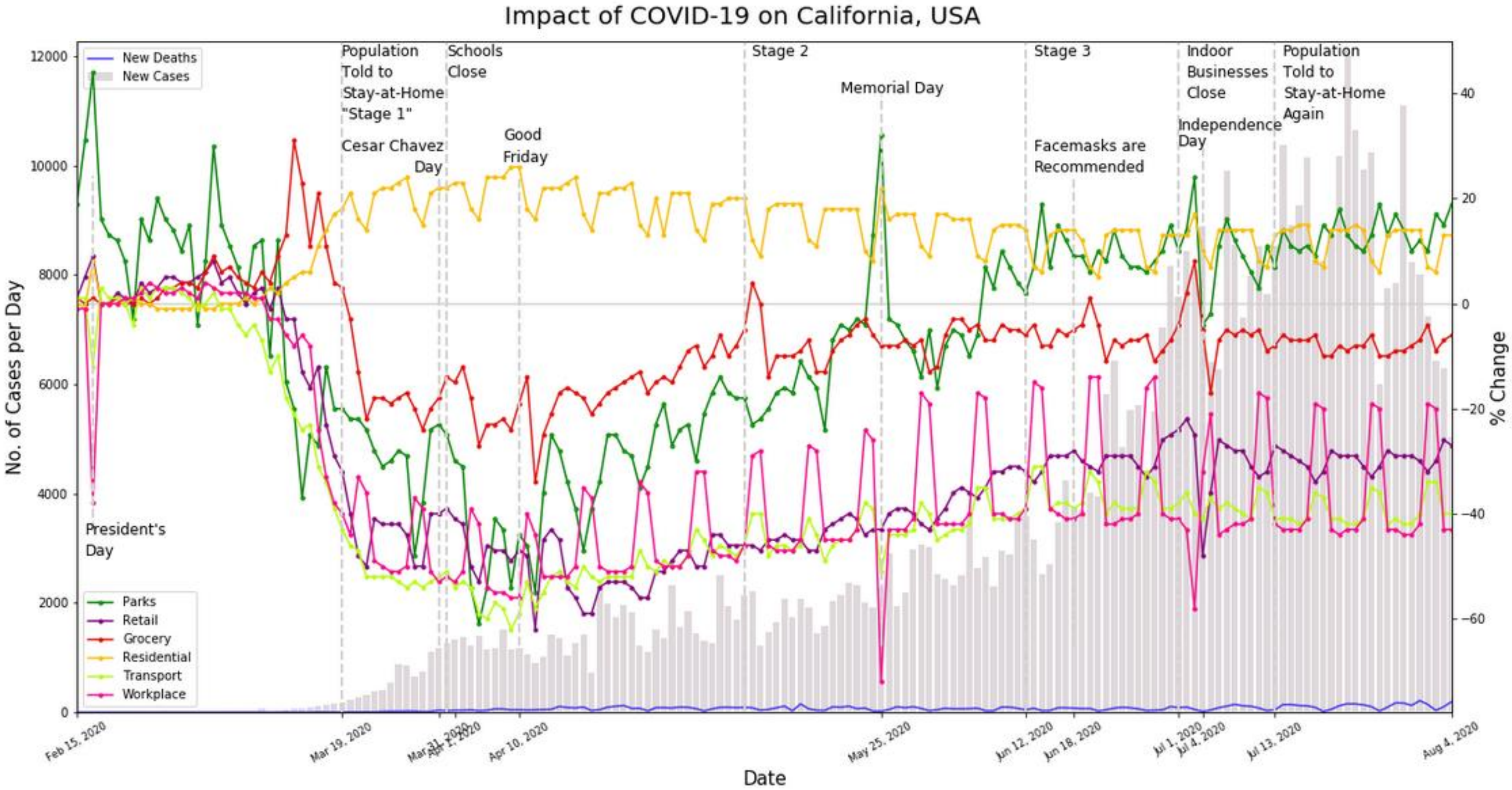


Figure A.3 : Graph of the temporal variability of the daily Google-derived mobility categories, the daily COVID-19 cases & death rates from OWID for California, USA (n=169) in relation to government announcements, including travel restrictions and lockdowns/stay-at-home orders and national holidays from 16/02/2020 to 04/08/2020. The data used is the raw unprocessed data. The Google-derived mobility categories are Retail & Recreation, Grocery & Pharmacy Stores, Parks, Transit Stations, Workplaces and Residential, and they are represented as the % change in relation to a 5 week baseline ranging from 03/01/2020 to 06/02/2020.

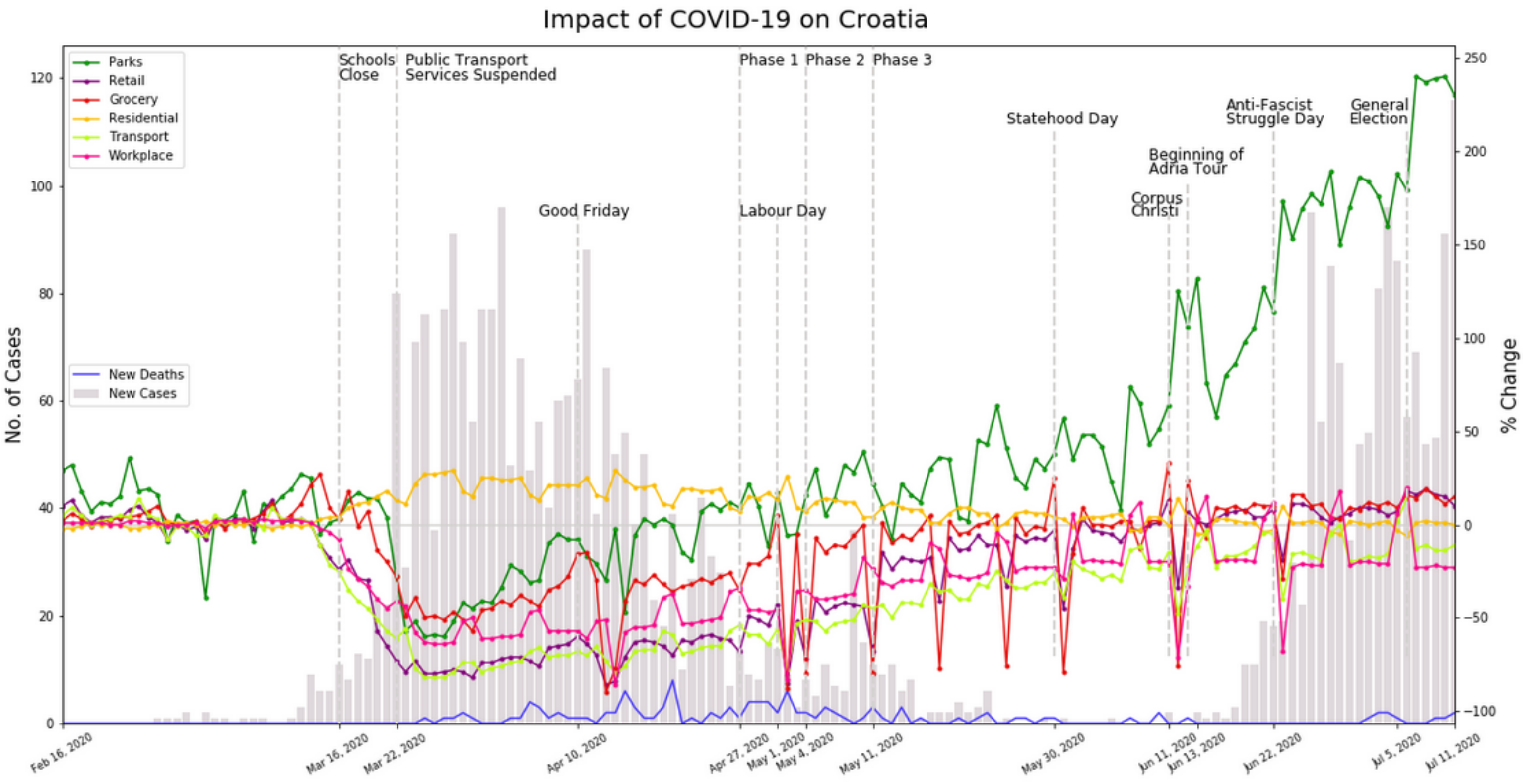


Figure A.4: Graph of the temporal variability of the daily Google-derived mobility categories, the daily COVID-19 cases & death rates from OWID for Croatia (n=145) in relation to government announcements, including travel restrictions and lockdowns/stay-at-home orders and national holidays from 16/02/2020 to 11/07/2020. The data used is the raw unprocessed data. The Google-derived mobility categories are Retail & Recreation, Grocery & Pharmacy Stores, Parks, Transit Stations, Workplaces and Residential, and they are represented as the % change in relation to a 5 week baseline ranging from 03/01/2020 to 06/02/2020.

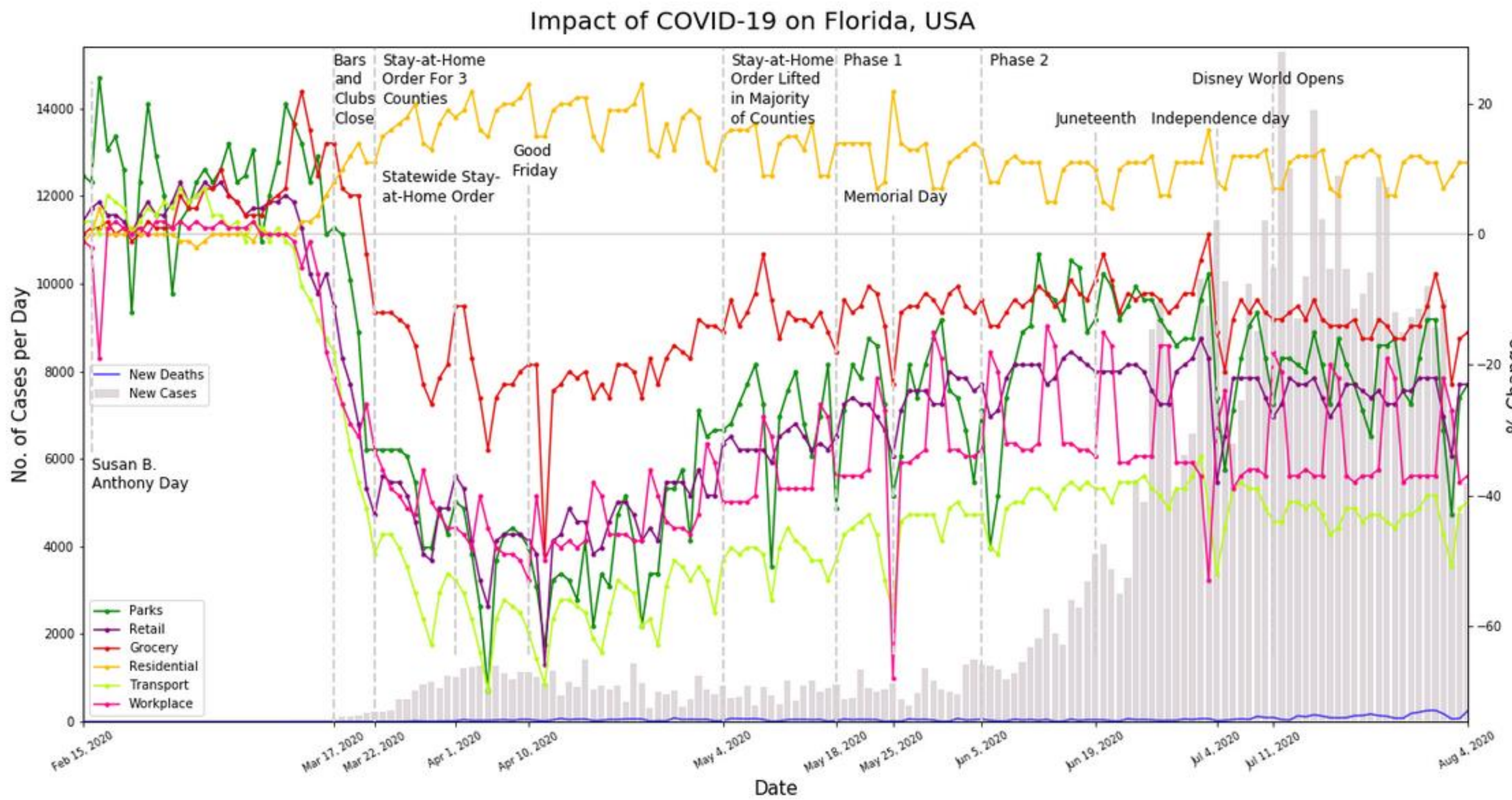


Figure A.5: Graph of the temporal variability of the daily Google-derived mobility categories, the daily COVID-19 cases & death rates from OWID for Florida, USA (n=169) in relation to government announcements, including travel restrictions and lockdowns/stay-at-home orders and national holidays from 16/02/2020 to 04/08/2020. The data used is the raw unprocessed data. The Google-derived mobility categories are Retail & Recreation, Grocery & Pharmacy Stores, Parks, Transit Stations, Workplaces and Residential, and they are represented as the % change in relation to a 5 week baseline ranging from 03/01/2020 to 06/02/2020.

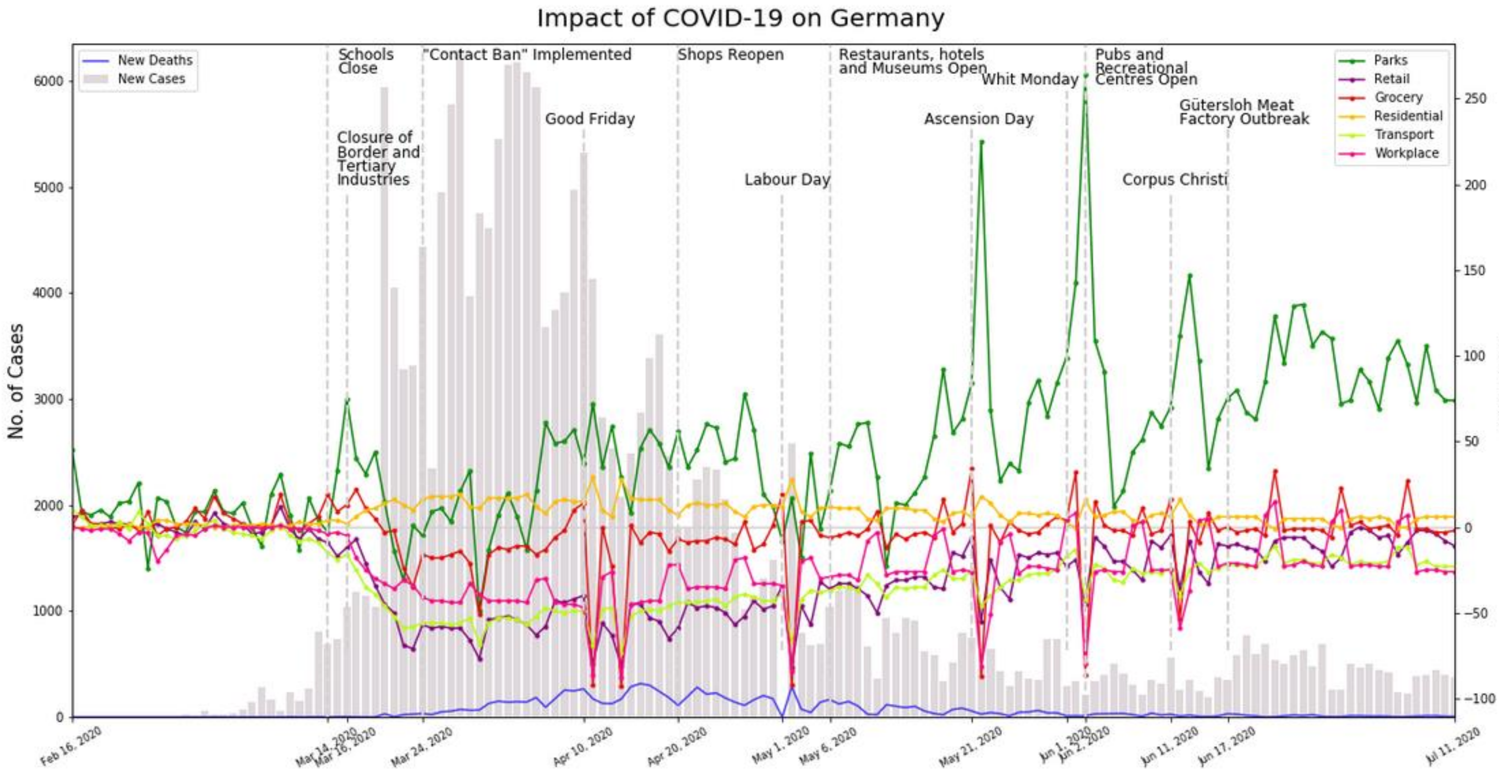


Figure A.6: Graph of the temporal variability of the daily Google-derived mobility categories, the daily COVID-19 cases & death rates from OWID for Germany (n=145) in relation to government announcements, including travel restrictions and lockdowns/stay-at-home orders and national holidays from 16/02/2020 to 11/07/2020. The data used is the raw unprocessed data. The Google-derived mobility categories are Retail & Recreation, Grocery & Pharmacy Stores, Parks, Transit Stations, Workplaces and Residential, and they are represented as the % change in relation to a 5 week baseline ranging from 03/01/2020 to 06/02/2020.

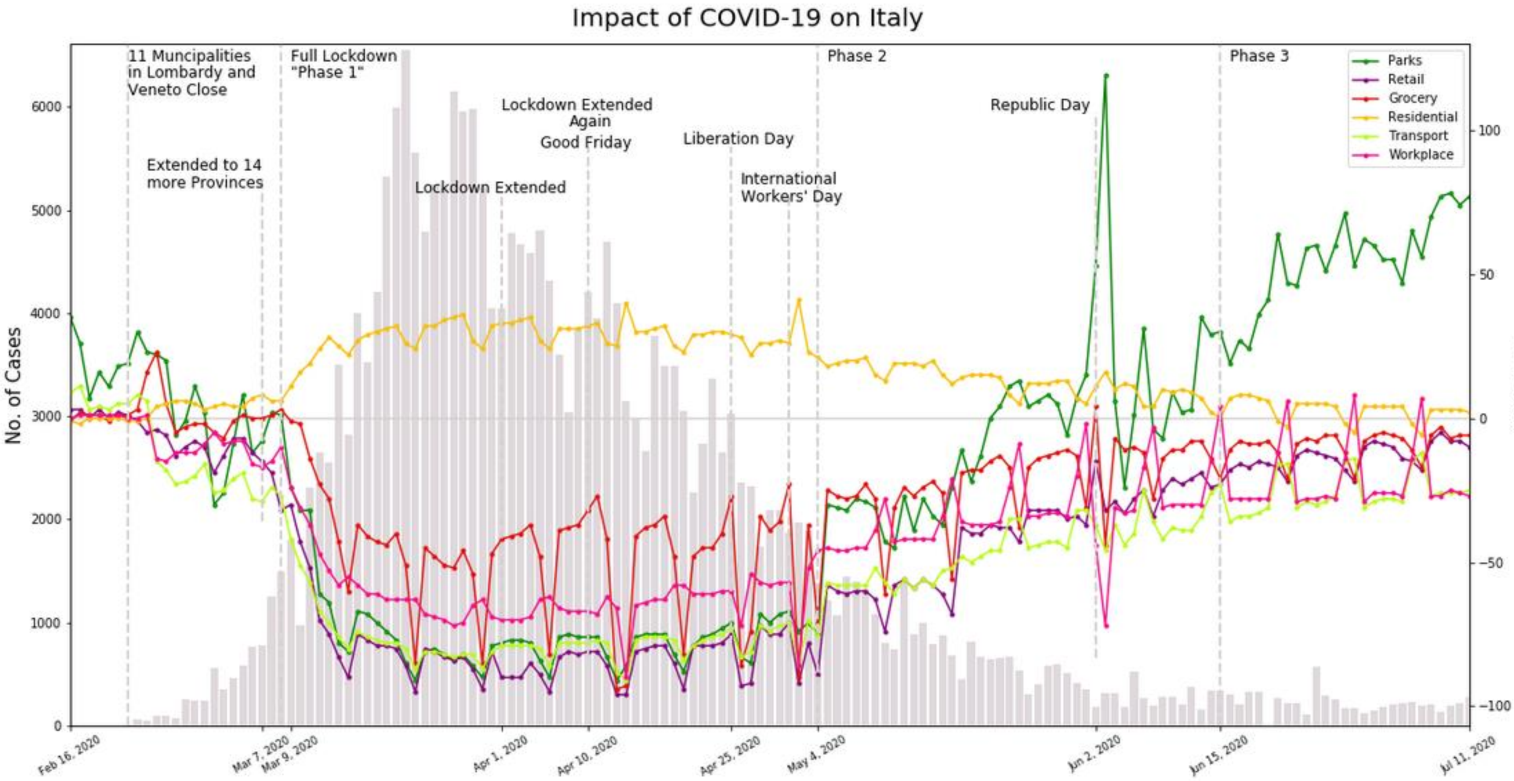


Figure A.7: Graph of the temporal variability of the daily Google-derived mobility categories, the daily COVID-19 cases & death rates from OWID for Italy (n=145) in relation to government announcements, including travel restrictions and lockdowns/stay-at-home orders and national holidays from 16/02/2020 to 11/07/2020. The data used is the raw unprocessed data. The Google-derived mobility categories are Retail & Recreation, Grocery & Pharmacy Stores, Parks, Transit Stations, Workplaces and Residential, and they are represented as the % change in relation to a 5 week baseline ranging from 03/01/2020 to 06/02/2020.

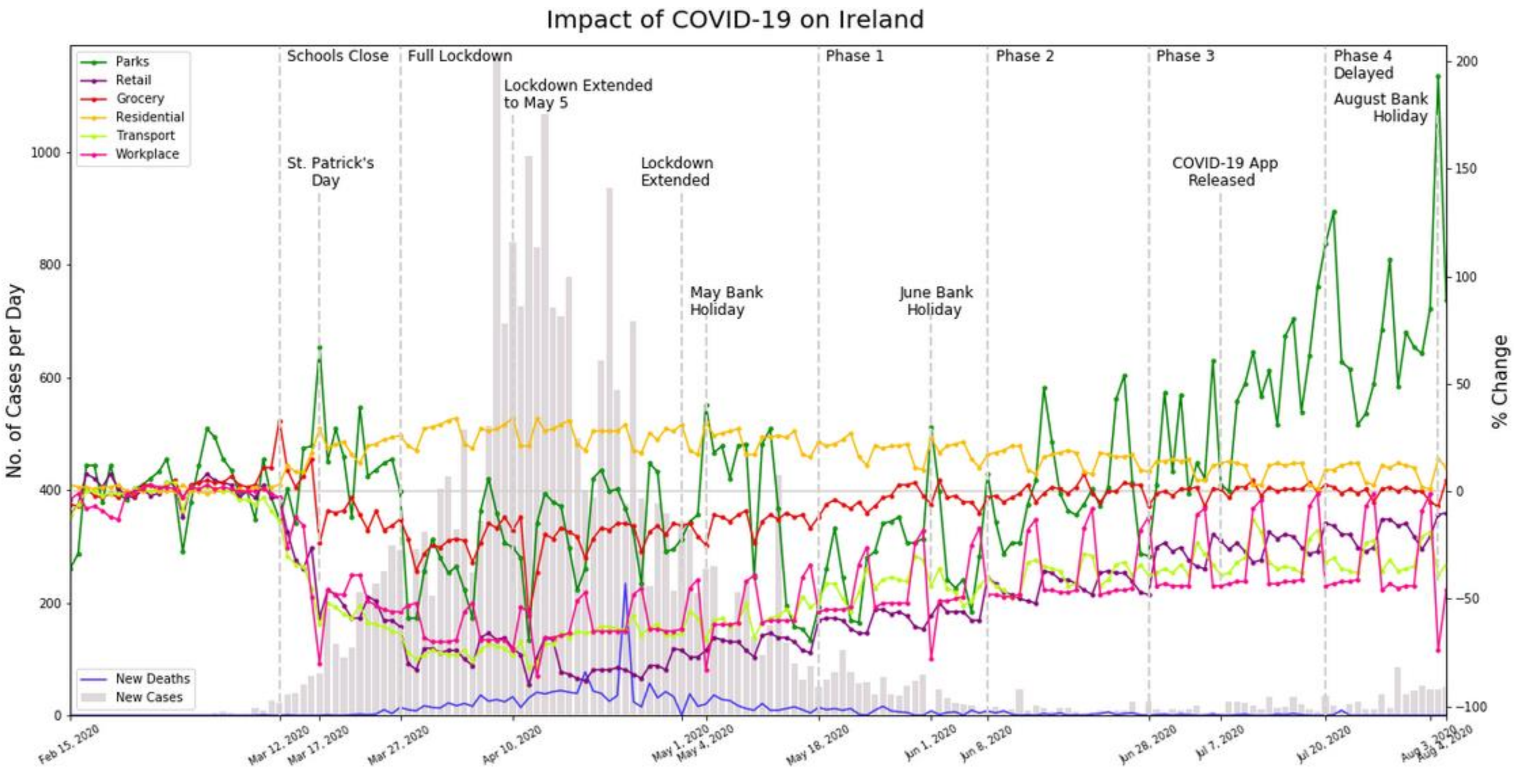


Figure A.8: Graph of the temporal variability of the daily Google-derived mobility categories, the daily COVID-19 cases & death rates from OWID for Ireland (n=169) in relation to government announcements, including travel restrictions and lockdowns/stay-at-home orders and national holidays from 16/02/2020 to 04/08/2020. The data used is the raw unprocessed data. The Google-derived mobility categories are Retail & Recreation, Grocery & Pharmacy Stores, Parks, Transit Stations, Workplaces and Residential, and they are represented as the % change in relation to a 5 week baseline ranging from 03/01/2020 to 06/02/2020.

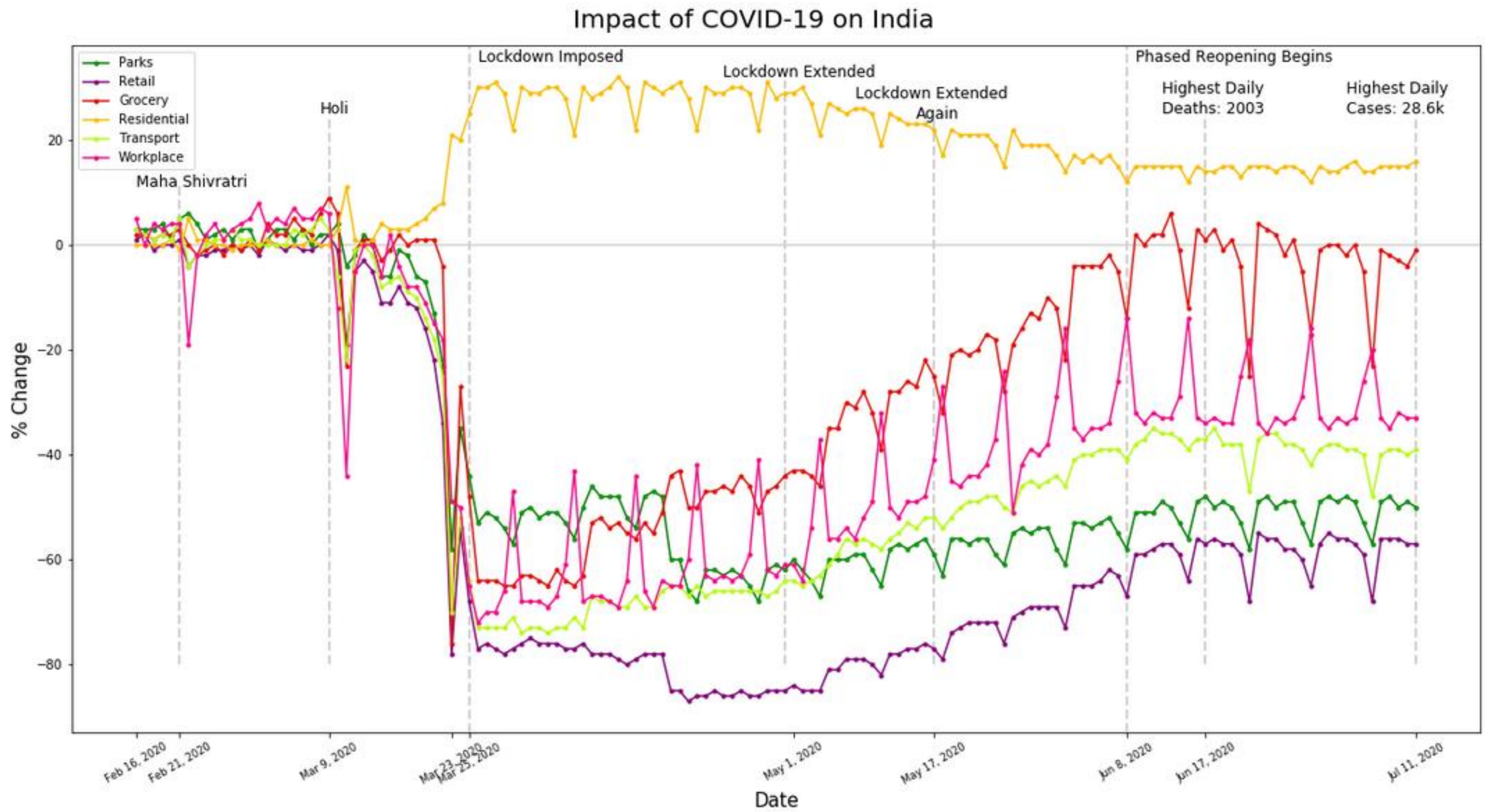


Figure A.9: Graph of the temporal variability of the daily Google-derived mobility categories, the daily COVID-19 cases & death rates from OWID for India (n=145) in relation to government announcements, including travel restrictions and lockdowns/stay-at-home orders and national holidays from 16/02/2020 to 11/07/2020. The data used is the raw unprocessed data. The Google-derived mobility categories are Retail & Recreation, Grocery & Pharmacy Stores, Parks, Transit Stations, Workplaces and Residential, and they are represented as the % change in relation to a 5 week baseline ranging from 03/01/2020 to 06/02/2020.

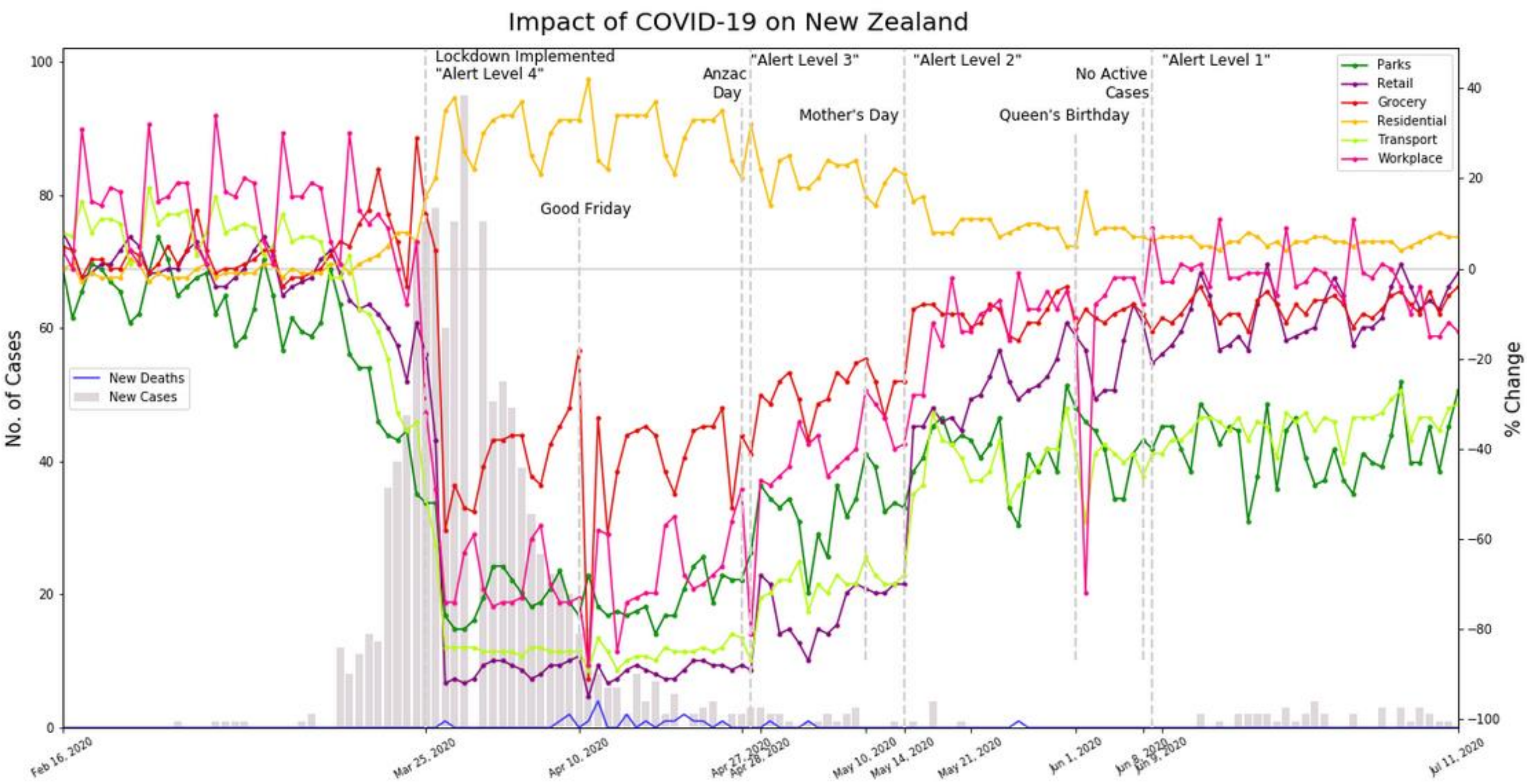


Figure A.10: Graph of the temporal variability of the daily Google-derived mobility categories, the daily COVID-19 cases & death rates from OWID for New Zealand (n=145) in relation to government announcements, including travel restrictions and lockdowns/stay-at-home orders and national holidays from 16/02/2020 to 11/07/2020. The data used is the raw unprocessed data. The Google-derived mobility categories are Retail & Recreation, Grocery & Pharmacy Stores, Parks, Transit Stations, Workplaces and Residential, and they are represented as the % change in relation to a 5 week baseline ranging from 03/01/2020 to 06/02/2020.

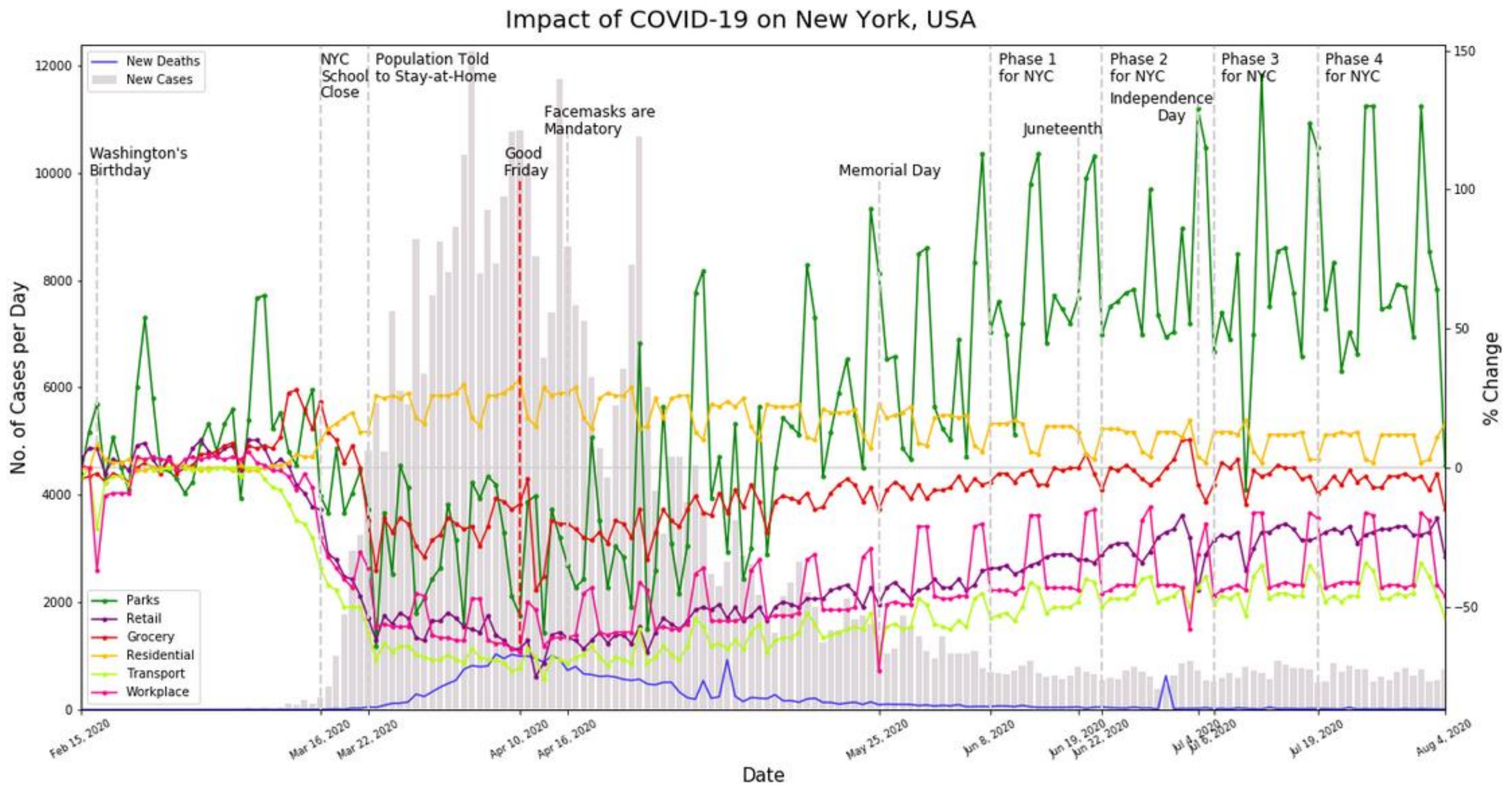


Figure A.11: Graph of the temporal variability of the daily Google-derived mobility categories, the daily COVID-19 cases & death rates from OWID for New York, USA (n=169) in relation to government announcements, including travel restrictions and lockdowns/stay-at-home orders and national holidays from 16/02/2020 to 04/08/2020. The data used is the raw unprocessed data. The Google-derived mobility categories are Retail & Recreation, Grocery & Pharmacy Stores, Parks, Transit Stations, Workplaces and Residential, and they are represented as the % change in relation to a 5 week baseline ranging from 03/01/2020 to 06/02/2020.

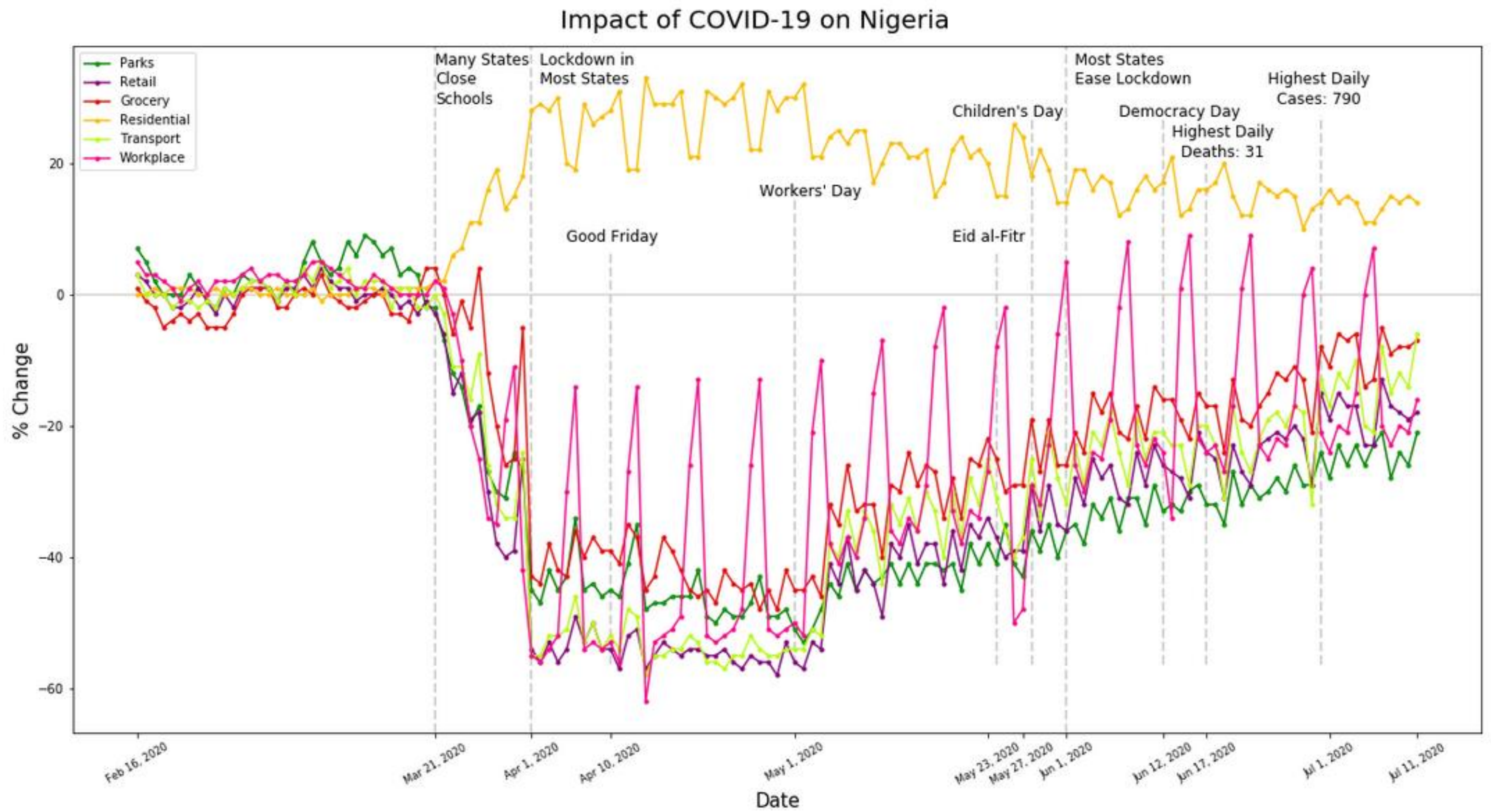


Figure A.12: Graph of the temporal variability of the daily Google-derived mobility categories, the daily COVID-19 cases & death rates from OWID for Nigeria (n=145) in relation to government announcements, including travel restrictions and lockdowns/stay-at-home orders and national holidays from 16/02/2020 to 11/07/2020. The data used is the raw unprocessed data. The Google-derived mobility categories are Retail & Recreation, Grocery & Pharmacy Stores, Parks, Transit Stations, Workplaces and Residential, and they are represented as the % change in relation to a 5 week baseline ranging from 03/01/2020 to 06/02/2020.

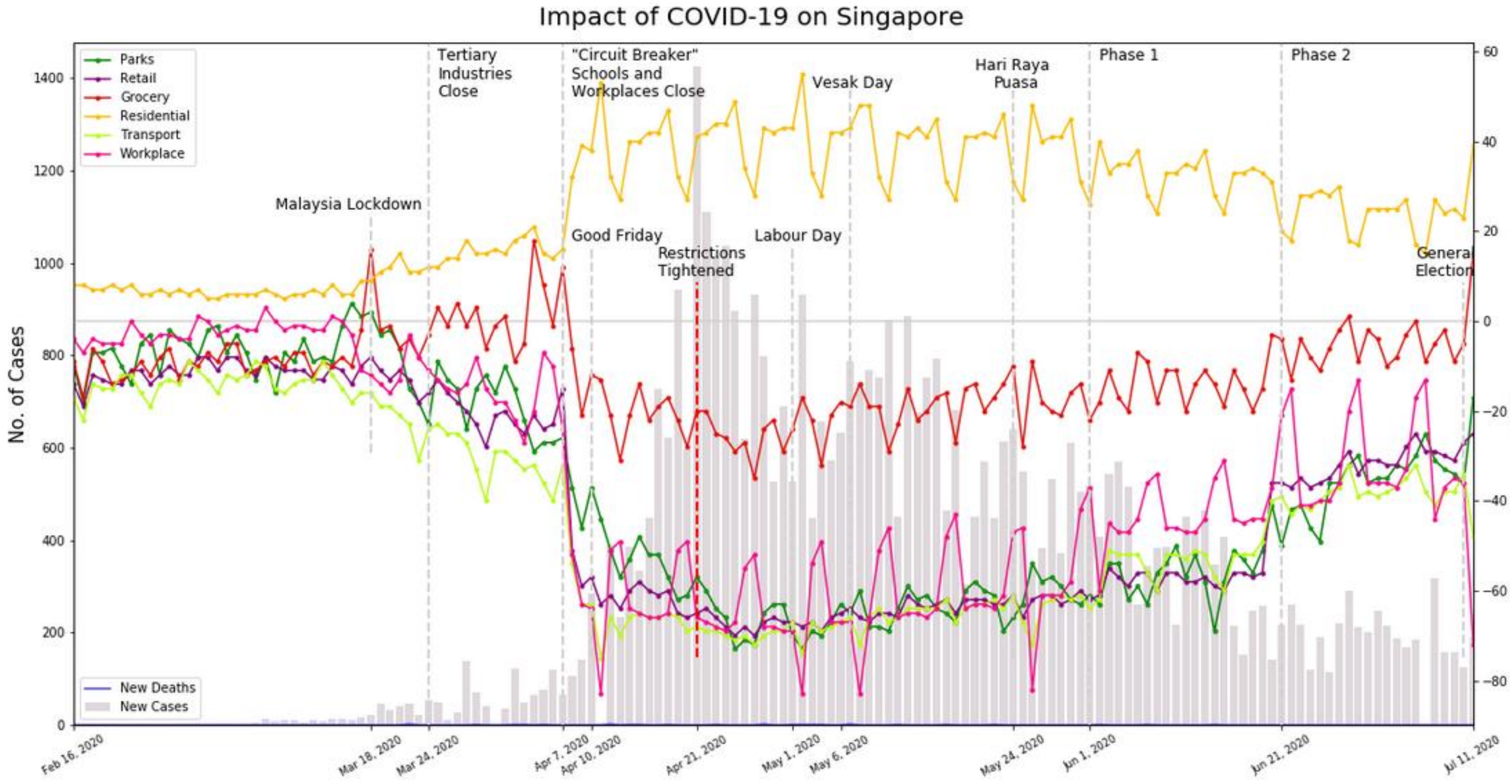


Figure A.13: Graph of the temporal variability of the daily Google-derived mobility categories, the daily COVID-19 cases & death rates from OWID for Singapore (n=145) in relation to government announcements, including travel restrictions and lockdowns/stay-at-home orders and national holidays from 16/02/2020 to 11/07/2020. The data used is the raw unprocessed data. The Google-derived mobility categories are Retail & Recreation, Grocery & Pharmacy Stores, Parks, Transit Stations, Workplaces and Residential, and they are represented as the % change in relation to a 5 week baseline ranging from 03/01/2020 to 06/02/2020.

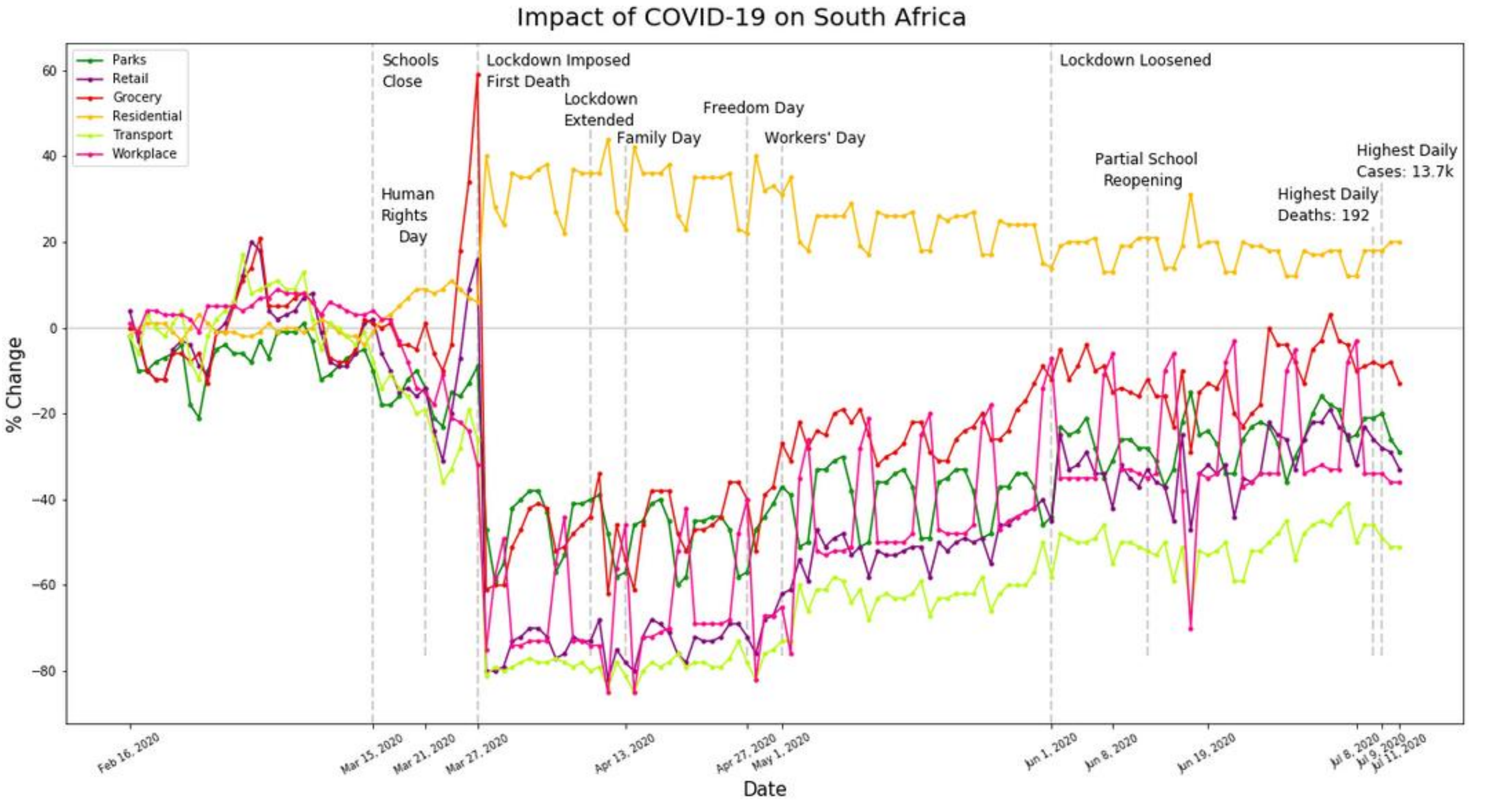


Figure A.14: Graph of the temporal variability of the daily Google-derived mobility categories, the daily COVID-19 cases & death rates from OWID for South Africa (n=145) in relation to government announcements, including travel restrictions and lockdowns/stay-at-home orders and national holidays from 16/02/2020 to 11/07/2020. The data used is the raw unprocessed data. The Google-derived mobility categories are Retail & Recreation, Grocery & Pharmacy Stores, Parks, Transit Stations, Workplaces and Residential, and they are represented as the % change in relation to a 5 week baseline ranging from 03/01/2020 to 06/02/2020.

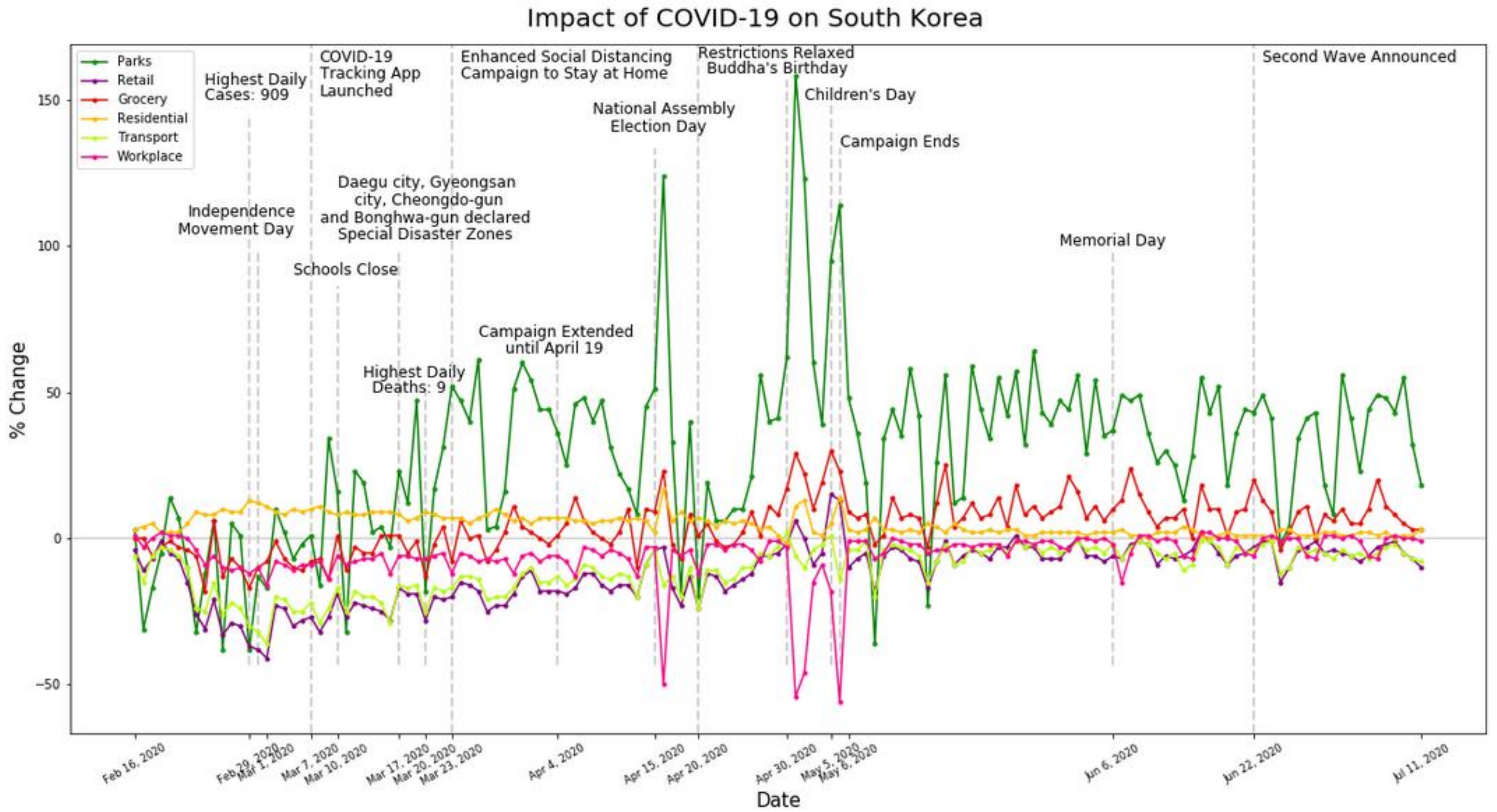


Figure A.15: Graph of the temporal variability of the daily Google-derived mobility categories, the daily COVID-19 cases & death rates from OWID for South Korea (n=145) in relation to government announcements, including travel restrictions and lockdowns/stay-at-home orders and national holidays from 16/02/2020 to 11/07/2020. The data used is the raw unprocessed data. The Google-derived mobility categories are Retail & Recreation, Grocery & Pharmacy Stores, Parks, Transit Stations, Workplaces and Residential, and they are represented as the % change in relation to a 5 week baseline ranging from 03/01/2020 to 06/02/2020.

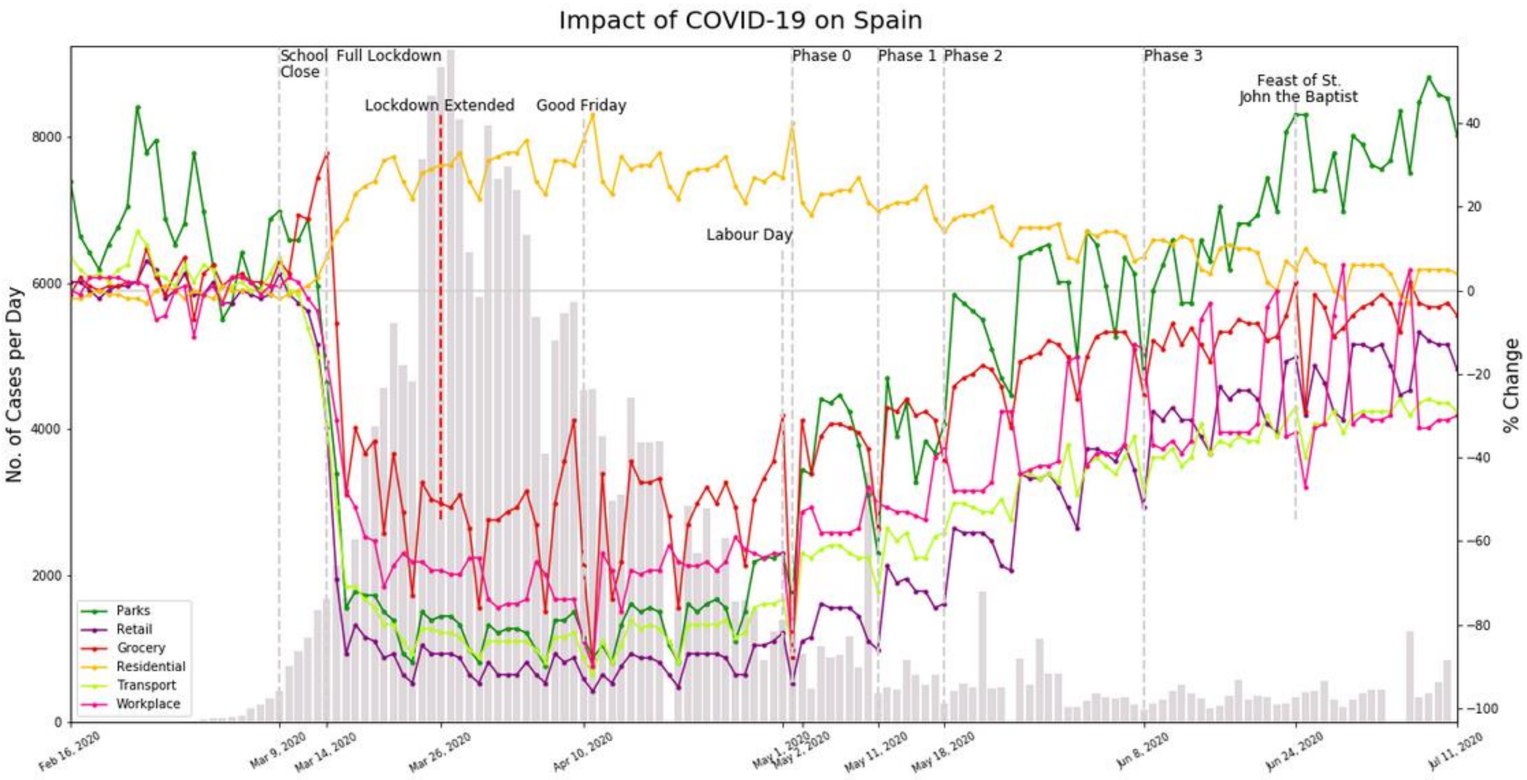


Figure A.16: Graph of the temporal variability of the daily Google-derived mobility categories, the daily COVID-19 cases & death rates from OWID for Spain (n=145) in relation to government announcements, including travel restrictions and lockdowns/stay-at-home orders and national holidays from 16/02/2020 to 11/07/2020. The data used is the raw unprocessed data. The Google-derived mobility categories are Retail & Recreation, Grocery & Pharmacy Stores, Parks, Transit Stations, Workplaces and Residential, and they are represented as the % change in relation to a 5 week baseline ranging from 03/01/2020 to 06/02/2020.

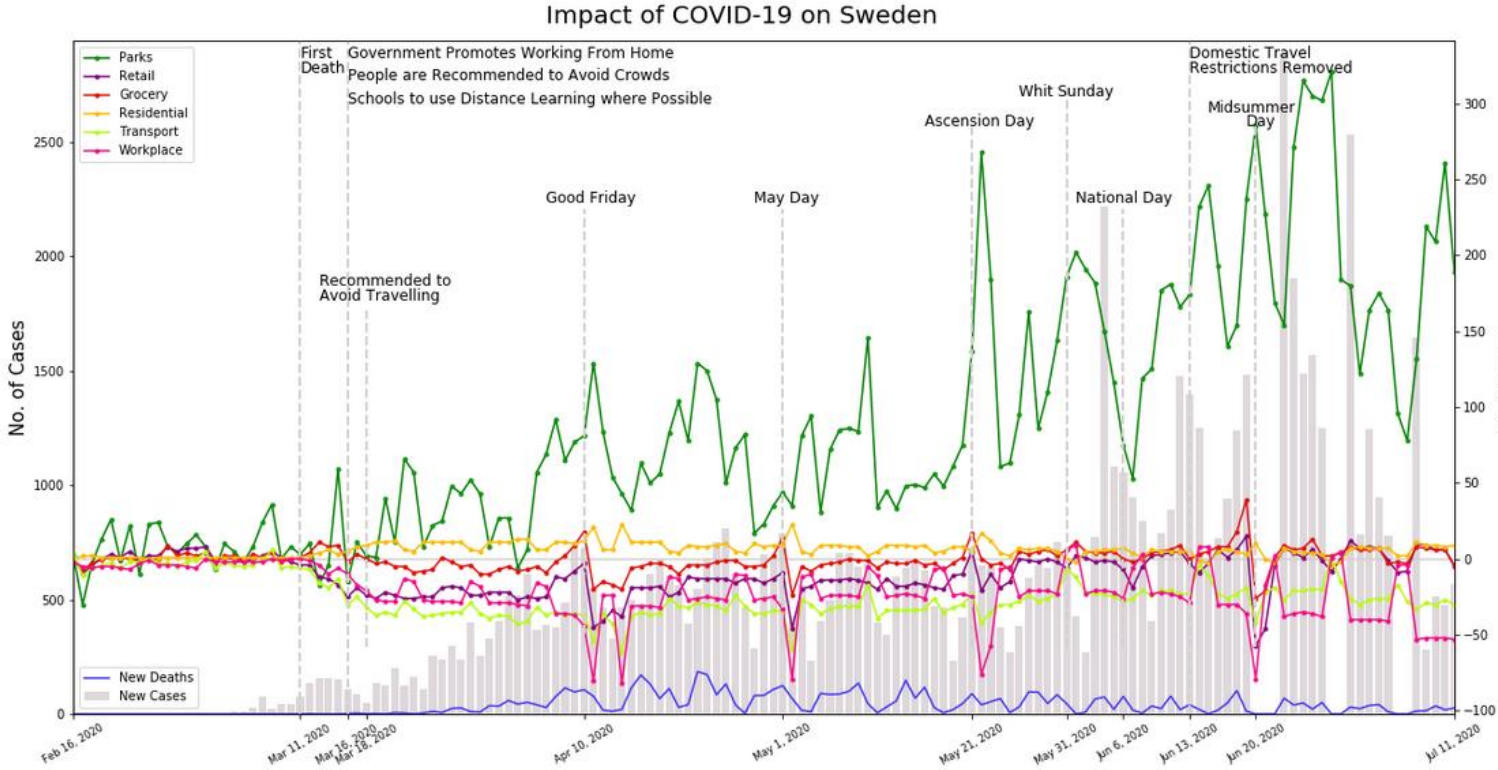


Figure A.17: Graph of the temporal variability of the daily Google-derived mobility categories, the daily COVID-19 cases & death rates from OWID for Sweden (n=145) in relation to government announcements, including travel restrictions and lockdowns/stay-at-home orders and national holidays from 16/02/2020 to 11/07/2020. The data used is the raw unprocessed data. The Google-derived mobility categories are Retail & Recreation, Grocery & Pharmacy Stores, Parks, Transit Stations, Workplaces and Residential, and they are represented as the % change in relation to a 5 week baseline ranging from 03/01/2020 to 06/02/2020.

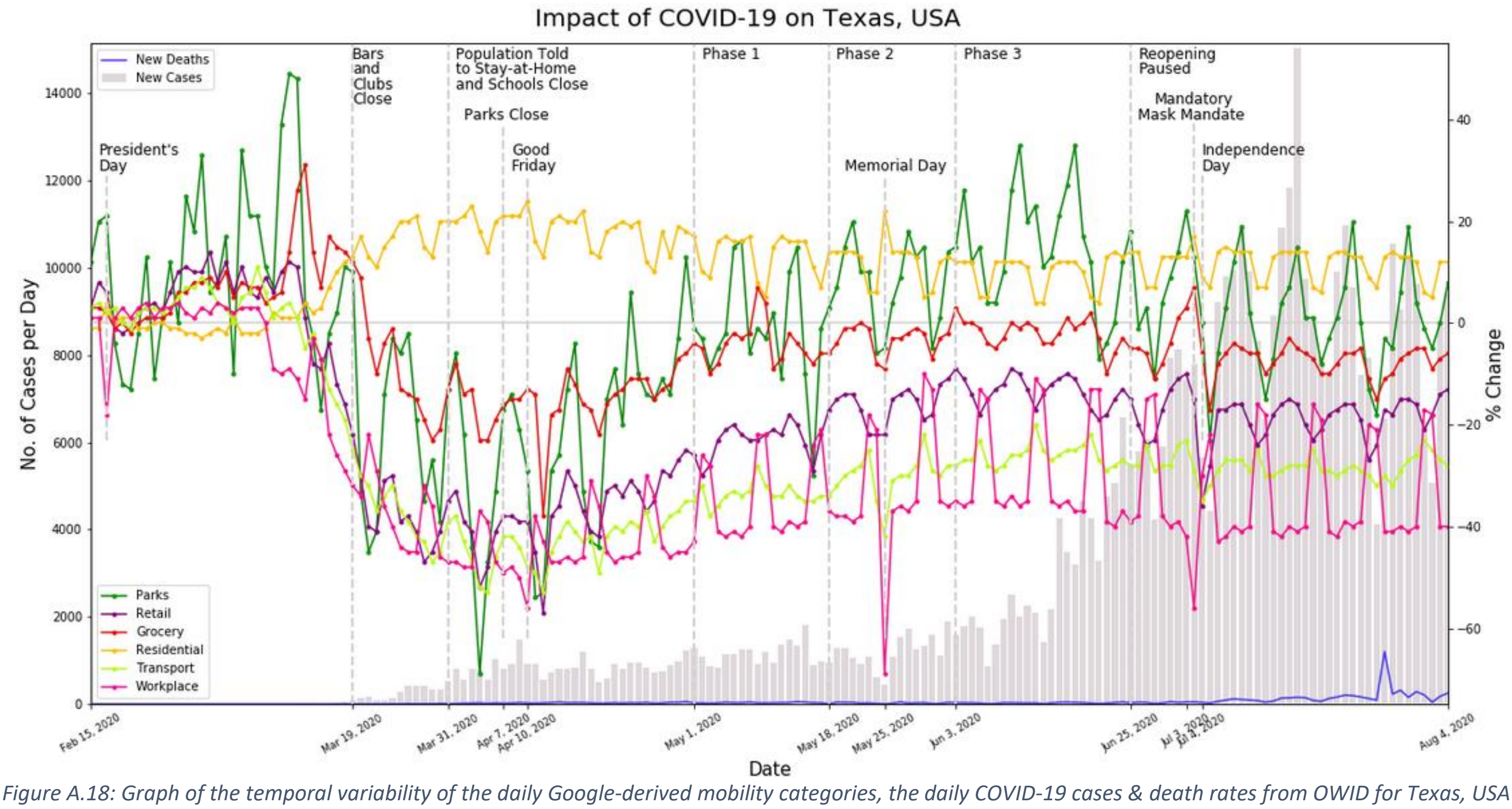


Figure A.18: Graph of the temporal variability of the daily Google-derived mobility categories, the daily COVID-19 cases & death rates from OWID for Texas, USA (n=169) in relation to government announcements, including travel restrictions and lockdowns/stay-at-home orders and national holidays from 16/02/2020 to 04/08/2020. The data used is the raw unprocessed data. The Google-derived mobility categories are Retail & Recreation, Grocery & Pharmacy Stores, Parks, Transit Stations, Workplaces and Residential, and they are represented as the % change in relation to a 5 week baseline ranging from 03/01/2020 to 06/02/2020.

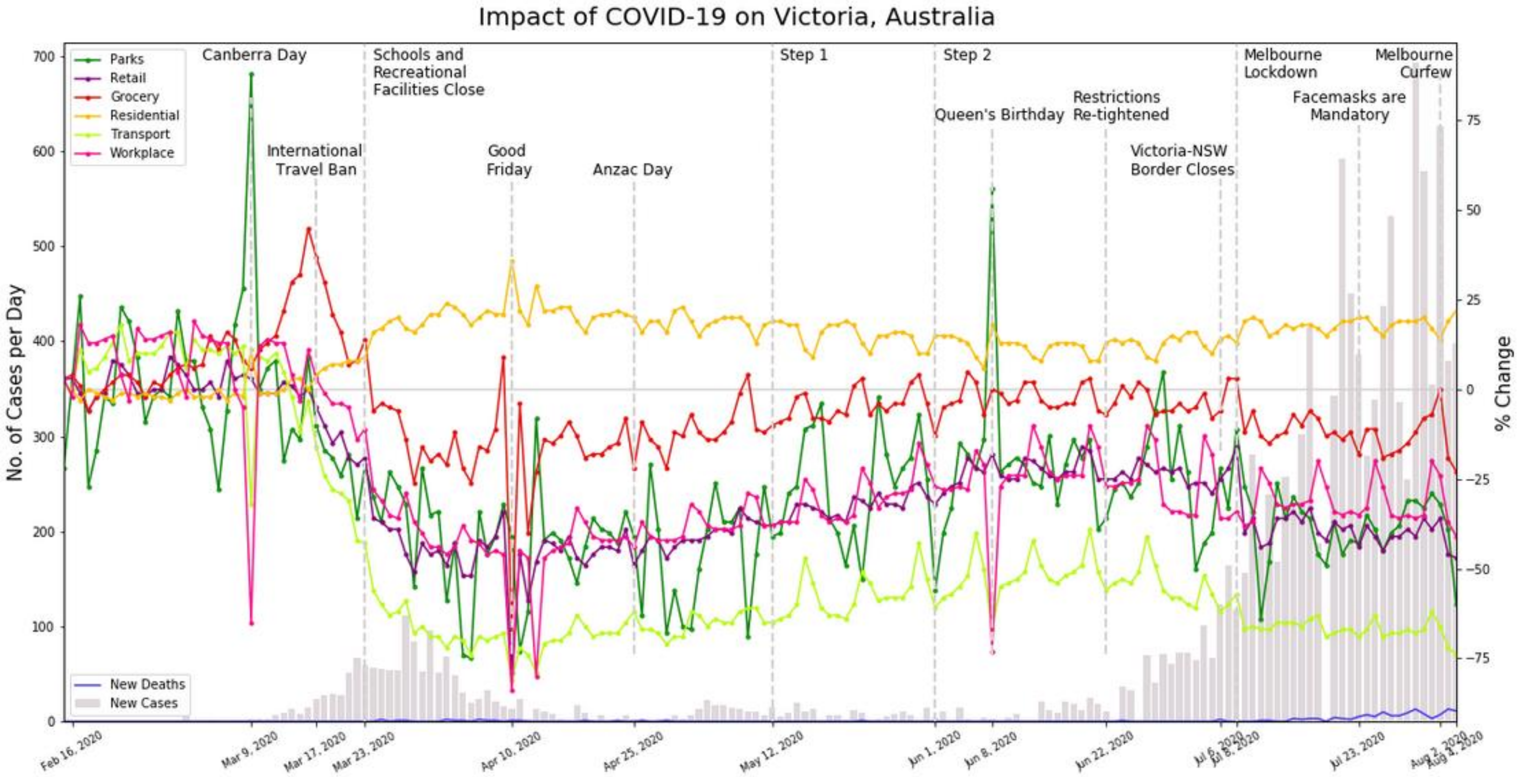


Figure A.19: Graph of the temporal variability of the daily Google-derived mobility categories, the daily COVID-19 cases & death rates from OWID for Victoria, Australia (n=169) in relation to government announcements, including travel restrictions and lockdowns/stay-at-home orders and national holidays from 16/02/2020 to 04/08/2020. The data used is the raw unprocessed data. The Google-derived mobility categories are Retail & Recreation, Grocery & Pharmacy Stores, Parks, Transit Stations, Workplaces and Residential, and they are represented as the % change in relation to a 5 week baseline ranging from 03/01/2020 to 06/02/2020.

Appendix B

```
# import all libraries
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
from sklearn.linear_model import LinearRegression
from mpl_toolkits.mplot3d import Axes3D
```

```
# read in all relevant csv files
visitorData = 'E:\Google CSV File'
dataVisitors = pd.read_csv(visitorData)
deathData = 'E:\OWID COVID-19 CSV File'
dataDeaths = pd.read_csv(deathData)
mobilityData = 'E:\Apple CSV File'
dataMobility = pd.read_csv(mobilityData)
```

```
# to organise the data for any country
def countryData(Country):
    x = Country
    Apple = dataMobility.T
    Apple.columns = Apple.iloc[0,:]
    Apple = Apple.drop(Apple.index[[0,0]])
    Apple = Apple.rename_axis(None, axis = 1)#organise Apple mobility data

    Country = Apple['Republic of Korea'] # select country for Apple data
    Country.columns = Country.iloc[0,:]
    Country = Country.drop(Country.index[[0,1]])
    Country[:] -= 100 # set Apple data to the same baseline as Google data
    indexValues = Country.index.values
    Dates = pd.DataFrame(indexValues, columns=['Date'])
    Country = Country.reset_index(drop=True)
    join = pd.concat([Dates,Country],axis=1) # tidy Apple data for merging

    finalCountry = dataVisitors.loc[dataVisitors.Entity == x]#selectGoogle
    Deaths = dataDeaths.loc[dataDeaths.location==x]#select death+case data
```

```
    Travel = join.copy() # select the Apple data


    merged = pd.merge(finalCountry, Deaths,how='outer') # merge datasets

    merged =
merged.drop(['total_cases','location','human_development_index','total_vac
cinations','new_vaccinations_smoothed_per_million','total_vaccinations_per
_hundred','new_vaccinations','new_vaccinations_smoothed','positive_rate','
tests_per_case','weekly_hosp_admissions','weekly_hosp_admissions_per_milli
on','weekly_icu_admissions','weekly_icu_admissions_per_million','reproduct
ion_rate','hosp_patients','hosp_patients_per_million','icu_patients','icu_
patients_per_million','new_cases_smoothed','new_deaths_smoothed_per_millio
n','new_deaths_smoothed','new_cases_smoothed_per_million','total_deaths','
total_cases_per_million','new_cases_per_million',
'total_deaths_per_million','new_deaths_per_million', 'total_tests',
'new_tests','total_tests_per_thousand',
'new_tests_per_thousand','new_tests_smoothed',
'new_tests_smoothed_per_thousand', 'tests_units', 'stringency_index',
'population', 'population_density', 'median_age','aged_65_older',
'aged_70_older', 'gdp_per_capita',
'extreme_poverty','cardiovasc_death_rate', 'diabetes_prevalence',
'female_smokers','male_smokers', 'handwashing_facilities',
'hospital_beds_per_thousand','life_expectancy' ], 1) # drop columns

    merged = pd.merge(merged, Travel,how='outer')

    merged = merged.loc[0:333]

    merged = merged.replace(np.nan, 0)#tidy merged dataset, filling blanks

    return merged
```

```
# to create graphs of the dataset values, where "diff" refers to days
passed since last milestone

def
googleGraph(nameOfCountry,yMaximum,Country,day1,Date1,a,day2diff,Date2,b,d
ay3diff,Date3,c,day4diff,Date4,d,day5diff,Date5,e):

    fig = plt.figure(figsize=(20,10))

    ax =fig.add_subplot(1,1,1)


    baseDate = Country['Date'][0]


    # plot case and death data

    plt.axvspan(0,day2diff,facecolor='#95c5e8',alpha=0.5)

    plt.axvspan(day2diff,day3diff,facecolor='#8858f6',alpha=0.5)

    plt.axvspan(day3diff,333,facecolor='#f8585a',alpha=0.5)

    ax.bar(Country['Date'],Country['new_cases'],color = '#9d9d9d', label =
'New Cases')
```

```
    ax.plot(Country['Date'], Country['new_deaths'], color='#ff0d0d', label
='New Deaths')
    ax.legend(loc='lower left')
    ax.set_xlim(xmin = Country['Date'][0],xmax=Country['Date'][333])
    ax2 = ax.twinx()

    # plot Google mobility data
    ax2.axhline(y=0, color='#d4d2d1', linestyle='-')
    ax.set_ylim(ymin = 0,ymax=Country['new_cases'].max() + 50)
    ax2.plot(Country['Date'], Country['Parks (%)'], 'g', marker = 'o',
markerfacecolor='#11bd01', markersize=3, label ='Parks')
    ax2.plot(Country['Date'], Country['Retail & Recreation (%)'],
'#85067d', marker = 'o', markerfacecolor='#85067d', markersize=3, label
='Retail')
    ax2.plot(Country['Date'], Country['Grocery & Pharmacy Stores (%)'],
'#e5100d', marker = 'o', markerfacecolor='#e5100d', markersize=3, label
='Grocery')
    ax2.plot(Country['Date'], Country['Residential (%)'], '#fbbe04',
marker = 'o', markerfacecolor='#fbbe04', markersize=3, label
='Residential')
    ax2.plot(Country['Date'], Country['Transit Stations (%)'], '#bbfc16',
marker = 'o', markerfacecolor='#bbfc16', markersize=3, label ='Transport')
    ax2.plot(Country['Date'], Country['Workplaces (%)'], '#fa0b8b', marker
= 'o', markerfacecolor='#fa0b8b', markersize=3, label ='Workplace')

    plt.xlabel("Date",fontsize=15)
    plt.ylabel("% Change",fontsize=15)

    Head = yMaximum - 2

    ax2.text(Date1, Head-10, 'Special Disaster' ,fontsize=12)# for event 1
    ax2.text(Date1, Head-13, 'Zones Declared' ,fontsize=12)# for event 1
    ax2.text(Date2, Head, b ,fontsize=12)# for event 2
    ax2.text(Date3, Head, 'Seoul' ,fontsize=12)# for event 3
    ax2.text(Date3, Head-3, 'Restrictions' ,fontsize=12)# for event 3
    ax2.text(Date4, Head, d ,fontsize=12)# for event 4
    ax2.text(Date5, Head, e ,fontsize=12)# for event 5

    Title = 'Impact of COVID-19 on ' + nameOfCountry
    plt.figtext(.5,.9,Title, fontsize=20, ha='center')
```

```
    ax2.legend(loc='best')

    plt.axvline(x=day1, linewidth=2, color='#d4d2d1', linestyle='--')#for full lockdown
    plt.axvline(x=day2diff, linewidth=2, color='#d4d2d1', linestyle='--')#for lockdown extended
    plt.axvline(x=day3diff, linewidth=2, color='#d4d2d1', linestyle='--')#for schools close
    plt.axvline(x=day4diff, linewidth=2, color='#d4d2d1', linestyle='--')#for phase 0
    plt.axvline(x=day5diff, linewidth=2, color='#d4d2d1', linestyle='--')#for good friday and lockdown extended again

    ax.set_ylabel('No. of Cases per Day', fontsize=15)
    ticks = ax.set_xticks([baseDate, Date1, Date2, Date3, Date4, Date5])
    labels = ax.set_xticklabels([baseDate, Date1, Date2, Date3, Date4, Date5],rotation=30, fontsize='small')
    ax.set_xlabel("Date",fontsize=15)
    return
```

```
from datetime import datetime
date_format = "%d/%m/%Y"

# calculate number of days between date and first day
def diffDays(firstDate,date,date_format):
    day = datetime.strptime(date, date_format)
    Sum = day - firstDate
    number = Sum.days
    return number
```

```
# country
x = 'Name'
country = countryData(x) # creates dataset for country
firstDate = datetime.strptime('17/02/2020', date_format)

date1 = '01/01/2020' # day 1 info
number1 = diffDays(firstDate,date1,date_format)
title1 = 'Day 1'
```

```
date2 = '02/02/2020' # day 2 info
number2 = diffDays(firstDate,date2,date_format)
title2 = 'Day 2'

date3 = '03/03/2020' # day 3 info
number3 = diffDays(firstDate,date3,date_format)
title3 = 'Day 3'

date4 = '04/04/2020' # day 4 info
number4 = diffDays(firstDate,date4,date_format)
title4 = 'Day 4'

date5 = '05/05/2020' # day 5 info
number5 = diffDays(firstDate,date5,date_format)
title5 = 'Day 5'

googleGraph(x,98,country,number1,date1,title1,number2,date2,title2,number3
,date3,title3,number4,date4,title4,number5,date5,title5)
dates = [date1,date2,date3,date4,date5]
```

```
# generates country statistics
def stats(df,column):
    mean = df[column].mean()
    std = df[column].std()
    Min = df[column].min()
    Max = df[column].max()
    stat =[mean,std,Min,Max]
    return stat

# loops though country categories
Columns = country.columns[2:10]
for column in Columns:
    print(column, ':', stats(country,column))
```

```
# correlation of the country
corr = country.corr(method='spearman')
plt.figure(figsize=(10, 8))
```

```
ax = sns.heatmap(
    corr, # correlation value r - strength of linear relationship
    vmin=-1, vmax=1, center=0,
    cmap='coolwarm',
    square=True,
    annot = True,
    fmt='.2g'
)
ax.set_xticklabels(
    ax.get_xticklabels(),
    rotation=45,
    horizontalalignment='right'
);
plt.figtext(.5,.9,'Correlation of COVID-19 Factors of ' + x, fontsize=15,
ha='center')
```

```
def correlation(mylist,number,title,days):

    '''
    Prints off correlation matrix of a lockdown period.
    Creating a certain number of "days" window of the visits compared to
the subsequent
    number of "days" of case rises before a lockdown and producing the
resultant
    subset.
    '''

    lockDown = mylist.iloc[number-days:number,2:8] # Gathering Values
    Cases = mylist.iloc[number:number+days,9]
    Deaths = mylist.iloc[number:number+days,10]
    maxTemp = mylist.iloc[lockdown-days:lockdown,13]
    minTemp = mylist.iloc[lockdown-days:lockdown,14]
    Precipitation = mylist.iloc[lockdown-days:lockdown,15]

    lockDown["Cases"]= Cases.values #Adding Values to lockDown DataFrame
    lockDown["Deaths"]= Deaths.values
    lockDown["Max Temp"]= maxTemp.values
```

```
    lockDown["Min Temp"]= minTemp.values
    lockDown["Precipitation"]= Precipitation.values
    lockDown.reset_index(drop=True, inplace=True)

    corrL = lockDown.corr(method='spearman')
    plt.figure(figsize=(10, 8))
    ax = sns.heatmap(
    corrL,
    vmin=-1, vmax=1, center=0,
    cmap='coolwarm',
    square=True,
    annot = True,
    fmt='.2g'
    )
    ax.set_xticklabels(
        ax.get_xticklabels(),
        rotation=45,
        horizontalalignment='right'
    );
    plt.figtext(.5,.9,'Correlation of COVID-19 Factors of ' + x + '
related to ' + title ,fontsize=15, ha='center')
    return lockdown
```

```
# event example for correlation matrix and statistics
lag = 14
lockDown1 = correlation(country,number1,title1,lag)
lock1Cols = lockDown1.columns
for column in lock1Cols:
    print(column, ':', stats(lockDown1,column))
```

```
def singleLinearRegression(mylist,xAxis,yAxis):
    '''Perform OLS Single Linear Regression'''
    X = mylist.iloc[:, xAxis].values.reshape(-1, 1)#values convert-nparray
    Y = mylist.iloc[:, yAxis].values.reshape(-1, 1)
    linear_regressor = LinearRegression()
    model = linear_regressor.fit(X, Y)  # perform linear regression
```

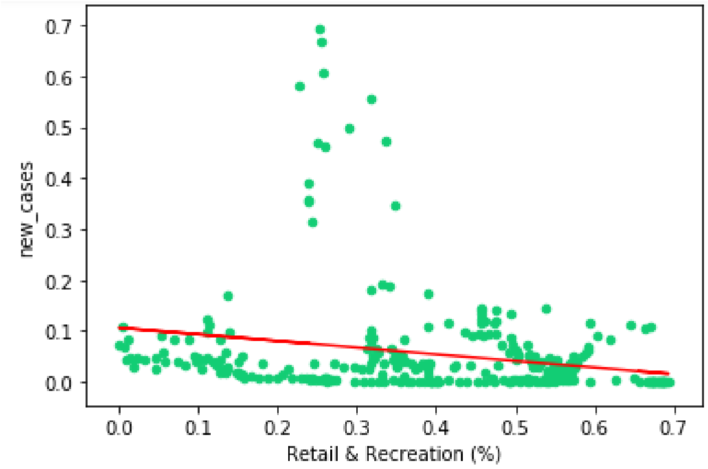
```
    Y_pred = model.predict(X)  # make predictions

    fig = plt.figure(figsize=(6,4))
    ax =fig.add_subplot(1,1,1)
    plt.scatter(X, Y, c='#12cd74', s=20)
    plt.plot(X, Y_pred, color='red')
    plt.title('Linear Regression Analysis',fontsize=15, ha='center')
    plt.xlabel(mylist.columns[xAxis],fontsize=10)
    plt.ylabel(mylist.columns[yAxis],fontsize=10)
    plt.show()
    r_sq = model.score(X, Y)

    X2 = sm.add_constant(X)
    est = sm.OLS(Y, X2)
    est2 = est.fit()
    print(est2.summary())
    print('regression coefficients:', est2.params)
    print('R-squared: %.3f' % r_sq) # coefficient of determination r2
    print('α constant (intercept): %.3f' % model.intercept_) # intercept
    print('β coefficient (slope): %.3f' % model.coef_) # slope of line
    return
```

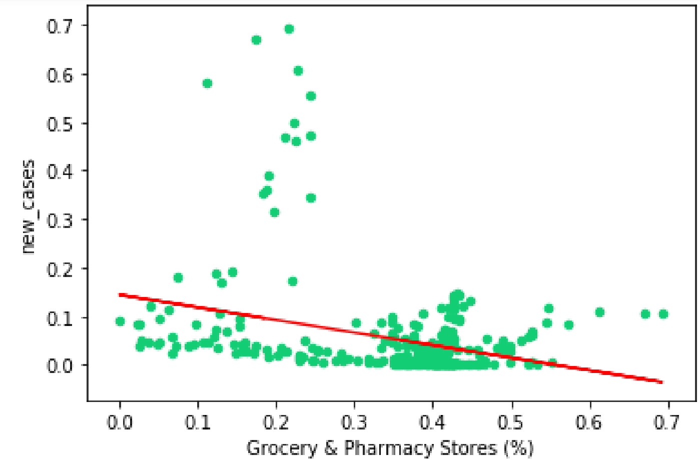
```
# Total OLS Regression Model
Length = [2,3,4,5,6,7,9,10,11,12]
for i in Length:
    singleLinearRegression(country,i,8)
```

Appendix C



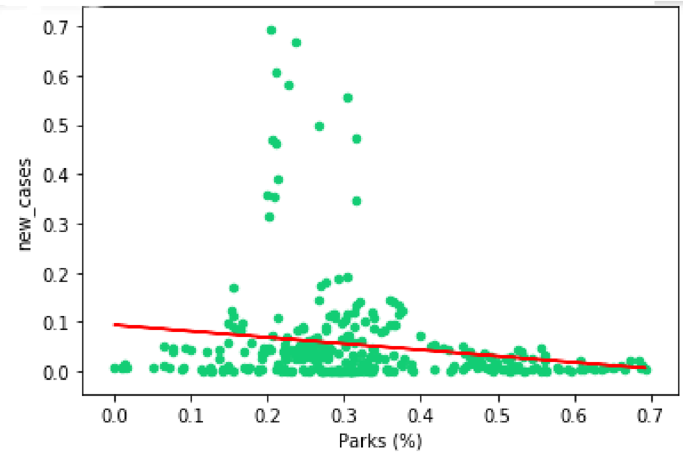
R-squared: 0.053
α constant (intercept): 0.106
β coefficient (slope): -0.130

Figure C.1: Relationship between Case Numbers and Retail & Recreational Visits between 17/02/2020 and 15/01/2021 in Ireland



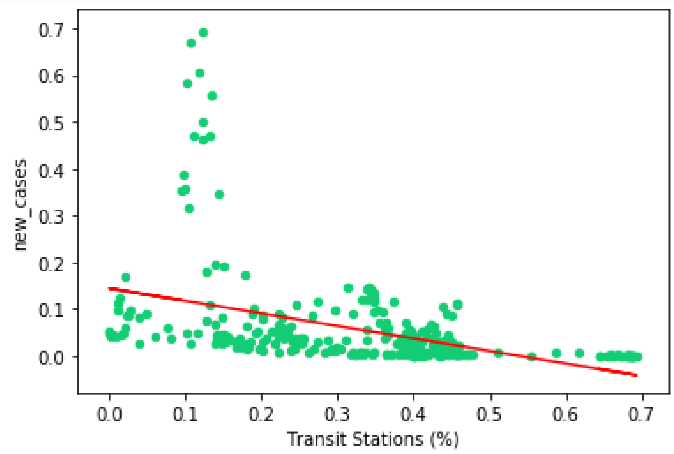
R-squared: 0.097
α constant (intercept): 0.144
β coefficient (slope): -0.259

Figure C.2: Relationship between Case Numbers and Grocery & Pharmacy Store Visits between 17/02/2020 and 15/01/2021 in Ireland



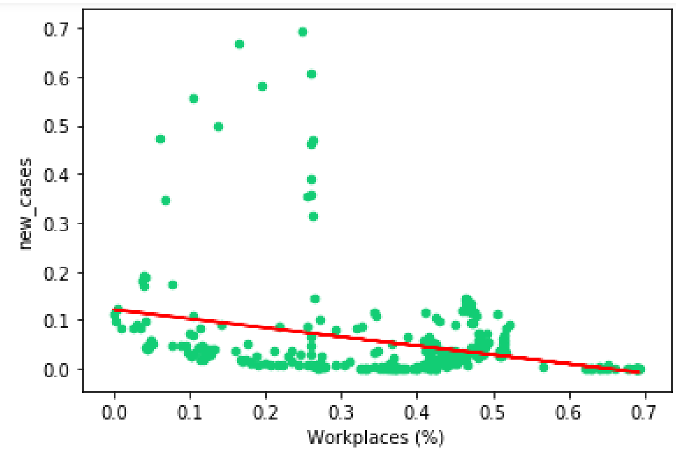
R-squared: 0.033
α constant (intercept): 0.094
β coefficient (slope): -0.127

Figure C.3: Relationship between Case Numbers and Park Visits between 17/02/2020 and 15/01/2021 in Ireland



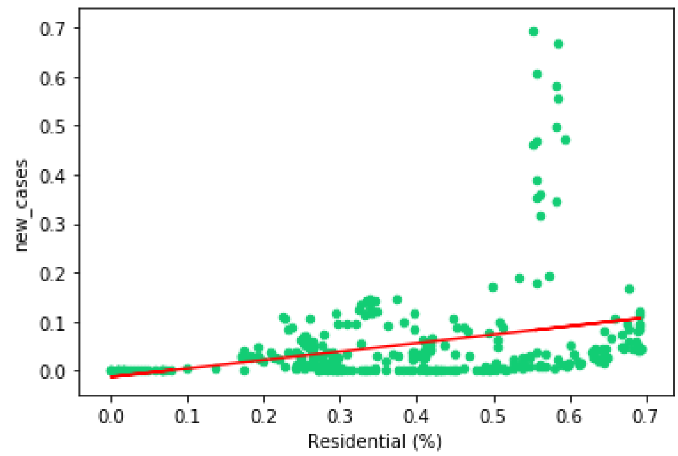
R-squared: 0.185
α constant (intercept): 0.144
β coefficient (slope): -0.268

Figure C.4: Relationship between Case Numbers and Transit Station Visits between 17/02/2020 and 15/01/2021 in Ireland



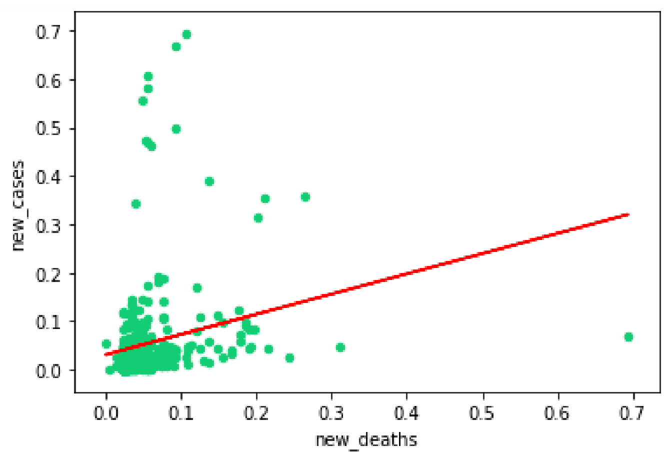
R-squared: 0.092
α constant (intercept): 0.121
β coefficient (slope): -0.186

Figure C.5: Relationship between Case Numbers and Workplace Visits between 17/02/2020 and 15/01/2021 in Ireland



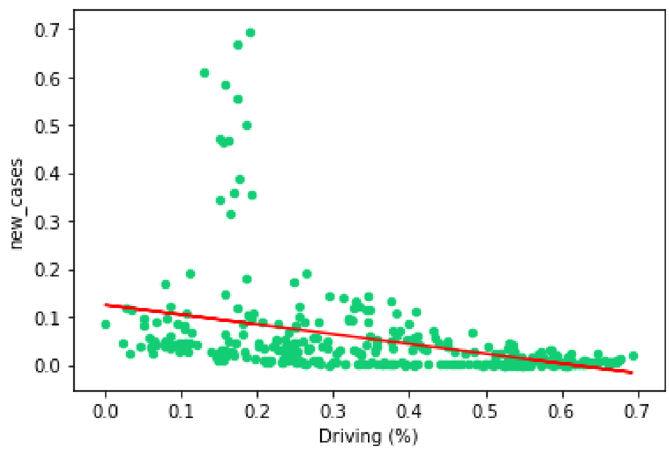
R-squared: 0.090
α constant (intercept): -0.013
β coefficient (slope): 0.172

Figure C.6: Relationship between Case Numbers and Residential Store Visits between 17/02/2020 and 15/01/2021 in Ireland



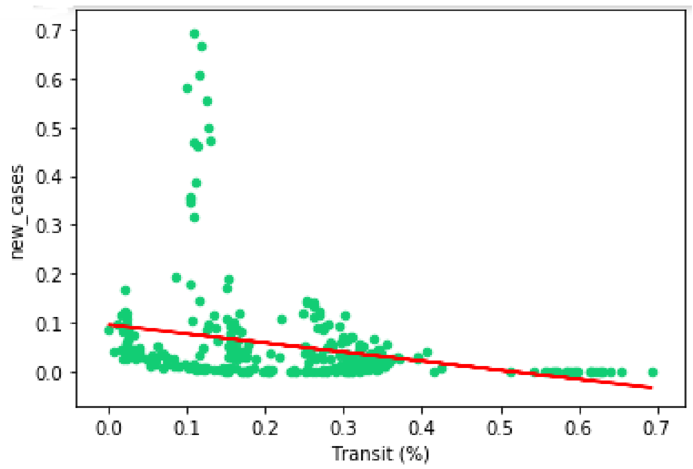
R-squared: 0.057
α constant (intercept): 0.031
β coefficient (slope): 0.417

Figure C.7: Relationship between Case Numbers and Deaths between 17/02/2020 and 15/01/2021 in Ireland



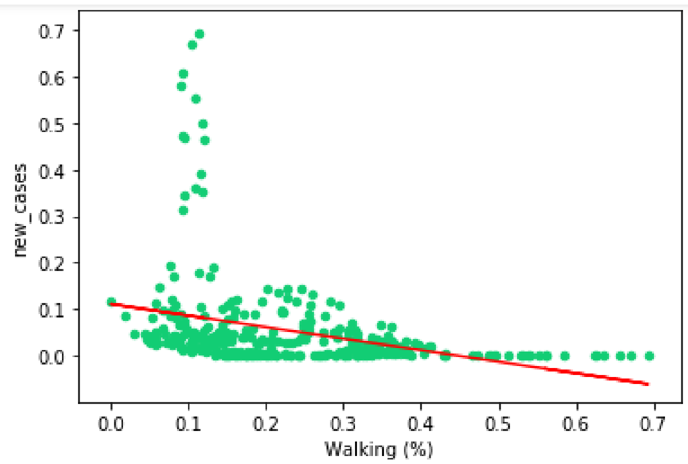
R-squared: 0.136
α constant (intercept): 0.125
β coefficient (slope): -0.203

Figure C.8: Relationship between Case Numbers and % Driving between 17/02/2020 and 15/01/2021 in Ireland



R-squared: 0.075
α constant (intercept): 0.096
β coefficient (slope): -0.186

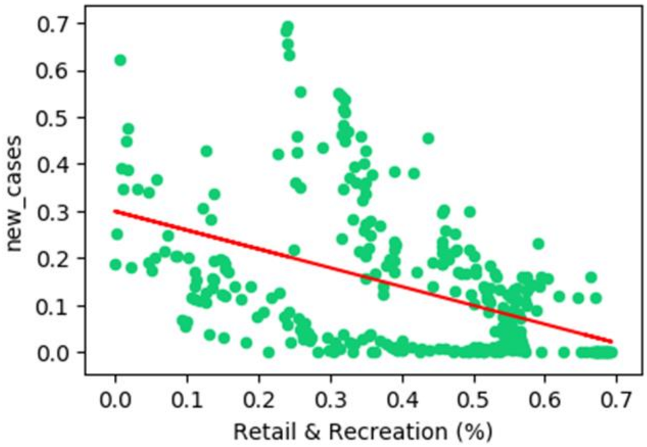
Figure C.9: Relationship between Case Numbers and % Transit between 17/02/2020 and 15/01/2021 in Ireland



R-squared: 0.107
α constant (intercept): 0.110
β coefficient (slope): -0.248

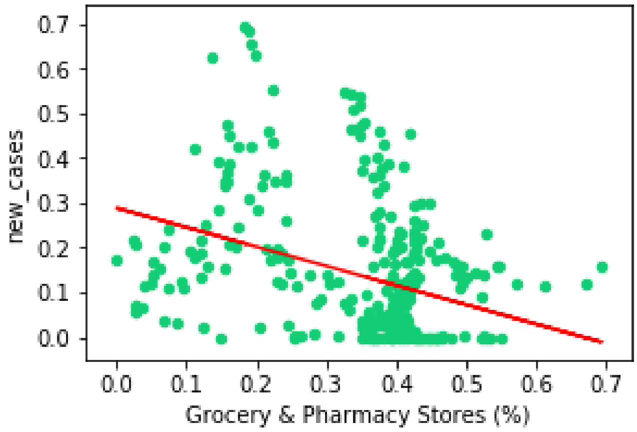
Figure C.10: Relationship between Case Numbers and % Walking between 17/02/2020 and 15/01/2021 in Ireland

Appendix D



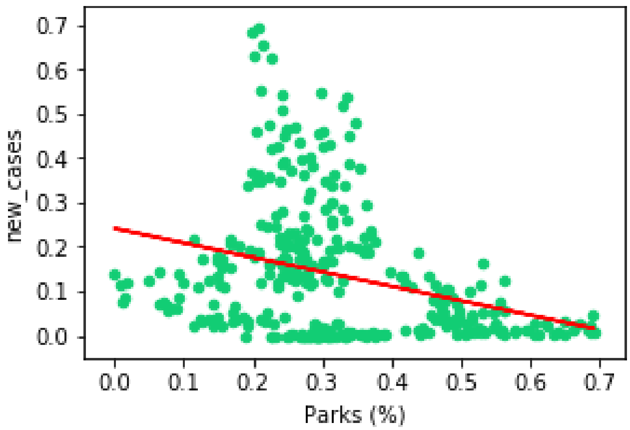
R-squared: 0.226
α constant (intercept): 0.300
β coefficient (slope): -0.400

Figure D.1: Relationship between Case Numbers and Retail & Recreational Visits between 17/02/2020 and 15/01/2021 in Ireland with a 14 day lag



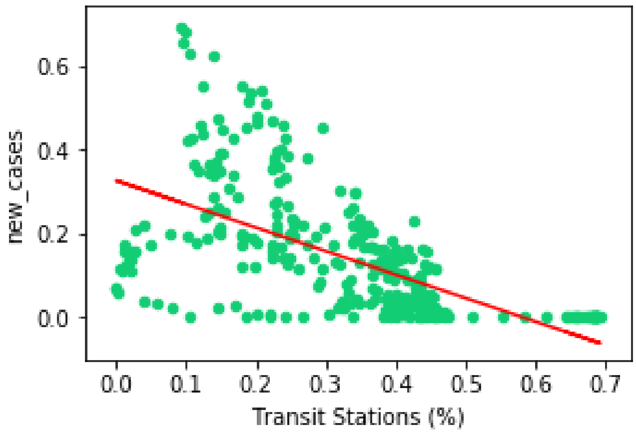
R-squared: 0.120
α constant (intercept): 0.288
β coefficient (slope): -0.431

Figure D.2: Relationship between Case Numbers and Grocery & Pharmacy Store Visits between 17/02/2020 and 15/01/2021 in Ireland with a 14 day lag



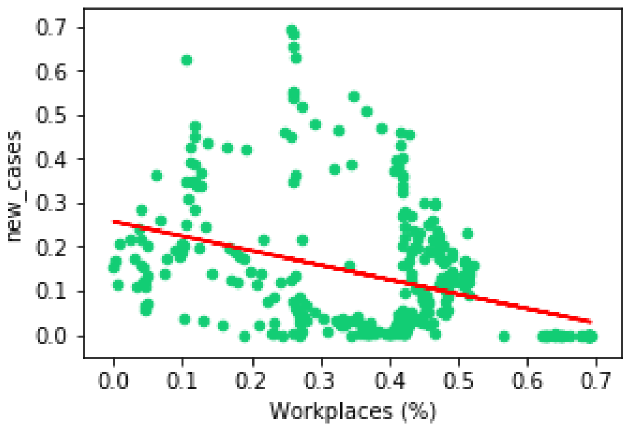
R-squared: 0.097
α constant (intercept): 0.241
β coefficient (slope): -0.325

Figure D.3: Relationship between Case Numbers and Park Visits between 17/02/2020 and 15/01/2021 in Ireland with a 14 day lag



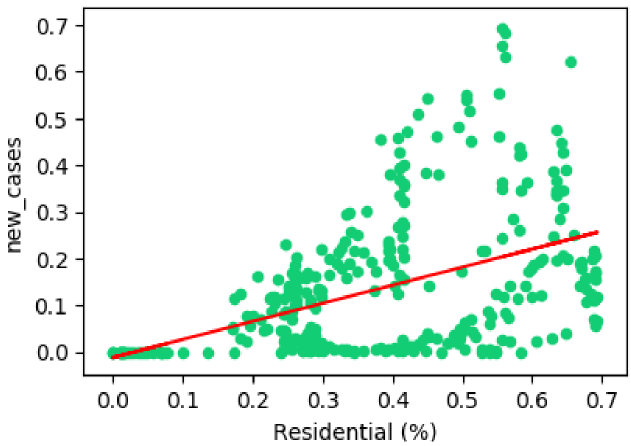
R-squared: 0.363
α constant (intercept): 0.325
β coefficient (slope): -0.561

Figure D.4: Relationship between Case Numbers and Transit Station Visits between 17/02/2020 and 15/01/2021 in Ireland with a 14 day lag



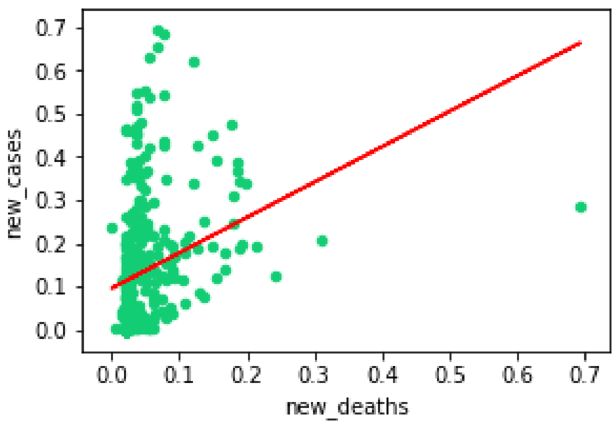
R-squared: 0.129
α constant (intercept): 0.256
β coefficient (slope): -0.329

Figure D.5: Relationship between Case Numbers and Workplace Visits between 17/02/2020 and 15/01/2021 in Ireland with a 14 day lag



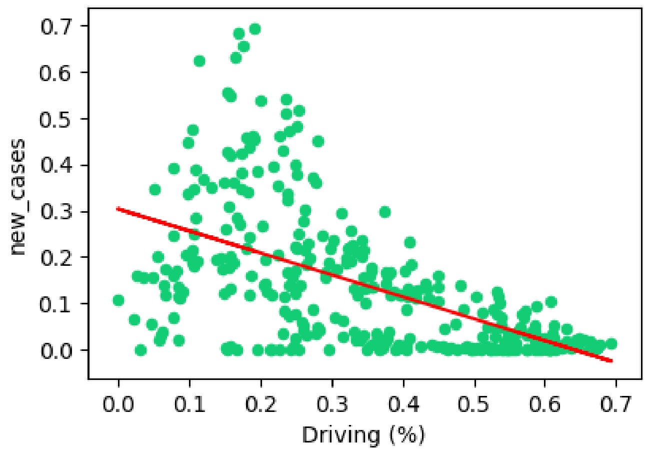
R-squared: 0.204
α constant (intercept): -0.012
β coefficient (slope): 0.387

Figure D.6: Relationship between Case Numbers and Residential Visits between 17/02/2020 and 15/01/2021 in Ireland with a 14 day lag



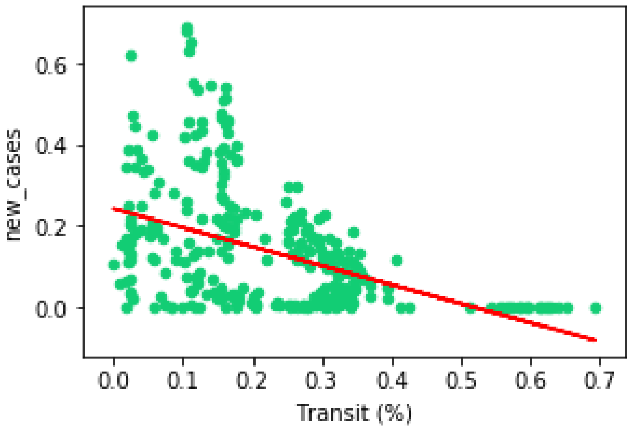
R-squared: 0.089
α constant (intercept): 0.096
β coefficient (slope): 0.817

Figure D.7: Relationship between Case Numbers and Deaths between 17/02/2020 and 15/01/2021 in Ireland with a 14 day lag



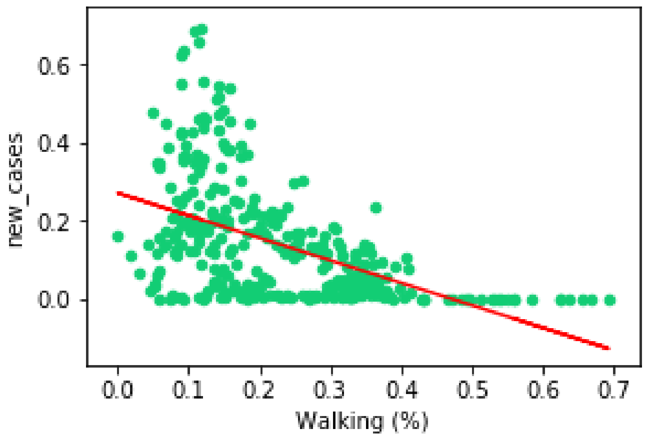
R-squared: 0.331
α constant (intercept): 0.304
β coefficient (slope): -0.473

Figure D.8: Relationship between Case Numbers and % Driving between 17/02/2020 and 15/01/2021 in Ireland with a 14 day lag



R-squared: 0.213
α constant (intercept): 0.243
β coefficient (slope): -0.468

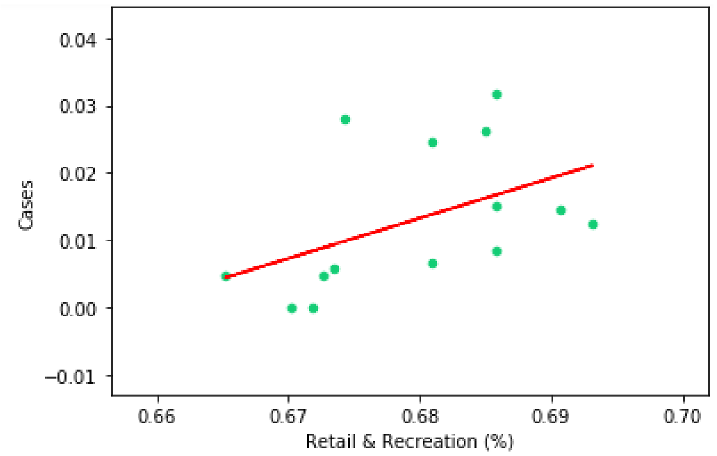
Figure D.9: Relationship between Case Numbers and % Transit between 17/02/2020 and 15/01/2021 in Ireland with a 14 day lag



R-squared: 0.258
α constant (intercept): 0.269
β coefficient (slope): -0.575

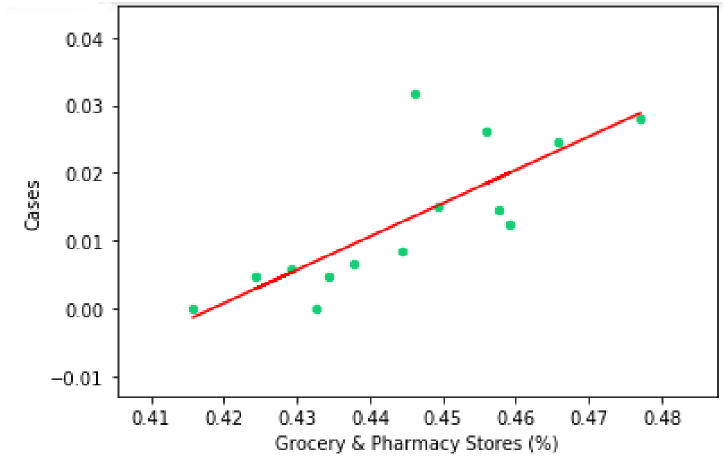
Figure D.10: Relationship between Case Numbers and % Walking between 17/02/2020 and 15/01/2021 in Ireland with a 14 day lag

Appendix E



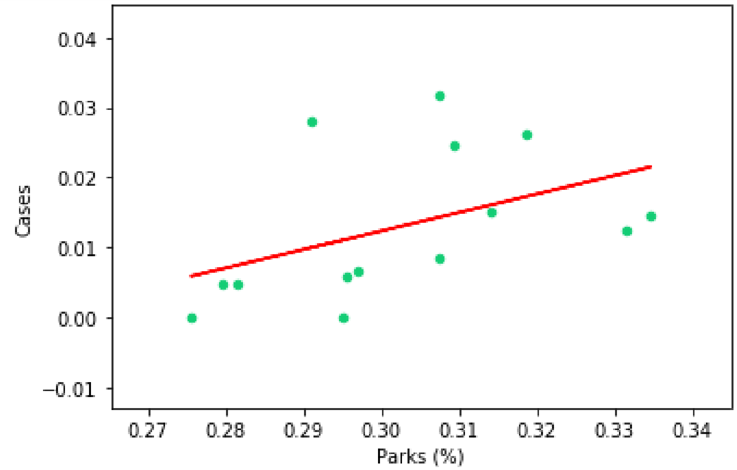

```
R-squared: 0.221
α constant (intercept): -0.392
β coefficient (slope): 0.596
```

Figure E.1: Relationship between Case Numbers and Retail & Recreation Visits around School Closures in Ireland



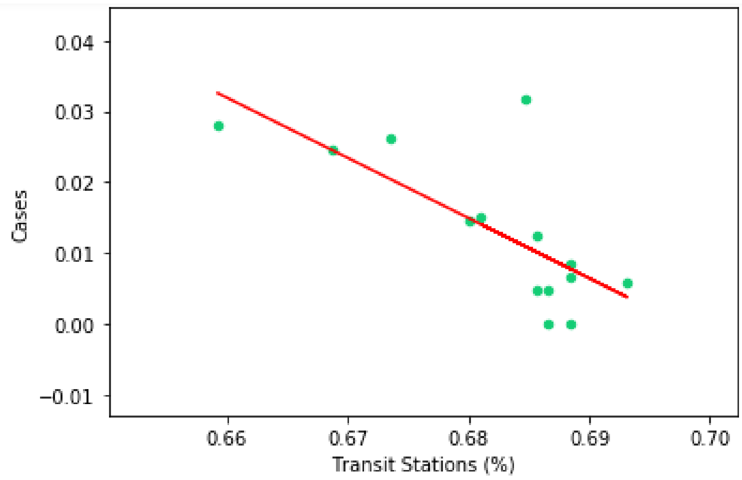

```
R-squared: 0.620
α constant (intercept): -0.206
β coefficient (slope): 0.492
```

Figure E.2: Relationship between Case Numbers and Grocery & Pharmacy Store Visits around School Closures in Ireland



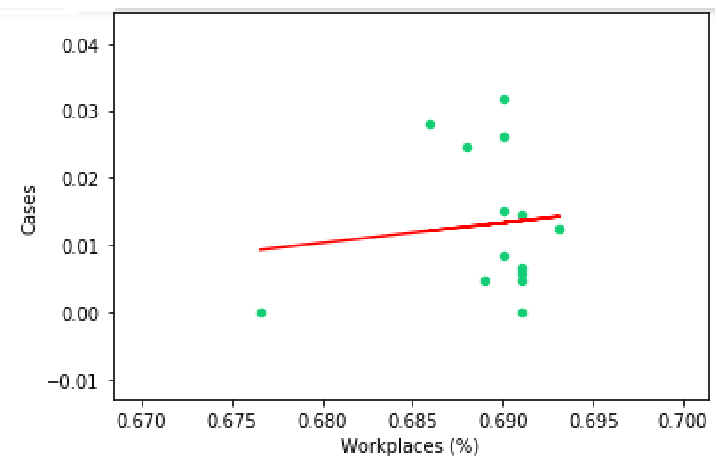

```
R-squared: 0.203
α constant (intercept): -0.067
β coefficient (slope): 0.264
```

Figure E.3: Relationship between Case Numbers and Park Visits around School Closures in Ireland



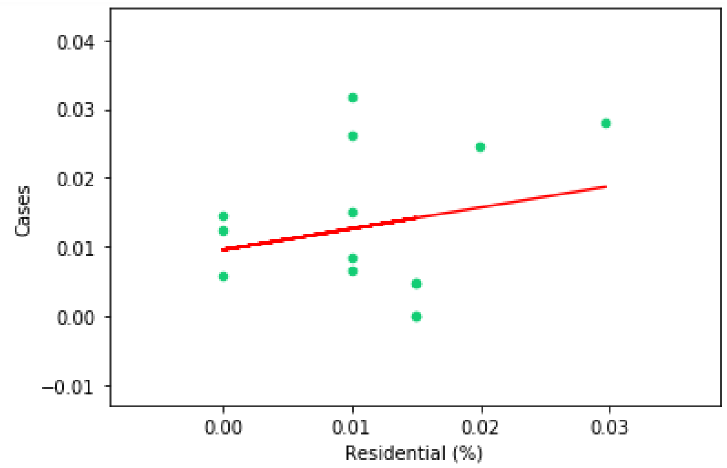

```
R-squared: 0.533
α constant (intercept): 0.592
β coefficient (slope): -0.849
```

Figure E.4: Relationship between Case Numbers and Transit Station Visits around School Closures in Ireland



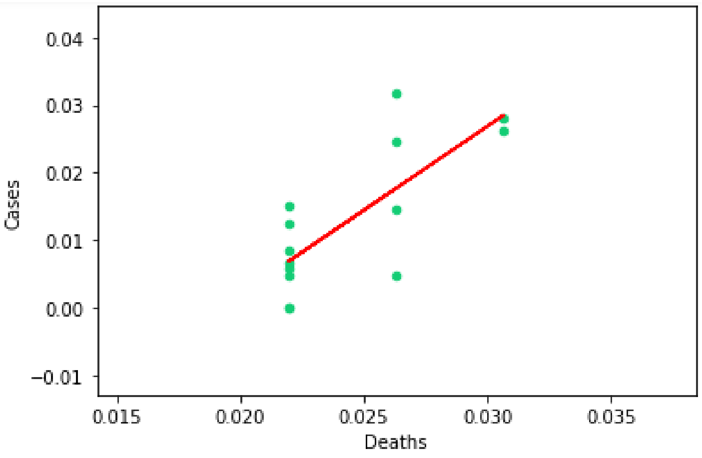

```
R-squared: 0.012
α constant (intercept): -0.192
β coefficient (slope): 0.298
```

Figure E.5: Relationship between Case Numbers and Workplace Visits around School Closures in Ireland



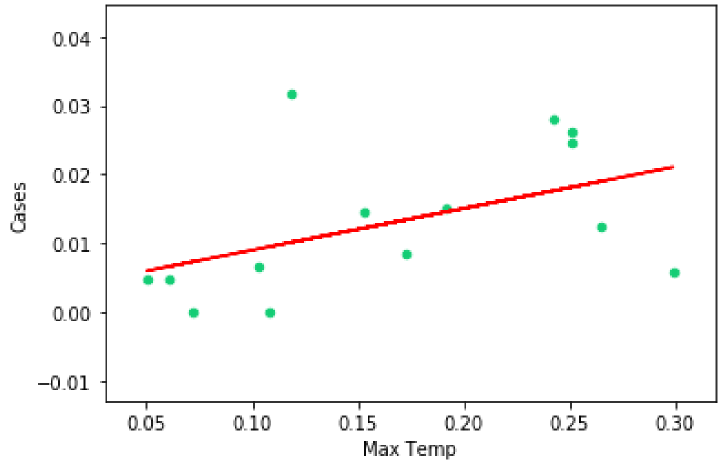

```
R-squared: 0.055
α constant (intercept): 0.010
β coefficient (slope): 0.308
```

Figure E.6: Relationship between Case Numbers and Residential Visits around School Closures in Ireland



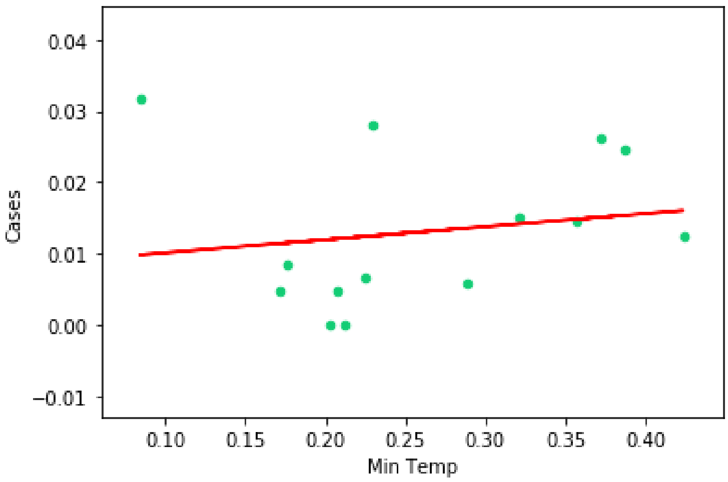
R-squared: 0.578
α constant (intercept): -0.048
β coefficient (slope): 2.483

Figure E.7: Relationship between Case Numbers and Deaths around School Closures in Ireland



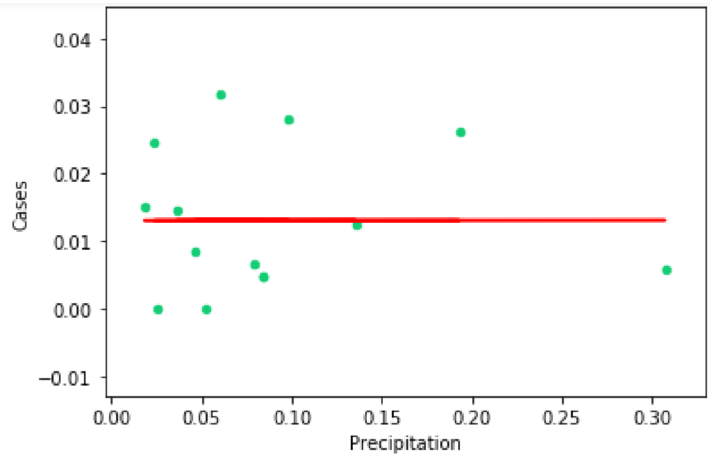
R-squared: 0.226
α constant (intercept): 0.003
β coefficient (slope): 0.061

Figure E.8: Relationship between Case Numbers and Max. Temperature around School Closures in Ireland



R-squared: 0.028
α constant (intercept): 0.008
β coefficient (slope): 0.018

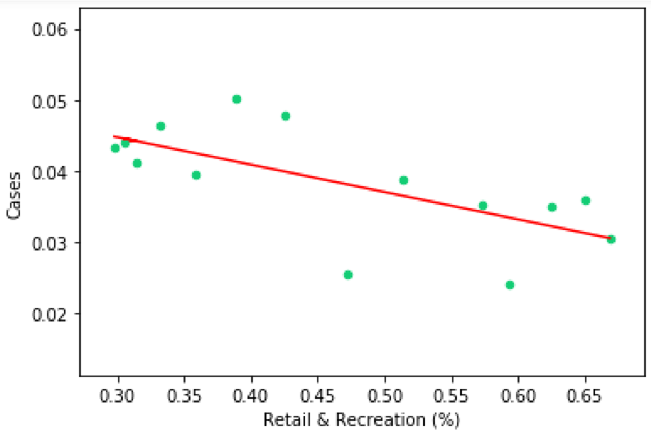
Figure E.9: Relationship between Case Numbers and Min. Temperature around School Closures in Ireland



R-squared: 0.000
α constant (intercept): 0.013
β coefficient (slope): 0.000

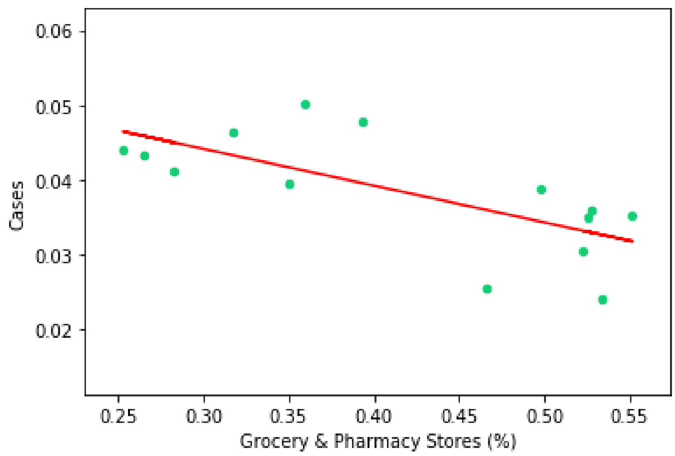
Figure E.10: Relationship between Case Numbers and Precipitation around School Closures in Ireland

Appendix F



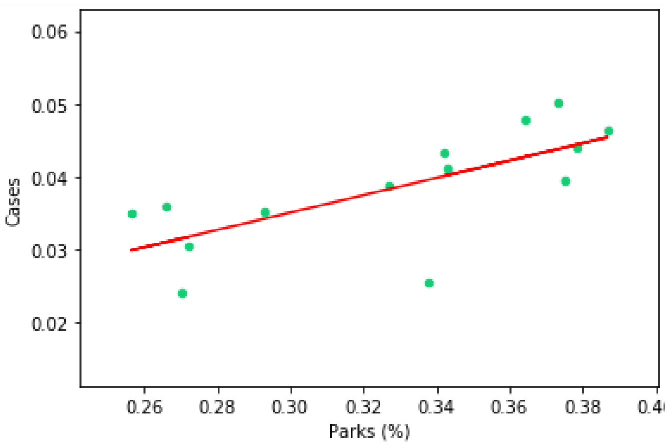

```
R-squared: 0.442
α constant (intercept): 0.056
β coefficient (slope): -0.038
```

Figure F.1: Relationship between Case Numbers and Retail & Recreational Visits during Lockdown 1 in Ireland



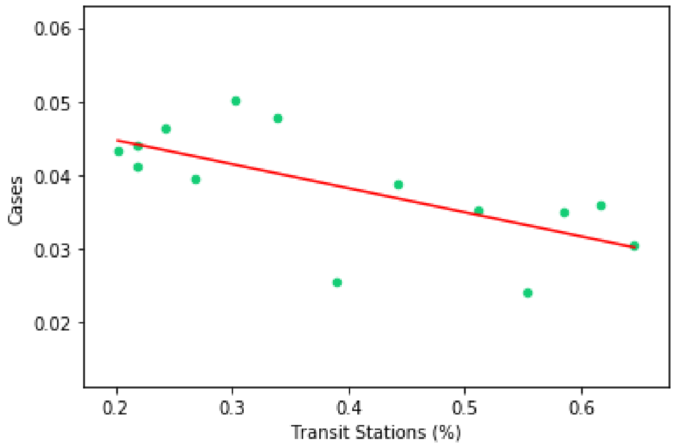

```
R-squared: 0.477
α constant (intercept): 0.059
β coefficient (slope): -0.049
```

Figure F.2: Relationship between Case Numbers and Grocery & Pharmacy Stores Visits during Lockdown 1 in Ireland



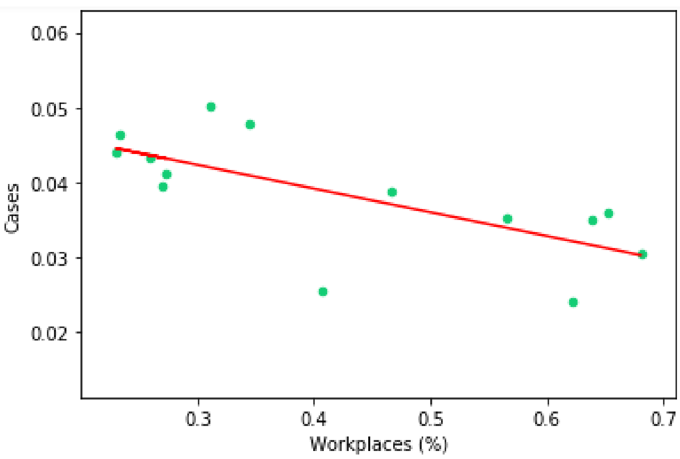

```
R-squared: 0.497
α constant (intercept): -0.001
β coefficient (slope): 0.119
```

Figure F.3: Relationship between Case Numbers and Park Visits during Lockdown 1 in Ireland



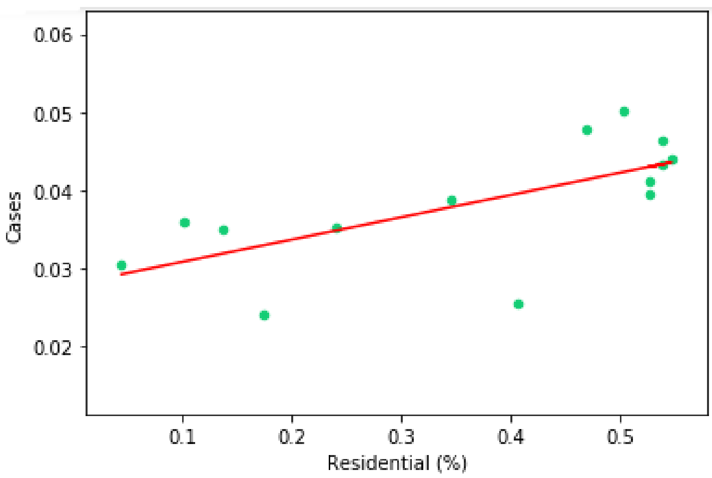

```
R-squared: 0.442
α constant (intercept): 0.051
β coefficient (slope): -0.033
```

Figure F.4: Relationship between Case Numbers and Transit Station Visits during Lockdown 1 in Ireland



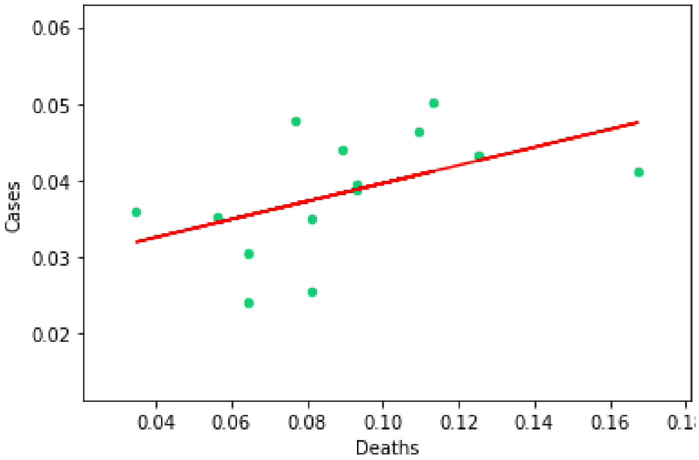

```
R-squared: 0.479
α constant (intercept): 0.052
β coefficient (slope): -0.032
```

Figure F.5: Relationship between Case Numbers and Workplaces Visits during Lockdown 1 in Ireland



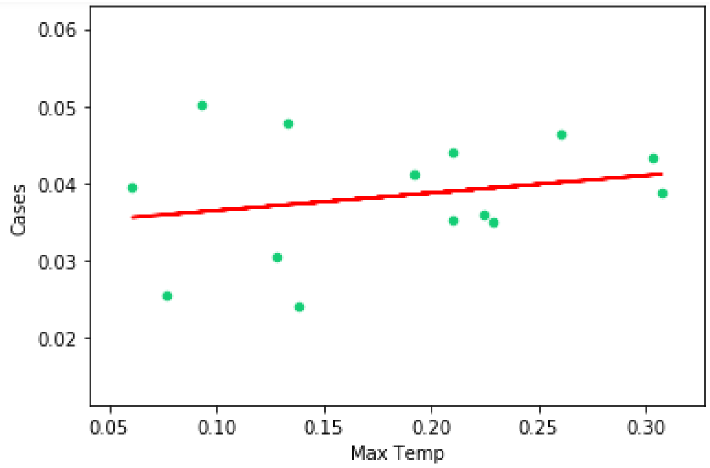

```
R-squared: 0.450
α constant (intercept): 0.028
β coefficient (slope): 0.028
```

Figure F.6: Relationship between Case Numbers and Residential Visits during Lockdown 1 in Ireland



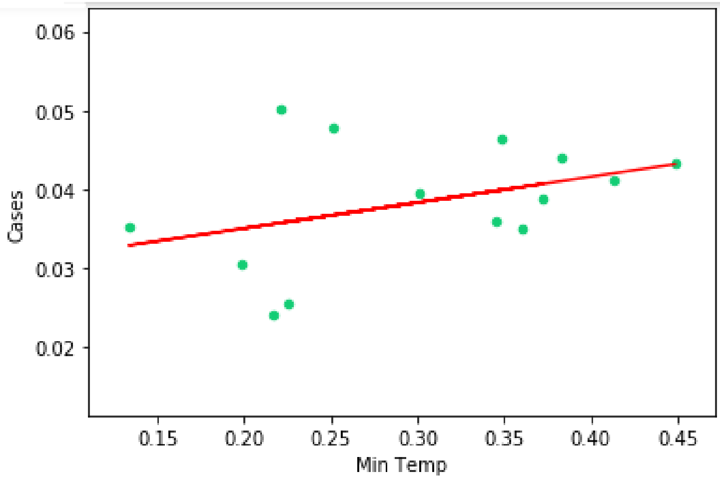

```
R-squared: 0.236
α constant (intercept): 0.028
β coefficient (slope): 0.117
```

Figure F.7: Relationship between Case Numbers and Deaths during Lockdown 1 in Ireland



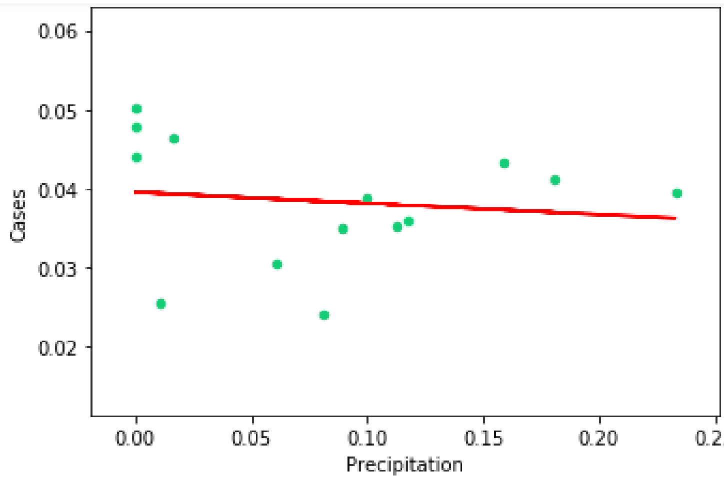

```
R-squared: 0.052
α constant (intercept): 0.034
β coefficient (slope): 0.023
```

Figure F.8: Relationship between Case Numbers and Max. Temperature during Lockdown 1 in Ireland




```
R-squared: 0.149
α constant (intercept): 0.029
β coefficient (slope): 0.033
```

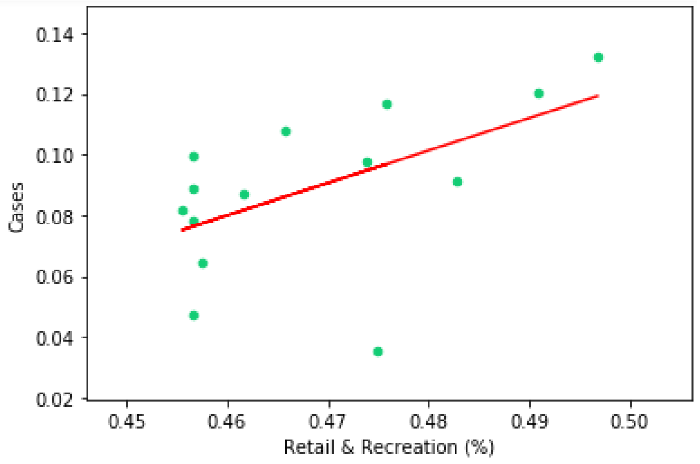
Figure F.9: Relationship between Case Numbers and Min. Temperature during Lockdown 1 in Ireland




```
R-squared: 0.017
α constant (intercept): 0.040
β coefficient (slope): -0.014
```

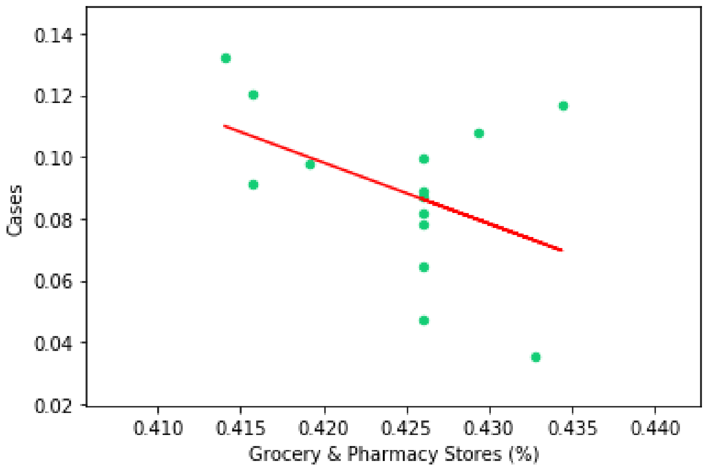
Figure F.10: Relationship between Case Numbers and Precipitation during Lockdown 1 in Ireland

Appendix G



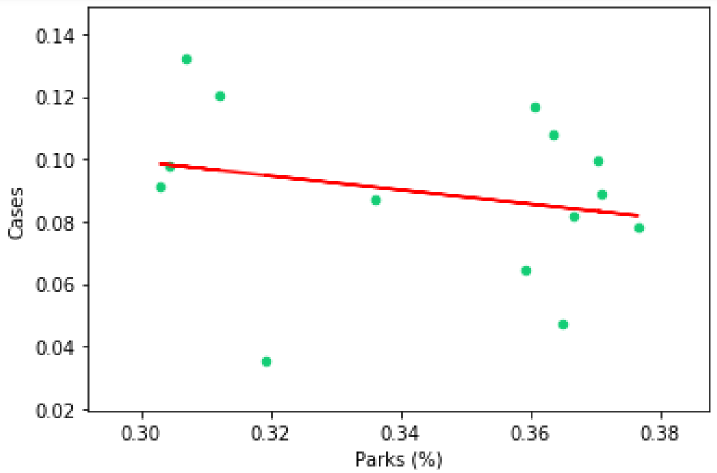

```
R-squared: 0.301
α constant (intercept): -0.411
β coefficient (slope): 1.068
```

Figure G.1: Relationship between Case Numbers and Retail & Recreation Visits during Lockdown 2 in Ireland



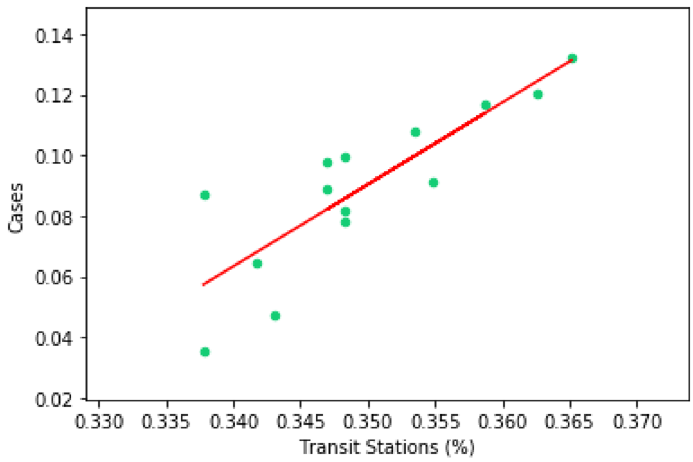

```
R-squared: 0.202
α constant (intercept): 0.931
β coefficient (slope): -1.984
```

Figure G.2: Relationship between Case Numbers and Grocery & Pharmacy Store Visits during Lockdown 2 in Ireland



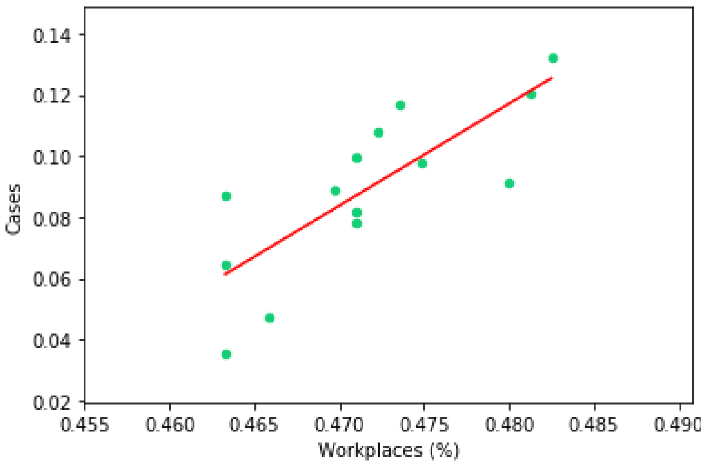

```
R-squared: 0.056
α constant (intercept): 0.167
β coefficient (slope): -0.225
```

Figure G.3: Relationship between Case Numbers and Park Visits during Lockdown 2 in Ireland



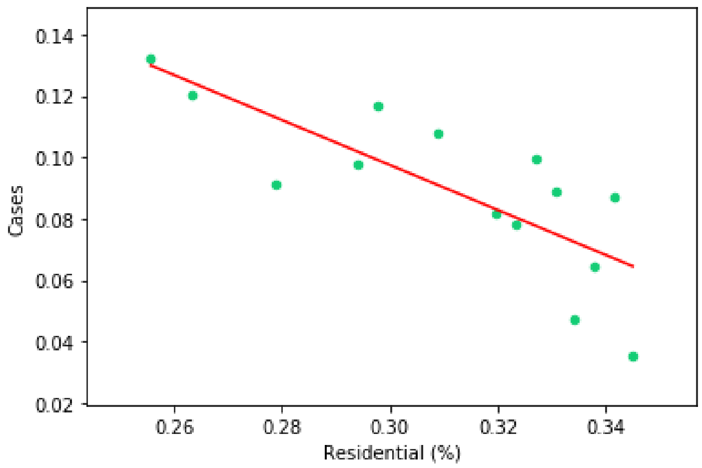

```
R-squared: 0.712
α constant (intercept): -0.856
β coefficient (slope): 2.705
```

Figure G.4: Relationship between Case Numbers and Transit Station Visits during Lockdown 2 in Ireland



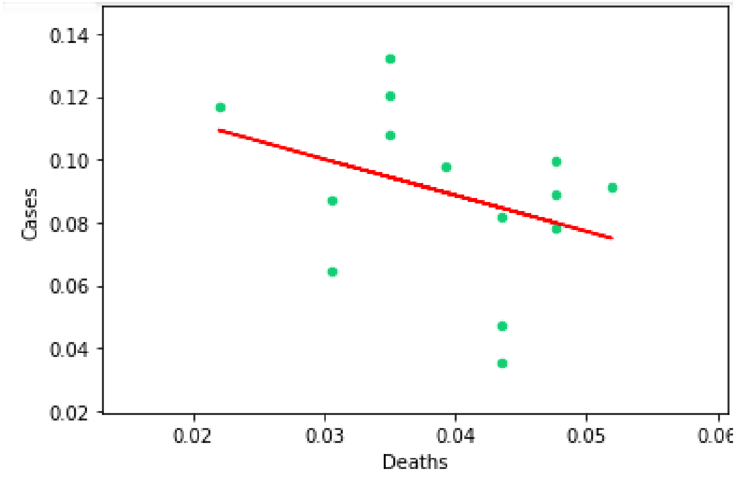

```
R-squared: 0.625
α constant (intercept): -1.486
β coefficient (slope): 3.340
```

Figure G.5: Relationship between Case Numbers and Workplace Visits during Lockdown 2 in Ireland



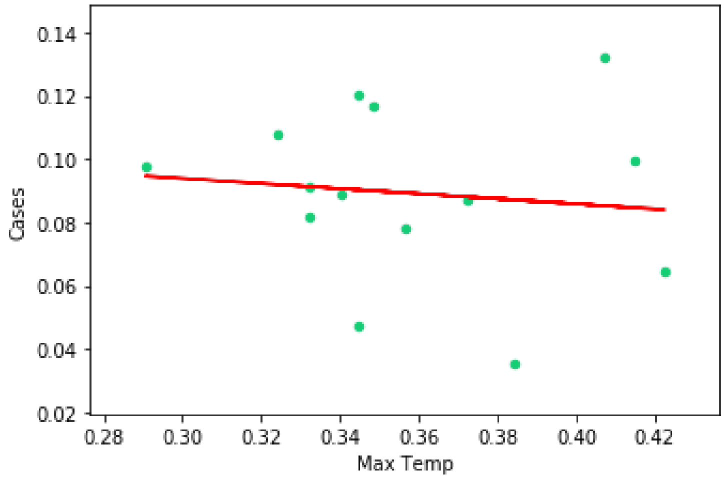

```
R-squared: 0.616
α constant (intercept): 0.317
β coefficient (slope): -0.733
```

Figure G.6: Relationship between Case Numbers and Residential Visits during Lockdown 2 in Ireland



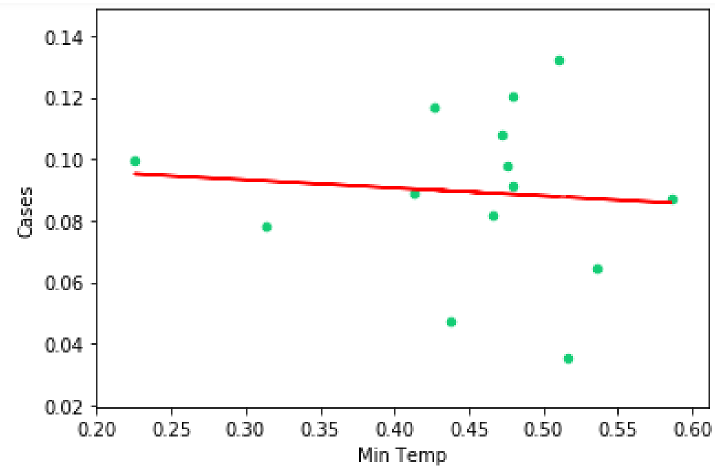
R-squared: 0.128
α constant (intercept): 0.135
β coefficient (slope): -1.149

Figure G.7: Relationship between Case Numbers and Deaths during Lockdown 2 in Ireland



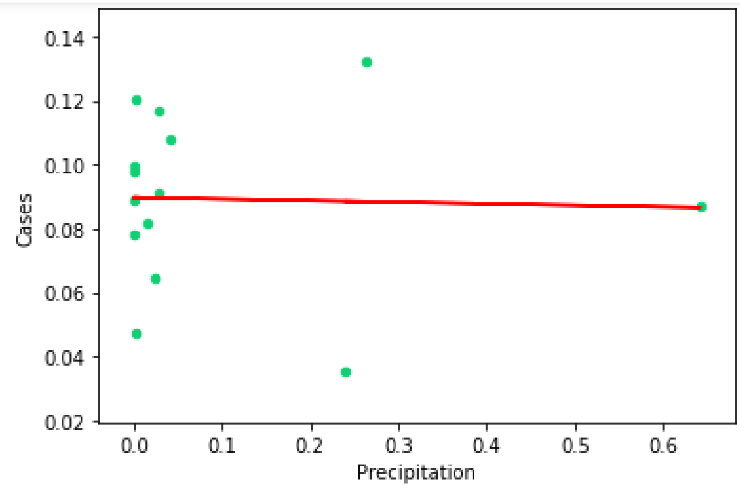
R-squared: 0.012
α constant (intercept): 0.118
β coefficient (slope): -0.080

Figure G.8: Relationship between Case Numbers and Max. Temperature during Lockdown 2 in Ireland



R-squared: 0.008
α constant (intercept): 0.101
β coefficient (slope): -0.026

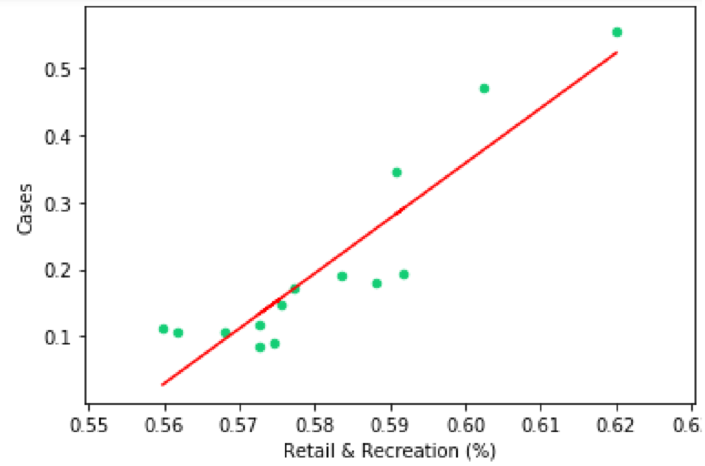
Figure G.9: Relationship between Case Numbers and Min. Temperature during Lockdown 2 in Ireland



R-squared: 0.001
α constant (intercept): 0.090
β coefficient (slope): -0.005

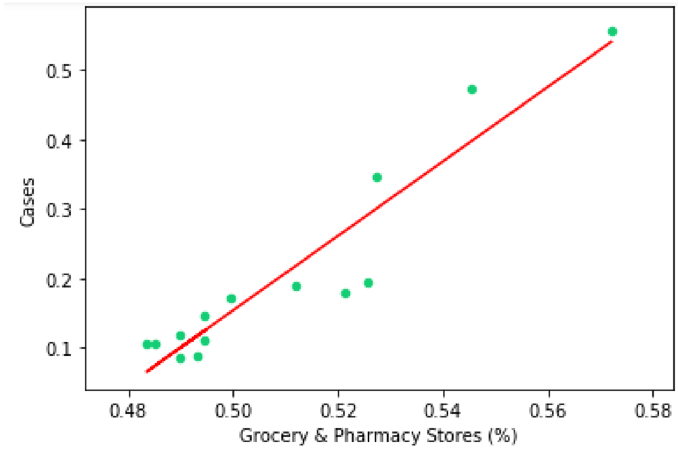
Figure G.10: Relationship between Case Numbers and Precipitation during Lockdown 2 in Ireland

Appendix H



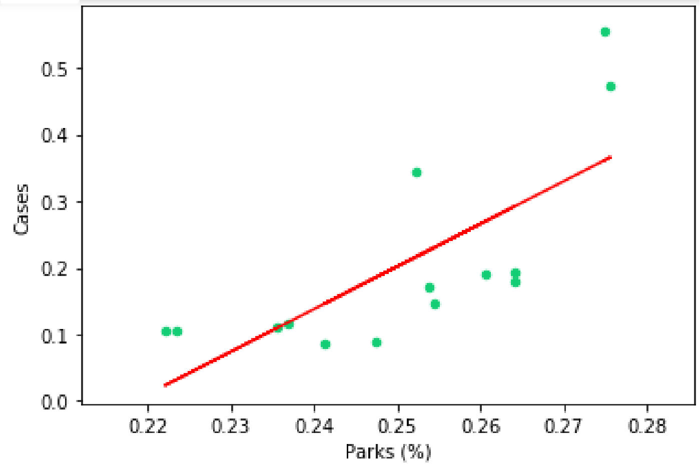

```
R-squared: 0.830
α constant (intercept): -4.587
β coefficient (slope): 8.242
```

Figure H.1: Relationship between Case Numbers and Retail & Recreation Visits during Lockdown 3 in Ireland



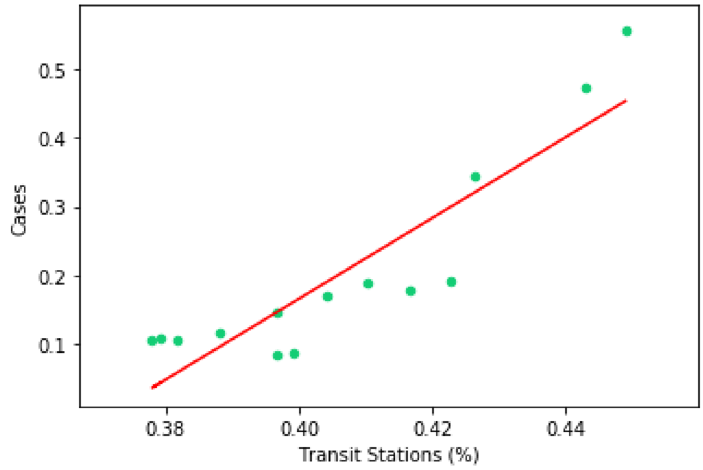

```
R-squared: 0.890
α constant (intercept): -2.524
β coefficient (slope): 5.355
```

Figure H.2: Relationship between Case Numbers and Grocery & Pharmacy Store Visits during Lockdown 3 in Ireland



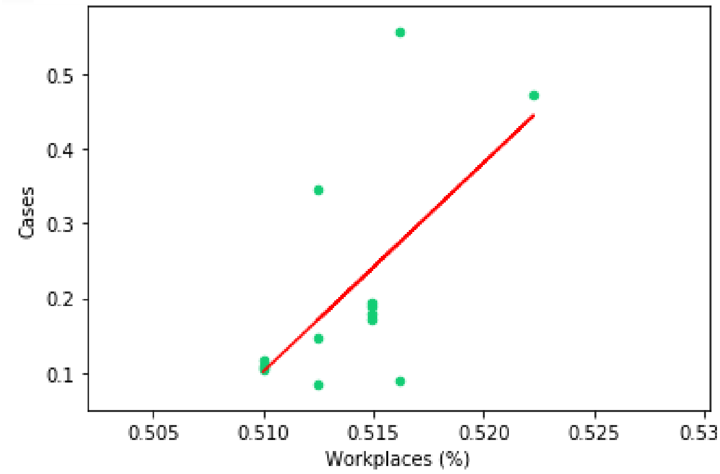

```
R-squared: 0.543
α constant (intercept): -1.397
β coefficient (slope): 6.397
```

Figure H.3: Relationship between Case Numbers and Park Visits during Lockdown 3 in Ireland



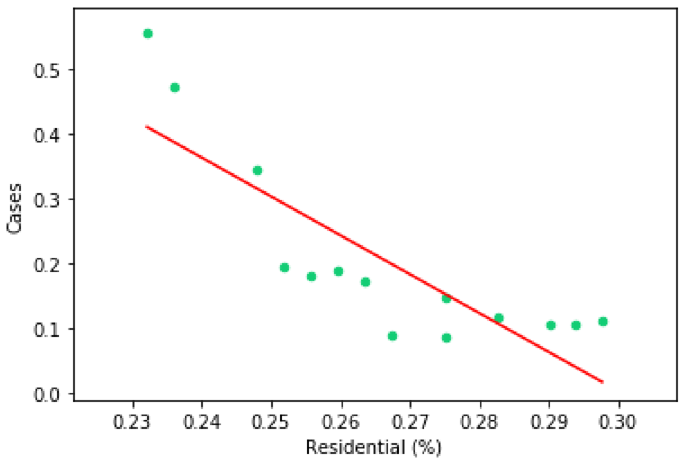

```
R-squared: 0.806
α constant (intercept): -2.175
β coefficient (slope): 5.853
```

Figure H.4: Relationship between Case Numbers and Transit Station Visits during Lockdown 3 in Ireland



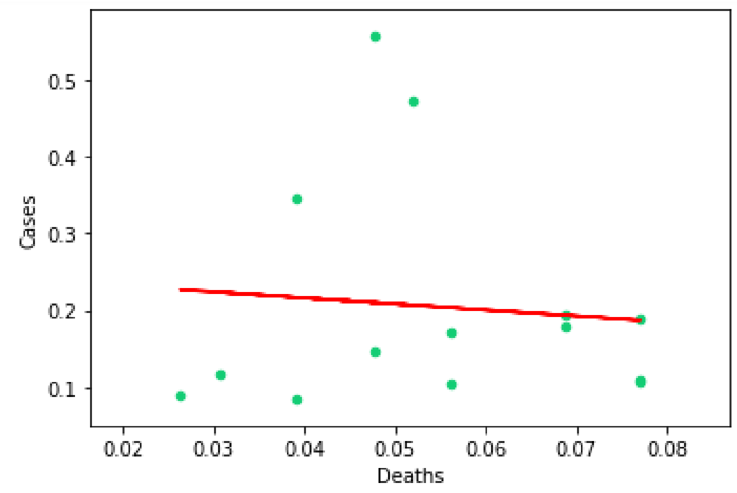

```
R-squared: 0.415
α constant (intercept): -14.157
β coefficient (slope): 27.958
```

Figure H.5: Relationship between Case Numbers and Workplace Visits during Lockdown 3 in Ireland



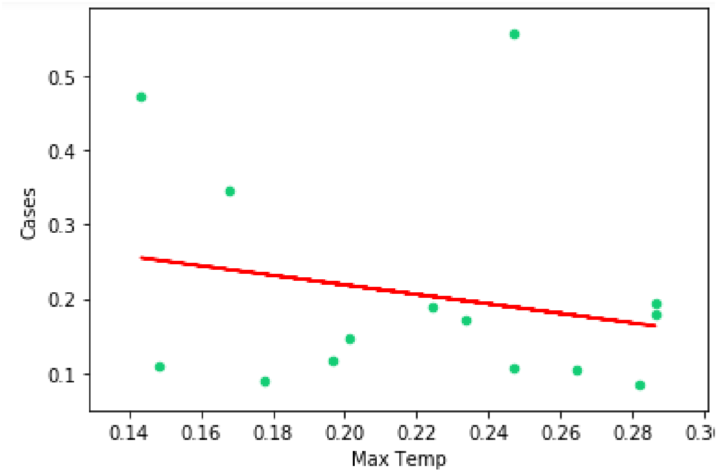

```
R-squared: 0.702
α constant (intercept): 1.802
β coefficient (slope): -5.998
```

Figure H.6: Relationship between Case Numbers and Residential Visits during Lockdown 3 in Ireland



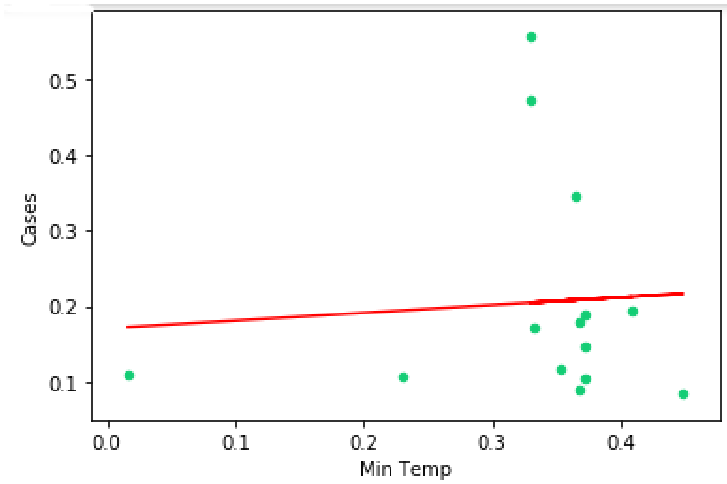
R-squared: 0.008
α constant (intercept): 0.248
β coefficient (slope): -0.787

Figure H.7: Relationship between Case Numbers and Deaths during Lockdown 3 in Ireland



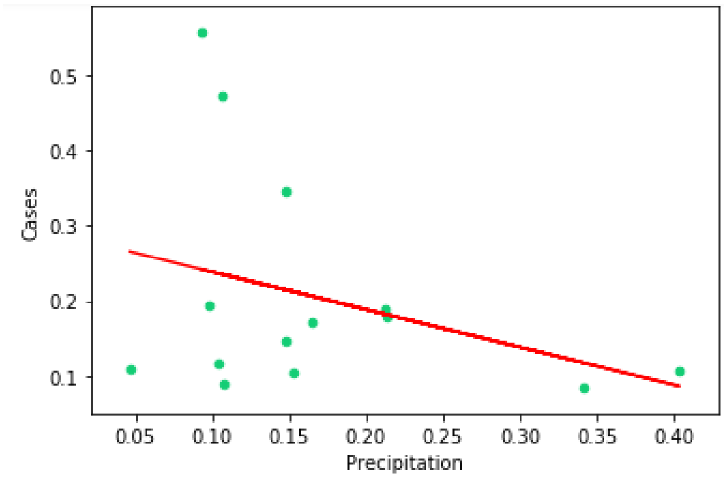
R-squared: 0.047
α constant (intercept): 0.347
β coefficient (slope): -0.640

Figure H.8: Relationship between Case Numbers and Max. Temperature during Lockdown 3 in Ireland



R-squared: 0.005
α constant (intercept): 0.171
β coefficient (slope): 0.102

Figure H.9: Relationship between Case Numbers and Min. Temperature during Lockdown 3 in Ireland



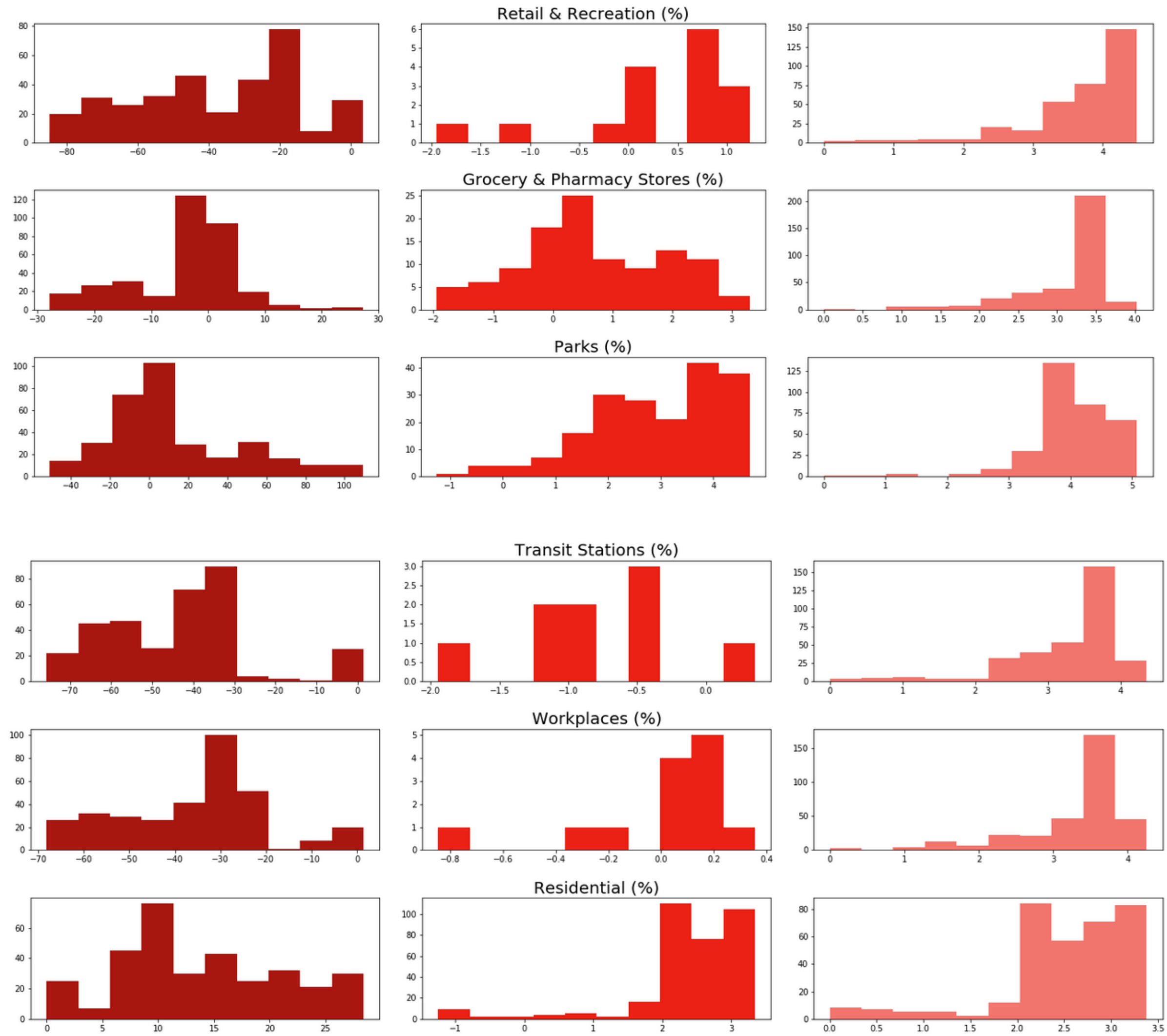
R-squared: 0.113
α constant (intercept): 0.288
β coefficient (slope): -0.500

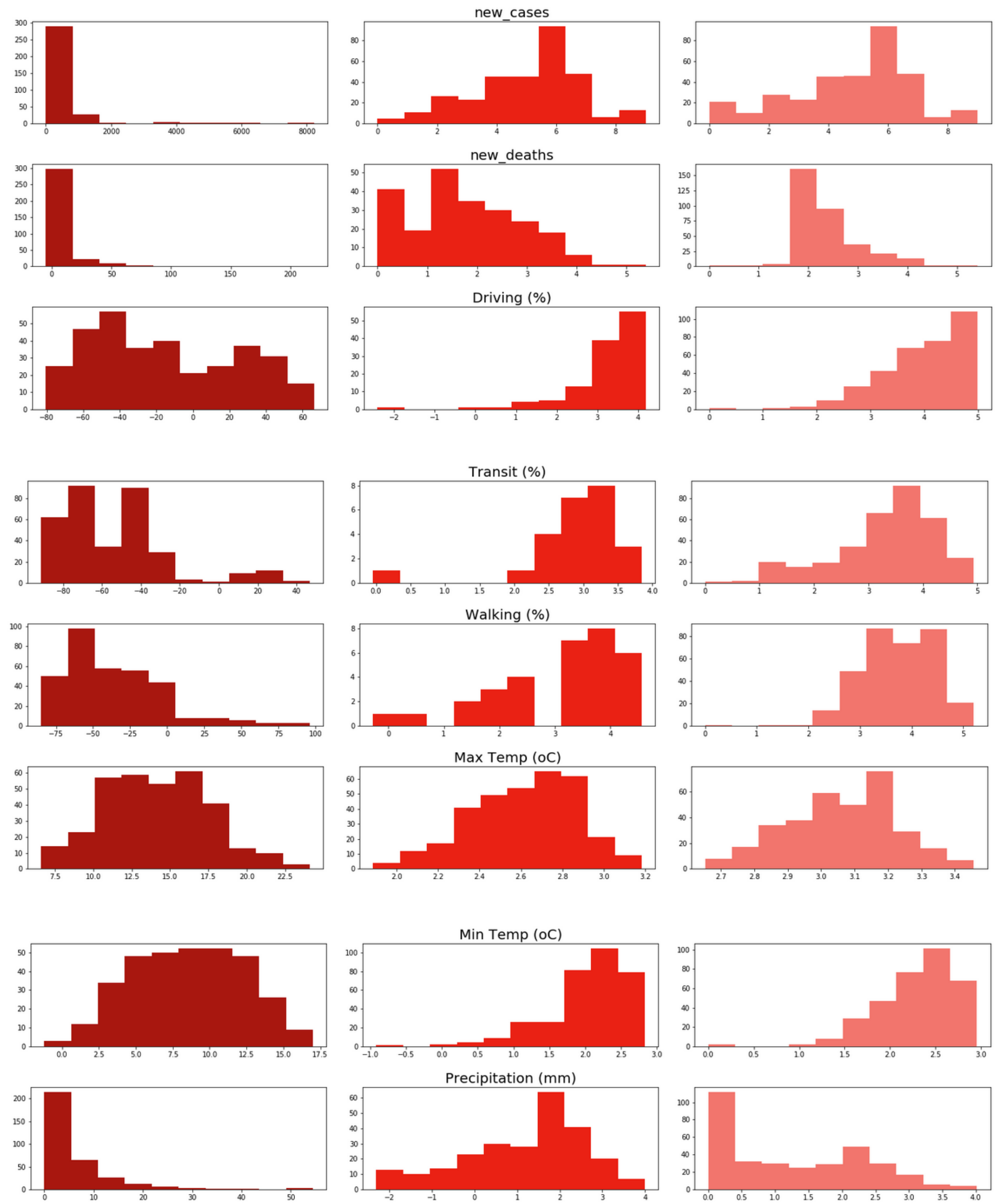
Figure H.10: Relationship between Case Numbers and Precipitation during Lockdown 3 in Ireland

Appendix I

Transformations of raw Ireland data in histogram form, where the x-axis represents the percentage difference relative to the 5 week baseline for the Google mobility data and the percentage difference when compared to 2019 for the Apple mobility data. The columns are in the form:

Raw Data	**ln(Translated Raw Data to the positive axis – 0 values)**	**ln(Translated Raw Data to the positive axis + 1)**

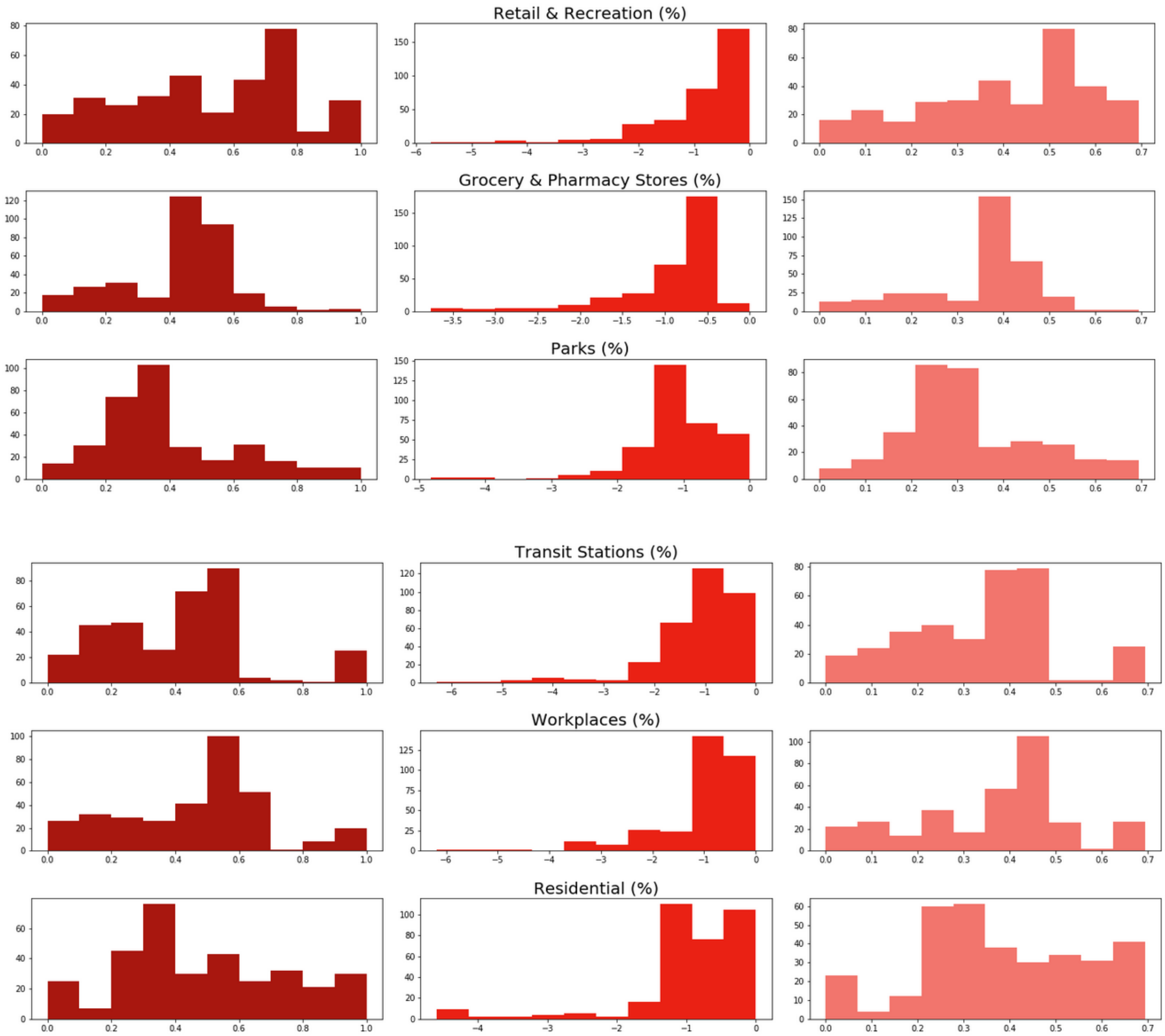


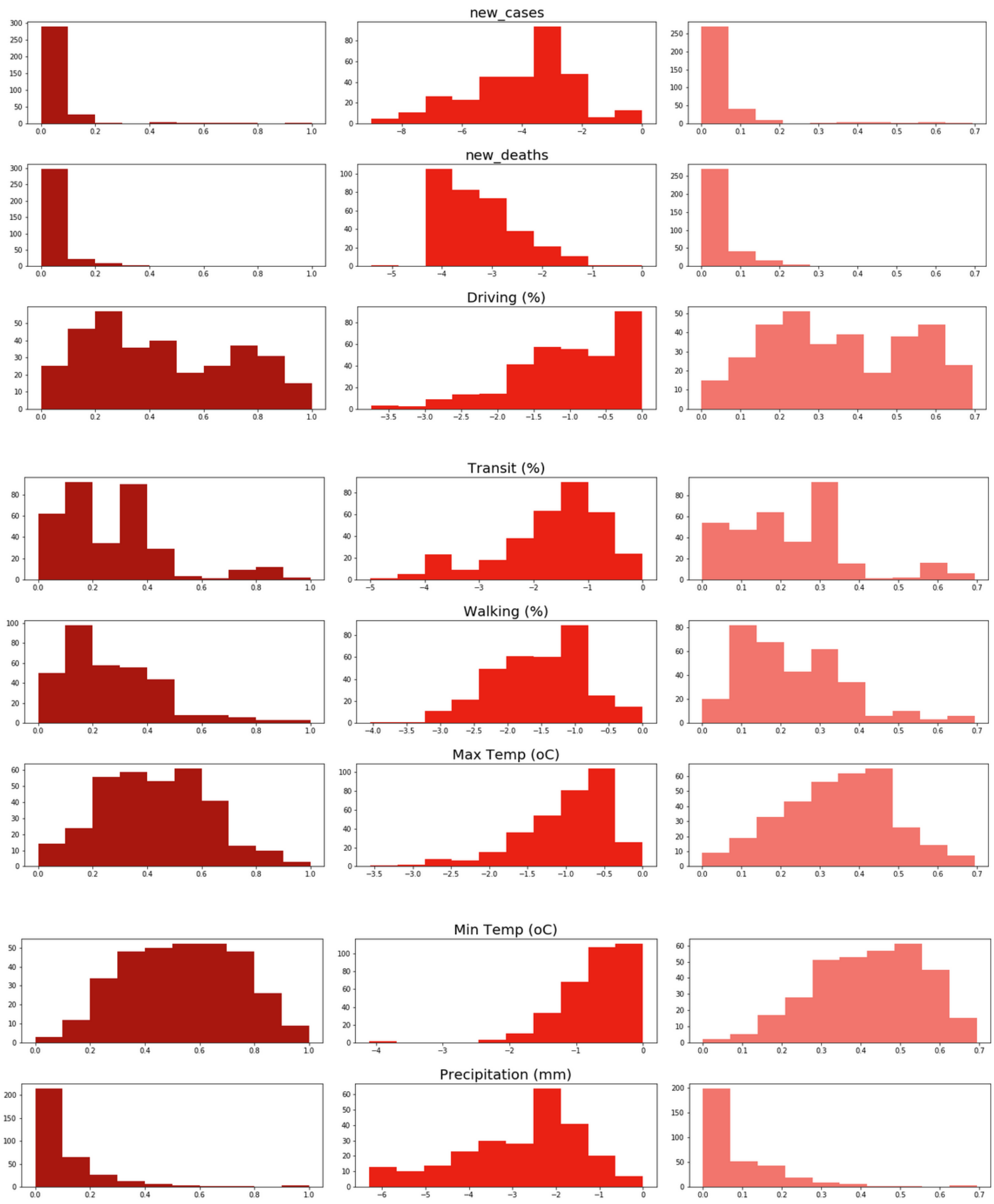

new_cases
new_deaths
Driving (%)
Transit (%)
Walking (%)
Max Temp (oC)
Min Temp (oC)
Precipitation (mm)

Appendix J

Transformations of scaled Ireland data in histogram form, where the x-axis represents the percentage difference relative to the 5 week baseline for the Google mobility data and the percentage difference when compared to 2019 for the Apple mobility data. The columns are in the form:

Scaled Data	ln(Translated Raw Data to the positive axis – 0 values)	ln(Translated Raw Data to the positive axis + 1)




new_cases
new_deaths
Driving (%)
Transit (%)
Walking (%)
Max Temp (oC)
Min Temp (oC)
Precipitation (mm)

Appendix K

Gráinne Donegan (117312963) FYP Logbook

Detailing FYP meetings, progress and any interesting sources/material that I come across.

Week 1 (19/10/20 – 25/10/20)

[Confirmation of titles on Monday by Email from Denis]

Meeting with Marguerite: Tuesday (12:00 – 13:00) – Discuss Literature Review and Aims and Objectives of FYP

Progress: Carried out all research for literature review

Interesting Sources:

- Our World in Data Interactive Coronavirus (COVID-19) Charts and Data (https://ourworldindata.org/coronavirus)

Week 2 (26/10/20 – 01/11/20)

Meeting with Marguerite: Tuesday (12:00 – 13:00) – Discuss Literature Review and Flow

Progress: Planned out entire Literature Review along with drafting out the majority if the first draft

Interesting Source:

- Interesting Forbes article: “Google Publishes Location Data Across 130 Countries To Show How Coronavirus Lockdowns Are Working” (https://www.forbes.com/sites/isabeltogoh/2020/04/03/google-publishes-location-data-across-130-countries-to-show-how-coronavirus-lockdowns-are-working/?sh=2acdea426562)

Week 3 (02/11/20 – 08/11/20)

Meeting with Marguerite: Tuesday (15:00 – 16:00) – Finalise Literature Review and Discuss Methodology

Progress: Ironed out Literature Review and did a brainstorm of a rough flow for the Methodology

Interesting Source:

- Facebook COVID-19 Mobility Data Network (https://visualization.covid19mobility.org/?date=2021-03-24&dates=2020-12-24_2021-03-24&region=WORLD). Interesting information on physical distancing efforts and their impact, but limited countries analysed, hence not selected.

Week 4 (09/11/20 – 15/11/20)

Meeting with Marguerite: Tuesday (15:00 – 16:00) – Examined and Discussed Suitable Statistical Analyses

Progress: Wrote out first draft of the Methodology apart from the statistical analyses section

Week 5 (16/11/20 – 22/11/20)

Progress: Wrote up the Aims and Objectives Section along with editing the Methodology section

Interesting Source:

- Social Impact of COVID-19 in Ireland Infographic – could be analysed in Literature Review (https://www.cso.ie/en/statistics/socialconditions/socialimpactofcovid-19surveynovember2020well-beingandlifestyleunderlevel5restrictions/)

Week 6 (23/11/20 – 29/11/20)

Progress: Focused on different types of statistical analyses available and potential forms of pre-processing for the dataset

Interesting Source:

- Interesting article from the Economist: "Why Europe's second, less severe lockdowns are working" (https://www.economist.com/graphic-detail/2020/11/28/why-europes-second-less-severe-lockdowns-are-working)

Week 7 (30/11/20 – 06/12/20)

Progress: Reviewed written work, but didn't write anything new since 5 assignments due in 7 days

Interesting Source:

- "The Data Dive" – A YouTube playlist by Sky News including short videos on COVID-19 data and impacts (https://www.youtube.com/playlist?list=PLG8IrydigQfcAwhKwzjxWcWJRnVLtuBeo)

Week 8 (07/12/20 – 13/12/20)

Progress: Finalised all sections apart from the Results, Discussion and Conclusion and wrote up python scripts with some of the processes mentioned in the Methodology.

Interesting Source:

- The Economist's "Off the Charts" newsletter – A data journalism newsletter, which discusses the creation of graphs based on topical events, such as the COVID-19 pandemic (https://www.economist.com/offthecharts/)

Week 9 – Week 14 (14/12/20 – 17/01/21)

Progress: Due to final week assignment deadlines and exams followed by a short Christmas period with exams at the end, no FYP work was carried out

Week 15 (18/01/21 – 24/01/21)

Meeting with Marguerite: Wednesday (14:00 – 15:00) – Discuss what is left with the FYP and the upcoming presentations

Progress: Worked on a rough template and flow for the presentation. Created a 3rd wave analysis based on the methodology.

Week 16 (25/01/21 – 31/01/21)

Progress: Did a full first draft for the presentation and analysed where elements/graphics of the presentation could be incorporated into the FYP itself.

Interesting Source:

- Excellent PowerPoint Slide Templates: Slidesgo (https://slidesgo.com/) A template from this website was used for the presentation.

Week 17 (01/02/21 – 07/02/21)

Meeting with Marguerite: Thursday (14:00 – 15:00) – Did a read through of presentation and discussed elements to add , such as a more in-depth 3rd wave-analysis insight

Progress: Acted on all feedback, adding more details to the slides. Also practised for the presentation next Thursday.

Week 18 (08/02/21 – 14/02/21)

Meeting with Marguerite: Tuesday (11:00 – 12:00) – Practiced presentation w/ feedback

FYP Presentation: Thursday (14:00 – 16:00)

Progress: Gave presentation and then focused on the FYP again, completing a rough set of Results.

Week 19 (15/02/21 – 21/02/21)

Progress: Produced more results for a 14 day lag for Ireland and event subsets along with finalising the OLS Multiple Linear Regression Model

Interesting Source: Interesting New Podcast: "The Jab" from The Economist – discusses the COVID-19 vaccine roll-out (https://podcasts.apple.com/us/podcast/id1551984673)

Week 20 (22/02/21 – 28/02/21)

Meeting with Marguerite: Monday (11:00 – 12:00) – Finalised the Statistical Analyses and looked at the first draft of the results section

Progress: Eked out any issues with the statistical analyses to ensure as much data was accurately used and the COVID-19 situation was fairly represented for Ireland.

Week 21 (01/03/21 – 07/03/21)

Progress: Finishing the results section – improving graph quality and increasing legibility and flow of the Results section.

Interesting Source: OWID Google Mobility Trends (https://ourworldindata.org/covid-google-mobility-trends). Useful website to compare my Google mobility graphs to.

Week 22 (08/03/21 – 14/03/21)

Meeting with Marguerite: Monday (16:00 – 18:00) – Discussed all elements of the FYP thus far – focussing on where to improve on

Progress: Acted on feedback to improve the standard of the FYP

Week 23 (15/03/21 – 21/03/21)

Meeting with Marguerite: Monday (12:30 – 13:30) – Discussed increasing accuracy of results by revisiting the preprocessing and transformation of data

Progress: Applied multiple forms of transformation of the datasets, to ensure accuracy was increased overall

Week 24 (22/03/21 – 28/03/21)

Meeting with Marguerite: Monday (11:00 – 12:00) – Reviewed these data quality revisions and finalised some tweaks to ensure that the datasets were ready for use

Progress: Applied new revisions for preprocessing and completely updated the results section

Week 25 (29/03/21 – 04/04/21)

Meeting with Marguerite: Monday (11:00 – 12:00) – Discussed finalising FYP and a full first draft of the report

Progress: Conducted a graphical international analysis for Brazil, New Zealand, Sweden, South Korea and Germany, similar to the graphical representation for Ireland.

Week 26 (05/04/21 – 11/04/21)

Progress: Wrote the entire first draft of the FYP and finalised the formatting and Appendices.

Week 27 (12/04/21 – 18/04/21)

Meeting with Marguerite: Tuesday (17:00 – 18:00) – Obtained feedback on first draft

Progress: Finished the FYP, based on feedback and am ready for submission

I can confirm that I kept up-to-date with my FYP throughout the year and met up with my supervisor – Dr. Marguerite Nyhan frequently to ensure that I could successfully complete my FYP.

Student: Date: 18/04/2021

Supervisor: Date: 20/04/2021