

Assessing the impact of mobility on the incidence of COVID-19 in Dublin City

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ABSTRACT

COVID-19 has had a major impact on the transport systems around the world. Several transport-related policies were implemented in short period of time to contain the spread of the pandemic. These policies had a major influence on travel behavior and people's perception towards the safety of different modes of transport, especially public transport, thus affecting several sustainable mobility initiatives. To build a resilient and sustainable transport system and to rebuild trust in public transport, it is important to understand the role of mobility in the spread of COVID-19 pandemic. The present study investigates the relationship between mobility and reported COVID-19 infections using data from Dublin city. Different modes of transport including traffic volume, bus passengers, pedestrians and cyclists were considered in the study during a forty week period. Multiple scenarios involving two-week lag and three-week lag of mobility data and COVID-19 infections were considered in building statistical models. Results showed that, 36.2% of the reported COVID-19 infections after a two-week lag and 33% of the infections after a three-week lag. Our research examines the links between movements and COVID-19 numbers, but clearly this was not the only reason for increased case numbers as many other events impacted on increased numbers. The study further discusses the policy implications and strategies for ensuring a resilient and sustainable transport system.

1. Introduction

Transportation system plays a major role in satisfying the demands of mobility within a region. At the same time, it also plays a significant role in transmitting and controlling the spread of epidemic outbreaks (Qian & Ukusuri, 2021). Hence, it is necessary to consider the epidemic resilience of a transportation system into sustainable mobility models. The COVID-19 pandemic outbreak in early 2020 has since then affected the normal lives and activities of several people around the world leading to more than 5.3 million deaths until November 2021. Future transportation planning strategies require that we understand and learn from what different cities and countries have experienced, understand the risk that mobility brings to the spread of epidemics and use that to develop sustainable and resilient mobility systems. Considering the uncertainty in the duration of the pandemic, there is a need to adapt the previously adopted transport planning strategies to account for COVID-19. Also, transport policies need to be assessed comprehensively before implementation to ensure sustainability (Simić, Ivanović, Đorić & Torkayesh, 2022).

This study explores whether patterns can be drawn between the levels of mobility in a city and then seeks to establish the extent to which the level of mobility can be used to explain the incidence of COVID-19. The study aims to understand the fluctuations in mobility data during the pandemic period by using data from a vast network of sensors across the city. Different modes of transport including passenger cars, bus passengers, bicyclists and pedestrians are considered in the study. Mobility data is then compared with Covid-related information to understand the relation between incidence of COVID-19 and the level of mobility. The present study also considers the incubation time of the virus to gain a better understanding of both mobility pattern and COVID-19 infections and the effect they have on each other. Understanding this impact will assist in the development of mobility policies and strategies to combat the spread of COVID-19 outbreaks or other pandemics, thus creating a resilient transportation system.

The paper is structured as follows. Section 2 reviews the literature on the impact of COVID-19 on transport and existing modeling techniques. The methodology adopted for the study is discussed in Section 3 along with the details of data collected. Section 4 presents the analysis and

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results. Discussion of results and inferences and conclusions from the study are presented in Section 5 and Section 6.

1.1. Literature review

This section reviews the existing research in the field of COVID-19 and mobility. For better readability, the review of literature has been categorized into impact of pandemic, transport measures specifically introduced during COVID-19, changes in mobility pattern as a result of COVID-19 and related policies, effect of mobility policies on different sections of the society and existing models explaining the relation between mobility and spread of infectious diseases.

1.2. Impact of pandemic on transportation

The COVID-19 pandemic has had an enormous impact on the ways in which people work, shop, socialize and communicate. This has also led to a significant impact on the transportation system, radically reducing travel levels. According to the [Dublin City Council \(2020\)](#), there was significant reduction in the car, bus, and rail traffic during the periods of maximum restriction where only essential workers were allowed to travel. The public transportation system including buses, trams, and metros which is considered the most sustainable mode of travel in any city became the least preferred mode because of its environment which favours the spread of infectious diseases ([Alemdar, Kaya, Çodur, Campisi & Tesoriere, 2021](#); [Qian & Ukkusuri, 2021](#)). It is most likely that people's attitude towards mode choice now and in the near future will be influenced by their experiences of perceived comfort and safety during the pandemic ([de Haas, Faber & Hamersma, 2020](#); [Eisenmann, Nobis, Kolarova, Lenz & Winkler, 2021](#); [Przybyłowski, Stelmak & Suchanek, 2021](#)). This will have consequential impact on how transportation modeling is carried out, including the manner in which assumptions regarding mode choice are accounted for ([Aaditya & Rahul, 2021](#)). Hence, it is important to understand if the mobility experienced during the course of the pandemic bears any relationship with the incidence of COVID-19. Such an understanding would provide a basis for ensuring that the right level of resources are assigned to rebuild trust in the transport system and to reform transport policy and mobility systems in a manner that builds resilience to infectious diseases, whether it is pandemics or seasonal influenzas.

1.3. Transport-related measures introduced to cope with COVID-19

The spread of COVID-19 pandemic placed a significant restraint on the mobility system mainly because of the requirement of social distancing. This also led to the need for framing *Covid Mobility Measures* for rapid deployment in order to move people safely for public health reasons and to enable economic recovery ([Combs & Pardo, 2021](#)). In Dublin, the capacity of both bus and rail was restricted and online booking was encouraged for train journeys. A similar approach of restricting passengers on public transport was taken in 54.6% of cities and online ticket booking was encouraged in 22.2% of the cities considered in an expert survey ([Zhang, Hayashi & Frank, 2021](#)). In addition, passengers were required to wear face masks in public transport, and vehicles were cleaned and disinfected regularly ([Eisenmann et al., 2021](#)). Measures for creating safe spaces for social distancing were implemented around the world with a sense of urgency. Several experimental initiatives were taken to reallocate the road spaces originally meant for cars and on-street parking to allow more pedestrians and cyclists as well as facilitating *low-risk* business activities such as outdoor dining and retail ([Combs & Pardo, 2021](#)).

1.4. Restrictions imposed in Ireland to combat COVID-19

The first case of COVID-19 was reported in Ireland on the 29th of February 2020. Following this, the Irish government declared a

complete lockdown from the 12th of March 2020 ([Caulfield, Browne, Mullin, Bowman & Kelly, 2021](#)). All schools, colleges, and childcare facilities closed on the 12th of March followed by closure of all non-essential services including most of the businesses ([Panda, O'Malley, Barry, Vallejo & Smith, 2021](#)). Government imposed a stay-at-home order, asking citizens to work from home and a ban on all non-essential travel ([Minihan et al., 2022](#); [Raman & Coogan, 2021](#)). By the 22nd of March 2020, COVID-19 cases were confirmed in all counties in Ireland ([Cullen, 2020](#); [Spikol, McBride, Vallières, Butter & Hyland, 2021](#)). The first stage of lockdown allowed people to travel within 2 km from their home for exercise. On the 18th of May, these restrictions began to be eased in a phased manner allowing people to travel within 5 km from their home ([Caulfield et al., 2021](#); [Quintyne, Kelly, Sheridan, Kenny & O'Dwyer, 2021](#)). However, it was instructed that all non-essential travel be kept to a minimum.

Restrictions were further strengthened in October 2020 as Ireland experienced heavy increase in infections leading to a second nationwide lockdown ([Quintyne et al., 2021](#)). The restrictions were again relaxed in December 2020. However, this was short-lived due to rapid rise in COVID-19 cases leading to return of full travel restrictions in late December 2020 and led to a third nation-wide lockdown in January 2021 ([Panda et al., 2021](#)). During the period from March 2020 until June 2021, Ireland experienced three strong waves of COVID-19 infection ([Burke, Parker, Fleming, Barry & Thomas, 2021](#); [Hannah et al., 2020](#)).

1.5. Transport-related measures implemented in Dublin during COVID-19

In May 2020, the Dublin City Council published a document entitled "Enabling the City to Return to Work" ([Dublin City Council, 2020](#)) which outlined the effect of Covid-related restrictions on transport and the way forward. The study reported that car traffic reduced to about 30% of pre-Covid levels, bus usage dropped by 90% and rail usage reduced by 97%. The study also suggested various policies that will be implemented to ensure safety of citizens. Since 2-metre spacing between passengers was a mandate, Dublin City Council mentioned that there will be a reduction in capacity of public transport down to about 20% of its normal levels.

Since public transport was operating at very low capacity, additional measures were taken to increase cycling and pedestrian infrastructure. Dublin City Council advised anyone living with 2 to 5 km radius of city centre to avail of walking and cycling for their movement to city centre instead of public transport or private cars. Consequently, several key locations in and around the city core were identified and radial links with the highest levels of cycling and walking were prioritized. Increased cycling and pedestrian spaces were provided in and around the city to ensure physical distancing during travel ([Caulfield et al., 2021](#); [Dublin City Council, 2020](#)).

Rapid temporary interventions were implemented using preformed materials to reorganise the road space. Existing road spaces adjacent to the foot paths were reviewed and pedestrian areas were extended depending on the location. At traffic signals, the maximum time allocated to complete a traffic cycle was reduced from 120 s to 80 s throughout the city resulting in shorter green times for vehicles and shorter waiting times for pedestrians ([Dublin City Council, 2020](#)).

Protected cycle lanes were also provided by reusing existing road space and removing on-street parking. These spaces were protected using protection bollards and other cyclist protection measures. The number of traffic lanes were also reduced at a few locations to accommodate cycling facilities on both sides of the road. Continuous bus lanes and bus priority measures including early start for buses at traffic signals were implemented. Vehicular speed limits were reduced to 30 kmph on many routes in line with other European cities to accommodate the increased number of vulnerable road users, pedestrians, and cyclists ([Dublin City Council, 2020](#)).

1.6. Changes in mobility pattern during the pandemic

The restrictions placed on travel to control the spread of COVID-19 had a major impact on the transport sector everywhere (Zhang et al., 2021). The average individual travel time was reduced by 66% across all age groups in Poland in the initial stage of the pandemic from March to April 2020 (Borkowski, Jażdżewska-Gutta & Szmelter-Jarosz, 2021). The overall mobility fell by 76% in Santander, Spain in the initial stage of the pandemic (Aloi et al., 2020). A 50% reduction in traffic demand was observed almost immediately after the introduction of mobility restrictions in Gdansk and Budapest (Borkowski et al., 2021; Bucsky, 2020). While traffic volumes in Ireland reduced to 30% during the strictest lockdown in March and April 2020, they eventually ranged between 60% and 70% for when reductions were eased, reflecting a time when more economic activity was permitted.

Public transport experienced so far the greatest reduction in demand (80%) in Budapest in March 2020, resulting in a drop in mode share, from 43 to 18% (Bucsky, 2020). This seems to be a consistent trend across many cities with 93% reduction in Santander (Aloi et al., 2020), and 90% in the Netherlands in the initial stage of the pandemic from March to April 2020 (de Haas et al., 2020). The measures introduced by governments and administrations to reduce the spread of infections negatively affected the public transport systems. One of the major impacts was on the mode share characteristics of people with majority of them shifting from public transport to other modes of travel (Bohman, Ryan, Stjernborg & Nilsson, 2021). Public transportation has always been the major sector to be affected in case of similar epidemic outbreaks even in the past (Kelly et al., 2015; Lau, Yang, Tsui & Kim, 2003; Petrie, Faasse & Thomas, 2016). In Ireland, people were discouraged to use public transport unless they were essential workers. Whether this was done to reduce contagion through transport or to ensure that public transport is available for essential workers, it led to a sense of discomfort towards public transport. In the Netherlands, attitudes towards public transport have deteriorated with survey results showing that 88% of respondents having a preference against public and shared mobility options (de Haas et al., 2020). The changing perceptions are reflected in a recent study conducted in Spain that concluded that people will expect increased measures for personal safety in public transport post COVID-19, but at the same time as pre-COVID-19 (Awad-Núñez, Julio, Moya-Gómez, Gomez & Sastre González, 2021). A recent study pointed out that the attributes like travel time and cost which had a major influence on people's travel choice became less relevant during the pandemic. Instead, factors such as fear of infection, perceived risk, and travel anxiety became the ruling factors in influencing travel choice (Chen, 2021). Shared mobility, which was considered an effective strategy for sustainability also suffered a major setback during COVID-19 because of its transmission dynamics in confined spaces (Shokouhyar, Shokouhyar, Sobhani & Gorizi, 2021).

The mode shift from public transport resulted in a significant shift towards the use of the private car and became a major setback for sustainable mobility policies. In Europe, there was a bigger shift towards walking and cycling than towards car (Liu & Stern, 2021; Zhang et al., 2021). This may be because Europe has the infrastructure and households have the resources to make that rapid shift possible. Further, active mobility policies were already in place in Europe thus helping in this shift. In Dublin, the cycling volumes during commuting hours dropped sharply. However, there was an increase in the number of cyclists during the inter-peak hours. The experience was similar in the Netherlands, where these local trips increased by over 70% compared to pre-COVID-19 in the months of March and April 2020 (de Haas et al., 2020). There was an increase in walking and bicycle activities in the less densely populated cities of United States including Indianapolis, Tallahassee, Clovis and Charlotte. However densely populated cities of San Francisco, Long Beach, New York City, and Boston experienced decline in walking and cycling activities. In New York, the average trip duration on a bikeshare increased by a third (Teixeira & Lopes, 2020). There was

an increase in longer trips between 30 and 60 min from January to September 2020, suggesting some mode shift from the subway, perhaps due to fear of contagion (Wang & Noland, 2021). In Washington DC, initially, walking and cycling increased rapidly, and then dropped off but stayed above pre-pandemic levels (Zhang & Fricker, 2021). Bike sharing systems seemed to be more resilient than the public transport system which also indicates the need to rethink the urban spaces and mobility (Benita, 2021). In light of behavioral changes during the pandemic, investing in walking and cycling infrastructure and designing cities to be more pedestrian friendly could be an effective strategy for building resilient transport systems (Zhang et al., 2021).

Despite the increased popularity of active modes of transport, one cannot ignore the fact that private cars became to be considered as the safest and most reliable means of transport during the pandemic. Budapest saw an unprecedented growth of car usage from 43% to 65% in the early stage of the pandemic (Bucsky, 2020). In Germany, the proportion of single occupancy car trips increased by 13% in March and April 2020 (Eisenmann et al., 2021). Additionally, results showed that one third of individuals in car-free households missed owning a car during the lockdown and 6% even considered buying one. Even in the Netherlands, there seems to be a noticeable increase in positive attitude towards cars (de Haas et al., 2020). In Turkey, a clear shift was observed from public transportation to private cars during the months February to April 2020 (Shakibaei, de Jong, Alpkökin & Rashidi, 2021). Strong efforts will be needed from policy makers and transport professionals to prevent increased car dependence due to adverse reactions to public transport services after the pandemic.

1.7. Impact of COVID-19 on road traffic volume in Dublin

A significant decrease in road traffic volume was observed in many countries especially in the initial stages of the pandemic. A comparison of road traffic volume from eight signalized intersections in Poland showed 23% to 43% reduction in traffic volume in 2020 compared to 2019 (Macioszek & Kurek, 2021). According to the Central Statistics Office of Ireland, the average weekly volume of passenger cars on roads decreased by 75% soon after the announcement of first nationwide lockdown in March 2020 (Central Statistics Office, 2021). After few weeks of reduced traffic volume, these values continued to increase. Passenger car volumes were highest in the months from July to September 2020. However, these values were still 20% less than the corresponding levels of traffic in 2019. The volume further decreased in December and again in January in response to the second and third nationwide lockdown in Ireland. Though the passenger car traffic volumes continued to rise slowly from January 2021 and reached close to 85% by June 2021, it still remained 10–15% lower than pre-Covid levels. The volume of heavy goods vehicles almost remained same during the COVID-19 scenario as compared to pre-Covid scenario except for a sudden decrease in the initial stage of the pandemic.

1.8. Equitable mobility

The travel restrictions imposed during COVID-19 pandemic caused an exacerbation of social and health-related inequalities between those able to do telework and those who must travel on a daily basis (Gutiérrez, Miravet & Domènech, 2020). High-income households and households with workers in lower middle-class occupations saw greater reductions in mobility compared to those with people in working-class occupations who tend to have less opportunities to work from home (Lee, Qian & Schwanen, 2021). In addition, those most reliant on public transport, were disproportionately impacted by reduced access, although a shift towards active mobility mitigated some of the impact (Hasselwander et al., 2021).

1.9. Mobility and spread of COVID-19

The incidence of any infectious disease is influenced by the transmissivity of the virus and the characteristics of the host population (Merler & Ajelli, 2010). The spread of COVID-19 is also influenced by biological as well as social and behavioral interactions of the population (Hisi, Macau & Tizei, 2019). However, the extent to which mobility impacts the spread of an epidemic is not yet clear. Delay in understanding the spreading dynamics of an epidemic can lead to the formation of complex epidemic networks (Hisi et al., 2019). Therefore, it is important that to understand the impact of COVID-19 on mobility behavior, and in turn, the role of mobility behavior on the spreading of the epidemic.

During an epidemic, people may choose to walk, cycle or use public transport because the necessary infrastructure is available and in close proximity to both their origins and to their destinations. Discrete choice theory, information theory and the multinomial logit and gravity models can be used to model travel demand (Anas, 1983). However, in making travel choices, “individuals do not internalize the external cost of infection risks they impose on others and the health care system” (Oum & Wang, 2020). In order to be better prepared for a future pandemic, a holistic understanding of the COVID-19 crisis across several disciplines is needed (Haghani, Bliemer, Goerlandt & Li, 2020). Models have been developed to understand and control the spread of epidemics, primarily focused on moderate measures. Given the experiences during COVID-19 pandemic, evaluation of more rigorous interventions, such as extensive travel restrictions and travel demand scheduling under strict control, are required (Li, Xiang & He, 2021). Further assessments are required on whether the travel restrictions imposed have made a significant and positive contribution to suppressing the spread of the disease. This is necessary in order to provide information to support for effective and timely decision making by policymakers.

1.10. Existing models explaining the relation between mobility and spread of an epidemic

Existing studies have modeled the spread of infectious diseases based on demographic characteristics. One such model, called the SIR model, compartmentalizes the population into three groups, namely, *susceptible*, *infected*, and *removed* and explains the spread of an epidemic using three coupled non-linear ordinary differential equations (Kermack & McKendrick, 1927). However, this model assumes that the outbreak is short lived, latent period is absent, and recovering confers lifetime immunity (Weiss, 2013). The SIR model was further expanded to take into account the incubation period, adding a fourth compartment, E and creating the SEIR model (Lloyd & May, 1996). However, these models do not consider the role of transportation system in the transmission of a disease.

Recently, few studies have attempted to explore the relationship between mobility and the spread of a pandemic. A study using the Toda-Yamamoto causality test concluded that there is a relationship between mobility and pandemic indicators (Kartal, Depren & Depren, 2021). The SEIR model (Lloyd & May, 1996) was further expanded to develop the Trans-SEIR model to account for infections associated with travel contagion in densely populated urban areas (Qian & Ukkusuri, 2021). The Trans-SEIR model accounts for the activity contagion that takes place during daily non-travel related activities such as work, school, entertainment and engagement with family members at home. In addition, the model also considers the travel contagion that arises from close contact with other commuters while traveling between major activity locations. Hence, the model can be used to determine direct infections and secondary infections arising from travel. Wei et al. (2021) developed a City-based Epidemic and Mobility Model (CEMM) to simulate intercity transmission in the initial stages of COVID-19. The CEMM considers the infections that are a result of internal contagion within the city and those that are brought into the city from other

regions.

Few studies suggest that even though transportation enables transmission of disease between major settlements, it does not influence the pattern of spread within a major settlement (Saba et al., 2018; Wu, Han, Sun & Han, 2018). However, it has also been shown that the level of mobility affects the persistence of the disease (Hisi et al., 2019). Few studies have also attempted to understand the most effective measures for controlling and preventing the spread of infections. Partial closure of bus routes may help to slow down the spread of an epidemic, but cannot fully contain its spread (Mo et al., 2021).

Understanding the role of urban mobility systems in the incidence of COVID-19 could assist in understanding the emerging perceptions and also aid the shaping of future transport policy. This study aims to understand the relation between mobility and the spread of COVID-19 while taking into consideration the various stages of restrictions which were imposed on mobility.

1.11. Methods and data collection

This section discusses the methodology and workflow adopted in the study. A brief description of the study area and data collected is also provided.

2. Methodology

The overarching goal of the study is to understand the relationship between the level of mobility and incidence of COVID-19. The study framework adopted to achieve this is illustrated in Fig. 1. The methodology has been described in detail below.

In order to establish a relation between the level of mobility during the pandemic and the number of positive COVID-19 infections, an initial exploratory analysis was conducted. Reported COVID-19 infections were compared with the level of mobility in different modes of transport as well as all modes combined. This analysis was carried out using Tableau software. The mobility data was investigated further to determine if there was a causal relationship between the COVID-19 infections and the level of mobility. The number of positive COVID-19 infections was considered as the dependant variable. Independent variables consisted of the various mobility modes including the traffic volume, cyclist volume, pedestrian volume, and number of public transport passengers.

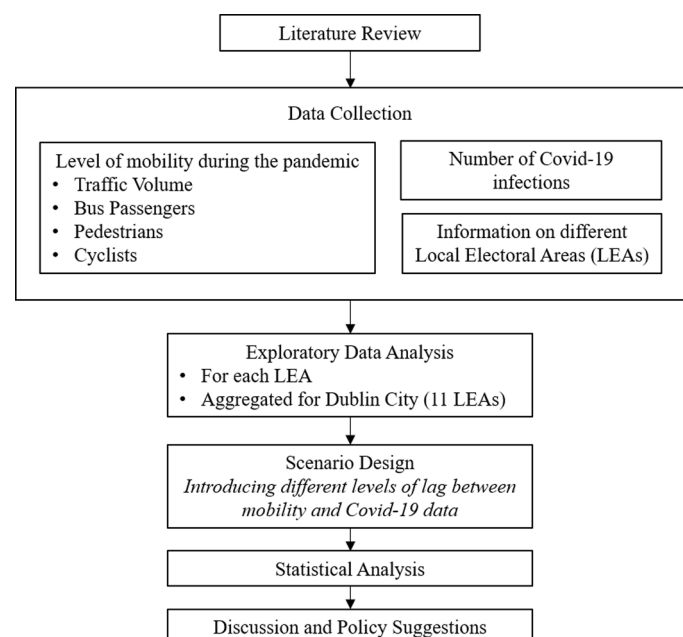


Fig. 1. Overview of the study framework.

Four different scenarios were used to investigate the relationship between the COVID-19 infections and level of mobility with different levels of lag between the time periods of COVID-19 and mobility data. First, the relation between COVID-19 infections and mobility data for the same week was examined as shown in Fig. 2.

Second, COVID-19 data reported one week from the relevant week for mobility data was used, that is, a one-week lag as shown in Fig. 3. Similarly, COVID-19 data reported two weeks and three weeks from the relevant week for mobility data was used for the other scenarios, corresponding to two-week lag and three-week lag as shown in Fig. 4 and Fig. 5, respectively.

Since weekly COVID-19 data is based on a 14-day moving average, the weekly data is made up of data collected over a three-week period. This means that in the scenario with a two-week lag, the Covid - 19 cases reported during the week that the mobility data is observed is also taken into account.

This approach was used to gain more understanding on the dynamics of transmission of the epidemic and the role of transport system. Further, statistical analysis was conducted to establish the relationship between COVID-19 infections and mobility related parameters.

2.1. Study area

Dublin which is the capital of the Republic of Ireland, is considered as the study area. The total confirmed COVID-19 cases in Ireland amounted to 5,78,064 until November 2021 and resulted in 5707 deaths. About 28% of Ireland's population lives in Dublin. County Dublin consists of several Local Electoral Areas (LEAs). Eleven of these LEAs which falls within the administrative area of the Dublin City Council are considered in the present study. The geographical location of these 11 LEAs considered in this study are shown in Fig. 6.

Different types of datasets including COVID-19 infections as well as the level of mobility in the city during different stages of Covid were required for the study. The following sections give a brief description of the data used in the study.

2.2. Data on COVID-19 infections

Data on the number of reported COVID-19 infections was obtained from the Central Statistics Office (CSO, 2021). COVID-19 cases were recorded in all LEAs within Dublin. The information on COVID-19 statistics and general population data related to each county and LEA which is used in the study is collated from the information provided by the Health Service Executive (HSE), Health Protection Surveillance Centre (HPSC), the Central Statistics Office (CSO) and Gov.ie. At the LEA level, the number of cases were reported as 14-Day incidence per 100,000 population. The data for 11 LEAs which falls within the administrative area of the Dublin City Council was used in this study. Since the number of reported COVID-19 infections was accurately available at the LEA level, the analysis in this study was made at this level and secondary data information was categorised accordingly.

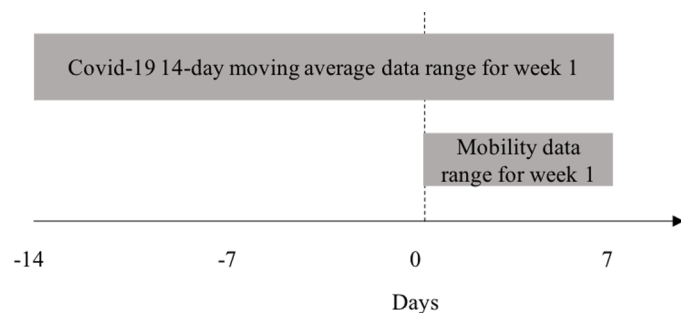


Fig. 2. Schematic showing range for mobility data and 14-day moving average Covid-19 data with no lag.

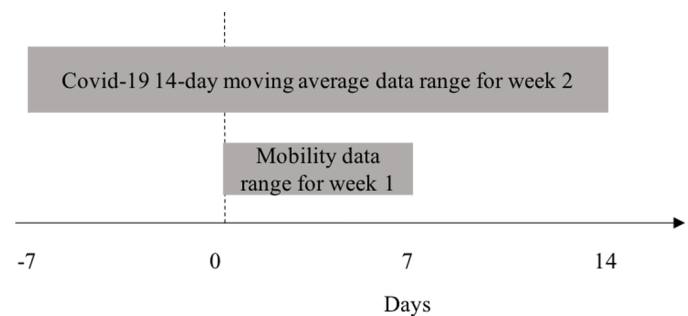


Fig. 3. Schematic showing range for mobility data and 14-day moving average Covid-19 data with one-week lag.

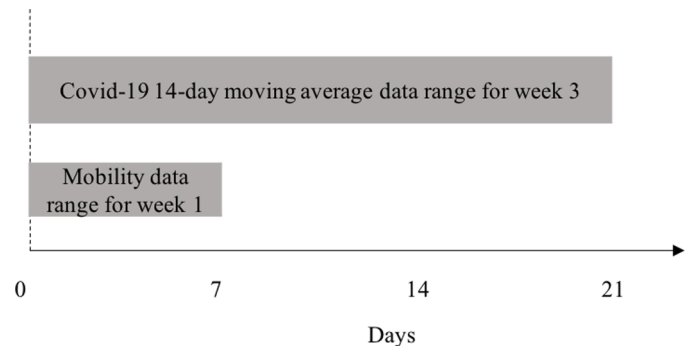


Fig. 4. Schematic showing range for mobility data and 14-day moving average Covid-19 data with two-week lag.

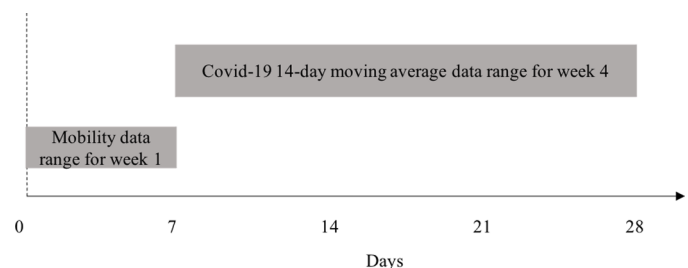


Fig. 5. Schematic showing range for mobility data and 14-day moving average Covid-19 data with three-week lag.

The data from August 2020 to May 2021 was considered for the study owing to several reasons such as availability of disaggregated data at the LEA level, sufficient sample size, and inclusion of multiple COVID-19 peaks. The total analysis period thus comprised of 40 weeks and included the second and third peaks of the reported COVID-19 infections.

While considering the different stages of Covid and corresponding number of infections and mobility data, it is also important to understand the specific restrictions that were in place during the analysis period. The next section gives a brief overview of the specific restrictions that were in place in Dublin during the analysis period.

2.3. COVID-19 restrictions in Ireland during the analysis period

The study considers a forty-week period from August 2020 to May 2021. As discussed in Section 2, Ireland was in complete lockdown prior to the study period starting from 12th March 2020 until 18th May 2020. From May 2020, restrictions began to be eased in a phased manner. The city was in much eased phase (Phase 2) during the start of analysis period in August 2020.

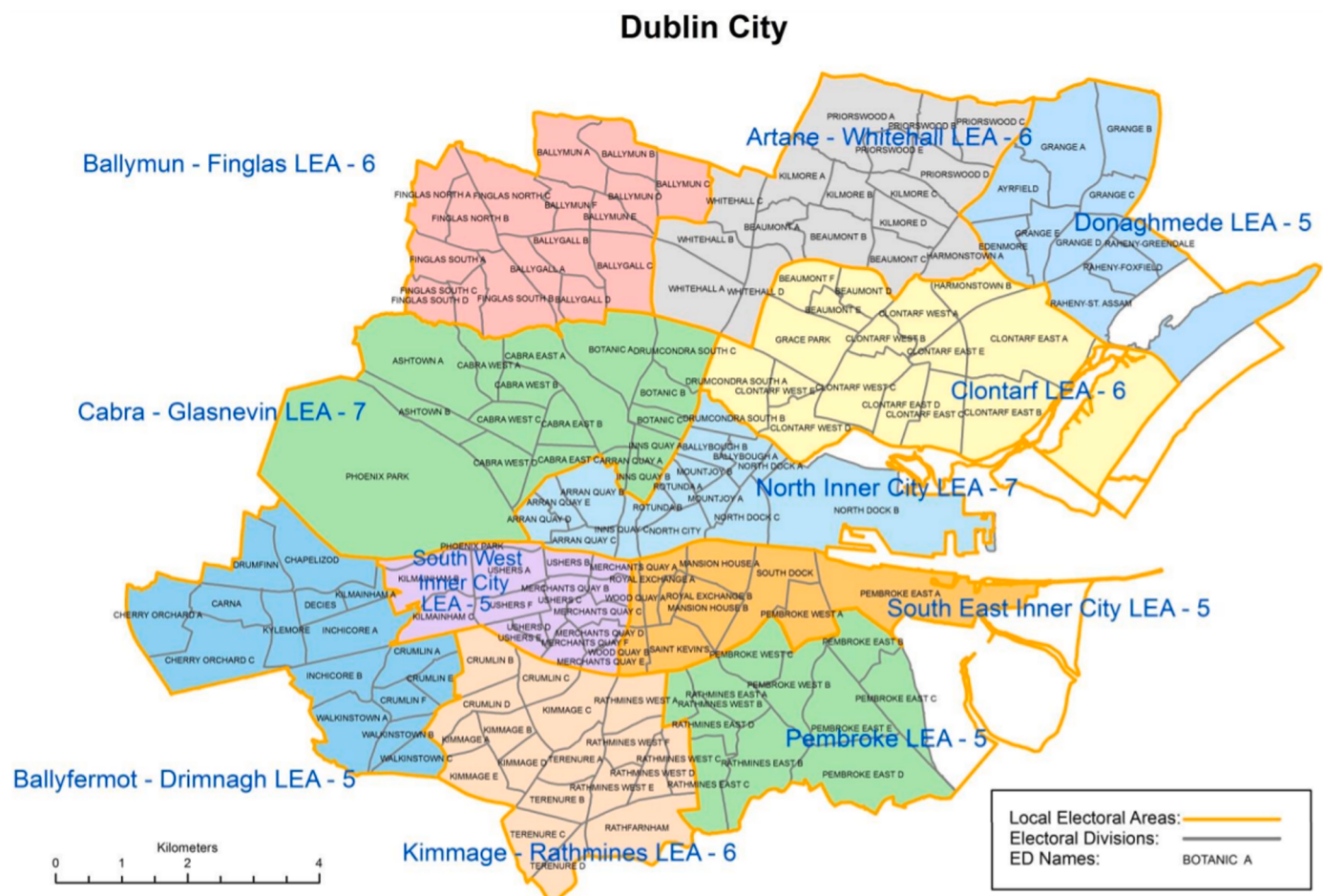


Fig. 6. Local Electoral Areas (LEAs) within Dublin City (Source: Ordnance Survey of Ireland, 2018).

The National Public Health Emergency Team (NPHE), which was formed by the Republic of Ireland to oversee the pandemic response in the country continued to suggest against all non-essential travel during this analysis period. The specific restrictions in place during the analysis period are (Department of Health, 2022): Face coverings were mandatory while traveling by public transport for all above the age of 13 years unless they have a reasonable excuse. The maximum permitted number of people in home gatherings were limited to 10. However, people were encouraged not to hold house parties. Maximum permitted number of attendees were 50 for indoor events and restaurants (including staff) and 200 for outdoor events. International passengers were required to fill a passenger locator form and follow necessary quarantine rules. Most of the shops and businesses were open with the exception of pubs and clubs. On the 6th of September, an additional requirement was included for home gatherings that people gathering shouldn't be from more than 3 different households.

2.4. Data regarding the level of mobility

Data regarding the level of mobility in the city during different stages of COVID-19 pandemic was required to understand the relation between mobility and the spread of infections. Mobility within the city comprises of vehicle traffic, bicyclists and pedestrians. Information regarding all these modes of mobility were collected from different sources within the city.

Traffic detectors are located at 843 signalised intersections and pedestrian crossings within the Dublin City and are linked to the Sydney Coordinated Adaptive Traffic System (SCATS) which is responsible for coordinating the timing of signal phases. These sites are well distributed

across the city and are shown in Fig. 7. Traffic volumes are counted at these intersections using induction loops. Traffic data was categorised at the LEA level to match the categorization of number of COVID-19 infections as mentioned in the previous section. Data for all the sites was available for the period of analysis from August 2020 to May 2021.

Public transport data consisting of number of bus passengers on all licensed and scheduled bus routes within the Dublin City during the analysis period was obtained from the National Transport Authority of Ireland. Other modes of public transport such as railways were not included in the study. Daily bicycle counts are recorded by Eco-Counters installed by the Dublin City Council for eleven sites. Additionally, data from Dublin Bike rental services were available for part of analysis period from August to December 2020. However, the cyclist volumes were excluded in the final analysis due to limited spatial distribution of cycling data collection sites and unavailability of data for the full analysis period.

The number of pedestrians are also recorded by the Dublin City Council using 34 Eco-Counters. However, only 13 of these sites had continuous data recorded over the period of interest. Seven of the sites are on the southern side of the Liffey River (South Side) and six are on the northern side of the river (North Side) as shown in Fig. 8.

The traffic data obtained was processed using big data analysis techniques and visualised using Tableau software. As mentioned earlier, initially, an exploratory analysis was conducted to understand the various characteristics of mobility and infections. Further, different scenarios were considered based on the lag between the COVID-19 infection data and the mobility data. The results from these analyses is discussed in the following section.

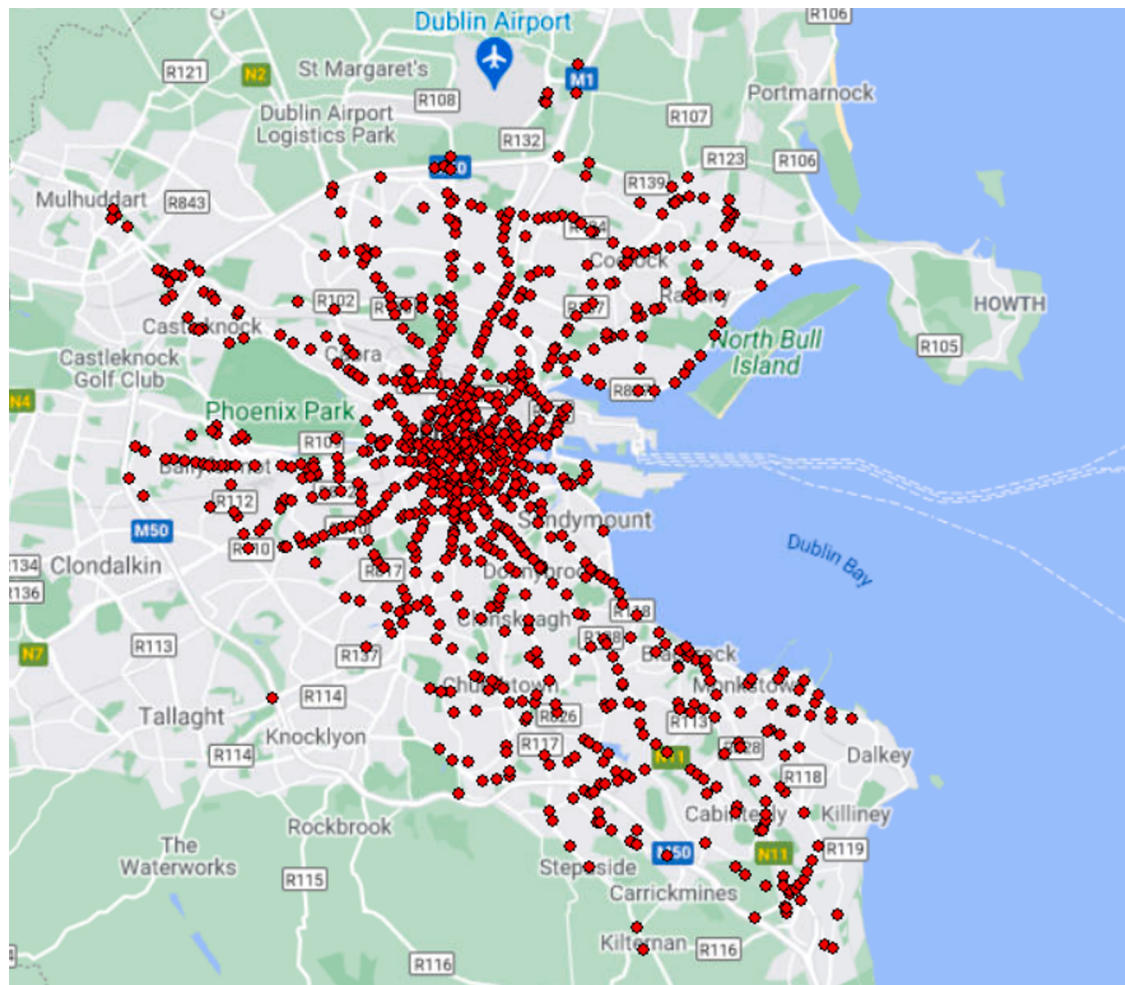


Fig. 7. Map showing locations of signalled junctions operating on SCATS.

3. Results and analysis

To understand the relation between mobility and COVID-19 incidence, the mobility data during the analysis period of August 2020 to May 2021 was examined and compared with the COVID-19 incidence data during the same period. Further, a model was developed to explain the relationship between these variables using different scenarios. These are explained in detail in the following subsections.

3.1. Variation in the level of mobility during analysis period

Traffic volume collected from 11 LEAs in Dublin during the analysis period from August 2020 to May 2021 is plotted in Fig. 9. Each line in Fig. 9 shows the variation of traffic volume in the corresponding LEA during the analysis period. A peak in traffic volume was observed in December 2020 close to the holiday season which further reduced drastically owing to stricter lockdown measures which came to effect from January 2021.

River Liffey, a major landmark in Dublin runs across the city dividing the city into North and South areas. Pedestrian volume from counters within the city centre from February 2020 to May 2021 was segregated into North and South based on the location of counters as shown in Fig. 10. There was a marked recovery in pedestrian volumes as recorded on the north side of the city, compared to the south side. A peak in pedestrian footfall was observed in December 2020, similar to the trend in traffic volume following which it dropped considerably.

3.2. Relation between mobility and COVID-19 cases at the LEA level

The mobility data during the analysis period was compared with the COVID-19 incidence rate during the same period for each LEA. The relation between number of COVID-19 cases and each of the parameters including traffic volume, pedestrian footfall, bus passengers and cyclist volume in one of the LEAs, namely, Ballyfermot-Drumcree are shown in Fig. 11, Fig. 12, Fig. 13 and Fig. 14, respectively.

A lag of 14 days to 21 days was observed between the peak in mobility data and the peak in the number of reported COVID-19 infections for the sample LEA. These observations were more pronounced for pedestrian data but less pronounced for traffic volume data and bus passenger data. Similar comparison of mobility data and COVID-19 infections was conducted individually for all LEAs and it was observed that these observations were consistent in most of the electoral areas.

3.3. Relation between mobility and COVID-19 cases for 11 LEAs

Total traffic volume obtained from the SCATS detectors for 11 LEAs in Dublin City were aggregated and compared against the reported COVID-19 cases as shown in Fig. 15.

A lag of 14 days to 21 days between the peak in traffic mobility data and the peak in the number of reported COVID-19 infections was observed in the aggregated data as well. However, there was a wider variation between the lag in the peak periods of cases and peak periods in mobility for aggregated data as compared to individual LEAs. Total pedestrian footfall and number of bus passengers were also aggregated



Fig. 8. Location of Eco-Counters for pedestrians in Dublin City (Indicated by red triangle).

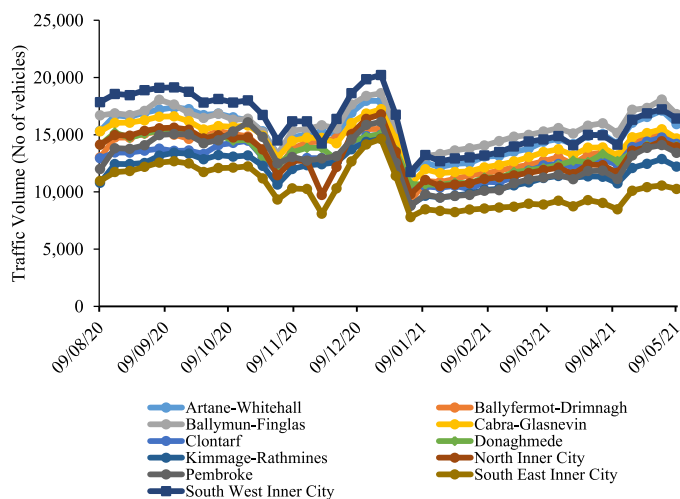


Fig. 9. Variation in traffic volume in 11 LEAs during the analysis period.

and compared against the reported COVID-19 cases as shown in Figs. 16 and 17.

3.4. Relation between mobility and COVID-19 cases for 11 LEAs with scenarios involving different lags

Considering the lag between peaks in number of COVID-19 infections

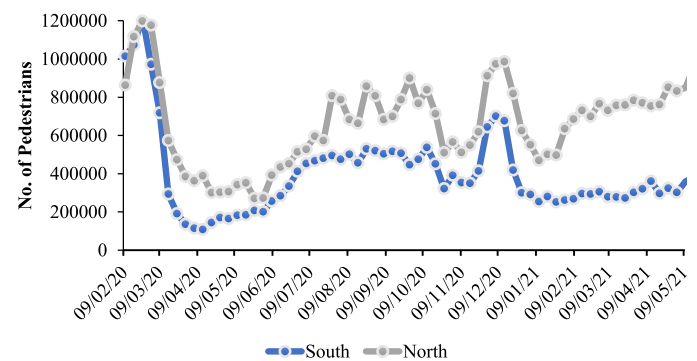


Fig. 10. Comparison of pedestrian volumes in the North and South of Dublin city centre.

and level of mobility, a scenario analysis was conducted. The mobility data was shifted by one week, two week, and three week and was compared with the corresponding number of COVID-19 infections. This was carried out to understand if the level of mobility in a particular week has an effect on the number of COVID-19 cases after one week, two weeks, or after three weeks. The traffic volume and number of COVID-19 cases for a sample LEA, namely, Ballyfermot-Drumragh for different scenarios involving lags of one week, two week, and three weeks are shown in Fig. 18.

As can be observed, the major peak in COVID-19 cases coincides with the traffic volume during three-week lag for Ballyfermot-Drumragh. The

Traffic Volume and Covid-19

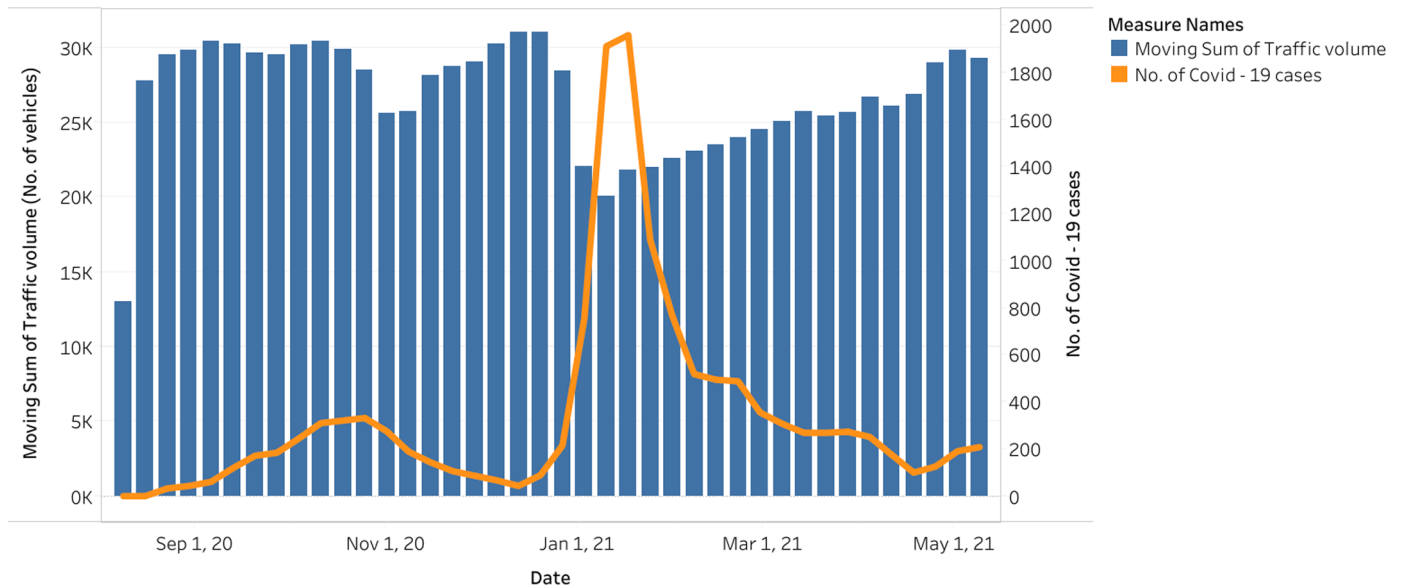


Fig. 11. Traffic Volume and Covid-19 incidents for a sample LEA, Ballyfermot-Drimnagh.

Pedestrians and Covid-19

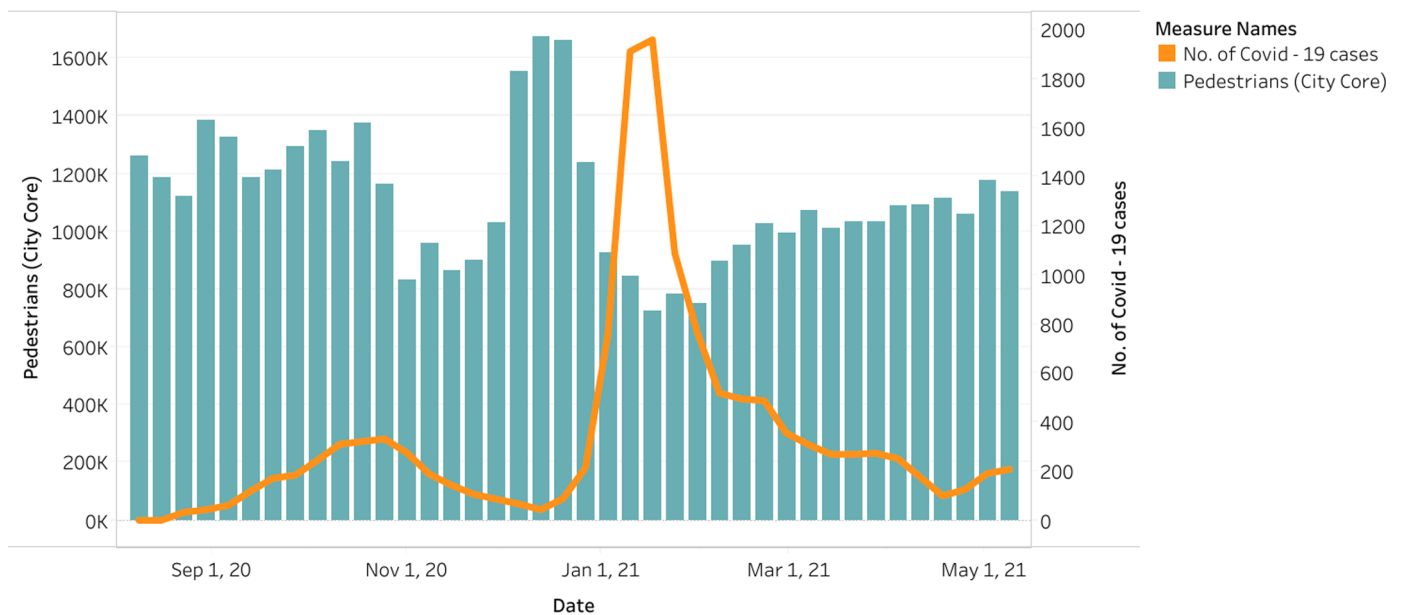


Fig. 12. Pedestrian volume and Covid-19 incidents for Ballyfermot-Drimnagh.

total traffic and total COVID-19 cases for all 11 for different scenarios involving lags of one week, two week, and three weeks are shown in Fig. 19.

Similar results can be observed in the aggregated plots also. The major peak in COVID-19 cases coincides with the traffic volume during three-week lag for combined plot considering all 11 LEAs. To verify the observations from exploratory analysis, a statistical model was developed between the level of mobility and number of COVID-19 cases. This is described in the following section.

3.5. Statistical model between mobility and COVID-19 cases for 11 LEAs

Reported COVID-19 infections is considered as the dependant variable in the study. The level of mobility consisting of traffic volume,

number of bus passengers on all licensed city bus services, and pedestrian footfall in the city centre were considered as the independent variables in the study. A basic regression modeling technique is used to assess the relationship between the dependant and independent variables considered in the study. Regression analysis was conducted for multiple scenarios involving no lag, one week lag, two week lag, and three week lag. Results of the regression analysis for two weeks lag in the number of reported COVID-19 infections are summarised in Table 1. The results from the one week lag analysis were poor and did not add to the narrative of the paper so they have been presented. The authors do note the low values of some of the r squared values presented for some of the individual modes. The comparison between them is useful to demonstrate how each mode of transport performs.

In the case of a two weeks lag, the R Squared for city wide assessment

Bus Passengers and Covid-19

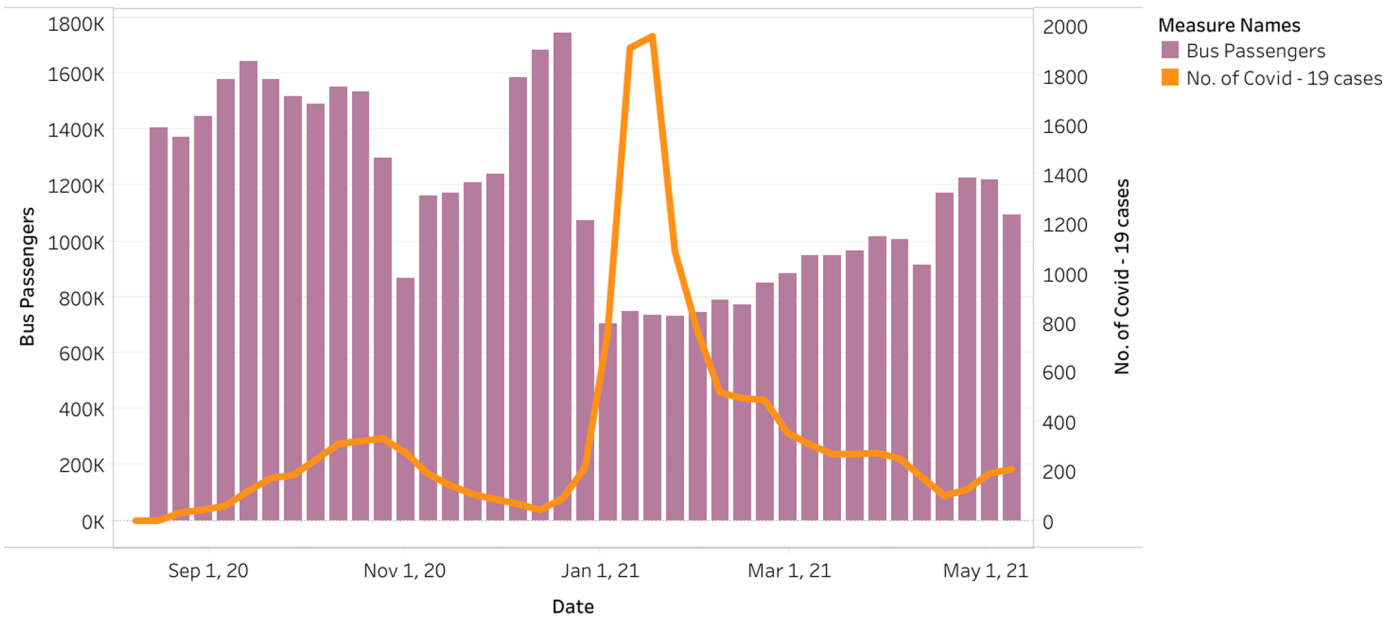


Fig. 13. Bus passengers and Covid-19 incidents for Ballyfermot-Drimnagh.

Cyclists and Covid-19

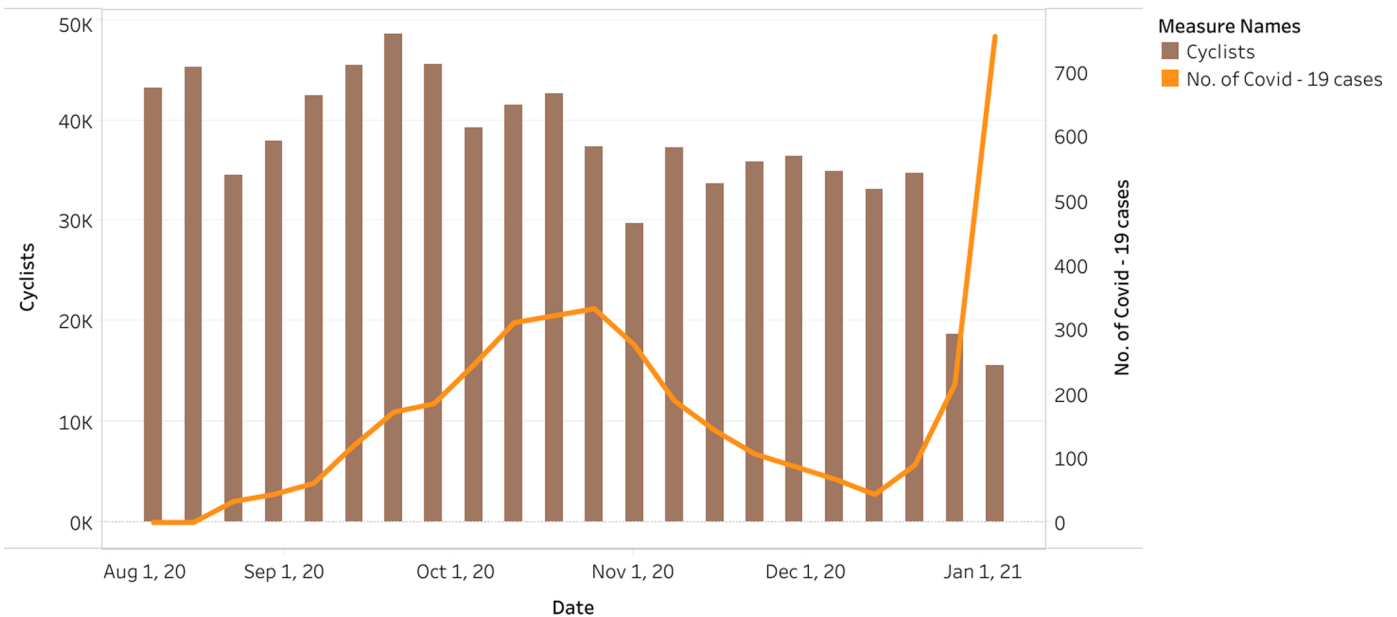


Fig. 14. Cyclists and Covid-19 incidents for Ballyfermot-Drimnagh.

retained a value of 0.312 when traffic volume, bus passengers and pedestrian footfall in the city centre were used as dependant variables. When regression was carried out at the LEA level, a mean value of R Squared of 0.362 across the 11 LEAs, standard deviation 0.1 was obtained. Results showed a positive correlation for pedestrian footfall and the number of reported Covid - 19 infections in each LEA. Partial Regression plots gave a mean R squared of 0.172 and standard deviation of 0.065 for pedestrian footfall. Partial regression results for bus passengers showed a mean R Squared of 0.076 and standard deviation of 0.085. Ten of the eleven LEAs, South East Inner City being the exception, showed a negative correlation between bus passenger numbers and the reported COVID-19 infections. Partial regression results for traffic volumes showed a mean R Square of 0.121 and standard deviation of 0.135.

There were negative correlations in ten of the eleven LEAs, South East Inner City being the exception.

Results of the regression analysis for three weeks lag in the number of reported COVID-19 infections are summarised in Table 2.

In the case of a three weeks lag, the R Square for a citywide assessment retained a value of 0.018 when traffic volume, bus passengers and pedestrian footfall in the city centre were used as dependant variables. When regression was carried out on a LEA basis, a mean R square of 0.330 across the eleven LEAs, standard deviation 0.067 was obtained. Results showed a positive correlation between pedestrian footfall and the number of reported Covid - 19 infections in each LEA. Partial regression plots gave a mean R square of 0.261, standard deviation of 0.078 for pedestrian footfall. Partial regression results for bus passengers

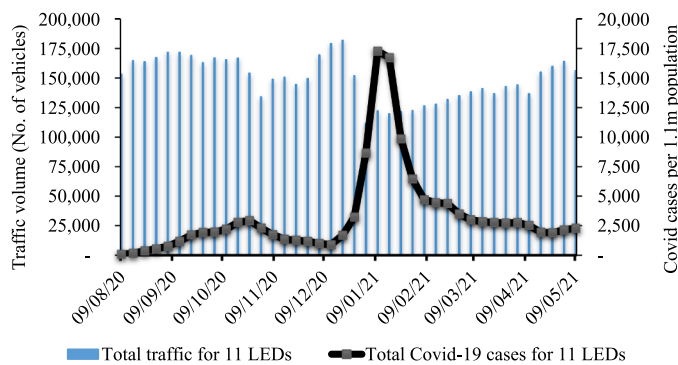


Fig. 15. Plot of city-wide traffic volume from SCATS detectors and reported Covid-19 cases for 11 LEAs in Dublin City.

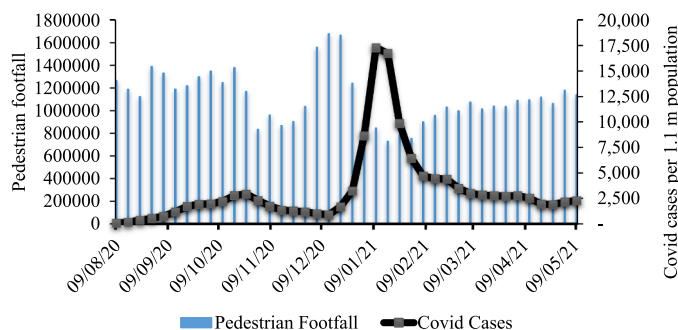


Fig. 16. Plot of city centre pedestrian volumes and reported Covid-19 cases for Dublin City.

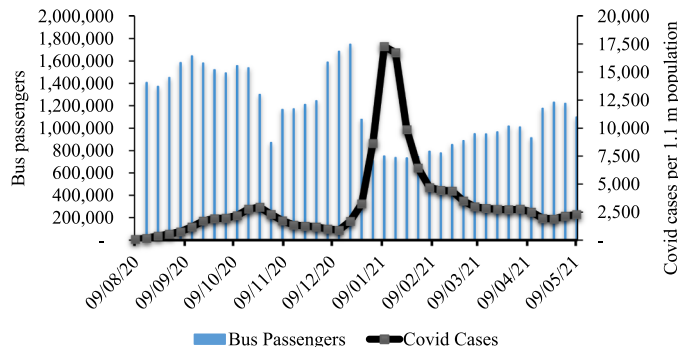


Fig. 17. Plot of bus passenger volumes and reported Covid-19 cases for Dublin City.

showed a mean R Square of 0.111 and standard deviation of 0.130. Nine out of eleven LEAs showed negative correlations. South East Inner City and South West Inner City showed positive correlations. Partial regression results for traffic volumes showed a mean R Square of 0.065 and standard deviation of 0.088. There were negative correlations for eight out of eleven LEAs. The three-city centre LEAs of South East Inner City, South West Inner City and North Inner City showed positive correlations. In particular, the South East Inner City, the main employment Area, had an R Squared of 0.219 for traffic volume and 0.351 for bus passengers, both 1.8 times higher than the respective mean values.

Based on regression models for each of the 11 LEAs, bus-based mobility shows more positive correlation with number of COVID-19 infections than other modes. Another interesting observation was the considerable difference in R squared values for two-week lag scenario (0.312) and three-week lag (0.018) scenarios. This indicates that the relation is getting smoothened with aggregation in long-term. Further

analysis showed that the LEA, namely, Ballyfermot-Drimnagh had a very high R squared, two standard deviations from the mean, for a two-week lag. In the second scenario, with a three-week lag, Ballyfermot-Drimnagh and South East Inner City had much higher values of R Square, at one and a half times the standard deviations from the mean. For Ballyfermot-Drimnagh, the partial regression R Square for traffic volume was 2.1 times above the mean. For South East Inner City, the partial regression R Square for bus passengers was 1.8 times standard deviations above the mean. In both cases, the correlations were calculated to be negative. Another LEA, namely, Kimmage-Rathmines had a much lower value of R Square, at two standard deviations from the mean. The partial regression R Square for bus passengers was 1.8 times standard deviations above the mean.

4. Discussion

Results from the study provides insights on how the pandemic has impacted the transportation system and the role of transport system in the spread of the pandemic. Further discussion on mobility trends during COVID-19, relation between mobility and COVID-19 and resulting transport policy implications are discussed in the following subsections.

4.1. Mobility trends during COVID-19

Findings from this paper suggests that pedestrian movement within Dublin city is generally linked to economic activity comprising work, education and tourism. This is reflected in the large drop in pedestrian footfall in April 2020 on the southern side of the city. With the closure of tourism and Trinity College Dublin, a major educational institute located at the southern side of the city, even the reopening of non-essential shops was not able to trigger a significant recovery in footfall. On the other hand, the proximity of residential areas on the north side of the city meant that the footfall did not drop by the same percentage as the south side. In addition, the recovery was more pronounced with footfall rising to above 70% in May 2021, compared to 35% on the south side.

Cyclist numbers remained relatively high between August and November 2020 and dropped in December 2020. It should be noted that this is traditionally the period when cycling numbers in the city are at their lowest due to unfavourable weather conditions.

Bus passenger numbers remained very low and dropped further in October 2020 and then in January 2021 to February 2020. This occurred immediately after the peak in the number of reported COVID-19 infections, reflecting the public's response to safety concerns associated with the use of public transport.

4.2. Relation between mobility and COVID-19 infection rates

A close inspection of the mobility data and reported COVID-19 infections shows that there is a pattern of delay between the peak in positive COVID-19 infections and the peak in mobility. The first peak in COVID-19 infections lags the peak in traffic volume by fourteen days. In October 2020, two *minor* peaks occurred after seven to fourteen days. On the other hand, the second peak in COVID-19 infections in January 2021, lags the peak in mobility volumes by fourteen to twenty-eight days. There may be two reasons to explain this; the number of reported cases during the second peak will have been impacted by the testing capacity or reporting and, there may have been an extended period of non-travel related contagion in the period between Christmas and New Year.

The results from the present study confirming a lag between mobility and reported COVID-19 infections of two to three weeks is consistent with the principles of the SEIR model which suggests that the disease may be going through an incubation period before the transfer of the infection (Qian & Ukkusuri, 2021).

Based on the conclusions from the initial exploratory analysis,

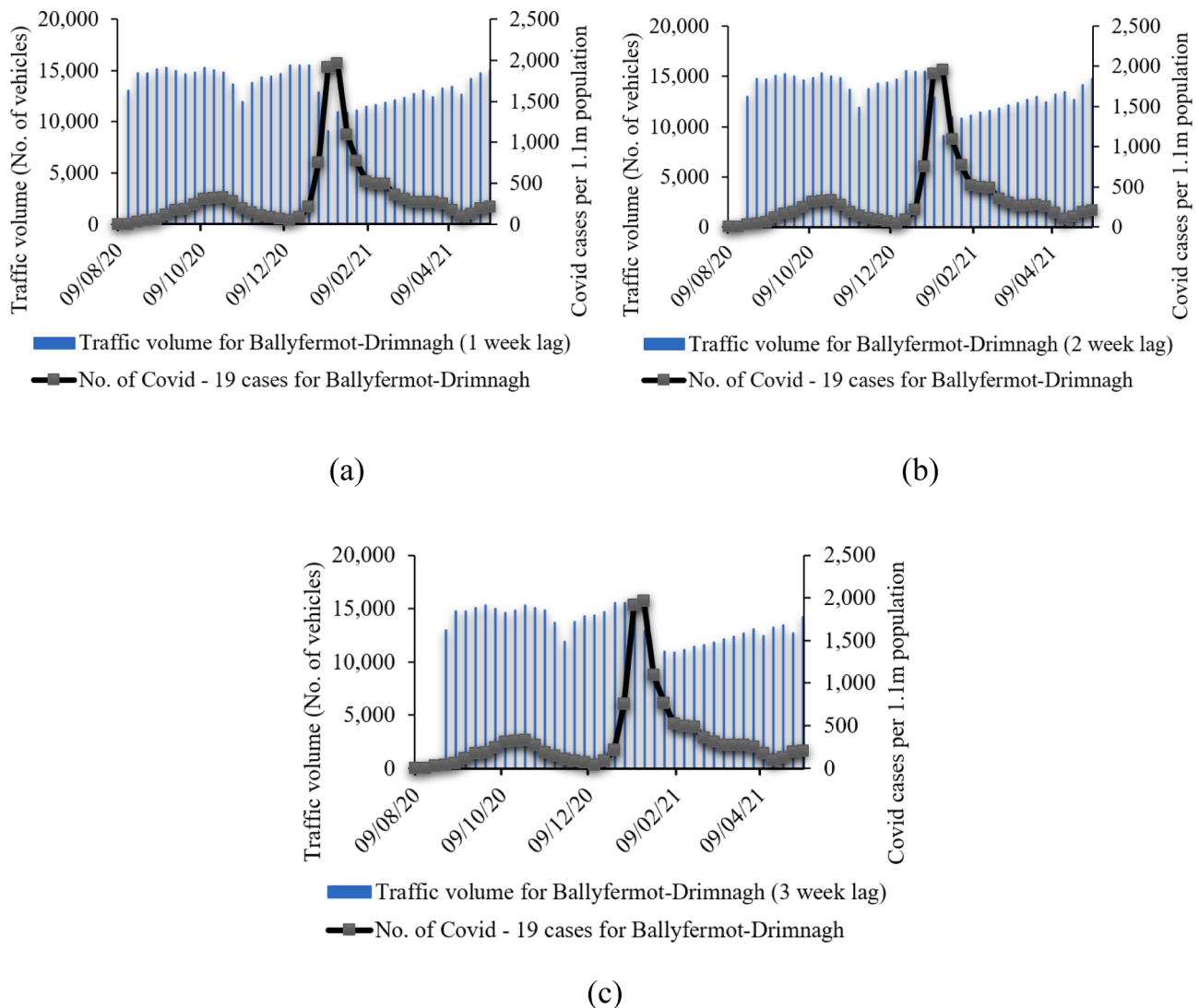


Fig. 18. Total traffic and total Covid-19 cases for a sample LEA Ballyfermot-Drimmagh for different scenarios.

different time lags of two weeks and three weeks was introduced while building statistical models to investigate the relation between mobility and COVID-19 infections. The results showed that, on average, 36.2% of the reported COVID-19 infections can be explained by mobility alone while considering a two-week lag in the 14-day moving average COVID-19 data. On the other hand, when a three-week lag was used, 33% of the reported COVID-19 infections could be explained using mobility data alone. Similarly, 17.2% and 26.1% of COVID-19 infections could be explained by pedestrian footfall in the city centre in two-week lag scenario and three-week lag scenarios, respectively. A separate study by Kartal et al. (2021) concluded that there was no relationship between car based mobility or walking with the number of COVID-19 infections in Turkey. In this study, only three out of 24 regression models showed positive correlation between car-based mobility and COVID-19 infections, while five out of 24 models showed positive correlation for bus-based mobility. However, the same study also suggested that there may be cointegration in the long term. It can therefore be reasoned that the pedestrian mobility in the city centre is a reflection of the economic activity and resultant societal interactions that result in non-travel related contagion.

Public transport-based mobility was observed to have a negative correlation on reported COVID-19 infections. This trend could be an outcome of people's travel behavior being influenced by the public information regarding increasing infections. Studies also suggests that

passengers using low-capacity travel modes has the least probability of getting infected while passengers using medium or high capacity modes are more likely to get infected (Qian & Ukkusuri, 2021). Given that during COVID-19, all public transport became low capacity, with additional hygiene measures in place, public transport users may not have been more vulnerable to contagion compared to single occupancy car-based mobility.

Results from the CEMM modeling from a recent case study in China that concluded 33.55% of the cases came from intercity transmission and 66.45% from internal city contagion (Wei et al., 2021). This suggests that more than 33.55% are associated with mobility, accounting for transmission associated with contagion as a result of exposure during travel between cities. Qian and Ukkusuri (2021) notes that there are two distinct types of disease transmission, the activity contagion that takes place during daily non-travel related activities such as work, school, entertainment and engagement with family members at home; and the travel contagion that arises from close contact with other commuters while traveling between major activity locations. In that sense, travel contagion arising from close contact with other commuters does not constitute the full explanation. While the results for this study have established that 33% of the COVID-19 infections could be explained by mobility alone, it cannot be said that 33% of the reported cases were a result of mobility. The largely negative correlations between mobility modes of car and bus suggest that these modes were not major drivers in

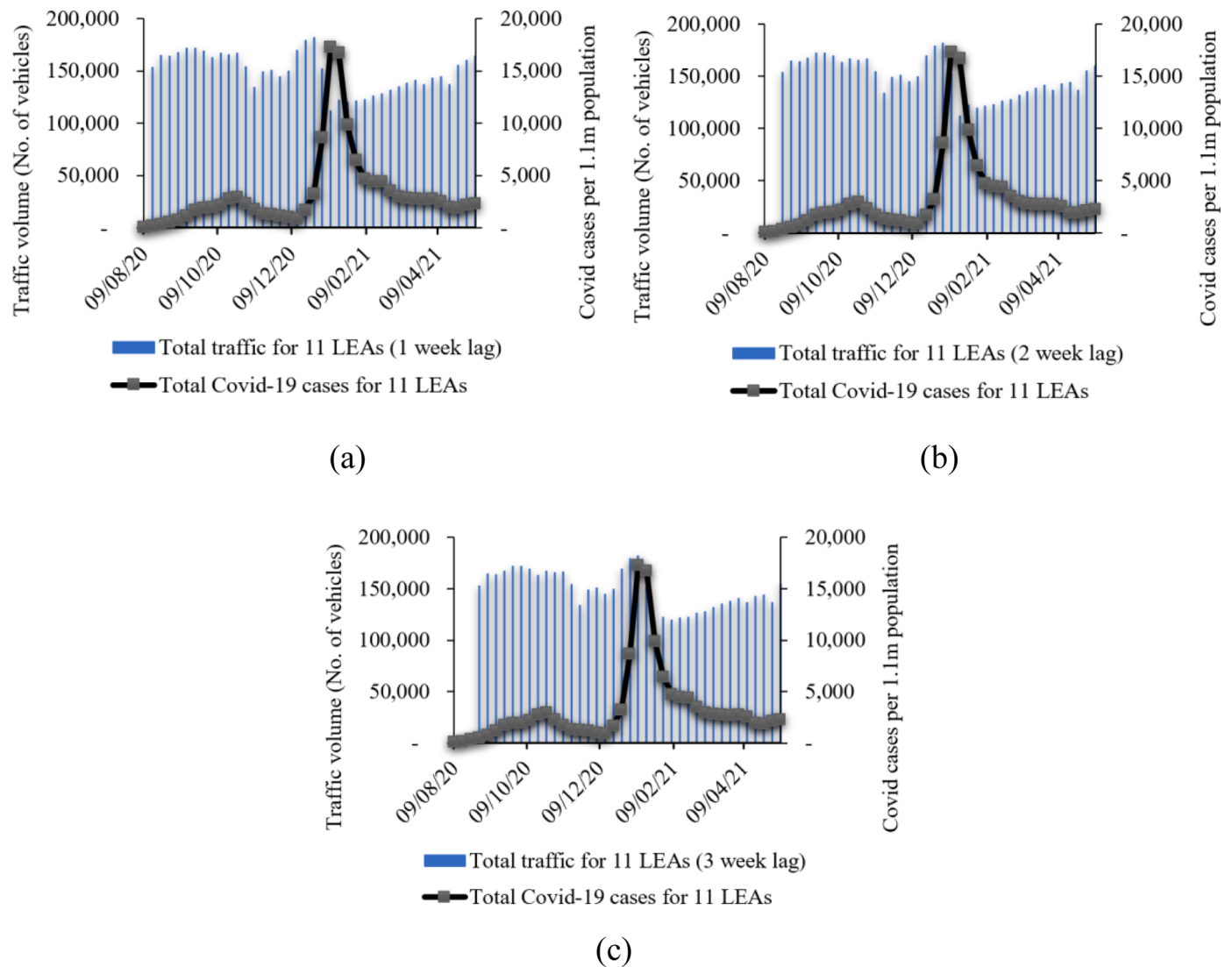


Fig. 19. Total traffic and total Covid-19 cases for 11 LEAs for different scenarios.

Table 1

Regression results for all LEAs for two weeks lag.

Local Electoral Area (LEA)	Regression R Squared	Partial Regression R Squared Traffic volume	Bus Passengers	Pedestrians
Citywide	0.312	0.093	0.003	0.213
Artane - Whitehall	0.372	0.125	0.000	0.245
Ballyfermot - Drimnagh	0.565	0.447	0.123	0.089
Ballymun - Finglas	0.434	0.209	0.033	0.233
Cabra - Glasnevin	0.290	0.064	0.000	0.173
Clontarf	0.272	0.016	0.101	0.212
Donaghmede	0.272	0.009	0.048	0.172
Kimmage - Rathmines	0.383	0.205	0.034	0.090
North Inner City	0.340	0.000	0.173	0.132
Pembroke	0.224	0.043	0.000	0.168
South East Inner City	0.287	0.120	0.271	0.039
South West Inner City	0.236	0.002	0.047	0.122
Mean	0.362	0.121	0.076	0.172
Standard Deviation	0.100	0.135	0.085	0.065

Table 2

Regression results for all electoral areas for three weeks lag.

Local Electoral Area (LEA)	Regression R Squared	Partial Regression R Squared Traffic volume	Bus Passengers	Pedestrians
Citywide	0.018	0.004	0.001	0.015
Artane - Whitehall	0.340	0.058	0.005	0.338
Ballyfermot - Drimnagh	0.427	0.253	0.035	0.229
Ballymun - Finglas	0.300	0.068	0.064	0.291
Cabra - Glasnevin	0.317	0.010	0.021	0.312
Clontarf	0.383	0.016	0.100	0.369
Donaghmede	0.337	0.031	0.018	0.298
Kimmage - Rathmines	0.195	0.021	0.351	0.171
North Inner City	0.297	0.003	0.184	0.218
Pembroke	0.329	0.028	0.002	0.290
South East Inner City	0.428	0.219	0.351	0.100
South West Inner City	0.280	0.003	0.092	0.253
Mean	0.330	0.065	0.111	0.261
Standard Deviation	0.067	0.088	0.130	0.078

the increase in the number of reported cases. The results though pose a question as to whether the negative correlation is an outcome of people's travel behavior and choices being influenced by the public

information regarding increasing infections. Specifically, that people were continuously adjusting their travel behavior and making less trips if the number of reported infections was increasing.

According to existing studies on the spread of infectious diseases, 58% to 67% of reported contacts occur at home, school or work (Merler & Ajelli, 2010; Mossong et al., 2008). Direct travel contagion may account for 10.0% to 17.6% of infections which could increase to 16.9% to 25.6% while considering travel induced contagion. Considering the strengths of travel transmission and activity transmission being the same, the total travel-related infections may eventually account for over 35% of the total infected cases during an urban disease outbreak (Qian & Ukkusuri, 2021). By establishing that 33 to 36.2% of the reported COVID-19 infections can be explained by mobility alone, the results of this study are consistent with these findings. On the other hand a research by Wu et al. (2018) concluded that there are no effective measures to be taken to prevent the epidemic spreading. According to them, increased level of mobility would increase the rate of spread of the epidemic, even though the final epidemic size is almost kept at the same level.

In this study, the citywide regression model showed an R squared of 0.312 for a two-week lag compared to an R squared of 0.018 for a three-week lag. This poses the question of whether there is smoothing of peaks when there is aggregation of analysis in the longer term. Studies suggest that, travel bans seem to be useful in the long-term only if strictly applied, as simple reduction in mobility rate may imply a non-negligible increase in epidemic (Hisi et al., 2019). This may explain why the results of this study could not explain the citywide COVID-19 reported cases using the aggregated independent mobility variables.

Thus, the key inferences from this study would be: mobility can be used to explain the transmission of COVID-19 to a certain extent, and bus-based mobility and car-based mobility do not have a significant adverse impact on COVID-19 infections. In the case of public transport, recent research in Singapore (Mo et al., 2021) suggests that although social distancing, wearing face masks and good hygiene are the most effective measures for preventing the spread of infections, reducing bus services is also effective. These measures will ensure that the risk of contagion may be significantly lower than that from non-travel activities. However, as noted by Merler and Ajelli (2010), the impact of an epidemic, and in this case COVID-19, will be different in different countries because of the different sociodemographic structures. It is evident that mobility plays an important role in how cities can have an improved control on the rate of contagion in the short to medium term. This means that experiences by the mobility sector during the COVID-19 pandemic and the resultant learnings should provide key inputs in the formulation of future transport policy in order to achieve a more sustainable and resilient transport system. Some of the important policy implications of the study are discussed below.

4.3. Transport policy implications

Firstly, in view of sustainable mobility, strong measures are required to reduce the affinity towards private cars which has increased during COVID-19 (Eisenmann et al., 2021). This should include investing in high quality walking and cycling infrastructure, improving the ambience of such spaces through planting greenery and encouraging people to work from home (Aaditya & Rahul, 2021; Zhang & Fricker, 2021). It is also important to ensure sufficient capacity in pedestrian and cycling infrastructure in the vicinity of amenities and facilitating servicing through cargo bikes (Bohman et al., 2021). However, this study also raises the question of whether our pedestrian areas are too congested that they provide a risk to mobility related contagion.

It is also important to rethink the role of public transport in a sustainable and resilient transport system. The pandemic has led to a fear of contracting infection through public transport and is bound have long term effect on travel behavior and mode choice. However, this study has shown that taking into account the safety measures that were put in place to contain the risk of contagion, mobility by bus did not have an adverse impact on reported COVID-19 infections. The development of the public transport system should therefore take necessary measures to

minimise unwanted contact between passengers and ensure safety without having to increase the cost of travel.

Social distancing is one of the most important factors, which is influencing people's perception of safety. Decongesting public transport systems through increased bus frequencies, and safety measures at bus stops could lead to reducing some of these fears and improving public transport usage. Intelligent solutions such as real time information on space availability within a service and updates on sanitization on a trip-by-trip basis could complement schedule information. Strategies to smoothen the peak hour demand including variable ticketing pricing in tandem with staggering working hours, opening hours for services and organisations, and school hours will also reduce congestion in public transport (Bohman et al., 2021).

The results presented in this paper demonstrate how powerful having a vast network of sensors and counters in a city can be for measuring demand. The investment in these networks paid dividends during the pandemic as they enabled city authorities monitor movements in the city. Our results demonstrate how the larger networks for cars provide more robust results and that if a similar network existed for cyclists and pedestrians that it might be possible to mirror those results. As our cities transition to low carbon modes a greater network of these sensors for active modes would empower cities to monitor and measure trends.

Finally, long-term transport policies should be developed following a holistic approach towards mobility by considering all modes of travel, environmental impact, congestion, equity among different groups, personal safety, and impact on the community (Vickerman, 2021). Walking and cycling should be encouraged through infrastructure investment and big data analysis should be used wherever possible to facilitate decision making (Hasselwander et al., 2021). Such an approach would facilitate adaptive capacity for mobility systems to disruptions, in particular public transport systems, and the resilience of the overall mobility ecosystem against pandemics (Zhang & Fricker, 2021). In the short-term this may require policymakers to promote active mobility and prioritize investment in public transport to reduce unequal access to transport and to rebuild public trust.

5. Conclusion

This research sought to investigate the relation between the level of mobility and the number of reported COVID-19 infections using data collected from 11 Local Electoral Areas in Dublin City. Different modes of travel including cars, bus, pedestrians, and cyclists were considered in the study. The study drew from experiences and research from around the world in terms of both epidemiological spreading and the impact of COVID-19 on mobility as well as mobility behaviors. The use of reported confirmed COVID-19 infections and traffic data collected through automatic detection provided a valid and credible dataset which led to reliable findings. Results indicate that only the city centre showed positive correlation between pedestrian mobility and the reported incidence of COVID-19.

The results confirm that mobility has changed as a result of the pandemic and shows that a relationship exists between mobility and incidence of COVID-19. A lag is observed between the peak in mobility and the peak in the number of COVID-19 infections. Specifically, the peak in the number of COVID-19 infections occur between fourteen to twenty-one days after the peak in mobility. Regression analysis was done with the number of COVID-19 infections as the dependant variable and the volume of traffic recorded via the SCATS system, number of bus passengers on licensed bus services, and the number of pedestrians counted in the city core as the independent variables. Results from regression analysis show that 36.2% of the reported COVID-19 infections after a two-week lag and 33% of the infections after a three-week lag could be explained using the level of mobility. Also, 17.2% of COVID-19 infections after a two-week lag and 26.1% of COVID-19 infections after a three-week lag could be explained using the pedestrian footfall at the city centre. Although 7.26% of COVID-19 infections

after a two-week lag and 11.1% of COVID-19 infections after a three-week lag could be explained using bus passengers, there was a negative correlation between these variables. It can be concluded that the measures that were in place to reduce the risk of mobility related contagion on public transport services were effective.

The public responded to the rising COVID-19 infections by staying away from public transport. As a result, this research was ineffectual in establishing the causal relationship between public transport and reported COVID-19 infections. There is no convergence between modeling techniques on the proportion of COVID-19 infections that can be directly linked to mobility. In spite of this lack of convergence, it is clear that COVID-19 has impacted the way people make their mode choices. This altered mobility behavior is likely to remain in the long-term, therefore presenting a challenge for transport policy development.

The altered perceptions, demonstrated by people staying away from public transport, mean that it is now necessary to rebuild trust in public transport, dampen the positive attitudes towards car use and build on the feel-good factor towards cycling and the gains in the public's increased tolerance for walking and cycling infrastructure. This will require a review of the existing business models because increased safety provisions will increase the operational costs for public and shared mobility options, which may impact on the level of subventions required for service providers.

Though the influence of these altered perceptions on mobility is still not known completely, what is clear is that a holistic approach to rebuilding a resilient transport system for a city, specifically Dublin City in this case, will require policy to focus on sustainable mobility in which personal safety and equitable mobility are just as important and that they are considered in the same way as the environment and congestion.

Future research that takes into account data from all mobility options will further improve our understanding of how mobility has impacted on the spread of the COVID-19 pandemic and may influence the way that traffic models are developed in the future.

The results from this study demonstrate the power of having a network of sensors that monitor movement across our cities to measure the potential impacts of phenomenon outside the control of city authorities, like a pandemic. The methods in this study would also be useful to follow as cities emerge from the pandemic, they could be used to demonstrate how people are returning to various modes of transport and if the anticipated sluggish return to public transport is occurring.

Arising from this study, it is suggested that future research on mobility and COVID-19 should seek to analyze transmission characteristics and mobility responses at disaggregated levels, such as Local Electoral Areas to gain more insightful knowledge. It is also suggested that a national travel community forum be set up that captures people's travel habits that can form a basis for longitudinal studies. Specific longitudinal studies may be necessary for public transport users to better understand the effectiveness of measures that are being put in place to enhance the safety of public transport systems against disease contagion.

Declaration of Competing Interest

All authors have participated in (a) conception and design, or analysis and interpretation of the data; (b) drafting the article or revising it critically for important intellectual content; and (c) approval of the final version.

This manuscript has not been submitted to, nor is under review at, another journal or other publishing venue.

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