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ORIGINAL ARTICLE

Spatial mobility patterns and COVID-19 incidence: A regional analysis of the second wave in the Netherlands

Bart Roelofs[1] | **Dimitris Ballas**[1] | **Hinke Haisma**[2] | **Arjen Edzes**[3]

[1]Department of Economic Geography, Faculty of Spatial Sciences, University of Groningen, the Netherlands

[2]Population Research Centre, Faculty of Spatial Sciences, University of Groningen, the Netherlands

[3]Department of Economic Geography, Faculty of Spatial Sciences, University of Groningen, and School of Law, Hanze University of Applied Sciences, Groningen, the Netherlands

Correspondence
Bart Roelofs, Department of Economic Geography, Faculty of Spatial Sciences, University of Groningen, Landleven 1, 9747AD Groningen, the Netherlands.
Email: b.j.roelofs@rug.nl

Funding information
University of Groningen

Abstract

A key policy measure introduced by governments worldwide at the beginning of the coronavirus disease 2019 (COVID-19) pandemic was to restrict travel, highlighting the importance of people's mobility as one of the key contributors to spreading severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2). However, there was little consistency regarding the geographical scale or the severity of these measures. Little use was made of commuting and travel data to inform decisions on when, where and at what level restrictions should be applied. We aim to contribute to regional policy by providing evidence that could be used to inform future policy debates on the most effective travel restrictions to impose during a pandemic. We present an analysis of the impact of mobility between municipalities on COVID-19 incidence in the Netherlands. We used multiple linear regression models and geographical information systems to gain insight into the association between mobility-related factors and demographic, socio-economic and geographical factors with COVID-19 incidence in municipalities. Our results indicate that spatial mobility patterns, when combined with COVID-19 incidence in municipalities of origin, were associated with increased COVID-19 incidence in municipalities of destination. In addition, various regional characteristics were associated with municipal incidence. By conducting our analyses over three different periods, we highlight the importance of time for COVID-19 incidence. In the light of ongoing mitigation measures (and possible future events), spatial mobility patterns should be a key factor in exploring regional mobility restrictions as an alternative for national lockdowns.

KEYWORDS
coronavirus, COVID-19, demography, mobility, spatial analysis

1 | INTRODUCTION

> *'Chinese authorities on Thursday morning closed off Wuhan – a city of more than 11 million people and the epicenter of a pneumonia-like virus that has spread halfway around the world – by canceling planes and trains leaving the city, and suspending buses, subways and ferries within it.'*
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> New York Times, 22 January 2020 (Qin & Wang, 2020).

The importance of space, place and physical mobility between places was a key factor affecting the spread of coronavirus disease 2019 (COVID-19), which rapidly developed into a pandemic, infecting millions of people and with over 190 countries reporting cases just 4 months after the virus was first identified. Now, after more than 2 years of COVID-19, over 500 million reported cases and more than six million deaths, it is worth noting that a number of demographic, geographical and socio-economic determinants have been found to be associated with COVID-19 incidence, although their significance varies greatly between countries, regions and cities. The importance of space and place, and in particular the regional dimension of the pandemic, has been the focus of academic and policy debates from the very early stages of the pandemic (Bailey et al., 2020).

The study we present aims to contribute to the regional science, policy and practice literature, by exploring the possible regional and local implications of the spread of the virus, in terms of both studying the areal distribution of relevant determinants and taking into account the spatial physical mobility patterns of populations. In particular, we present an analysis of COVID-19 incidence and a number of variables that are (according to the literature to date) thought to be key determinants, as well as inter-municipal mobility patterns in the Netherlands using the 2020 national mobility survey (*Onderweg in Nederland*, CBS, 2021a). The analysis was conducted over three time periods to identify whether the association between various regional variables and municipal COVID-19 incidence varied over time.

This study had three aims. First, we aimed to identify the potential of using spatial mobility patterns to better understand the development of COVID-19 incidence on the municipal level. Second, we aimed to test the determinants of COVID-19, as identified by other studies, on the municipal level in the Netherlands. These determinants are the regional characteristics that can affect the development of COVID-19 incidence, such as population age, income levels or population density. Third, we aimed to identify the extent to which determinants of COVID-19 are affected by the time period in which the study is conducted. To investigate this, the study was divided into three periods each 2 months long. To the best of our knowledge, this is the first study to report on COVID-19 incidence in relation to spatial mobility patterns, regional characteristics and different time frames on a municipal level over the whole Netherlands.

This paper is structured as follows: first, we discuss the literature on the incidence of COVID-19 and its determinants, focusing on issues pertaining to regional and local determinants, and on the impact of people's spatial mobility between places. In section 3, we present the data and our methods for operationalizing and analysing the variables reported in the literature as important determinants of COVID-19 at different geographical levels. We discuss our modelling approach in detail. In section 4, we discuss the modelling results and highlight our key findings. In section 5, we offer some conclusions, with a particular focus on regional science policy and practice.

2 | COVID-19, SPACE, PLACE AND SPATIAL MOBILITY OF POPULATIONS

Since the outbreak of the COVID-19 pandemic, there has been a rapidly growing number of studies on the development of COVID-19 at various geographical levels, ranging from international overviews to regional comparisons, to inner-city neighbourhood analyses.

At the global level (and in some cases sub-national level), dashboards such as those set up by Johns Hopkins University (Baltimore, USA) and the European Centre for Disease Control (ECDC) provided initial insights into the distribution of COVID-19 (Dong et al., 2020; ECDC, 2020). There were also efforts to provide detailed international comparisons (Arsalan et al., 2020; Cao et al., 2020). Mobility policy at the international level was characterized by a nearly complete halt to international travel, as most countries implemented some form of international travel ban (Hale et al., 2021). These restrictions did slow the initial spread of COVID-19 (Bou-Karroum et al., 2021), but they became less effective as the pandemic took hold (Chinazzi et al., 2020). In addition, in many countries the strict, untargeted restrictions on international travel were found to be largely ineffective owing to the minimal effects that international travellers had on existing local outbreaks (Russell et al., 2021).

Various studies have investigated COVID-19 development using regional data, such as county-level comparisons in the United States (Correa-Agudelo et al., 2021; Oster, 2020), China (Jia et al., 2020; Xie et al., 2020) and Europe (Kapitsinis, 2020; Kashnitsky & Aburto, 2020), and national analyses of regions such as in the Netherlands and Belgium (Boterman, 2020; Verwimp, 2020). These regional studies identified factors such as population size, a higher share of older people, and population density to be related to higher COVID-19 mortality. The effect of population density, however, has been widely debated. Multiple studies found a relationship between population density and COVID-19 (Wong & Li, 2020), whereas other studies attributed this effect to factors such as metropolitan size (Hamidi et al., 2020). There is an ongoing debate about whether these factors are universally applicable (Teller, 2021). In addition, a high share of young people, larger household sizes and more people belonging to an ethnic minority were also found to be related to more COVID-19 infections (Martin et al., 2020; Oster, 2020).

At the regional level, local, regional and national policies affected people's mobility between places, but the extent to which it was affected differed around the world. Along with closing international borders, many countries implemented national lockdowns, which often included closing non-essential stores and strong recommendations and guidelines to work from home. These national lockdowns resulted in an overall decrease in mobility, such as in France, Italy and the UK (Galeazzi et al., 2021). Various nations implemented regional- or state-level restrictions, including regional lockdowns. The first regional lockdown related to COVID-19 was that of the City of Wuhan and Hubei Province in China, which is deemed to be the original epicentre of the pandemic. This regional lockdown and associated mobility restrictions resulted in significantly less COVID-19 case growth in China (Lau et al., 2020). Regional lockdowns were also enforced in Australia (Australian Department of Health, 2021) and were found to be effective in reducing COVID-19 case development (Saul et al., 2020). As the impacts of national lockdowns are still being widely discussed (Haug et al., 2020), regional lockdowns might offer a similarly good solution, but with fewer detrimental effects on society. Spain was another country that implemented regional COVID-19 measures. There, after an initial nationally coordinated response, as of October 2020, the regional authorities had autonomy in deciding on their response, including on regional mobility (Spanish Government, 2020). Similar decisions were made in

Italy, where, as of November 2020, regional measures were implemented, which reduced COVID-19 infection risk (Guaitoli & Pancrazi, 2021). Della Rossa et al. (2020) proposed regional interventions and highlighted their potential effectiveness in Italy.

At a smaller area level (intra-city and neighbourhoods), there have been efforts to disaggregate the analysis geographically. For example, in New York City (Whittle & Diaz-Artiles, 2020), Toronto (Vaz, 2021) and London (Harris, 2020), efforts were made to identify factors influencing COVID-19 incidence and mortality within cities. Many of these local studies found relationships between the lower socio-economic status of neighbourhoods and higher COVID-19 incidence or mortality. For example, Harris (2020) identified relationships between lower-income areas and higher COVID-19 mortality in London, while in Toronto, Vaz (2021) established a link between the percentage of the population on welfare benefits and higher COVID-19 risk. In addition, the share of people in jobs that do not allow for working from home, such as food production, construction and maintenance (Dingel & Neiman, 2020), is expected to be related to higher numbers of COVID-19 infections. At the local level, mobility was affected mainly by national or regional policies, such as lockdowns or stay-at-home orders.

As COVID-19 spreads through human hosts, investigating the mobility patterns of the hosts is a crucial part of understanding the development of infections over time. The association between mobility and COVID-19 is bi-directional. Population flows between and within cities and regions was found to drive COVID-19 infections in China (Jia et al., 2020), while a reduction in inter- and intra-city movements resulted in a decrease of the daily effective reproduction number (Fang et al., 2020). Research conducted on mobility in Latin America found that a decrease in mobility was related to fewer COVID-19 cases (Kephart et al., 2021). Similar patterns were found in other studies, including Schlosser et al. (2020) and Ilin et al. (2021), who identified that reduced mobility resulted in a slower spread of COVID-19, but variations between countries depended on infrastructure and the measures taken. The policy response to these findings has been to introduce mobility restrictions that aim to prevent the spread of the virus, and these resulted in less mobility at all levels. This was identified at an early stage in the pandemic by Chinazzi et al. (2020) and confirmed by later studies around the world. For instance, in France, Italy and the UK, long-distance mobility decreased, although the extent of this decrease depended on the infrastructure (Galeazzi et al., 2021). Similarly, research by Habib et al. (2021) concluded that in 10 selected countries the overall mobility declined owing to the COVID-19 pandemic.

Many of the papers that investigated the relationship between mobility and COVID-19 make use of data that are derived from real-time mobile phone datasets (Galeazzi et al., 2021; Habib et al., 2021; Kephart et al., 2021; Schlosser et al., 2020). Another approach to investigate the effect of mobility on COVID-19 is to use more general mobility patterns, such as in the study by Kondo (2021), which utilized mobility data from 2016. De Palma et al. (2022) provide a very relevant recent overview of the effects of COVID-19 on mobility and lifestyle that highlights the major sources of the pandemic's impact on mobility decisions, such as mode of transport, commuting and travel times, teleworking, car ownership, work and residential locations, and choice of job.

These studies have demonstrated the need to take inter-regional mobility data into account when analysing the incidence of COVID-19 and its socio-spatial determinants. The remainder of this paper presents our analysis that takes up this challenge for the Netherlands, using the most recent data available. It should be noted that there are some contextual factors of Dutch policy that are relevant to this study. A key aspect of Dutch COVID-19 policy was that all the government's responses to COVID-19 were implemented uniformly at the national level, disregarding regional variations in incidence. In addition, the Dutch government prohibited international travel from various countries (Rijksoverheid, 2021), but there were no internal movement restrictions other than general advice against non-essential travel (Rijksoverheid, 2020a). In the next section, we present the data and methods used to take into account all these considerations and to capture as many of the relevant variables as possible for the analysis of COVID-19 at the geographical level of Dutch municipalities.

3 | DATA AND METHODS

The main data source for this research was the official register of COVID-19 infections in the Netherlands over the 6 months between 1 September 2020 and 3 March 2021, which is the period called the second wave. We focused on the second wave for two reasons: first, the virus had already spread to all the regions. Second, on 1 June 2020, the Netherlands implemented a widespread testing policy, which resulted in a major increase in COVID-19 tests (Rijksoverheid, 2020b). These data originated from the National Institute for Public Health and the Environment (RIVM, 2021a). Figure 1 is a graph of the number of daily and cumulative cases, highlighting relevant events on the timeline from the start of the epidemic until March 2021.

We used other data of 355 municipalities in the Netherlands [comparable to Local Administrative Units (LAU-level 2) in international definitions]. The independent variables were categorized into four themes: demographics, geography, mobility and socio-economic status. The data were derived from Statistics Netherlands (CBS, 2020), unless otherwise specified. Table 1 lists all the variables that we considered, together with summary statistics.

The data were analysed using three multiple linear regression models in which municipal COVID-19 incidence, the infections per 100,000 persons in a municipality, was used as the dependent variable. To capture differences over time, the same independent variables were used in all three models. Figure 1 shows the different study periods. The data were analysed using R (R Core Team, 2021), and the maps were created using QGIS 3.16 (QGIS.org, 2021).

The multiple linear regression model takes the following form:

$$yi = \beta 0 + \sum_{k=1}^{K} \beta kxki + \epsilon i, \tag{1}$$

where yi is the dependent variable, that is, COVID-19 incidence per municipality. $\beta 0$ is the y-intercept, xk is the independent variables from the four categories for each municipality, βk is the coefficients for each of the independent variables, and ϵ is the error term.

To assess the spatial interaction between municipalities, an inter-municipal mobility variable was created using the national mobility survey ODiN, which is conducted by Statistics Netherlands (CBS, 2021b). This survey covers the mobility patterns of Dutch citizens in 2020 and uses weighting factors to create a dataset that is representative of the total population. This dataset was used to create an origin–destination matrix that displays the mobility patterns between municipalities. One municipality (the island of Vlieland) was excluded owing to data limitations. The spatial population mobility patterns were calculated by taking the yearly mobility between an origin and a destination municipality as a share of the mobility between all municipalities and the destination municipality. The resulting spatial population mobility variable is thus a snapshot of the 2020 mobility between municipalities, given as percentages, where a higher percentage between two municipalities indicates higher geographical mobility. These spatial mobility patterns can be combined with COVID-19 incidence per municipality as:

$$\sum_{j=1}^{J} cjrji, \tag{2}$$

where cj is the COVID-19 incidence in the municipality of origin (j) and rij is the share of trips that arrive from municipality j into municipality i.

This formula is used to calculate the following: for every municipality (j) that was linked as an origin of trips into the municipality i, the share of mobility from the origin municipality j, as part of the total of arrivals into i, was multiplied by the COVID-19 incidence rate in j. Arrivals in i from origin municipality i were excluded, as we were interested in the effect of incoming mobility from different municipalities. The 'external mobility' was calculated as the percentage of total arrivals minus the internal mobility (the percentage of trips that started within the destination municipality). With the creation of this 'COVID-19 mobility variable', we highlight the links in the mobility network

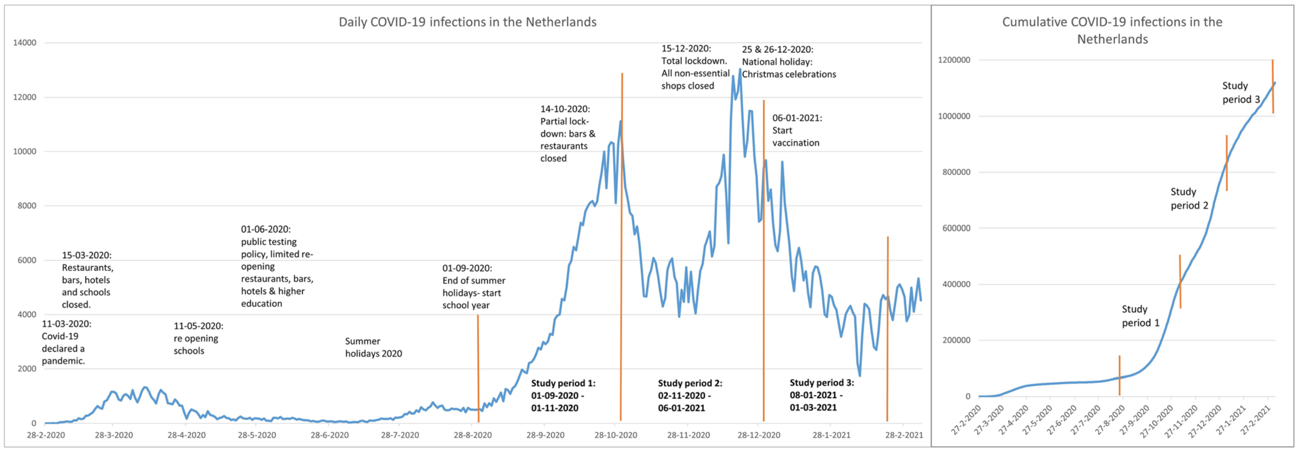

FIGURE 1 Daily and cumulative COVID-19 infections and relevant events

TABLE 1 Descriptive statistics and inclusion criteria

	Minimum	Maximum	Median	Mean	Inclusion and notes:
COVID-19 incidence in September/October	317	3,844	1,813	1,775	
COVID-19 incidence in November/December	422	8,223	2,731	2,808	
COVID-19 incidence in January/February*	354	3,204	1,358	1,450	*For January/February there is one municipality with missing data, which is excluded in this period.
Estimated number of tests per municipality in September/October	91	140,747	3,693	6,078	
Estimated number of tests per municipality in November/December	127	147,974	5,049	8,160	
Estimated number of tests per municipality in January/February	115	105,895	3,892	6,136	
Youth (%)	8.9	22.4	11.6	11.7	COVID-19 infection data indicated that this age group was experiencing the highest share of COVID-19 infections during the second wave of COVID-19 infections in the Netherlands (RIVM, 2021b).
Single households (%)	6	34.6	13.6	14.7	Household structure has been found to be related to COVID-19 incidence (Harris, 2020; Kapitsinis, 2020; Martin et al., 2020).
Residential dwelling density	208	6,074	941	1,162	The relevance of density variables has been stressed (Whittle & Diaz-Artiles, 2020; Wong & Li, 2020). We included the residential dwelling density, which is defined as the average number of residential addresses within a 1 km^2 radius around each residential address. This variable is calculated and used by Statistics Netherlands to measure urbanity (CBS, 2019).
Floorspace occupancy	36.9	109.7	57.4	58.5	As confined and enclosed spaces are among the risk factors for COVID-19 infections, it is hypothesized that a larger average residential floor space per person is related to fewer COVID-19 infections. Thus, the floorspace occupancy, which is the number of persons in a municipality divided by the total residential living area, was included.

(Continues)

TABLE 1 (Continued)

	Minimum	Maximum	Median	Mean	Inclusion and notes:
Jobs in industry (%)	2.7	44	19.5	19.7	The population working in the sector industry (Sectors A–F in the European Activity Classification) (CBS, 2008). These categories include sectors such as agriculture, production and construction, which were identified as sectors with limited opportunity to work from home (Dingel & Neiman, 2020).
Standardized income ×1,000	23.8	67	31.6	32.1	Socio-economic status is found to be related to COVID-19 risk (Vaz, 2021; Whittle & Diaz-Artiles, 2020).
Low education (%)	10.1	40.2	29.2	28.9	The percentage of the population that has experienced a low education is included owing to the relevancy of socio-economic status.
Welfare benefits (%)	0.9	7.5	2.7	3	People receiving welfare benefits are identified as higher-risk groups (Vaz, 2021).
COVID-19 mobility links September/October	40.05	1,592.42	584.25	629.51	The creation of this variable is discussed below.
COVID-19 mobility links November/December	62.91	1,965.52	871.67	876.88	
COVID-19 mobility links January/February	23.12	1,181.39	421.42	443.41	

that have the highest potential of COVID-19 incidence, based on the 2020 mobility patterns and the actual number of infections. Insight into these incidence links were gained by creating a network of nodes (the municipalities), in which the links were weighted by the intensity of the mobility patterns and the periodical COVID-19 incidence, in which the darker colours correspond to a higher flow intensity, as shown in Figure 2b–d.

Figure 2a shows the spatial mobility patterns observed in the Netherlands in 2020. Figure 2b shows the COVID-19 links in period 1, created using Equation (2). Figure 2c shows the COVID-19 links in period 2, created using Equation (2). Figure 2d shows the COVID-19 links in period 3, created using Equation (2).

In the first period, the epicentre of the epidemic appeared to be in the Randstad conurbation in the central western part of the Netherlands. Many of the highlighted connections in this period appeared to be directed at this epicentre. In the second period, the spread was much more diffuse and not all links were directed at the Randstad. In the third period, the focus shifted towards the border areas, such as the northwest, north and south.

This series is included in the model as an independent variable *xi*4, making the final equation:

$$yi = \beta 0 + \beta 1 \sum_{j=1}^{J} cjrji + \sum_{k=1}^{K} \beta kxki + \epsilon i, \tag{3}$$

where *yi* is the dependent variable, that is, COVID-19 incidence per municipality. $\beta 0$ is the *y*-intercept, $\beta 1$ is the coefficient for the COVID-19 spatial mobility variable, *cj* is the COVID-19 incidence in the municipality of origin (*j*)

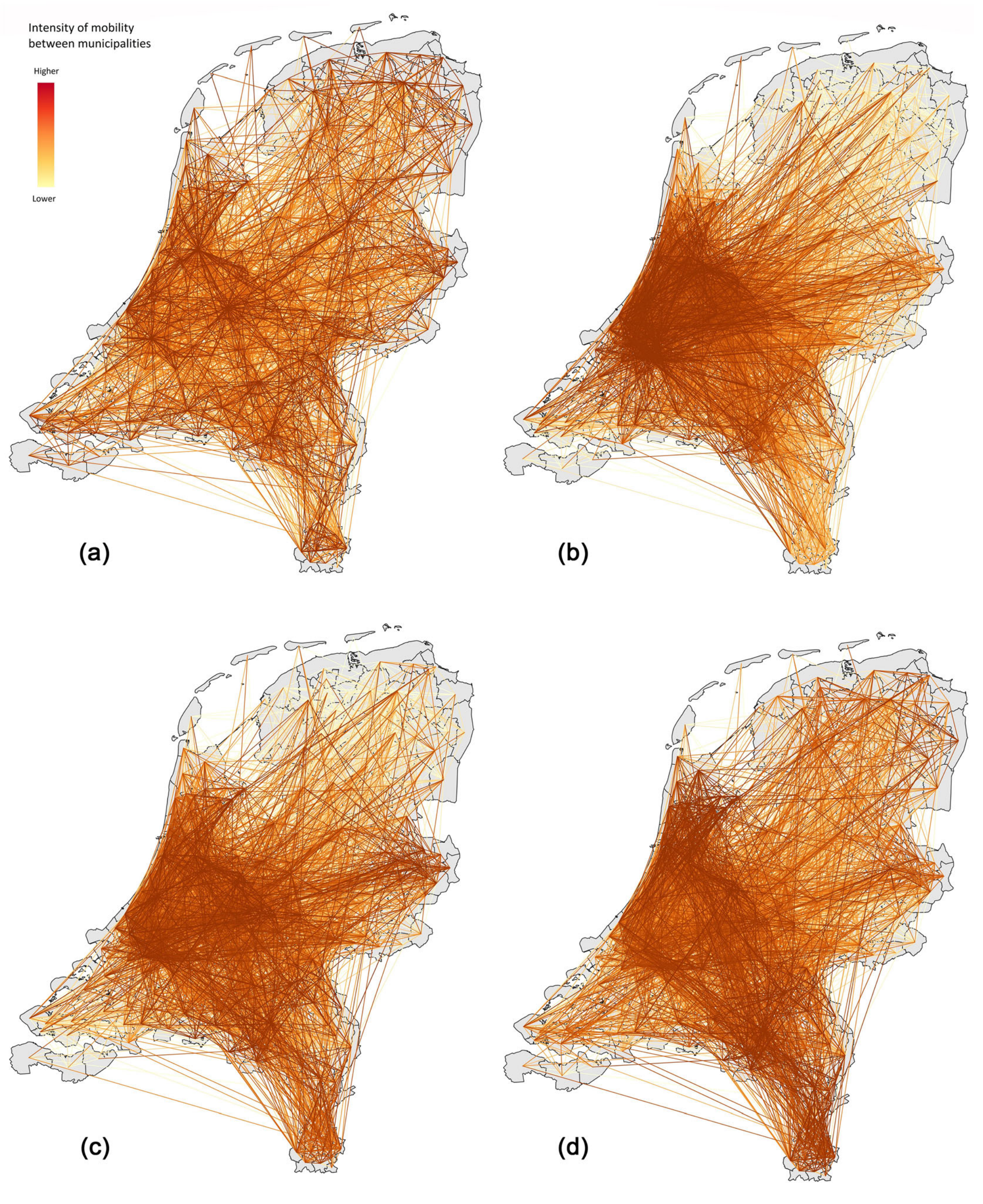

FIGURE 2 Spatial mobility patterns (a) and high COVID-19 links based on geographical mobility patterns (b–d)

and *rij* is the share of trips that arrived from municipality *j* into municipality *i*. βk is the coefficients for each of the independent variables, *xk* is the independent variables from the four categories for each municipality, and ϵ is the error term.

3.1 | Regression diagnostics

The data were subjected to the assumptions of linearity, normality and the absence of multicollinearity that must be met to conduct a valid multiple linear regression. The correlation matrix indicated no highly correlated variables with correlations over 0.8. Scatterplots of the relationship between the dependent and independent variables indicated linear relationships (Appendix 1). The variance inflating factor (VIF) was used to assess the degree of multicollinearity, but all values were <10, which indicates no severe multicollinearity (Montgomery et al., 2012).

4 | RESULTS

Figure 1 shows the development of COVID-19 incidence in the Netherlands. The study spanned from 1 September 2020 to 3 March 2021, with the number of daily cases ranging from 462 on 1 September 2020 up to 13,032 at the peak on 20 December 2020.

Figure 3 presents three maps showing COVID-19 incidence in the three study periods. The geographical distribution of COVID-19 incidence varied during the study. In the first period, COVID-19 incidence was concentrated in the west and southern part of the Netherlands (Figure 3a); the virus became more dispersed in the second period (Figure 3b), and even more so in the third period (Figure 3c). The infections appear to have spread outwards from the west, central and southern parts to the northern parts of the country and the border regions.

4.1 | Regression analysis

The results of the multiple linear regressions on the three periods are presented in Table 2.

Similar to the variation in the distribution of COVID-19 incidence, the factors associated with COVID-19 infections appeared to differ over time. The demographic variables were all significantly associated with infections in the first period, during which a higher share of young people in a municipality was related to a higher average COVID-19 incidence. The percentage of single households was negatively associated, that is, municipalities with a higher share of single households reported fewer cases. In the second period, the associations between the demographic variables and municipal infections remained significant and became stronger. In the third period, the demographic variables were not able to explain the average COVID-19 incidence at the municipal level.

The geographical variables display similar patterns. In the first and second periods, the residential dwelling density was associated with higher COVID-19 infections. In the third period, this effect disappeared. The floorspace occupancy was found to be significantly associated with infections only in the first period.

Two socio-economic variables displayed an association with the municipal COVID-19 incidence: (1) the percentage of the population with a low education level, which was significant throughout all three periods; (2) the share of the population on welfare benefits, which was significant in the first two periods. Significantly, we found the effect of welfare benefits on COVID-19 *was negative*, that is, a higher share of people receiving welfare benefits was related to a lower COVID-19 incidence. This is in contrast to earlier research (e.g., Vaz, 2021), which identified neighbourhoods with high numbers of social assistance recipients as being associated with more COVID-19 infections.

The association between COVID-19 incidence and potential incidence links, based on spatial mobility patterns, was found to be significant in all three periods. Destination municipalities with high population inflows from municipalities with a high COVID-19 incidence during the study period experienced higher COVID-19 incidence throughout all three periods. More connected municipalities also showed higher COVID-19 incidence.

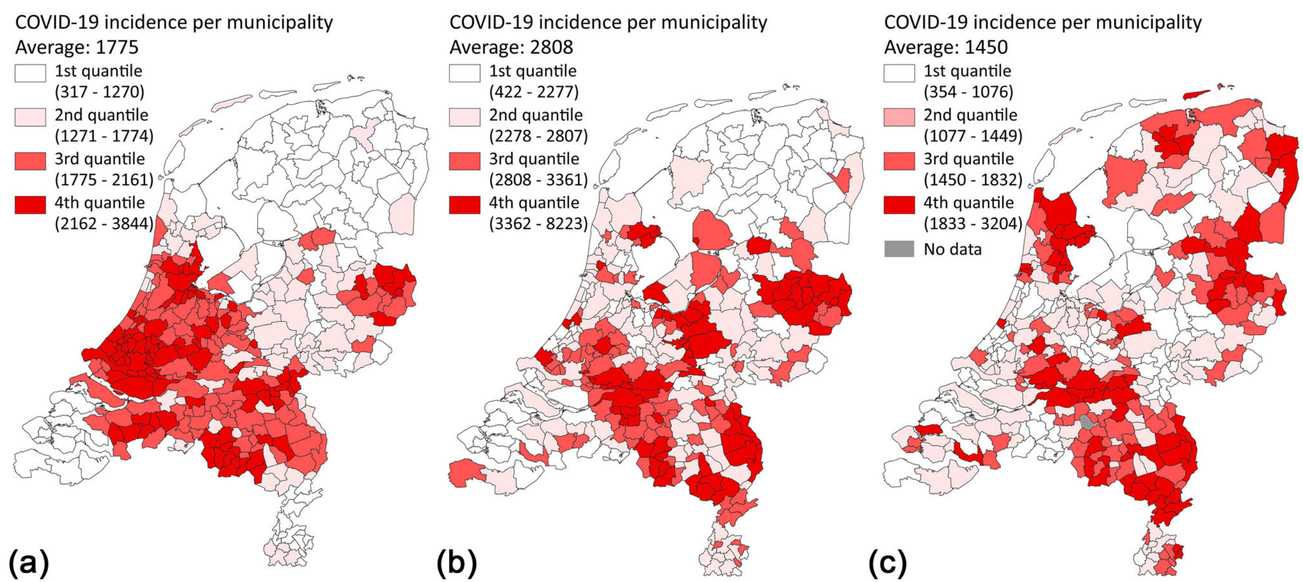

FIGURE 3 The distribution of municipal COVID-19 incidence in our three study periods

TABLE 2 Regression results of municipal variables

Model Coefficients	Study period 1 (September/October) Estimate	p-Value	Study period 2 (November/December) Estimate	p-Value	Study period 3 (January/February) Estimate	p-Value
Intercept	−814.80	0.173	−151.21	0.886	−1,013.14	0.113
Youth (%)	65.99	0.000[a]	134.37	0.000[a]	33.92	0.057
Single households (%)	−22.15	0.018[b]	−79.61	0.000[a]	6.41	0.521
Residential dwelling density	0.33	0.000[a]	0.39	0.000[a]	−0.07	0.268
Floorspace occupancy	7.78	0.026[b]	4.03	0.508	3.64	0.321
Jobs in industry (%)	2.26	0.369	−2.11	0.635	0.04	0.987
Standardized income	−6.82	0.415	−13.31	0.358	−8.75	0.312
Low education (%)	28.73	0.000[a]	68.35	0.000[a]	53.13	0.000[a]
Welfare benefits (%)	−122.52	0.000[a]	−212.49	0.000[a]	−65.01	0.072
Structural COVID-19 mobility links (September/October)	1.48	0.000[a]				
Total tests (September/October)	0.01	0.000[a]				
Structural COVID-19 mobility links (November/December)			1.11	0.000[a]		
Total tests (November/December)			0.00	0.360		
Structural COVID-19 mobility links (January/February)					1.67	0.000[a]
Total tests (January/February)					0.01	0.061
Adjusted R^2	0.634		0.417		0.379	
F-statistic	61.99		26.12		22.49	

[a]Statistically significant in 1%,
[b]Statistically significant in 5%.

5 | DISCUSSION

The outcomes of our analysis illustrate first the importance of disentangling different time periods in analysing the distribution of COVID-19 incidence, since different periods had their own sets of explanatory variables as COVID-19 spread over the country. Second, geography or place does matter, in the sense that COVID-19 was not present everywhere at the same moment or with the same incidence. It is therefore important to have a better understanding of the virus distribution in relation to place characteristics to see how the pandemic developed. Third, spatial mobility patterns channelled the spread of COVID-19.

The regression analysis highlighted multiple variables that were relevant in studying COVID-19 incidence. The share of young people in a municipality was positively associated with COVID-19 incidence, indicating that younger populations played an important role in spreading COVID-19 during the study period. This is consistent with previous research on demographic structure and COVID-19 incidence (e.g., see a relevant study in the United States by Monod et al., 2021).

Our analysis showed the importance of scale and time as important background variables for understanding the spread of COVID-19. This could explain why different studies around the world found different determinants of spread. For example, in the first two periods, the share of young people in a municipality was an important determinant, whereas in the third period, this was no longer true. One explanation for this might be that the Dutch lockdown rules led to closing secondary and higher education in the third period, which resulted in far fewer interactions between people aged 15–25 years. The negative association of household size and the positive association of higher residential dwelling density during the first two periods indicates that there was a lower COVID-19 incidence in municipalities with more space per person on average, in terms of built-up environment and within the household. This result is similar to findings by other studies. However, note that this association disappeared in the third period, which shows that, by then, COVID-19 was so deeply embedded in society that place characteristics no longer mattered.

In contrast, socio-economic characteristics did still matter. The share of people with a low education level in a municipality was found to be related to more COVID-19 incidence throughout all three periods, which is in line with findings by other studies. The share of people receiving welfare benefits was negatively associated with COVID-19 incidence, which is unexpected when compared with findings by other studies. An explanation for this might be that these people were more cautious owing to other issues (e.g., underlying health problems). Testing bias may partly explain this, as research by the CBS (2021c) indicated this group was less likely to get tested. The distribution of jobs per industry sector in a municipality was not found to be associated with COVID-19 incidence, possibly due to the data not being detailed enough, or to people working outside the municipality in which they were registered. Standardized income was not found to be associated, which is unexpected as it contrasts the findings of other studies. One explanation might be the relatively low income inequality in the Netherlands, which makes it difficult to find differences on the municipal level. Research on a finer geographical scale might be able to establish this relationship.

We have presented two key findings:

1. Spatial mobility patterns are a useful tool for understanding municipal COVID-19 incidence over time.
2. Regional characteristics such as demographics and residential dwelling density are associated with COVID-19 incidence, but the associations are time dependent.

These findings are relevant for several reasons. Intra-regional mobility was not considered in Dutch COVID-19 mitigation policy, so that the research presented here is a starting point for taking spatial mobility patterns into consideration. It is also important to consider regional characteristics as they can further our understanding of municipal variation in COVID-19 incidence. In addition, to be able to better capture the value of the findings, it is important to include the temporal aspect, and to approach the development of COVID-19 incidence as a continuous, path-dependent process. Depending on the time period, the explanatory factors change, and because there are constant changes in municipal COVID-19 incidence, partly due to mobility, the effects of the regional characteristics are also constantly changing. This leads to a sequence of effects and considerable variation in each consecutive period. We highlight the importance of taking into account the temporal context, geographical context and intra-regional mobility, when studying the impact of regional characteristics on COVID-19 incidence and deciding what restrictions should be imposed to limit the virus spread.

There are several strengths to our analysis. First, to the best of our knowledge, it is the first study to include spatial mobility patterns in relation to COVID-19 incidence at the level of municipalities (LAU-2). Second, it is the first nationwide analysis on the effect of regional characteristics on COVID-19 incidence in the Netherlands at the municipal level. This is relevant, since analysis on a nationwide scale can provide insights that cannot be determined using international- or neighbourhood-level analysis, for example, by including regional spatial mobility patterns.

Nonetheless, there are a few limitations, the most prevalent being potentially unidentified confounding variables. The effects of a high share of people with a lower level of education in a municipality might be explained by unidentified confounders such as job occupation/unemployment, smaller and more crowded housing, or income levels. Another explanation could be that the relaxation of COVID-19 mitigation measures after the first wave (Rijksoverheid, 2020c) led to more possibilities for international and national travel, and restaurant visits. It can be argued that people receiving social assistance may be less likely to take part in such activities. Coincidentally, there is a link between the first wave of COVID-19 infections throughout Europe and skiing holidays in the Alps in February 2020 (Kreidl et al., 2020), which is another activity typically not accessible to most on social assistance. Further research on the relationship between socio-economic status and COVID-19 infections is required. Another limitation, related to all COVID-19 research that makes use of infection data, is testing bias. This research includes only infected people who got tested and excludes those who did not get an official (registered) test. During the study period, free testing was widely available to all inhabitants of the Netherlands. However, there were still differences in the extent to which different socio-economic groups got tested. For example, those on social assistance were less likely to get tested compared with employed people (CBS, 2021c). There might be several reasons for this: those on social assistance may have fewer daily interactions and thus a lower chance of catching COVID-19, but other potential reasons include lack of transportation options or distrusting the government. Finally, the spatial mobility patterns, in contrast to real-time mobility data, do not account for periodical changes in mobility due to COVID-19 measures. Since these data are a snapshot of the total mobility in 2020, it is not possible to differentiate between lockdown and non-lockdown mobility. Using real-time data is, of course, important in research into the effect of COVID-19 policy on mobility patterns, but these data are not available in a detail and format that would enable us to carry out this analysis at the moment. We did carry out pilot aggregate analysis but found that, when looking at the relative yearly patterns between municipalities, there was not much difference overall between pandemic (2020) and pre-pandemic patterns (2019). Moreover, to understand the reverse effect, that is, the effect of mobility patterns on regional COVID-19 incidence, the usage of real-time mobility data is not required as yearly spatial mobility patterns have been proven to be an effective tool. This is relevant for researchers and policymakers who are interested in regional COVID-19 incidence – and its prevention – by means of limiting mobility, particularly in regions that are unable to access real-time mobility data. In that respect, structural data are even to be preferred because they provide insight into where action can and needs to be taken.

6 | CONCLUSIONS

Our exploratory analysis of factors related to municipal COVID-19 incidence in the Netherlands highlights the relevance of spatial mobility patterns, the effect of regional determinants and the importance of time. The research presented here demonstrates that, in the Netherlands, municipalities with a structural high share of mobility inflow from municipalities that had a high COVID-19 incidence was related to the destination municipality having a higher internal COVID-19 incidence. This makes it interesting to reflect on the lack of any policies to restrict movement between areas within the Netherlands (other than the general government advice not to travel except for essential reasons). Thus, the government allowed for spatial interactions between areas of low and high COVID-19 incidence, while at the same time imposing restrictions on movements in and out of the country (e.g., in the border regions with Belgium and Germany). Our findings can help inform a new strategy that takes spatial mobility patterns between regions into account to propose and apply tailor-made mobility restriction policies within and between countries.

Overall, mapping of spatial mobility flows highlighted patterns that help explain the geographical distribution of COVID-19 incidence in relation to mobility patterns in 2020, while investigating the effects of determinants such as urban density or demographics can help explain COVID-19 incidence and development on the municipal level. This information can be valuable to researchers and policymakers during the early stages of an epidemic, when real-time mobility data are not, or not yet, available. The variation over time we report in the associations between regional factors and municipal COVID-19 incidence highlights the importance of understanding the temporal aspect in COVID-19 research. Our research was innovative in that it shows the importance of time frames and ‘waves’ in COVID-19 incidence. A deeper investigation into the underlying mechanisms will be part of future analyses.

As spatial mobility patterns were shown to be related to an increase in COVID-19 incidence in the Netherlands, our advice to policymakers is to target the spatial mobility links with municipalities that experience high COVID-19 incidence. At the present time in the Netherlands, only restrictions on international mobility are being considered (border closures; Rijksoverheid, 2021), although their effect has proven to be of limited value in countries that had major local outbreaks (Russell et al., 2021). Other countries, such as Australia, that implemented measures to prevent intra-regional mobility between regions with high-COVID-19 incidence were successful in controlling the virus (Saul et al., 2020), proving the potential usefulness of regional mobility measures. By specifically targeting mobility originating in regions with high COVID-19 incidence, it is possible to reduce the rate of spread without enforcing a national lockdown. As many regions, specifically in Europe, are now entering the post-COVID era (with widespread vaccination of the population), there seems to be a decline in academic and media attention on how to prevent disease outbreaks. However, there are ongoing concerns about waves of new COVID-19 variants – or other diseases – and there are many lessons to be learned, which should inform future decisions and planning. Our work highlights the importance of forming evidence-based transport and human mobility policies in relation to disease outbreaks. In particular, our results can be used to inform decisions with a more regional and local focus on the better monitoring of outbreaks and spatial mobility patterns affecting future disease evolution.

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DATA AVAILABILITY STATEMENT

Dutch COVID-19 data are available from the Ministry of Health, Welfare and Sport (URL: https://data.rivm.nl/covid-19/). Municipal-level data are available through the public data platform of Statistics Netherlands (URL: https://opendata.cbs.nl/statline/#/CBS/nl/dataset/70072ned/table?dl=503BB). Researchers who would like to use the Dutch Mobility Survey (ODiN) need to request permission and register in EASY (URL: https://easy.dans.knaw.nl/ui/datasets/id/easy-dataset:213321) to download the dataset.

ORCID

Bart Roelofs https://orcid.org/0000-0003-2635-3181
Dimitris Ballas https://orcid.org/0000-0003-4955-850X
Hinke Haisma https://orcid.org/0000-0002-9676-0463
Arjen Edzes https://orcid.org/0000-0002-1471-6961

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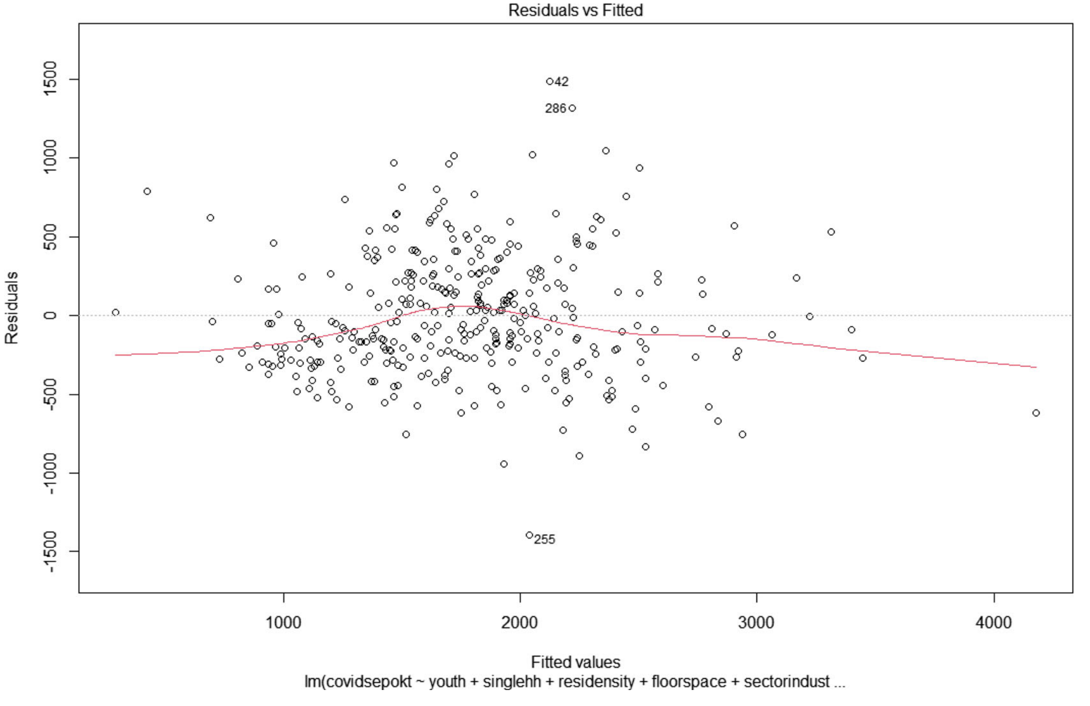
APPENDIX 1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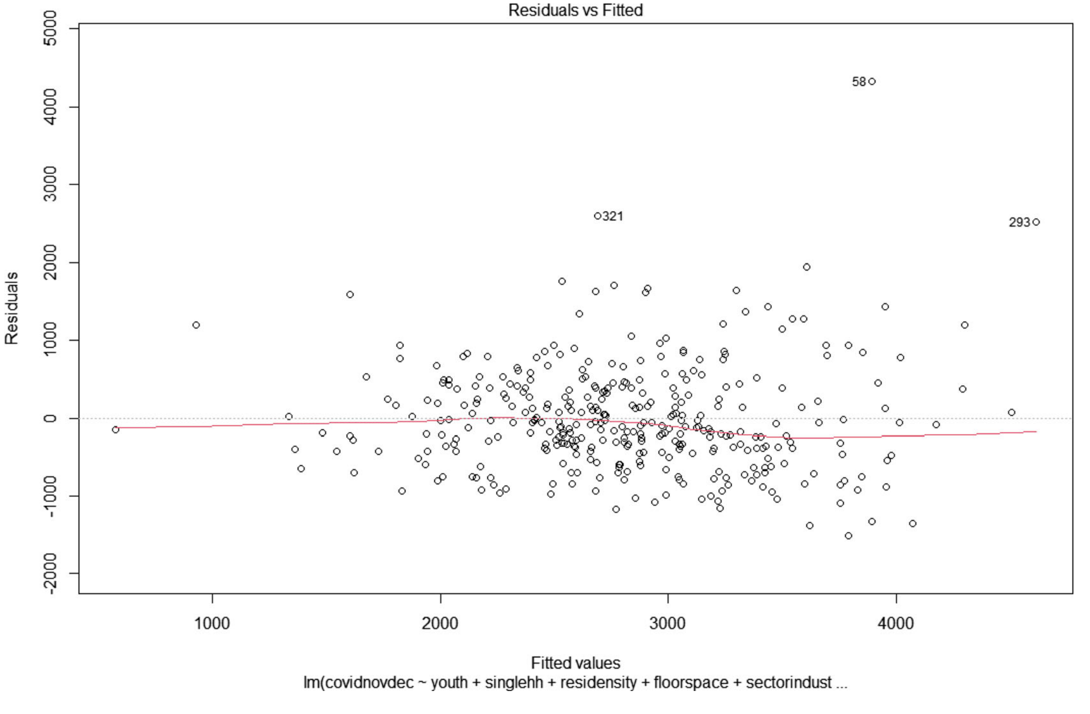
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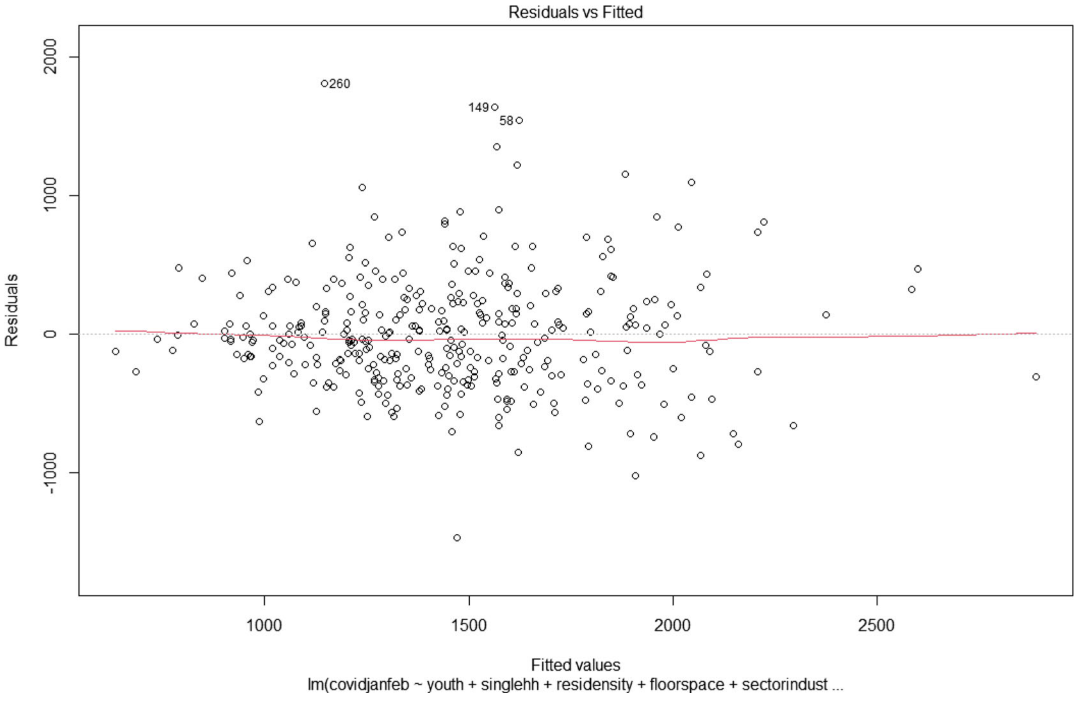
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