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Vulnerability and COVID-19 infection rates: A changing relationship during the first year of the pandemic

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ABSTRACT

In the first year of the COVID-19 pandemic, Spain was one of the worst-hit countries, although not all areas and social groups were affected equally. This study focuses on Malaga, a cosmopolitan tourist destination located on the southern Mediterranean coast that has the sixth largest population in Spain. Specifically, it examines the relationship between multidimensional vulnerability and COVID-19 infection rates across the city's census tracts for the period February 2020 to February 2021. The analysis uses high frequency (daily) data on the accumulated incidence of the disease at 14 days and shows that COVID-19 did not spread symmetrically across the census tracts of Malaga but had a greater impact on the most vulnerable neighbourhoods. However, the pattern of this relationship was not uniform in the period examined, with specific contextual factors driving the higher infection rates across time. Our findings show that pandemic containment regulations cannot overlook vulnerability considerations and universal restrictions to reduce the spread of disease should be supplemented by targeted regulations for specific areas.

1. Introduction

In the last century, viruses have been responsible for many more deaths than armed conflicts. Smallpox, influenza or HIV are some of the main viruses that have claimed the lives of millions of people worldwide (see Koplow, 2003; Cauchemez et al., 2014; Taubenberger and Morens, 2006; Cutler et al., 2006; Adda, 2016). Even in modern societies where individuals are in good health, viruses are an important cause of morbidity and mortality. In recent years, after the outbreak of the COVID-19 coronavirus disease, the pandemic has become the most worrying problem faced by our societies, as it has hit all regions of the world, infecting millions of people and causing countless deaths.

In the first year of the pandemic, Spain was one of the countries hardest hit by the COVID-19 health crisis in Europe, with high infection rates affecting all sectors of Spanish society through several waves of coronavirus cases. However, it is worth examining whether COVID-19 spread symmetrically across space or whether it followed a gradient determined by the multidimensional vulnerability of the population. In this regard, a number of studies have pointed to links between level of vulnerability and COVID-19 infection rates in diverse geographical environments. Differences in housing conditions, types of job, mobility and possibilities to take preventive measures are some of the major reasons that may explain this relationship (see, e.g., Aleta et al., 2020; Baena-Díez et al., 2020; Brandily et al., 2020; Flaxman et al., 2020; Public Health England, 2020; Zhong et al., 2020; Zhang et al., 2021).

This study focuses specifically on the municipality of Malaga. Located in the region of Andalusia in southern Spain, Malaga is the prime tourist destination on the Costa del Sol and an open, cosmopolitan city. It is the sixth most populated city in Spain (578,460 inhabitants in 2020) and has the fourth busiest airport in the country by passenger traffic and four large hospitals. Given its size, Malaga presents considerable heterogeneity among its neighbourhoods. This makes the city an interesting case to analyse the links between the neighbourhoods' levels of vulnerability and infection rates taking into consideration the measures adopted by the Spanish Government during the pandemic (see detailed description of the restrictions in each event in the Online appendix). Apart from being a very relevant international tourist destination with a significant number of tourist movements, Malaga is also the location of the Technological Park of Andalusia. This technological hub is home to national and international companies which employed over 20,000 workers in 2019, many of whom do telework. Bearing in mind that understanding the risk of COVID by geographical units requires monitoring the number of cases in small, well-characterized areas of the population (Baena-Díez et al., 2020), this paper addresses the link

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between vulnerability and COVID-19 cases with a high level of spatial disaggregation (434 census tracts of the municipality of Malaga), which allows capturing patterns that would be hidden in larger areas.

Particularly, we intend to examine two questions regarding the relationship between vulnerability and COVID-19 infection rates across neighbourhoods of Malaga in the first year of the pandemic: i) if census tracts with a more vulnerable population have suffered the highest COVID-19 infection rates and ii) whether this association (vulnerability and COVID-19) has exhibited a uniform pattern over the period examined. To this end, we consider high frequency (daily) data on the accumulated incidence of the disease at 14 days in each census tract of the city of Malaga for the period February 2020 to February 2021. We contribute to the existing literature by examining the possible changeable links between vulnerability and COVID-19 infection rates in the first year of the pandemic through a highly geographical disaggregated analysis; an issue that has not been previously addressed to the best of our knowledge.

The remainder of this paper is structured as follows. Section 2 briefly reviews the main factors explaining the links between multidimensional vulnerability and the incidence of COVID-19 infections. Section 3 describes the data and empirical strategy. Results are presented and discussed in Section 4. Finally, Section 5 concludes.

2. Literature review

Although the impact of COVID-19 has been widespread, the empirical evidence indicates that not all regions or social groups have been equally affected by the pandemic (OECD, 2020). In fact, analyses of infection rates have shown that certain individual and spatial characteristics, especially those related to the multidimensional vulnerability of people, are associated with a higher likelihood of contracting the SARS-CoV-2 virus (Chung et al., 2020; Khalatbari-Soltani et al., 2020).

The literature on the relationship between vulnerability and coronavirus infection is not scarce. As regards the COVID-19 pandemic, previous studies have identified a number of factors affecting transmission patterns, such as access to testing services, confinement, social distancing and contact tracing (Aleta et al., 2020; Hellewell et al., 2020; Kucharski et al., 2020; Vargas Hill and Narayan, 2020); occupational exposure levels (Almagro et al., 2020; Public Health England, 2020); biological factors related to susceptibility and infectivity (Byrne et al., 2020); self-isolation behaviour and compliance (Flaxman et al., 2020; Smith et al., 2020) and circumstances within the home (Brandily et al., 2020). Because these factors tend to vary somewhat by socioeconomic status, infection rates would also be expected to differ between social groups (Alobuia et al., 2020; Marí-Dell'Olmo et al., 2021; Zhong et al., 2020).

A review of the literature suggests various potential causal mechanisms through which people of low economic status tend to be more exposed to COVID-19. In this vein, an important source of inequality arises, for instance, from differences in the housing conditions of households during confinement (Marí-Dell'Olmo et al., 2021; Ayala et al., 2022). For example, living in overcrowded accommodations (a risk factor for respiratory tract infections) reduces the possibility of maintaining physical distance between household members (Tunstall, 2020). It is also well known that vulnerable people have fewer opportunities for working remotely (Stantcheva, 2021), as in the case of supermarket or warehouse workers, or that the stress caused by financial uncertainty weakens the immune system. According to Algren et al. (2018), residents with perceived stress in low socioeconomic neighbourhoods have a greater tendency for health-risk behaviours, which indirectly support health-risk coping strategies. Disposable income, economic deprivation and strain are also strongly associated with perceived stress, which may partly explain why residents of deprived neighbourhoods have a higher risk of perceived stress than the general population (Baena-Díez et al., 2020).

Additionally, it is usually argued that people of low socioeconomic status visit health centres at a more advanced stage of the disease and are less confident that they will be treated respectfully, thus resulting in worse health outcomes (Szczepura, 2005). Moreover, in situations when access to healthcare is limited – as occurred in the first year of the COVID-19 pandemic– some minority groups may encounter more difficulties in accessing healthcare services and even situations of discrimination on the grounds of socioeconomic status, racial or ethnic origin and sex (Orzechowski et al., 2020).

Empirical data from various economically developed countries confirm that poor and minority groups, that is, vulnerable populations, marginalized groups and people with complex needs, tend to be at increased risk of COVID-19 disease. Hence, it could be argued that the pandemic has merely reflected the social inequalities and exclusions that existed prior to the COVID-19 crisis.

Focusing on the United States, Alobouia et al. (2020), Figueroa et al. (2020) and Millett et al. (2020) showed that community-level factors are associated with racial and ethnic disparities in COVID-19 rates. The authors found that counties with larger proportions of Black residents have a higher prevalence of comorbidities and greater exposure to air pollution, in addition to higher COVID-19 case rates. Likewise, Abedi et al. (2020) and Kim and Bostwick (2020) examined the effects of COVID-19 on African American communities and found that racial, economic and health inequality has an important effect on COVID-19 infections and deaths in this population.

Chiou and Tucker (2020) examined the ability to self-isolate in response to state requirements in the United States in March 2020 and found that households living in high-income areas and benefiting from higher internet speeds were more able to respect social distancing. Irlacher and Koch (2021) noted that poorer regions in Germany have a lower proportion of jobs that can be performed remotely. In the United Kingdom, De Fraja et al. (2021) also documented a very heterogeneous potential for telecommuting across regions, with the proportion of residents who can work from home varying from 30 % to 60 %. In general, as Brandily et al. (2020) reported for France, occupations that involve physical proximity and are considered 'essential' are more common in poorer areas. They emphasize that this effect is magnified by the prevalence of poor housing conditions, air pollution, the lack of healthcare facilities and the higher proportion of elderly people.

In the case of Spain, according to the most recent data on remote work from the Active Population Survey of 2019 (National Statistics Institute, 2022), an estimated 4.8% of the population normally works remotely (or more than half the days). However, Palomino et al. (2020) indicated that the teleworking capacity differs across the country due to the differential productive structure of each region. They point out, for instance, that the capacity of working under lockdown is much greater for workers with primary education in Extremadura or Andalusia (where they occupy essential jobs) than in the Balearic Islands or Canary Islands (where they are mostly occupied in the tourism sector). Furthermore, as mentioned above, the presence in Malaga of numerous technological companies linked to the Technological Park of Andalusia provides a comparatively high number of workers in the city the possibility to telework.

Although most studies conclude that individuals of lower socioeconomic status are more likely to contract COVID-19, in line with other previous episodes of viral infections (Cutler et al., 2006; Adda, 2016), certain contagion-related factors have also been found to be associated with the least socio-economically vulnerable people. Among others, these factors include the greater geographical mobility of middle- and high-income individuals in rich countries for leisure or business travel or to attend mass gathering events (see Bonaccio et al., 2020; González-Val and Marcén, 2022) or the higher proportion of workers in occupations most likely to be exposed to COVID-19, such as doctors or nurses, who generally have a high socioeconomic status (Public Health England, 2020). Hospitals could therefore be major carriers of COVID-19, at least in the first phase of the pandemic, as they were quickly overrun with infected patients, which facilitated transmission to uninfected patients and doctors and nurses (Nacoti et al., 2020).

According to Schmitt-Grohé et al. (2020), although the probability of being tested for COVID-19 in New York (the city most affected by COVID-19 in 2020) was evenly distributed across income levels measured at the zip code unit, the test results show significant inequality across incomes. In particular, the probability of testing negative for COVID-19 in zip codes with the lowest per capita incomes was 38% compared to 65% in zip codes with the highest per capita incomes, even if the tests were equally distributed. In Europe, the results of Bonaccio et al. (2020) revealed that COVID-19 started to spread more rapidly among middle- and high-income individuals in wealthier countries where the number of industries is much higher, and that interpersonal interactions at work, travel within and outside the country and social gatherings also presumably differ from poorer regions. In the case of Italy, the first European country affected by the virus, the COVID-19 outbreak barely affected the northern regions where the heart of Italy's manufacturing and financial industries are located, but had a very strong impact on Lombardy, so much so that the disease was renamed the 'Ebola of the rich' (Nacoti et al., 2020). In contrast, the southern regions of Italy recorded (at least until May 15, 2020) relatively fewer cases and deaths from COVID-19 (Bonaccio et al., 2020). Likewise, according to Suárez-Álvarez and López-Menéndez (2021), a significant part of the variability of infection rates in Europe was due to tourist arrivals, which may explain the ease of spread of the virus in some wealthy tourist destinations. In Germany, for instance, regions with tourism-oriented economies saw a significant increase in the incidence of COVID-19 in the summer of 2020 due to tourist movements (Backhaus, 2022).

In the Spanish case, when comparing Malaga with other large cities such as Madrid, the map is notably different. The first wave affected the capital of Spain more than Malaga, while the incidence during the second wave was much lower, probably because many infected people had developed antibodies that protected them from becoming reinfected (Soriano et al., 2021). For Barcelona, Roso-Llorach et al. (2022) reported that the proportion of hospitalized patients in the lowest socioeconomic level increased after the first wave. They emphasize that limited access to personal outdoor space, overcrowding and jobs with limited opportunities to work from home are among the main features that could increase people's exposure economically.

To sum up, it seems clear that certain factors associated with higher infections rates are more present among the most vulnerable and others are more common among the less vulnerable. Thus, depending on the specific circumstances of each stage, and especially the mobility restrictions imposed by governments, different implications could be expected by level of vulnerability. More specifically, in periods with high mobility restrictions the most vulnerable would be the most affected because they have worse housing conditions and teleworking options, while in periods with less mobility restrictions the least vulnerable might be more likely to have higher rates of infection due to their greater social interactions and international mobility (tourism).

Based on the literature review, we formulate two hypotheses on the relationship between vulnerability and COVID-19 infection rates across census tracts of the municipality of Malaga. First, we speculate that the most vulnerable census tracts have suffered the highest COVID-19 infection rates. Second, we hypothesize that the pattern of association between vulnerability and COVID-19 cases across the census tracts of Malaga city is not necessarily uniform in the first year of the pandemic, as the main factors driving infection rates might vary depending on the mobility restrictions at each point in time. Hence, we analyse COVID-19 infection rates at different time points and their connections with the degree of vulnerability across census tracts of Malaga.

3. Data and methodology

As mentioned, the municipality of Malaga is located on the western Mediterranean coast in the southernmost part of Spain. The total land area of the municipality is 398.25 km^2 and comprises 434 census tracts; a partitioning of the municipal area preferably defined by easily identifiable boundaries, such as geographical features of the land, permanent constructions and roads (see Fig. 1).

To perform the analysis, data on the accumulated incidence of the disease at 14 days in each census tract of Malaga for the period February 28, 2020 to February 28, 2021 were used. The data come from the Ministry of Health of the Regional Government of Andalusia, Spain. The addresses of all cases were geocoded and their geographical coordinates were obtained to assign each case to its census tract of residence.

Fig. 2 displays the time series pattern of the daily incidence rate at the city level over the period. This temporal dynamic has allowed us to define five time intervals with five corresponding events that are analysed separately.

The dynamics of infection spread show, first, the arrival of the virus in Malaga, and its expansion in two subsequent waves. In the first stage, which lasted until May 28, 2020, the incidence of COVID-19 increased but did not reach the record high that would be reported later. As can be seen, cases increased significantly until the end of March 2020, when the incidence rate began to fall after the stay-at-home order. In the second wave (from June 6, 2020 to December 9, 2020), the incidence rate increased again, presenting a curve with two humps. The first hump corresponds to a reduction in the rate of infections around the end of September and reflects the impact of the increase in number of cases during the summer holidays. The second hump of the second wave started on October 10, 2020, when there was another increase in cases after bank holidays around October 12th (National Day of Spain), which led to a ban on mobility between municipalities during the third state of emergency decreed on October 25, 2020. This period ended on December 9, 2020.

The third wave began on December 10, 2020, just before the Christmas holidays and after the national holiday of December 6th (Spanish Constitution Day). This wave saw a substantial increase in infections (higher than in previous periods) until December 23, 2020 due to the lifting of mobility restrictions in Andalusia. The wave reached its maximum peak in mid-January 2021, after which the infection rates began to fall. From February 1 to February 15, 2021, essential activity in the municipality of Malaga was again restricted due to an infection rate of more than 1000 cases per 100,000 inhabitants.

The singularity of our data stems from the fact that we break down the city of Malaga into 434 census tracts, as shown in Fig. 1. The accumulated incidence of the disease in each census tract is divided by the total population of the tract so it is expressed in relative terms. We will refer to this as the incidence rate.

We are interested in analysing the incidence rate by geographical unit, level of multidimensional vulnerability and time. To assess the level of vulnerability of each census tract we use a multidimensional vulnerability index for 2019 (see Bárcena-Martín et al., 2021). This index is composed of 19 variables classified in four dimensions: demographic, socioeconomic, care needs of inhabitants and the territorial quality of the space where they reside (see Table A1 in the Online Appendix). The selected variables, among more than 200 originally collected and considered, were obtained from a variety of sources, such as the Municipal Register of Inhabitants, the National Institute of Statistics (INE), the National Meteorological Agency (AEMET), the Information System for Users of Social Services (SIUSS), the Urban Environment Observatory of Malaga (OMAU), the Spanish Public Employment Service (SEPE), and surveys. Most of these variables use heterogeneous spatial units, ranging from postal codes to districts, classical neighbourhoods, etc. To overcome the drawback of different spatial units, all the variables were transformed into the minimal spatial unit (the census tracts) using a cartographical algorithm specifically designed for the city of Malaga, thus allowing all the information to be converted into the same (minimal) units. This algorithm uses the cartographical information on the frontier of the different spatial units, as well as the Municipal Register of Inhabitants, which contains the

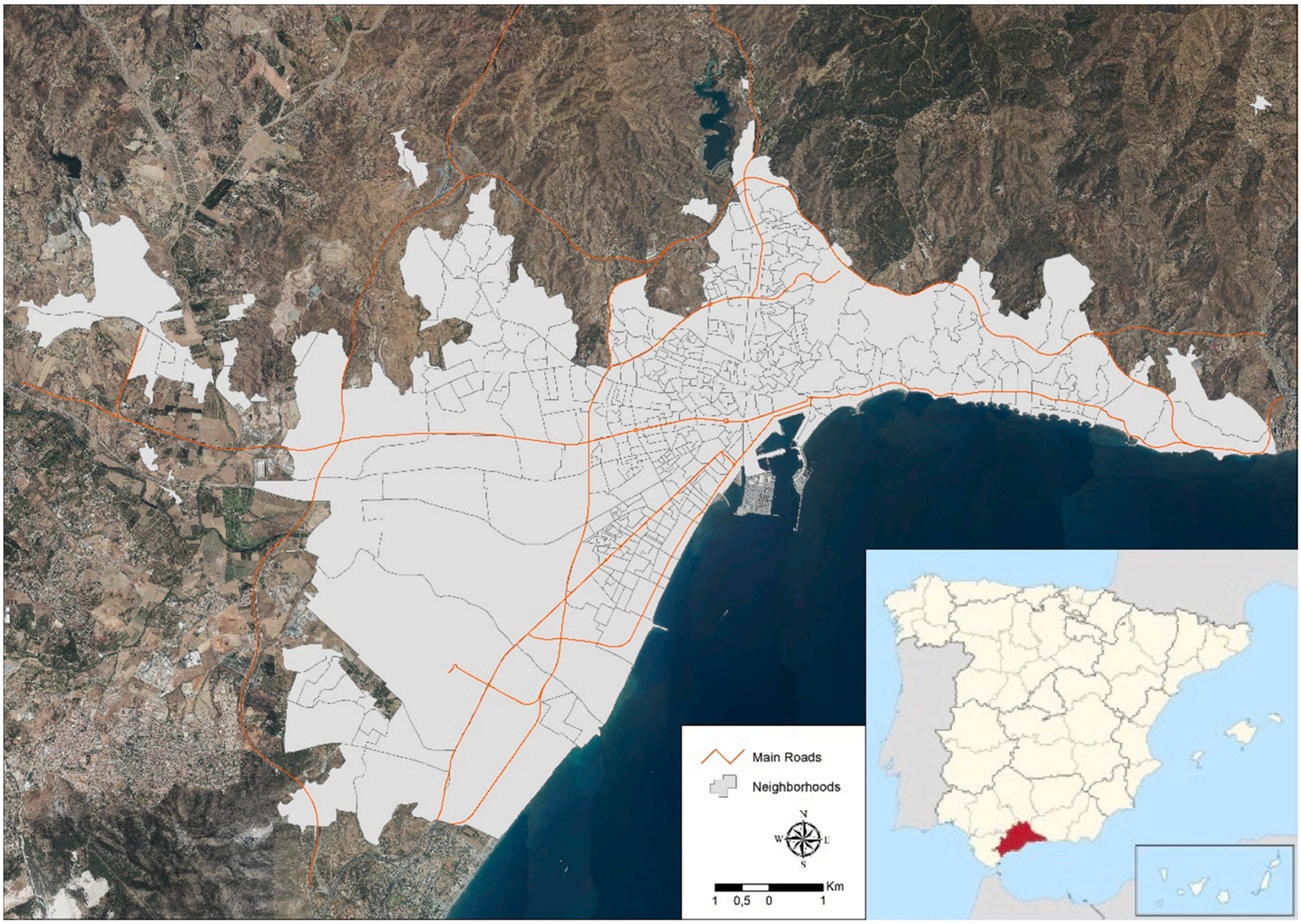

Fig. 1. Location of Malaga and municipal census tracts.
Source: Own elaboration.

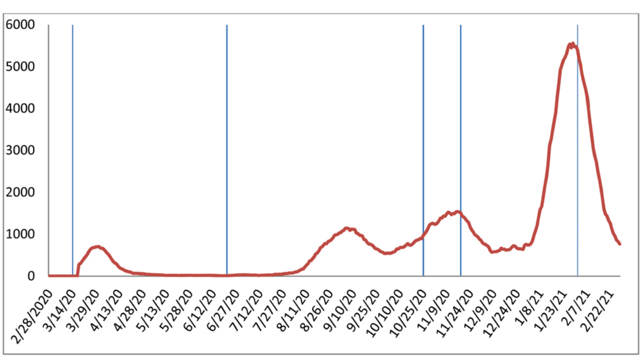

Fig. 2. Daily incidence rates at city level from February 28, 2020 to February 28, 2021, Note*:* The vertical lines correspond to the analysed events: March 14, 2020 (first day of first state of emergency in Spain); June 21, 2020 (end of first state of emergency); October 25, 2020 (first day of third state of emergency); December 18, 2020 (day regional-level mobility restrictions were lifted in Andalusia); and February 1, 2021 (closure of non-essential activity in the city of Malaga as the number of contagions exceeded 1000 cases per 100,000 inhabitants). Additionally, detailed information on each of the events is specified in the Appendix.
Source: Ministry of Health of the Regional Government of Andalusia and own elaboration.

exact address of each inhabitant in the city.

Our variables, together with their definition, territorial unit, source and reference date, largely coincide with those used by other studies and authors to perform vulnerability analyses for other cities of Spain (see, for instance, Egea Jiménez et al., 2008; Ayuntamiento de Madrid, 2018; Esteban y Peña et al., 2021; Gayen et al., 2021).

Once all the variables were referenced to the same spatial units, a normalization process was applied so that all of them were in the range [0,1], where 0 is the best situation and 1 the worst in all cases. That is, all the variables were normalized so that a higher value in both the maximizing and minimizing variables means a worse situation in that characteristic.

Finally, the normalized variables were grouped into the four categories (demographic, socioeconomic, care needs of inhabitants and the territorial quality of the space where they reside) and a linear weighted aggregation was conducted to obtain a final vulnerability index. We chose to give the same weight to the dimensions and distribute the weights proportionally within each dimension. Note that this dimension's aggregation method allows compensation between them. For example, we assume that a low score in level of income can be compensated (according to the assigned weights) by an increase in level of education and that this compensation is constant.

A first approximation to the relationship between vulnerability levels and infection rates across census tracts and possible changes in patterns over the period is presented in Fig. 3, which shows the linear correlation between vulnerability level and incidence rate for each census tract for each date under study.

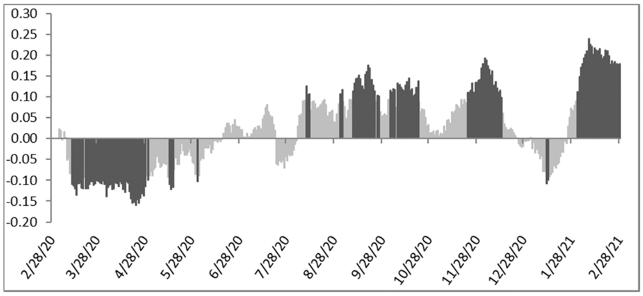

Fig. 3. Daily linear correlation between vulnerability level and COVID-19 incidence rate in census tracts of Malaga. February 28, 2020–February 28, 2021, Note: Bold bars indicate correlation coefficients significantly different from zero. Overall correlation is 0.1519,
Source: Ministry of Health of the Regional Government of Andalusia and own elaboration.

As can be seen in the figure, there is a significant association between vulnerability and COVID-19 infections across census tracts, even though the sign of the association is not maintained throughout the period examined. As regards our research hypotheses, we can state that the pandemic spread asymmetrically across space following a gradient determined by vulnerability factors, but the influence of this gradient is not constant over time, and even changes sign. In general, in the entire period fewer cases are observed in the census tracts with lower vulnerability, as revealed by the positive and significant correlation between vulnerability level and overall COVID-19 incidence rates.

Nevertheless, note that this is just a first approximation since we imposed a linear association between the level of vulnerability and the COVID-19 incidence rate, which may be a rigid assumption. Neither did we account for heterogeneity across census tracts, that is, characteristics that vary over the geographical units but remain constant for each unit over time. Hence, a more sophisticated analysis is in order.

Since the descriptive analysis requires us to define different periods of time in which the influence of the vulnerability gradient is changeable, and to avoid the assumption of a linear association, we divide the census tracts into 4 vulnerability groups of equal size (see Fig. 4), which we refer to as Q^1, Q^2, Q^3, and Q^4. Q^1 corresponds to 25% of census tracts with lowest vulnerability, Q^2 to 25% of census tracts between the first and second quartile of vulnerability, Q^3 to 25% of census tracts between the second and third quartile and Q^4 to 25% of census tracts with highest vulnerability. We consider different scenarios in which policies to restrict and reduce interpersonal contacts (i.e. limitations on economic activity or mobility, school closures, etc.) have been implemented to slow the spread of the disease. We analyse the dynamics of the incidence of COVID-19 infections in each census tract before and after each event that correspond to the entry into force of key policy decisions: March 14, 2020 (first day of first state of emergency in Spain); June 21, 2020 (end of first state of emergency); October 25, 2020 (first day of third state of emergency); December 18, 2020 (day regional-level mobility restrictions were lifted in Andalusia); and February 1, 2021 (closure of non-essential activity in the city of Malaga as the number of contagions exceeded 1000 cases per 100,000 inhabitants). See the Online Appendix for a more detailed description of the restrictions in each period.

Thus, we analyse five different periods spanning 15 days before each event and 75, 110, 45, 28 and 28 days after events 1, 2, 3, 4 and 5, respectively. By doing so, we cover the duration of each of the three waves.

For each of the five periods, we can implement several valid econometric strategies to analyse the association between vulnerability by census tract in Malaga and the COVID-19 incidence rate and evaluate the possible change in the sign of this association. We estimate the difference-in-difference (DID) regressions and the event regression controlling for fixed effects, even though event regression is a more flexible strategy than DID for modelling the evolution of contagion rates.

As is usual in other studies, we use the DID strategy as a benchmark. The identification assumption in the DID models is a 'parallel trend' assumption with a single post-event indicator in each period for all days after the occurrence of the event. That is, we assume that if the corresponding event had not occurred, then the incidence rate in the census tracts would have followed the same trend after the policy measure or intervention was implemented. We analyse a DID model as a benchmark where vulnerability groups are the control variable as follows:

$$y_{t,c} = \alpha + \gamma_2 Q_c^2 + \gamma_3 Q_c^3 + \gamma_4 Q_c^4 + \beta Postevent_{t,c} + \delta_2 Q_c^2 \bullet Postevent_{t,c} + \delta_3 Q_c^3 \bullet Postevent_{t,c} + \delta_4 Q_c^4 \bullet Postevent_{t,c} + \theta_c + \varepsilon_{t,c}, \tag{1}$$

where t refers to a given day and c to a census tract; $y_{t,c}$ is the incidence rate of COVID-19 cases per 1000 inhabitants with a 14-day cumulative daily frequency by census tract; and $Postevent_{t,c}$ is an indicator variable that takes the value of 1 on the days after the event, and 0 otherwise. The variable Q_c^2 is a binary variable that takes the value of 1 if the census tract corresponds to 25% of tracts between the first and second quartile, and 0 otherwise; Q_c^3 is a binary variable that takes the value of 1 if the census tract corresponds to 25% of tracts between the second and third quartile, and 0 otherwise; and Q_c^4 is a binary variable that takes the value of 1if the census tract corresponds to 25% of tracts with highest vulnerability, and 0 otherwise. The reference category is the lowest vulnerability level, which comprises 25% of the tracts. These variables capture differences in the infection rates by vulnerability level before the intervention. To capture if the intervention affects the difference between vulnerability groups, we introduce the interactions of each of the vulnerability groups with the variable $Postevent_{t,c}$. Finally, the model includes fixed effects for the census tract, θ_c, and an unobserved error term, $\varepsilon_{t,c}$.

Note that DID models do not provide information on the structural change and subsequent evolution of the event. The assumption that, in the absence of intervention, the difference between the 'treatment' and 'control' group is constant over time (parallel trend assumption) is too restrictive, since the differences in incidence rates by vulnerability group may have changed after the intervention. Thus, it seems appropriate to introduce a more flexible estimation strategy. The event study specification allows for the inspection of parallel trends in the pre-treatment period and the natural treatment effects, as well as any dynamics related to the appearance of effects (they can grow or shrink over time) and whether the effects are transitory or permanent. The key assumption underlying consistent estimation in event study models is that the occurrence of the event in a particular area is not systematically related to changes in levels that will occur in the future (Clarke and Tapia, 2020).

Although the event regression method is mostly used in the fields of telecommunications, electricity and other market studies, it has also been applied to study events related to COVID (Hoehn-Velasco et al., 2021; Arin et al., 2022; Backhaus, 2022; González-Val and Marcén, 2022, among others). This way, the incidence of COVID-19 can also be modelled by this model to analyse how infection rates vary before and after events, such as when the Spanish government declared the state of emergency or the reopening of business activity. In our study, we are interested in taking five events as references since the linear correlation inspection has provided some evidence that they could be points where the influence of vulnerability factors may change.

In general terms, for the event study we take s days before the event and T days after, while we set to 0 the exact day the measure entered into force. The most general model would be:

$$y_{t,c} = \sum\nolimits_{t=-s}^{T} \alpha_t L_{t,c} + \theta_c + \varepsilon_{t,c}, \tag{2}$$

where $L_{t,c}$ are binary variables indicating that the census tract was a

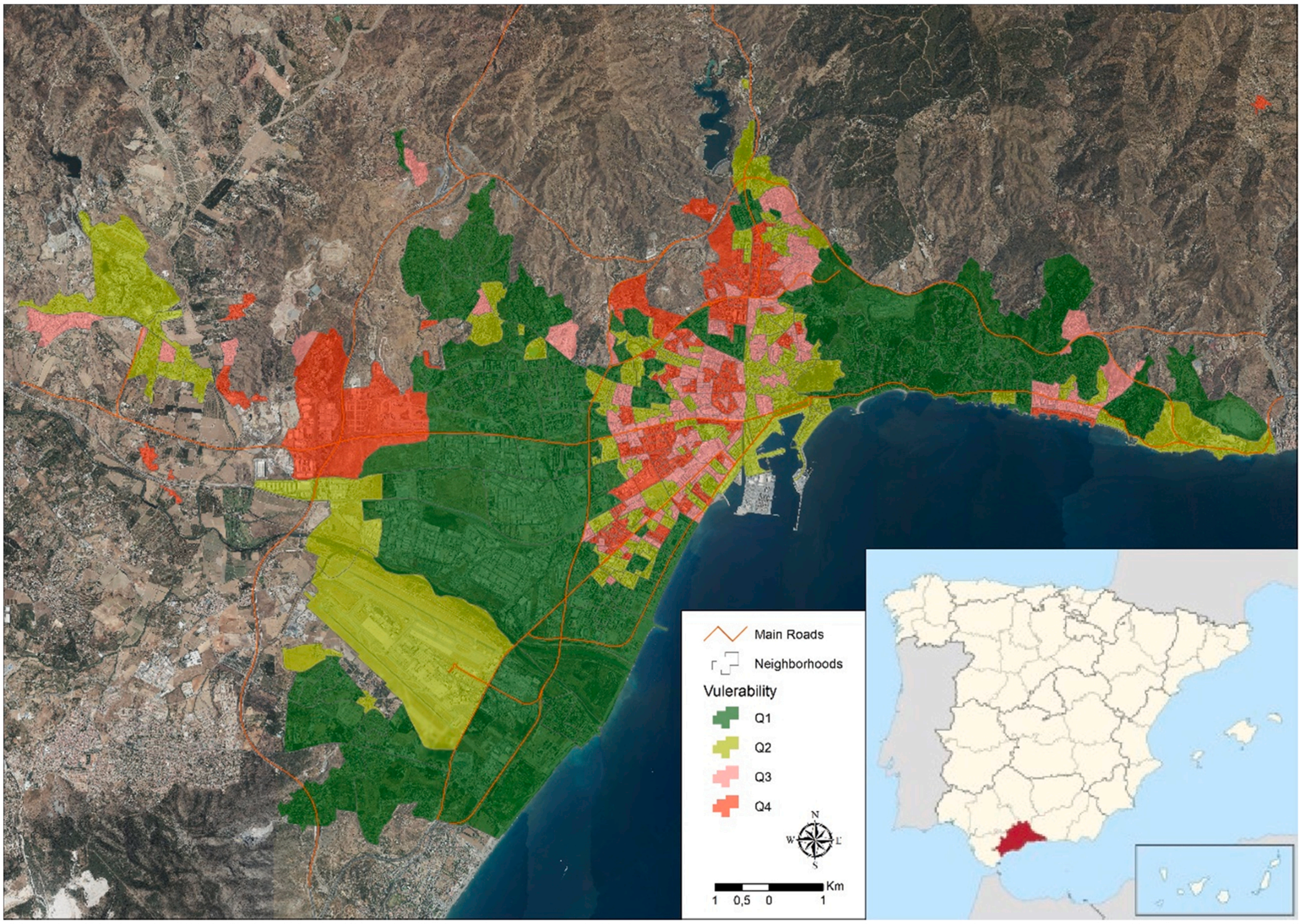

Fig. 4. Vulnerability in Malaga census tracts by quartile (4 groups), Note: Q^1 corresponds to 25% of census tracts with lowest vulnerability, Q^2 to 25% of census tracts between the first and second quartile of vulnerability, Q^3 to 25% of census tracts between the second and third quartile of vulnerability and Q^4 to 25% of census tracts with highest vulnerability.
Source: Bárcena-Martín et al., 2021 and own elaboration.

given number of periods (common for all census tracts) at a distance from the event of interest in the respective time period. As is standard in the literature, the reference period is set to -1: the period immediately preceding the event. Finally, the same number of fixed effects as in Eq. (1) are included in the model. For example, $t = 10$, α_{10} informs us about the effect of the event 10 days after it occurred in the vulnerability group for which the regression was estimated and compares this information to the day before the event ($t = -1$). We estimate separate regressions for each vulnerability group, that is, we estimate four separate regressions.

As we are interested in the link between the evolution of infection rates and the vulnerability of the census tract, we study the significance of differences in the event regression by expanding the model to control for vulnerability level and introduce an interaction term as follows:

$$y_{t,c} = \gamma_2 Q_c^2 + \gamma_3 Q_c^3 + \gamma_4 Q_c^4 + \sum\nolimits_{t=-s}^{T} \alpha_t L_{t,c} + \sum\nolimits_{t=-s}^{T} \delta_{2,t} Q_c^2 L_{t,c} + \sum\nolimits_{t=-s}^{T} \delta_{3,t} Q_c^3 L_{t,c} + \sum\nolimits_{t=-s}^{T} \delta_{4,t} Q_c^4 L_{t,c} + \theta_{t,c} + \varepsilon_{t,c} \tag{3}$$

4. Results

We analyse the dynamics of the COVID-19 incidence rate within and across census tracts following five events and using two identification strategies, as explained above.

We start with a DID model to quantify the average effect by degree of vulnerability (grouped into four levels) of each of the five events. We compare the incidence rate in each census tract before and after each event (each column refers to an intervention) within the same geographical unit controlling for the vulnerability group of each census tract. Additionally, we allow the effect of the intervention to vary according to the vulnerability level of the geographical unit (Table 1).

The results indicate that prior to the state of emergency (i.e. the first event, March 14, 2020, first column of Table 1), the most vulnerable census tracts had lower incidence rates ($\gamma_4 = -0.214$, suggesting that the group with highest vulnerability had on average 2.14 less cases per 100 inhabitants than the group with the lowest vulnerability). However, when the state of emergency was declared, the overall incidence increased significantly ($\beta = 0.456$, on average the increase was 4.56 cases per 100 inhabitants), even though the magnitude of the increase varied depending on the degree of vulnerability of the geographical unit. That is, the increase was greater for the less vulnerable census tracts ($\delta_4 = -0.153$, that is, the highest vulnerability group increased 1.53 less cases per 100 inhabitants than the least vulnerable group).

In line with Bonaccio et al. (2020) and González-Val and Marcén (2022) for Italy and Spain, respectively, we also observe that COVID-19 began to spread more rapidly among less vulnerable areas (middle- and upper-income individuals) due to factors such as their interpersonal interactions at work, more frequent international mobility within and outside the country and social gatherings. Furthermore, we can also speculate that there is a larger number of doctors and nurses among the individuals of the less vulnerable census tracts, and, as is well-known, anyone providing direct healthcare to an affected patient has more chances of being infected by occupational exposure levels (Almagro

Table 1
Results of the difference-in-difference estimation.

	March 14, 2020: First state of emergency declared	June 21, 2020: End of first state of emergency	October 25, 2020: Beginning of third state of emergency	December 18, 2020: Lift off mobility restrictions in Andalusia	February 1, 2021: Closure of non-essential activity in Malaga
Q^2	0.315***	-0.195	0.001	-2.453***	-2.583***
	[0.101]	[0.147]	[0.259]	[0.429]	[0.824]
Q^3	0.164	-0.198	0.427*	-1.480***	2.606***
	[0.101]	[0.147]	[0.259]	[0.429]	[0.823]
Q^4	-0.214**	0.135	0.953***	-2.284***	-1.585*
	[0.101]	[0.147]	[0.259]	[0.429]	[0.824]
post	0.456***	0.682***	0.684***	1.332***	-4.714***
	[0.018]	[0.030]	[0.040]	[0.061]	[0.115]
Q^2#post	-0.130***	-0.006	-0.037	-0.574***	0.788***
	[0.026]	[0.042]	[0.057]	[0.086]	[0.163]
Q^3#post	-0.140***	0.043	-0.009	-0.186**	1.189***
	[0.025]	[0.042]	[0.057]	[0.086]	[0.163]
Q^4#post	-0.153***	0.190***	-0.004	-0.561***	1.539***
	[0.026]	[0.042]	[0.057]	[0.086]	[0.163]
Census tract FE	yes	yes	yes	yes	yes
Observations	39,494	54,684	26,474	19,096	19,096

Note:. Q^1 (reference) takes the value of 1 if the census tract corresponds to 25% of tracts with lowest vulnerability, Q^2 takes the value of 1 if the census tract corresponds to 25% of tracts between the first and second quartile, Q^3 takes the value of 1 if the census tract corresponds to 25% of tracts between the second and third quartile and Q^4 takes the value of 1 if the census tract corresponds to 25% of tracts with highest vulnerability.

* $p <.1$
** $p <.05$
*** $p <.01$

et al., 2020; Public Health England, 2020).

In the second event (June 21, 2020, second column in Table 1), that is, at the end of the state of emergency, the situation is the opposite. The incidence rate was similar for all the vulnerability groups before resuming activity. Once activity resumed, the incidence rate increased ($\beta = 0.682$, 6.82 cases per 100 inhabitants), but this time the increase was similar for all the vulnerability groups, except for the most vulnerable census tracts, which experienced a greater increase in the incidence rate ($\delta_4 = 0.190$, 1.9 more cases per 100 inhabitants than the least vulnerable group). In this case, we venture that the reopening of activity did not affect all census tracts equally.

As a renowned tourist destination, Malaga was particularly affected when mobility was allowed (summer), as occurred in other touristic cities and regions of Germany, where the second wave considerably increased the number of infections in general terms (Backhaus, 2022). In our case, along with the census tracts of the centre of Malaga (the most touristic ones), the most vulnerable census sections (i.e. those with a higher share of low-income employees who could not work remotely and/or their household facilities did not allow teleworking) were the most exposed to the virus.

The third event, which corresponded to the beginning of the third state of emergency (third column in Table 1), shows that from this date onwards there were no significant differences between the vulnerability groups. Before the event, however, the most vulnerable census tracts (groups 3 and 4) had a higher incidence rate compared to the least vulnerable group (4.27 and 9.53 cases per 100 inhabitants, respectively). In addition, the overall increase in infection rates was similar to that of event 2 ($\beta = 0.684$, 6.82 cases per 100 inhabitants).

Before the Andalusian government allowed mobility in the region (event 4, fourth column in Table 1), the incidence rate was significantly lower for the three most vulnerable groups (24.53, 14.80 and 22.84 less cases per 100 inhabitants for vulnerability groups 2, 3 and 4, respectively), even though the Christmas holidays (right after event 4) may be associated with a very large increase in the incidence rate ($\beta = 1.332$, 13.32 cases per 100 inhabitants).

During Christmas 2020, most countries placed limitations on travel. In Andalusia, however, mobility between provinces was allowed, leading to a considerable increase in infections, although the rate was not uniform across census tracts. As in the first event (the beginning of the pandemic), those who could afford to travel were the most infected, with the least vulnerable showing a significantly higher increase in infection rates. Therefore, mobility once again seems to play an important role in the sense that individuals living in less vulnerable geographical units were more likely to travel during the holidays and have more multiple contacts, thus increasing their chances of becoming infected.

Finally, the closure of activity (event 5, fifth column in Table 1) reduced the incidence rate ($\beta = -4.714$, 47.14 cases per 100 inhabitants), although less so for the most vulnerable census tracts ($\delta_4 = 1.539$, 15.39 less cases per 100 inhabitants), whose individuals with occupational exposure (supermarkets, housecleaners, etc.) and smaller households could possibly benefit less from this closure than the less vulnerable individuals. They could take advantage of remote work and protective measures such as masks and frequent COVID-19 testing.

Taking the DID results as our benchmark, now we move to a more flexible model using the event regression model. In this model, we no longer impose restrictive assumptions on the difference among vulnerability groups. As concluded in the DID model for the first event, when the first state of emergency was declared, there was a significant increase in the incidence rate (see Fig. 5). However, unlike what was assumed in the DID model, the effect of the state of emergency was not immediate. For at least 15 days after the state of emergency was declared, the incidence rate continued to increase, with the least vulnerable geographical units showing the largest increases in incidence rates. The incidence rate would not decrease until 20 days after the event, although on this occasion the least vulnerable groups showed the greatest differences in the incidence rate prior to the state of emergency. Moreover, the incidence rates of the different vulnerability groups were not equal until 55 days after the event. [1]

As shown in the DID model, the incidence rates in event 2 (Fig. 6) are similar across the vulnerability groups and remained so 40 days after the end of the state of emergency. Thereafter, the most vulnerable census tracts showed the largest increases, which was probably due to greater exposure to contacts at work, along with smaller dwellings and possibly

[1] For a more in-depth analysis, see Figure 10–14 in the Online Appendix showing the differences by vulnerability group.

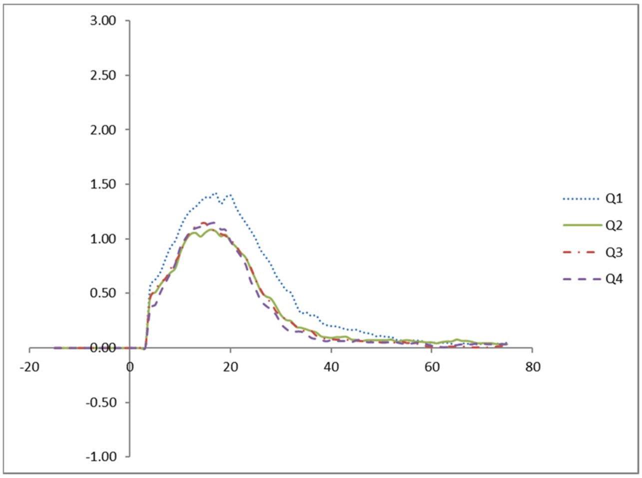

Fig. 5. Separate event regressions by vulnerability group. Event 1, Note: Event 1, declaration of state of emergency, March 14, 2020. Refer to Fig. 4 for definitions of Q^1, Q^2, Q^3 and Q^4.

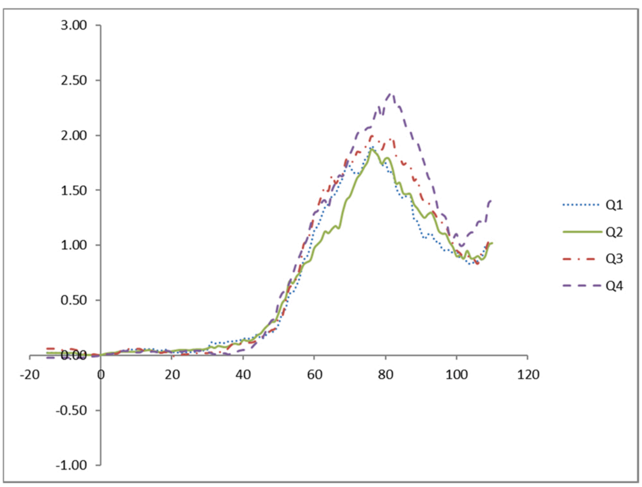

Fig. 6. Separate event regressions by vulnerability group. Event 2, Note: Event 2, end of state of emergency, June 21, 2020. Refer to Fig. 4 for definitions of Q^1, Q^2, Q^3 and Q^4.

less ventilation in homes. Again, unlike what is assumed in the DID model, the effect of the event, in this case the end of the state of emergency, was not immediate. Moreover, the trend in incidence rates was not linear. The event study model shows an upward curve with a hump (around day 80 after the second event) for all the vulnerability groups, with a predominance of the most vulnerable. Around 100 days after the event, another increase was observed in cases analysed in the next event.

It should be noted that in the periods when the incidence rate increased (see the upward slope in Fig. 6), vulnerability group 2 showed lower incidence rates than the least vulnerable group, but the difference is not significant (see Figure 11 in the Online Appendix).

Event 3 (Fig. 7) corresponds to the second hump of the second wave shown in Fig. 2. This time the incidence rate was similar across the vulnerability groups. All groups show the same upward trend in the third state of emergency (October 25, 2020) with a general increase thereafter until mid-November. From December onwards (more than 20 days after the event), the incidence rate decreased.

Fig. 7 shows possible differences for vulnerability groups 2 and 3 with respect to the rest of the groups for the period T = 10 to T = 25 (November 4, 2020-November 19, 2020). However, when analysing the interaction in Figure 12 in the Online Appendix, the differences are not

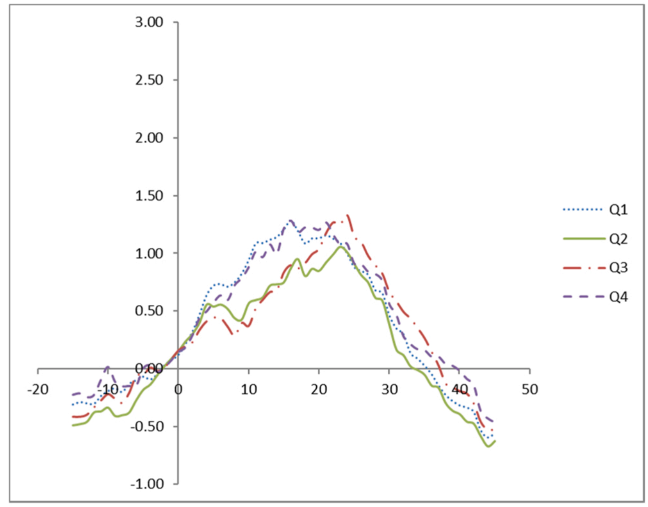

Fig. 7. Event study estimation by vulnerability group. Event 3, Note: Event 3, third state of emergency, October 25, 2020. Refer to Fig. 4 for definitions of Q^1, Q^2, Q^3 and Q^4.

significant.

The event regression for the Christmas period (event 4, Fig. 8) shows a significant increase in the incidence rate and, as in the first event, the least vulnerable census tracts again show the largest increases. As speculated above, this increase may have been due to the wider interprovincial mobility (December 18 to January 10) and interregional mobility (December 23 to January 10) allowed during the holiday season. During this period, individuals from less vulnerable census tracts may have taken more advantage of the relaxation of restrictions, resulting in an increase of about 4 more cases per 1000 inhabitants on average in all census tracts around January 3 (day 25 after the event).

Finally, as regards the last event (event 5), the incidence rate shows a downward trend for all census tracts. This time the closure of all nonessential activity reduced the incidence rate in all the groups, even though the least vulnerable ones showed a less staggered trend (unlike in the DID model), that is, smaller differences in incidence rates (Fig. 9) with respect to February 1.

Summing up, our empirical results reveal that the analysed events are associated with a change in the incidence rate that cannot be assumed to be a parallel shift. The effect of the restrictions was found to vary over time or emerge with delay, thus indicating that event

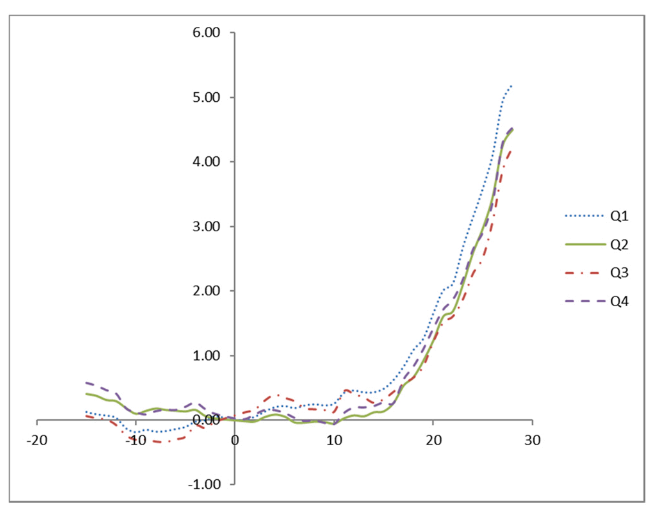

Fig. 8. Event study estimation by vulnerability group. Event 4, Note: Event 4, December 18, 2020. Refer to Fig. 4 for definitions of Q^1, Q^2, Q^3 and Q^4.

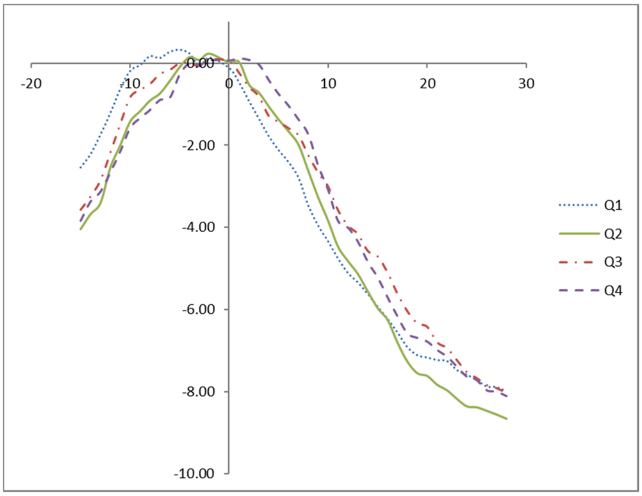

Fig. 9. Separate event regressions by vulnerability group. Event 5, Note: Event 5, closure of essential activity, 1st February 2021. Refer to Fig. 4 for definitions of Q^1, Q^2, Q^3 and Q^4.

regression analysis is the most suitable estimation strategy. A remarkable association was also found between level of vulnerability and the incidence rate of the census tracts, even though this association varied from one event to another due to changes in the mobility restrictions imposed by the authorities to contain the virus. We thus confirm two main channels of contagion that affected the census tracts differently by vulnerability level. When mobility restrictions were not imposed, people in the less vulnerable census tracts were the most affected due to their higher social interaction and international mobility. However, when mobility restrictions were imposed, people living in the most vulnerable tracts suffered the highest infection rates due to their worse conditions at home and lack of teleworking possibilities.

5. Conclusions

This study addresses the links between multidimensional vulnerability and COVID-19 infection rates across census tracts of Malaga in the first year of the pandemic. Our findings reveal that the pandemic spread asymmetrically across the census tracts of the metropolitan area and followed a gradient determined by vulnerability factors, even though the effect of this gradient was not constant over time.

Specifically, five events related to infection rates in the first year of the COVID-19 pandemic have been analysed. In the first and fourth events (March 14, 2020 and December 18, 2020, respectively), when mobility was permitted, the incidence rate increased more for the least vulnerable census tracts. In addition to factors associated with the greater social interactions and international mobility of this group, in line with Jackson et al. (2020), the large share of physicians and other healthcare workers lacking personal protective equipment in the first event may have driven the larger increase in the incidence rate among the least vulnerable.

Moreover, the increase in infection rates during the second event (June 21, 2020) and the decrease in infection rates in the fifth event (February 1, 2021), periods with rigid mobility restrictions, were greater in the most vulnerable census tracts. This indicates that these tracts, usually with poorer housing conditions, were more sensitive to the restrictions, given the greater difficulties for their residents to work remotely. Let us recall that exposure to and infection from COVID-19 are higher for those who work outside of the home and are less able to work remotely. This is in line with Vargas Hill and Narayan (2020), who found that workers not working from home or those employed in jobs requiring close physical proximity are more likely to live in more vulnerable geographical units.

In sum, our findings show that although preventive interventions appear to be vulnerability neutral in their formulation, their application might be associated with different effects in terms of infection rates across neighbourhoods according to their level of vulnerability. Overall, the most vulnerable geographical units suffered higher infection rates in the first year of the COVID-19 pandemic, although the association between the vulnerability level of the census tracts and the incidence of COVID-19 infections was not uniform across time, and significant differences were found depending on mobility restrictions.

From our results, it follows that restrictions which are imposed to contain the pandemic cannot ignore vulnerability issues. In this vein, it seems advisable to recommend that universal restrictions to reduce the contagion rate should be complemented with specific policy measures that take into consideration the different vulnerability contexts. This premise would be extensible to other cities and regions and highly relevant in the face of future pandemics. Nevertheless, it is important to consider the productive structure and socioeconomic conditions of each territory, as they could modulate the prevailing and changing links between vulnerability level and infection rates over time.

Our analysis reinforces the idea that location-based policies constitute valid tools to tackle infections and their consequences during pandemics. Furthermore, such a place-based policy approach also seems relevant from a post-pandemic recovery point of view: while governments implement unprecedented fiscal stimuli, specific vulnerable peripheral areas could be prioritised and spatially targeted policies aimed at mitigating the centre-periphery vulnerability gap across large cities should be pursued.

Our study has several limitations and strengths. As regards the limitations, we focus on COVID-19 infection rates regardless of the degree of severity of the disease, which goes beyond the scope of this work and entails a potential natural extension of it. We analyse five different periods in the first year of the pandemic. They may be not strictly comparable as a better understanding of the transmission of the virus in the later periods made it possible to adopt more selective restrictive measures. In any case, it seems relevant to highlight the existence of different patterns of association between vulnerability and COVID-19 cases across the census tracts in the first year of the pandemic. We should also account for the possible underreporting of COVID-19 contagions in the first months of the pandemic. Nonetheless, our estimates are consistent with other studies that have shown an overall positive correlation between infection rates and vulnerability. Moreover, even though it could be questioned that the negative correlation of the first period was driven by the underreporting of cases, this negative association between vulnerability and contagion rate was also found in the third wave, during the Christmas holidays. Thus, we adventure that our results are not driven by possible underreporting at the beginning of the pandemic, but rather that there is a pattern associated with higher infection rates of the less vulnerable when mobility is not restricted. As strengths of this study, we might stress the use of a multidimensional index of vulnerability that accounts for multiple characteristics of the geographical units; the high level of geographical disaggregation, which allows going deeper than regional or neighbourhood studies and unmasking possible confounding forces; and the high frequency data, which has permitted us to identify changing patterns in the association between vulnerability and COVID-19 infection rates.

CRediT authorship contribution statement

Elena Bárcena-Martín: Conceptualization, Methodology, Formal analysis, Writing. **Julián Molina:** Conceptualization, Methodology, Data curation. **Ana Muñoz-Fernández:** Data curation, Formal analysis, Writing. **Salvador Pérez-Moreno:** Conceptualization, Methodology, Writing.

Statements and declarations

N/A.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.ehb.2022.101177.

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