Impact of immobility and mobility activities on the spread of COVID-19: Evidence from European countries

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Abstract
To limit the spread of COVID-19, most countries in the world have put in place measures which restrict mobility. The co-presence of several people in the same place of work, shopping, leisure or transport is considered a favourable vector for the transmission of the virus. However, this hypothesis remains to be verified in the light of the daily data available since the first wave of contamination. Does immobility reduce the spread of the COVID-19 pandemic? Does mobility contribute to the increase in the number of infections for all activities? This paper applies several pooled mean group–autoregressive distributed lag (PMG–ARDL) models to investigate the impact of immobility and daily mobility activities on the spread of the COVID-19 pandemic in European countries using daily data for the period from 12 March 2020 to 31 August 2021. The results of the PMG–ARDL models show that immobility and higher temperatures play a significant role in reducing the COVID-19 pandemic. The increase in mobility activities (grocery, retail, use of transit) is also positively associated with the number of new COVID-19 cases. The combined analysis with the Granger causality test shows that the relationship between mobility and COVID-19 goes in both directions, with the exception of grocery shopping, visits to parks and commuting mobility. The former favours the spread of
COVID-19, while the next two have no causal relationship with COVID-19. The results confirm the role of immobility in mitigating the spread of the pandemic, but call into question the drastic policies of systematically closing all places of activity.

**KEYWORDS**

COVID-19 spread, European countries, immobility, mobility, PMG–ARDL

## 1 | INTRODUCTION

The quantitative analysis of space–time contagion patterns of infectious diseases already has a long history in the medical, mathematical and geographical sciences. This has led to the formulation of various medical disease-spread models, often in the form of differential equations. The core model in this long-standing research tradition was developed almost a century ago by Kermack et al. (1927). This model is sometimes referred to as the susceptible–infectious–recovered (SIR) model, which maps out the experimental growth of infectious diseases. Clearly, the outcomes of such an SIR model are co-determined by intervention measures (e.g., quarantine measures, mobility restrictions, vaccination measures).

An important intervening variable in any epidemic model is the frequency and intensity of interpersonal contacts, as described by social networks of physical contacts. Enabling interaction at different places of work, shopping, leisure or transport, mobility is considered a favourable vector for the transmission of the virus. To limit the spread of COVID-19, most countries in the world have put in place measures which restrict mobility. These measures may include the total closure of all places of activity, including parks, and the injunction to stay at home. However, it is not clear that all activities contribute to the spread of the virus. Given the socioeconomic cost of these restrictions, it is legitimate to ask what the real impact of different mobility activities is on the spread of the virus. Does immobility reduce the spread of COVID-19 pandemics? Does mobility contribute to the increase in the number of infections for all activities? Disaggregated temporal data are needed to generate knowledge on this issue. But, owing to privacy regulations, the mapping and analysis of such human contact patterns is rather cumbersome, so that in practice anonymized data (e.g., from mobile phone use) are often being used (Kryven & Stegehuis, 2021; Lopez et al., 2021). Physical contact patterns from mobility data are, therefore, a rich source of information for modelling contagion phenomena (Schlosser et al., 2020).

Using Google open data from March 2020 to August 2021, the aim of this paper is to analyse the impact of immobility and mobility activities on the spread of COVID-19 in a panel of 29 European countries. The paper is structured as follows. First, we present a literature review on the determinants of the spread of COVID-19, questioning the role of mobility (Section 2). We then present the data and methodological elements necessary for the analysis adopted (Section 3). Section 4 is dedicated to the presentation and interpretation of the results. Finally, we provide conclusions, policy implications and research perspectives (Section 5).

## 2 | THE DETERMINANTS OF THE SPREAD OF COVID-19: WHAT IS THE ROLE OF MOBILITY?

The theoretical and empirical literature on the spread of COVID-19 points to several factors. In the epidemiology of infectious diseases, the evolution of new cases depends on the dynamics of the phenomenon itself, and in particular
on the depletion of the number of susceptible individuals. It is dependent on mobility, which is the vehicle for social interaction and contact par excellence, and also on the political measures put in place to counter contamination. Finally, it is also linked to climatic conditions and temperature changes in particular.

The spread of the pandemic is a self-sustaining phenomenon, depending on the number of infections and the individuals likely to be infected in a given space (Arroyo-Marioli et al., 2021). The transmission of the virus occurs through social interactions and the physical proximity of these two types of individuals in the same place. Mobility plays an important role in the constantly changing likelihood of contact between these two populations at different locations, and thus promotes the spread of the virus.

Restricting mobility, including staying at home, is the oldest measure to limit the spread of pandemics in human history. Other stringent measures may target the closure of places of interaction that generate this mobility, such as workplaces, schools, shopping and leisure facilities and transport, as well as the prohibition of events that lead to the concentration of populations in the same space. The Oxford COVID-19 Government Response Tracker (OxCGRT) collects systematic information on policy measures from different countries around the world. They have developed a composite indicator (the stringency index) to track these measures and assess their impact on the spread of COVID-19 (Hale et al., 2021). These measures have a direct impact on mobility practices (Huang et al., 2020), but this can vary depending on the behaviour of the population in different countries and the coercive nature of the measures. For example, containment measures were more widely followed during the first wave of the COVID-19 pandemic, owing to fear of the new virus and the effects of images coming from the most affected countries, but also because of the strict controls in some countries. Milani (2021) shows that the sensitivity of mobility to the government measures is very different among countries. While the negative correlation is very strong in European countries such as France, Italy, Portugal and Spain, it is close to zero in the Netherlands and the Scandinavian countries. He argues that using only policy responses to explain the spread of COVID-19 would miss the extent of social responses in many countries. Maloney and Taskin (2020) show that the reduction in mobility in the United States is more voluntary than linked to compulsory stay-at-home measures. While several studies have looked at the impact of stringency measures and mobility restrictions on the evolution of the COVID-19 pandemic (Brauner et al., 2021; Chung et al., 2021; Fiore et al., 2021; Herby et al., 2022; Khan et al., 2021; Md Zamri et al., 2021; Pan et al., 2021; Violato et al., 2021), few have focussed on analysing the direct effect of mobility practices (Milani, 2021; Xiong et al., 2020; Yilmazkuday, 2021).

Using mobile device location data from 1 March to 9 June 2020, Xiong et al. (2020) find a strong and positive relationship between the mobility inflow and the number of infections in US counties. Their simultaneous equations analysis (i.e., model lag = 7) shows that a 10% increase in the inflow on a particular day leads to a 2.34% increase in the number of infections a week later. In his study, Milani (2021) investigates the effects of social distancing on new COVID-19 cases through a global VAR analysis, using Google mobility data in 41 countries from 15 February 2020 to 14 June 2020. He shows that social distancing leads to declines in the growth rate of COVID-19 cases, reaffirming its importance, whether through mandatory policy or voluntary behaviour, in reducing the spread of the virus. Yilmazkuday (2021) investigates the causal relation between the change in mobility and the corresponding COVID-19 cases/deaths. He uses the same daily data regarding COVID-19 cases and deaths, as well as Google mobility data covering 130 countries around the world for the period between 15 February 2020 and 2 May 2020. The difference-in-differences analysis results suggest, after controlling for different fixed effects, that, on average across countries, a 1% weekly increase in being in residential places leads to about 70 less weekly COVID-19 cases, whereas a 1% weekly decrease in visits to transit stations leads to about 33 less weekly COVID-19 cases. Similarly, a 1% weekly reduction in visits to retail establishments & recreation facilities results in about 25 less weekly COVID-19 cases, or a 1% weekly reduction in visits to workplaces results in about 18 less weekly COVID-19 cases. The effects of visits to groceries & pharmacies or parks on COVID-19 cases are statistically insignificant.

Other simulation-based studies have also demonstrated the impact of mobility on the spread of COVID-19. Schlosser et al. (2020) have analysed the data from the mobile phones of 43.6 million individuals in Germany, using simulations of a commuter-based Susceptible-Infected-Removed (SIR) model. They demonstrate that the structural
decrease of mobility has an important effect on the spread of the virus, by ‘flattening the epidemic curve’ and delaying the arrival of the disease into distant regions. Manout & Ciari (2021) combine two agent-based models: multi-agent transport simulation (MATSim) for the simulation of daily activities and mobility, and EPISIM for the simulation of the spread of the virus, using household travel survey data and other data sources in Montreal. They show that the most favourable places for the transmission of COVID-19 are home, work and schools, followed by shopping and leisure places.

The spread of the virus also depends on exogenous factors related mainly to climatic conditions, such as temperature. The highest rates of growth of the pandemic are recorded in particular during periods of falling temperatures, which favour the concentration of populations in closed places that are conducive to the transmission of the virus. Several studies show that the temperature differential explains a large part of the evolution of the number of infections (Palialol et al., 2020; Pan et al., 2021; Rios & Gianmoena, 2021). Temperature is an important control variable to include when analysing the role of other variables, such as mobility, on the spread of COVID-19.

3 | DATA AND METHODS

The main objective of the paper is to investigate the influence of immobility and mobility activities on the spread over time of the COVID-19 pandemic in 29 European countries. The study used daily data for the time span from 12 March 2020 to 31 August 2021. Co-integration tests and pooled mean group–autoregressive distributed lag (PMG–ARDL) models were applied to investigate the impact of immobility and daily mobility activities on the spread of the COVID-19 pandemic. As the relationship between the two variables is complex, a Granger causality test was applied to identify the existence and direction of this causality.

3.1 | Data sources

Four sources of data were used in this study of the 29 countries. The first is the number of new confirmed COVID-19 cases per million per day. The up-to-date OxCGRT data and documentation are available via the project GitHub repository at https://github.com/OxCGRT/covid-policy-tracker (Ritchie et al., 2020). The second source is the daily time series indicators on Google mobility. Six indicators are obtained using aggregated, anonymized POIs data from GPS tracking of mobile devices, for users who opted in to ‘Google Location History’. These data measure the change in the number of visits for four place categories (grocery and pharmacies, parks and beaches, transit stations, retail and recreation) and length of stay at home (residential) compared with a baseline (the median value calculated during the 5-week period between 3 January and 6 February 2020). In our article, the first four indicators represent mobility activities, while the fifth (residential) represents immobility. The third source on policy measures also comes from the OxCGRT data. The stringency index is a composite measure of nine of the response metrics, each taking a value between 0 and 100: school closures; workplace closures; cancellation of public events; restrictions on public gatherings; closures of public transport; stay-at-home requirements; public information campaigns; restrictions on internal movements; and international travel controls (Hale et al., 2021). These data from the three sources mentioned can be viewed for each country over the entire analysis period via the associated dashboards (Ritchie et al., 2020). The last data source for temperature is from the daily dataset of the twentieth-century surface air temperature and precipitation series for the European Climate Assessment (Klein Tank et al., 2002). This data, available at http://www.ecad.eu, has been verified and completed for some countries to allow analysis over the same period. The maximum

Austria, Belgium, Bulgaria, Croatia, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, the Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, Switzerland and the United Kingdom. Cyprus was excluded from study owing to unavailability of data on daily mobility.
(TX) and minimum (TN) temperatures are used to calculate the daily average for each country, using the data of the nearest weather station to the capital of each country. The variables used are described in Table 1.

### 3.2 The model

This study used a PMG–ARDL model to investigate the impact of mobility activities in reducing the COVID-19 pandemic in European countries (Pesaran et al., 1999). The specification of the ARDL empirical model is expressed as follows:

$$\Delta \text{COV}_it = \alpha_0 + \sum_{j=1}^{p-1} \beta_{ij} \Delta \text{COV}_{i,t-j} + \sum_{k=1}^{q-1} \beta_{ik} \Delta \text{STR}_{i,t-k} + \sum_{l=1}^{r-1} \beta_{il} \Delta \text{TEM}_{i,t-l} + \sum_{m=1}^{s-1} \beta_{im} \Delta \text{MOB}_{i,t-m} + \delta_1 \text{COV}_{i,t-1} + \delta_2 \text{STR}_{i,t-1} + \delta_3 \text{TEM}_{i,t-1} + \delta_4 \text{MOB}_{i,t-1} - \phi \text{ect}_{i,t-1} + \epsilon_{it}$$

where:

- $i = 1, 2 \ldots, N = 29$ denotes the country; and $t = 1, 2 \ldots, T$ represents the days of the period.
- The dependent variable COV is the number of COVID-19 cases per million inhabitants.
- The independent variables are STR, TEM, and MOB. STR is the stringency index, TEM is the temperature and MOB is the mobility indicator: parks, transit, workplace, grocery, retail, residential. $\Delta$ is the difference operator; $\beta$ and $\delta$ are the ARDL short-run and long-run coefficients, respectively; ect is the error correction term; and $\epsilon_{it}$ is the residual term.

First, the model was defined. Before analysing the relationship between the series, to choose the appropriate testing methods, the correlation between variables and the stationarity of the series was tested. After determining the optimum lag length, the PMG estimator was used to determine both the long-term and the short-term relationship between the variables in the model. As we will see in the next section, the mobility variables are highly correlated with each other. Different models will therefore be estimated, each time introducing a mobility variable (MOB) to the basic model composed of the stringency index (STR) and the mean temperature (TEM) variables.

### Table 1 Description of the data series used

| Variable group | Indicator | Description |
|----------------|-----------|-------------|
| COV: COVID-19  | COVID-19  | The number of new confirmed cases per million inhabitants per day |
| STR: Stringency| Stringency index | A composite index of nine of the response metrics, taking a value between 0 (no stringency) and 100 (full stringency) |
| MOB: Mobility  | Parks visitors | The change in the number of park visitors compared with the baseline (3 Jan. to 6 Feb. 2020) |
|                | Transit visitors | The change in the number of transit visitors compared with the baseline (3 Jan. to 6 Feb. 2020) |
|                | Workplaces visitors | The change in the number of workplaces visitors compared with the baseline (3 Jan. to 6 Feb. 2020) |
|                | Grocery and pharmacy visitors | The change in the number of grocery and pharmacy visitors compared with the baseline (3 Jan. to 6 Feb. 2020) |
|                | Retail and recreation | The change in the number of visitors of retail and recreation places compared with the (3 Jan. to 6 Feb. 2020) |
|                | Residential visitors | The change in the time spent at residential places compared with the baseline (3 Jan. to 6 Feb. 2020) |
| TEM: Temperature | Temperature | Mean temperature calculated as average of the minimum (TN) and maximum (TX) temperature (°C) |
3.3 Descriptive statistics and correlation analysis

The panel dataset is composed of nine variables observed throughout the 29 European countries (N = 29) over a duration of 538 days (t = 538), which amounts to 15,574 observations (Table 2). The number of new daily cases of COVID-19 per million inhabitants varies greatly over the period. The variance is much larger within countries than between countries. The highest value (3,197) is recorded in Sweden on 29 December 2020, where there were 32,485 new cases in a total estimated population of just over 10 million.

The average daily temperature, an important factor in the spread of the virus, is very variable between seasons and between northern countries (−18°C in Finland) and those of the Mediterranean (+35°C in Greece). To counter the spread of the virus, especially during the first wave, European countries have implemented a number of stringency measures. The stringency index is 58% on average. It reached 96% in Croatia, 94% in Italy, 91% in Ireland and more than 80% in most European countries during the spring of 2020. Other countries, such as the United Kingdom, applied these measures later. In the United Kingdom, the stringency index reached its maximum of 88% during the winter of 2021.

Constrained by these measures or by fear of contamination, mobility has been strongly impacted. The time spent at home increased by 7% on average, and by more than 30% in Luxembourg, Italy, France, Portugal and Spain, compared with the baseline period. Considering that the baseline is in winter, when the time spent at home is already higher owing to shorter and colder days, an increase of 30% can represent several hours. The comparison between France and the Netherlands, in the following example, shows the difference in the variation of the immobility level (Figure 1). For a relatively similar level of stringency during the first confinement (90% in France and 80% in the Netherlands), the level of immobility was twice as high in France. This confirms that an important part of the decrease in mobility is related to people’s behaviour and attitudes, beyond the injunction to stay at home (Maloney & Taskin, 2020; Milani, 2021). The smaller decrease in mobility in the Netherlands was not accompanied by a larger spread of COVID-19, compared with France. Although the link is intuitive, and works both ways for these two factors, these two cases illustrate the complexity of the interactions between immobility/mobility and COVID-19 spread (Figure 1).

Public transportation ridership decreased by 28%, on average. The highest decreases (−80%, at least) were recorded in Spain, Italy and France during the first containment. This decrease also affected workplaces (−26%) and retail (−23%), where the highest decrease was recorded in Spain (−76% and −92%, respectively) during the same period. Leisure trips, related to the visits to parks, increased strongly (+76%), especially during the good weather seasons, where they increased sixfold. Grocery and pharmacy trips remained relatively stable, on average (0.2%), throughout the period as they were considered to be a necessity. Unlike visits to parks, the purchases in these places were made in closed places favourable to the transmission of the virus.

| Variable      | Observations | Mean  | Standard deviation | Minimum | Maximum  |
|---------------|--------------|-------|--------------------|---------|----------|
| COVID-19      | 15,574       | 159.20| 241.56             | 0.00    | 3,197.29 |
| Stringency    | 15,574       | 58.23 | 15.92              | 11.11   | 96.30    |
| Temperature   | 15,574       | 13.24 | 8.12               | −18.30  | 35.10    |
| Parks         | 15,574       | 53.03 | 75.82              | −83.71  | 595.57   |
| Transit       | 15,574       | −28.31| 19.89              | −86.14  | 52.71    |
| Workplaces    | 15,574       | −25.85| 12.81              | −75.57  | 4.14     |
| Grocery       | 15,574       | 0.19  | 16.52              | −60.86  | 73.29    |
| Retail        | 15,574       | −23.03| 24.26              | −91.71  | 52.43    |
| Residential   | 15,574       | 7.23  | 6.90               | −7.29   | 34.33    |
The findings of the correlation analysis in Table 3 indicate a high correlation between residential and mobility indicators. The correlation with transit, workplace and retail is above 0.80. For this reason, seven models will be estimated: the basic model with the stringency index and the mean temperature and six other models which include each independent variable of mobility.

### 3.4 Panel unit root and co-integration tests

Non-stationary data series may lead to inconsistent results. Four panel unit root tests are applied to examine each data series for non-stationarity: The cross-sectionally augmented Im, Pesaran and Shin (CIPS) test (Im et al., 2003; Pesaran, 2007); the Fourier augmented Dickey–Fuller (FADF) test (Enders & Lee, 2012); the cross-sectionally augmented Dickey–Fuller (CADF) test (Pesaran, 2007); and the Breitung test (Breitung, 2001). The finding of all the unit root tests used confirm the stationary data series, at the 1%, 5% and 10% levels of significance (Table 4). Some variables (COVID-19, temperature, transit, workplace, grocery) are stationarized at level $I(0)$, while the other variables (stringency, parks, retail, residential) are stationarized at the first integrated order $I(1)$. Owing to these mixed orders of integration, a panel ARDL model is appropriate (Pesaran et al., 1999). The analysis can go further with the panel co-integration tests.

The four panel co-integration tests developed by Westerlund (2007) are used for detecting the co-integration relationship between the variables of study through the 29 series of European countries (Table 5). Model 1 contains two covariates and models 2, 3, 4, 5, 6 and 7 contain three covariates. The average AIC-selected lag and lead length is 3. For the seven models, the null hypothesis of no co-integration is rejected, and the alternative hypothesis is accepted. The tests indicate the presence of co-integration for the seven variable associations: (1) COVID-19, stringency, temperature; (2) COVID-19, stringency, parks; (3) COVID-19, stringency, transit; (4) COVID-19, stringency, workplace; (5) COVID-19, stringency, grocery; (6) COVID-19, stringency, retail; (7) COVID-19, stringency, residential. The two other tests, Kao and Pedroni, are estimated. They confirm the presence of co-integration for the seven models (Annex 1).

## 4 RESULTS

Before presenting the results of the regression model, it is necessary to complete the results of the diagnostic tests. First of all, the Hausman tests (Hausman, 1978) are statistically insignificant at the 5% significance level for all seven models. The $p$-value is between 0.15 and 0.67 each time (Table 6). This implies that the null hypothesis is accepted and that the PMG–ARDL approach is preferred to the mean group (MG–ARDL) approach (Pesaran et al., 1999).
### TABLE 3  Correlation matrix

| Variable     | COVID-19 | Stringency | Temperature | Parks | Transit | Workplaces | Grocery | Retail | Residential |
|--------------|----------|------------|-------------|-------|---------|------------|---------|--------|-------------|
| COVID-19     | 1.000    |            |             |       |         |            |         |        |             |
| Stringency  | 0.201    | 1.000      |             |       |         |            |         |        |             |
| Temperature | −0.353   | −0.400     | 1.000       |       |         |            |         |        |             |
| Parks       | −0.267   | −0.552     | 0.523       | 1.000 |         |            |         |        |             |
| Transit     | −0.175   | −0.753     | 0.540       | 0.612 | 1.000   |            |         |        |             |
| Workplaces  | −0.063   | −0.561     | 0.252       | 0.269 | 0.735   | 1.000      |         |        |             |
| Grocery     | −0.103   | −0.550     | 0.380       | 0.611 | 0.756   | 0.651      | 1.000   |        |             |
| Retail      | −0.243   | −0.770     | 0.551       | 0.739 | 0.858   | 0.691      | 0.751   | 1.000  |             |
| Residential | 0.202    | 0.758      | −0.478      | −0.624| −0.897  | −0.803     | −0.765  | −0.892 | 1.000      |
Then, the existence of a long-run relationship between the COVID-19, the stringency and the mobility variables requires the coefficient on the error correction term to be negative and not lower than $-C0$ in the different models. This coefficient is located between $-C0.214$ and $-C0.217$ in the seven models (Annex 2), confirming the long-run relationship among the variables of interest. Only the long-run PMG results will be presented in the following section.

4.1 Modelling results

The long-run results from the PMG-ARDL series confirm the negative impact of temperature on the spread of COVID-19 (Table 6). This variable has negative and significant effects in the seven models, confirming the results of other studies on the regions of the same country (Palialol et al., 2020; Rios & Gianmoena, 2021). It also has the most important effect among all the other variables. Stringency policies also have a negative and significant effect on the number of new cases. This confirms the findings of the extensive literature on the impact of containment and

### Table 4 Panel unit root findings

| Variable   | IPS test | FADF test | Breitung test | CADF test |
|------------|----------|-----------|---------------|-----------|
|            | I(0)     | I(1)      | I(0)          | I(1)      |
| COVID-19   | –26.96*  | –150.00*  | 784.69*       | –18.44*   |
| Stringency | –1.42    | –94.55*   | 92.97**       | –3.61*    |
| Temperature| –10.67*  | –120.00   | 236.68*       | –14.15*   |
| Parks      | –0.13    | –57.75*   | 50.79         | 0.26      |
| Transit    | –3.62*   | –45.85*   | 104.49*       | –5.56*    |
| Workplace  | –12.67*  | –54.23*   | 285.27*       | –3.27**   |
| Grocery   | –10.57*  | –83.52*   | 244.68*       | –3.62*    |
| Parks      | –1.03    | –52.45*   | 60.64         | –3.27*    |

Null hypothesis $H_0$: non-stationarity; *, ** and *** indicate 1%, 5% and 10% level of significance, respectively.

### Table 5 Westerlund co-integration tests

| Statistic tests | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 | Model 7 |
|-----------------|---------|---------|---------|---------|---------|---------|---------|
| $G_t$           | –3.653*** (–11.673) | –3.755*** (–10.759) | –3.943*** (–11.744) | –3.737*** (–10.663) | –3.925*** (–11.649) | –4.028*** (–12.192) | –3.895*** (–11.495) |
| $G_a$           | –55.500*** (–48.921) | –57.543*** (–42.879) | –62.403*** (–47.069) | –57.113*** (–45.547) | –60.638*** (–46.416) | –61.646*** (–44.965) | –59.962*** (–43.522) |
| $P_t$           | –24.861*** (–14.912) | –25.273*** (–13.872) | –26.427*** (–14.753) | –25.431*** (–13.993) | –26.426*** (–14.752) | –26.503*** (–14.811) | –26.041*** (–14.458) |
| $P_a$           | –63.222*** (–66.719) | –64.749*** (–51.572) | –69.554*** (–55.669) | –65.241*** (–51.992) | –69.823*** (–55.899) | –68.994*** (–55.191) | –67.625*** (–54.024) |

Null hypothesis $H_0$: no co-integration; *** statistically significant at the 1% level; the z-value in parentheses.

$G_t$ and $G_a$ are Group-mean tests that examine the alternative hypothesis that at least one unit is cointegrated. $P_t$ and $P_a$ are Panel tests that examine the cointegration hypothesis of the panel as a whole.
mobility restriction policies (Brauner et al., 2021; Chung et al., 2021; Fiore et al., 2021; Khan et al., 2021; Md Zamri et al., 2021; Pan et al., 2021; Violato et al., 2021). However, the effect of the stringency index becomes insignificant when the mobility/immobility variables are introduced, except in the case of the parks and workplace variables. Actual mobility practices, while also influenced by stringency policies, better explain the spread of COVID-19 (Milani, 2021).

All the mobility variables have a significant effect on the number of daily confirmed cases, except for park visits. Other work has shown no evidence of a link between growth in park visits and growth in the spread of COVID-19 (Curtis et al., 2021), despite the growth in demand during periods of confinement (Venter et al., 2020). These activities are carried out outdoors in open spaces, which is not conducive to contamination. They are also highly dependent on temperature, which, when higher, also reduces the spread of the virus. Given the importance of mobility to physical and mental health, this result argues for not enforcing restrictive park closures during confinement. It also argues for the development of parks within cities. Of the mobility variables with a significant effect, time spent at home or immobility most affects the daily number of COVID-19 cases. It is the second most influential factor after temperature. This result is close to that of Yilmazkuday, (2021). Grocery store shopping increases the number of new cases of COVID-19. It is mobility activity that contributes most to the spread of the virus along with transit ridership. This basic activity, carried out in enclosed spaces, was also the least constrained during the periods of confinement.

### 4.2 Causality test

Granger’s causality test (Dumitrescu & Hurlin, 2012) confirms the complex relationship between the spread of COVID-19 and the other variables. In most cases, the increase or decrease in new COVID-19 cases is both a

| TABLE 6 PMG-ARDL long-run estimations |
|----------------------------------------|
| **COVID-19** | **Model 1 (1,0,0)** | **Model 2 (1,0,0)** | **Model 3 (1,0,0)** | **Model 4 (1,0,0)** | **Model 5 (1,0,0)** | **Model 6 (1,0,0)** | **Model 7 (1,0,0)** |
| Stringency    | −1.845*** (−4.48) | −1.870*** (−4.34) | −0.245 (−0.46) | −1.206* (−2.52) | −0.714 (−1.63) | −0.0569 (−0.10) | −0.257 (−0.06) |
| Temperature   | −12.07*** (−16.90) | −12.07*** (−13.14) | −13.05*** (−17.54) | −12.14*** (−17.08) | −12.56*** (−17.73) | −13.48*** (−16.93) | −12.98*** (−17.48) |
| Parks         | 0.0003 (0.00) |
| Transit       | 1.864*** (4.78) |
| Workplaces    | 1.178** (2.70) |
| Grocery       | 2.061*** (5.65) |
| Retail        | 1.619*** (4.38) |
| Residential   | −5.054*** (−4.22) |

| Hausman test  | \(\chi = 1.59\) | \(\chi = 3.88\) | \(\chi = 3.23\) | \(\chi = 2.10\) | \(\chi = 1.61\) | \(\chi = 2.82\) | \(\chi = 5.24\) |
|              | \(p = 0.453\) | \(p = 0.2753\) | \(p = 0.3580\) | \(p = 0.5520\) | \(p = 0.6561\) | \(p = 0.4197\) | \(p = 0.1550\) |
|              | PMG          | PMG          | PMG          | PMG          | PMG          | PMG          | PMG          |

| t-Statistics in parentheses; *, **, and *** indicate 1%, 5% and 10% level of significance, respectively. 

| 10 BOUZOUINA ET AL. |
cause and a consequence of policy measures and mobility practices, with the exception of grocery- and workplace-related activities. On the one hand, stringency, temperature, parks, transit, retail, grocery and residential do Granger-cause COVID-19 for at least one panelvar. Workplaces do not Granger-cause COVID-19 (Table 7, Figure 2). On the other hand, COVID-19 does Granger-cause stringency, parks, transit, retail and residential for at least one panelvar. COVID-19 does not Granger-cause workplaces and grocery (Table 7, Figure 2).

Granger causality should not be considered as a cause-and-effect analysis. It is complementary to the regression modelling. If we combine the causality results with the previous results regarding the significance of the effects of the mobility, temperature, and stringency variables on the spread of COVID-19, we can propose the following cause and effect relationships (Figure 2). These relationships are shown in blue for the COVID-19 determinants.

Five main results can be highlighted. First, immobility reduces COVID-19 new cases. A 1% increase in time spent at home decreases the number of infected persons per million population per day by 50. Then, mobility increases the number of cases through grocery, transit and retail activities. A 1% increase in grocery and retail visits increases the number of daily cases per million population by 20 and 16, respectively. A 1% increase in transit ridership increases the number of new daily cases by 19 per million population. Next, park visit mobility has no effect on the spread of COVID-19. Also, despite the effect shown by the regression, it is not possible to conclude that there is a causal link between the workplace and COVID-19. After that, the strong causal relationship of temperature to the spread of Covid-19 is confirmed. A drop in temperature of one degree centigrade increases the number of new cases by 120 to 135 per day, per million inhabitants. Finally, the causal relationship of stringency policies to the spread of COVID-19 is also confirmed. A 1% increase in the stringency index decreases the number of cases by about 18 per day, per million inhabitants. This cause and effect is more indirect through the application of the mobility restrictions.

| Causal linkage X→Y (null hypothesis) | Z-bar  | p-Value | Decision |
|-------------------------------------|--------|---------|----------|
| Stringency does not Granger-cause COVID-19. | 11.6748 | 0.0000 | Causality |
| Parks does not Granger-cause COVID-19. | 24.0665 | 0.0000 | Causality |
| Transit does not Granger-cause COVID-19. | 18.7155 | 0.0000 | Causality |
| Workplaces does not Granger-cause COVID-19 | 1.5785 | 0.1144 | No causality |
| Grocery does not Granger-cause COVID-19. | 8.1948 | 0.0000 | Causality |
| Retail does not Granger-cause COVID-19 | 15.7232 | 0.0000 | Causality |
| Residential does not Granger-cause COVID-19. | 13.7561 | 0.0000 | Causality |
| Temperature does not Granger-cause COVID-19. | 42.3972 | 0.0000 | Causality |

| Causal linkage Y→X (null hypothesis) | Z-bar  | p-Value | Decision |
|-------------------------------------|--------|---------|----------|
| COVID-19 does not Granger-cause stringency. | 7.2117 | 0.0000 | Causality |
| COVID-19 does not Granger-cause parks. | 3.1433 | 0.0017 | Causality |
| COVID-19 does not Granger-cause transit. | 7.4295 | 0.0000 | Causality |
| COVID-19 does not Granger-cause workplaces. | −0.0736 | 0.9413 | No causality |
| COVID-19 does not Granger-cause grocery | −1.6155 | 0.1062 | No causality |
| COVID-19 does not Granger-cause retail. | 15.5177 | 0.0000 | Causality |
| COVID-19 does not Granger-cause residential. | 7.4782 | 0.0000 | Causality |
The joint analysis of the evolution of the number of new COVID-19 cases, stringency policies, temperature and mobility throughout the 29 European countries, from 12 March 2020 to 31 August 2021, confirms the impact of temperature, stringency and immobility on the decrease of virus spread. However, the impact of mobility varies according to the type of activity. If shopping and public transportation increase the number of new daily cases, there is no evidence of park use or mobility to workplace increasing COVID-19 spread.

These results have important implications for our daily lives. First, the variability of temperature influences the cyclical spread of COVID-19 spread, especially with the appearance of new variants of the virus. It also highlights potential inequalities between countries and regions, depending on climate and adaptation capacities. Stringency policies have proven to be effective, especially through mobility restrictions. However, immobility has an economic

**FIGURE 2** Cause and effect relationships

5 | CONCLUSION

The joint analysis of the evolution of the number of new COVID-19 cases, stringency policies, temperature and mobility throughout the 29 European countries, from 12 March 2020 to 31 August 2021, confirms the impact of temperature, stringency and immobility on the decrease of virus spread. However, the impact of mobility varies according to the type of activity. If shopping and public transportation increase the number of new daily cases, there is no evidence of park use or mobility to workplace increasing COVID-19 spread.

These results have important implications for our daily lives. First, the variability of temperature influences the cyclical spread of COVID-19 spread, especially with the appearance of new variants of the virus. It also highlights potential inequalities between countries and regions, depending on climate and adaptation capacities. Stringency policies have proven to be effective, especially through mobility restrictions. However, immobility has an economic
and psychological cost, and this solution risks becoming burdensome and difficult to apply with successive waves. The systematic use of closing down all places of activity to counter the spread of the virus, as was the case in several countries during the first wave, is not justified.

Mobility is essential for the realization of daily activities. Certainly, all activities carried out in closed and shared places, such as shopping or leisure activities, favour contagion. However, activities carried out outdoors, such as visiting parks, have no impact on contamination. From a public policy point of view, this argues in favour of keeping these spaces open during periods of health crises. On the one hand, this argues for the development of parks and other places where activities can be carried out in the open air in cities while adapting to the climate. It also raises the issue of developing technical solutions to maintain ambient temperatures in closed areas without promoting the spread of the virus. This issue is all the more important as the sharing of spaces and infrastructures, such as public transport, is essential. The decline in the use of public transport during the pandemic was largely in favour of car use. The growth of telecommuting, whose causality with COVID-19 is difficult to establish here, as well as that of e-commerce practices, does not seem to challenge traditional proximity-based models.

This work has explored the complex links between the propagation of COVID-19, mobility, and stringency policies using open data. Further work using finer panel data and longer time spans will deepen the analysis and refine the understanding of causality.

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### APPENDIX A

#### ANNEX 1  Kao and Pedroni co-integration tests

| Test          | Model 1          | Model 2          | Model 3          | Model 4          | Model 5          | Model 6          | Model 7          |
|---------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|
| Kao Statistic | −40.514 (−4.73)  | −40.731 (−4.74)  | −41.096 (−4.75)  | −40.785 (−4.73)  | −41.469 (−4.77)  | −41.114 (−4.73)  | −41.035 (−4.74)  |
| p-Value       | 0.000            | 0.000            | 0.000            | 0.000            | 0.000            | 0.000            | 0.000            |
| Pedroni Statistic | −41.165 (−4.78) | −41.298 (−4.74) | −42.624 (−4.75) | −41.237 (−4.77) | −42.746 (−4.73) | −42.059 (−4.73) | −41.875 (−4.74) |
| p-Value       | 0.000            | 0.000            | 0.000            | 0.000            | 0.000            | 0.000            | 0.000            |

#### ANNEX 2  ARDL–PMG short run estimations

| COVID-19   | Model 1          | Model 2          | Model 3          | Model 4          | Model 5          | Model 6          | Model 7          |
|------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|
| Error correction | −0.214*** (−4.73) | −0.214*** (−4.74) | −0.217*** (−4.75) | −0.215*** (−4.73) | −0.218*** (−4.77) | −0.217*** (−4.73) | −0.217*** (−4.74) |
| Stringency | 1.541* (1.790)   | 1.544 (1.78)     | 1.442 (1.60)     | 1.545 (1.79)     | 1.413 (1.65)     | 1.198 (1.36)     | 1.422 (1.60)     |
| Temperature | 2.053*** (3.52)  | 2.131*** (3.46)  | 2.087*** (3.46)  | 1.988*** (3.47)  | 2.036*** (3.49)  | 2.221*** (3.60)  | 2.099*** (3.51)  |
| Parks      | −0.248 (−1.54)   |                  |                  |                  |                  |                  |                  |
| Transit    | 1.041 (0.91)     |                  |                  |                  |                  |                  |                  |
| Workplace  | 1.395* (2.09)    |                  |                  |                  |                  |                  |                  |
| Grocery    | 1.258 (1.76)     |                  |                  |                  |                  |                  |                  |
| Retail     | −0.285 (−0.38)   |                  |                  |                  |                  |                  |                  |
| Residential | −2.334 (−0.88)   |                  |                  |                  |                  |                  |                  |
| Constant   | 95.476*** (4.49) | 95.97*** (4.49)  | 90.74*** (4.45)  | 95.09*** (4.46)  | 85.01*** (4.41)  | 87.04*** (4.42)  | 87.80*** (4.40)  |

t-Statistics in parentheses.

* $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$.  

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BOUZOUINA ET AL. 15

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