MOBILITY AND MORTALITY IN COVID-19 EPIDEMIC: A SPATIAL ANALYSIS

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1. Mobility and mortality in COVID-19 disease

The global epidemic of coronavirus disease 2019 (COVID-19) has threatened the loss of human life (Hu *et al.,* 2021), public health, safety, and disruption of face-to-face communication due to intangible, clinical severity of the infection, and fatal symptoms and has inhibited social-economic development worldwide in 2020, too (Liu *et al.*, 2020). The COVID-19 epidemic has forced public decision makers to implement mobility blocking policies to reduce the spread of the disease and, consequently, of the mortality through social distancing, school closures, and general lockdown of economic activities. Since the general non-uniform spread of the contagion within a country, a relevant policy issue is whether to have a differentiated implementation of the lift of the lockdown restrictions for different geographic areas, called a zone-based social distancing (Friedman *et al.,* 2020), or the geographic segmentation by World Health Organization (2020).

The public health rationale behind lockdowns is the risk of disease spread associated with movement of people. These policies have included working from home (so-called, *smart working*), reducing the number of commuters with the implicit assumption that restricting the movement of people, the risk of infection for travellers and other commuters in their areas of residence, work, and all of other activities decreases since the people mobility is a known vector for the spread of disease.

Despite the fact that lockdowns are aimed at restricting movement of people, this spatial dimension of infections is often overlooked in many empirical and theoretical papers addressing COVID-19 (Francetic and Munford, 2021). Since a consistent method to measure the evolution of contagion is missing, in the analyses of the spread and the consequences of the COVID-19 epidemic the spatial effects - in terms of dependence and heterogeneity (Bourdin *et al*., 2020) of the relationships among variables in different territorial areas - have been taken into account because the infection is concentrated in some areas and follows specific patterns according with territorial proximity (Kraemer *et al.,* 2020; Gatto *et al.,* 2020). The mobility restrictions play a key role in the spread of infection diseases mainly through social contacts between infectious and susceptible individuals (Zhang *et al.,* 2020; Riley,

2007) in order to save lives (Jia *et al.,* 2020; Wu *et al.*, 2020). Mobility data, indeed, can be useful to understand the dynamics of the epidemic and limit the impact of future waves and excess deaths. Mobile positioning personal data, as proxy of human mobility, shows a high correlation of the mobility and the spread of COVID-19 in the initial phase of outbreak (Iacus *et al.,* 2020).

In the present study an analysis is proposed to gauge for spatial patterns in the data on excess deaths, as a reliable indirect indicator, less affected by territorial assumptions and available at provincial level. The relationship between human mobility variations and increasing of excess mortality in Italy is analysed by the means of spatial effect estimation models, comparing the epidemic period from February to December 2020 to the pre-epidemic period from 2015 to 2019.

To analyse mobility flows among Italian provinces accounting spatial correlation, a spatial regression model is specified to estimate the effects of reduced human mobility on excess mortality using digital mobility data at provincial level after controlling for the time trend of the epidemic and provincial differences. The ongoing COVID-19 epidemic has highlighted the potential benefit of geo-located smartphone data to inform public health (Oliver *et al.,* 2020) and assess the impact of mobility restrictions on social distancing in near real-time (Pepe *et al.,* 2020; Badr *et al.,* 2020). Then, the relationship between mobility data, provided by Google Community Mobility Reports (GCMR, 2021) - a good source to assess changes in mobility due to different social distancing measures (Basellini *et al.,* 2020) - and data on excess mortality, registered by ISTAT (2021) from January to December 2020, is examined. Since the variation in human mobility may take a long time before producing an effect on mortality, the potential effect of changes of 'delayed' or lagged indicators of human mobility on excess mortality is mediated by a time lag of predictors (from the symptom onset to the death, the median value is equal to 24 days in June-September 2020) as estimated by National Institute of Health-ISS (2021).

The study aims at testing if the mobility indicators affect the excess mortality in 2020 both globally and locally in order to take into account temporal lag disparity among Italian provinces. In the first step, stepwise regression models have been specified selecting predictors related to human mobility. Afterwards, Geographically Weighted Regression (GWR) models (Wu *et al.,* 2021) are employed to test for spatial heterogeneous effects of the mobility on the mortality variation.

2. Spatial models for mobility and mortality data analysis

Spatial-temporal analysis of COVID-19 is crucial to understanding the spread of COVID-19. Specifically, for the spatial study, we explore the inter-correlations among independent variables before building the models. The GWR modelling is taken into account for the geographical disproportion of the number of deaths. More importantly, compared to OLS models, GWR models are local linear regression models. They embrace the calculation of a parameter estimate of variations over space in the link between independent and dependent variables. The ordinary least square (OLS) is a traditional method for estimating a linear regression between dependent and independent variables. OLS assumptions involve the disturbances that have 0 mean and constant variance, in addition to no correlation among explanatory variables. The ordinary least squares (OLS) regression is an empirical approach that has generally been applied in the field of demography. Model parameters are assumed to be applied globally over the entire territory where measurements have been taken into account under the assumption of spatial stationarity (Brunsdon *et al*., 1996; Fotheringham *et al*., 2002) in the relationship among the variables. Therefore, OLS generates 'global' regression coefficients assuming that the relationships are constant over space.

This approach may mask spatial variability in the relationships and ignores the spatial dependency among variables. This circumstance may sometimes provide biased estimates and overstated statistical significance of relationships. Moreover, ignoring spatial effects in a modelling process causes misleading significance tests and suboptimal model specification (Huang and Leung, 2002). Several approaches for controlling spatial variability have been developed in a regression model, including use of a term representing or spatial autocorrelation in the dependent variable or in the residuals of the independent variables (Crase *et al.,* 2012) and the use of simultaneous autoregressive models (Pioz *et al.,* 2012). Among these, the Geographically Weighed Regression (GWR) models are particularly suitable for analysing territorial phenomena characterized by non-stationary variability, in contrast to standard regression models (OLS) (Brunsdon *et al.,* 1996; Fotheringham *et al.,* 2002).

The GWR procedure is founded upon two conditions. First, similarities between more adjacent geographical entities exist according with the Tobler's first law of geography, widely adopted as a basic principle in Geographic Information Science (Tobler, 1970). Each local regression of GWR is estimated with data whose influence decays with distances, commonly defined as straight line or Euclidean. Second, there are disproportionate distributions of explanatory variables in different territorial units, due to spatial autocorrelation and spatial heterogeneity. Based on Foster's spatial varying parameter regression, a Geographically Weighted Regression model (GWR) is localized through weighting each observation in the dataset. As pointed out by Fotheringham *et al.* (2002), local smooth processing was used to address the spatial heterogeneity. Under the consideration of spatial disparity, geographic coordinates and core functions are employed to carry out local regression estimation on adjacent elements. We recall that GWR model extend the traditional regression models by allowing the estimation of local parameters, so that the model can be written as:

$$y_i = \beta_0(u_i, v_j) + \sum_k \beta_k(u_i, v_j) x_{ik} + \epsilon_i \qquad \text{for } i = 1, \ldots\ldots, n \tag{1}$$

where: (u_i, v_j) denote the coordinates of the i-th location in space; $\beta_k(u_i, v_j)$ is a realization of the continuous function $\beta_k(u, v)$ at location i; y_i is the dependent variable at location I; x_{ik}, is the k-th independent variable at location I; ε_i is random error at location i with normal distribution and variance a constant.

GWR provides a regression equation for each observation weighted by location, which takes into account spatially varying relationships. To calibrate the model (1) Fotheringham *et al.* (2002) suggested using n local models (one for each location point) introducing a kernel weighting function. The principle of the kernel weighting function is to set a distance decay model (with weight range from 1 to 0 based on the distance of the points) around a point or spatial unit and to compute the local coefficients $\beta_k(u_i, v_j)$ using all the observations. Thus, around each regression point, nearer observations have more influence in estimating the local set of coefficients than observations farther away (Fotheringham *et al.*, 2002). In essence, GWR measures the inherent relationships around each regression point i, where each set of regression coefficients is estimated by weighted least squares.

3. Mortality and mobility variation data

The human mobility changes are observed through the data collected from Google Community Mobility Reports (GCMR, 2021) sources referred to human movement trends across different categories of settings: retail and recreation, grocery and pharmacy, parks, transit stations, workplaces and residential areas, during February-December 2020 at the Italian territorial provincial level. The GCMRs show how the visits and their lengths change compared to the baseline day, calculated for a specific calendar date as a positive or negative percentage. A baseline day represents a normal value for that day of the week. Mobility data from the GCMR are considered as an additional fixed effect. Thus, the regression coefficient has been interpreted as the change in *per capita* excess mortality for a unit change in the mobility indicator, always as compared to the baseline period (Basellini *et al.*, 2020).

GCMRs define the baseline as the median value, for the corresponding day of the week, during the 5-weeks period from January 3rd to February 6th, 2020. Next, the GCMR database is linked with the total deaths in the year 2020 at the provincial level compared with the average deaths in the period 2015-2019 (ISTAT, 2021). Since the high uncertainty surrounding the number of infections and deaths, in line with the growing general consensus in the scientific community (National Academies of Sciences, Engineering, and Medicine, 2020) on the excess mortality as the best indicator to assess the impact of the epidemic, the present analysis is focused on estimation of the excess mortality rate in terms of number of deaths above what would be expected in a non-crisis period, controlling for the size of the population. So, the excess mortality variation (MV) is compared with the human variation mobility, measured through the GCMR variables shown in table 1.

Table 1 – *Mobility and mortality variables.*

Variable	Label	Source
Retail and recreation	Mobility trends for places like restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theaters.	Google
Grocery and pharmacy	Mobility trends for places like grocery markets, food warehouses, farmers markets, specialty food shops, drug stores, and pharmacies.	Google
Parks	Mobility trends for places like local parks, national parks, public beaches, marinas, dog parks, plazas, and public gardens.	Google
Transit stations	Mobility trends for places like public transport hubs such as subway, bus, and train stations.	Google
Workplaces	Mobility trends for places of work.	Google
Residential	Mobility trends for places of residence.	Google
Mortality variation	Mortality variation between 2020 and mean 2015-2019.	ISTAT

Since the analysis aims at assessing if an association between excess mortality and human mobility changes over time still exists, after controlling for the variation in provinces, it focuses on the period between May-September 2020 only to avoid mobility constraints imposed by national and local lockdowns. Moreover, considering that changes in human mobility may take some time to have an effect on mortality, the relationship between excess mortality and lagged indicators of human mobility is analysed. In other studies, accounting for a time lag of 5 or more weeks, a positive correlation between increased mobility and excess mortality, and a negative correlation between time spent at home and excess mortality has been measured. These relationships were significant within a mixed-effects regression setting that controls for the time trend of the epidemic and the different regional effects (Basellini *et al.*, 2020). The time period is set in about 30 days considering four times: 1) the onset of the symptoms of the disease; 2) the SARS-CoV-2 test; 3) hospitalization and 4) deaths as reported by Italian National Institute of Health-ISS (2021). In figure 1, the monthly trends for all the mobility categories, except for *residential*, show a strong decrease in mobility compared to the baseline.

The mortality variation (MV) is shown in the figure 2A. The highest values are concentrated in northern provinces despite the average national value: 15.57% (ISTAT, 2021). The Moran’s index in figure 2B shows spatial correlation in the mortality data such just to support the spatial regression analysis. The trend for MV follows the so-called ‘waves’ of March and October (figure 2C).

Figure 1 – *Mobility trends by places from February to December 2020 – (Change from the baseline).*

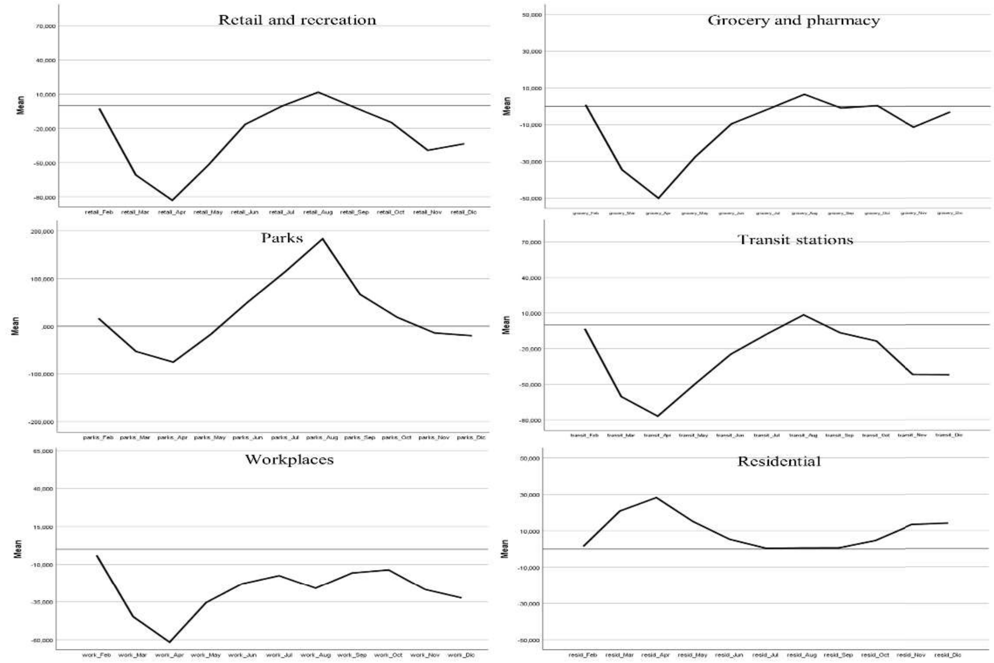
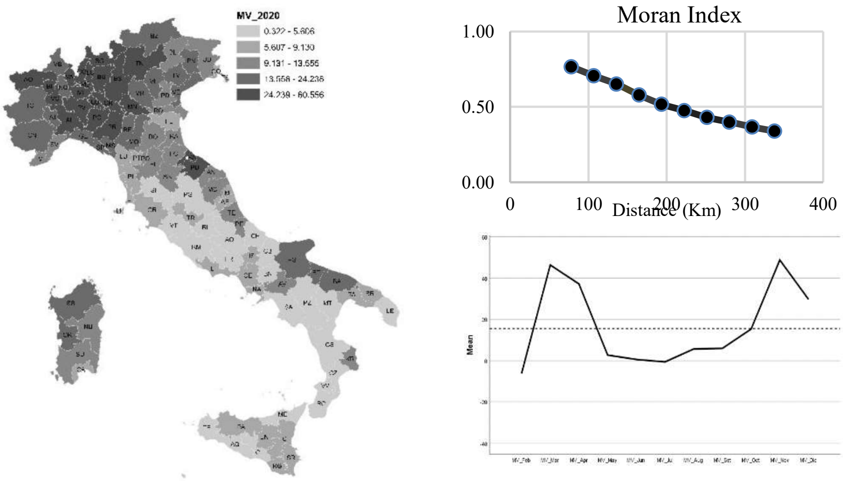


Figure 2 – *MV in Italian provinces (2020 vs 2015-2019) - (A); Moran index - (B); MV trend from February 2020 to December 2020 (C).*



4. Results

Before using the GWR model, stepwise regression models are specified to select the best lagged predictor of human mobility for the variable MV. Afterwards, the spatial analysis proceeds specifying the GWR model out the lockdown period (June, July, and August). The GWR model is specified if the test for spatial non-stationarity of the parameters is significant. A Monte-Carlo test has been employed to perform the analysis (Brunsdon *et al.*, 1996; Fotheringham *et al.*, 2002).

The results of the estimates for the 3 months are shown in table 2, where the correlation is positive (0.377) between MV in June 2020 and the time that people spent for retail and recreation in May 2020; negative correlation (-0.987) between MV in July 2020 and time that people spent at home in June 2020 and negative correlation (-0.938) between MV in August 2020 and time that people spent at home in July 2020.

Table 2 – *Estimates for the OLS and GWR model.*

Variable	OLS	Min	I Quartile	Median	III Quartile	Max	Test for non-stationarity
Model 1 - Dependent variable - MV_June							
(Constant)	20.121*	18.656	19.743	20.838	21.793	23.812	1.258
Retail_May	0.377*	0.345	0.370	0.389	0.412	0.449	0.026
Model 2 - Dependent variable - MV_July							
(Constant)	4.868*	-6.844	2.071	4.910	6.359	31.863	6.642*
Residential June	-0.997**	-5.669	-1.372	-1.062	-0.587	0.439	1.112*
Model 3 - Dependent variable - MV_August							
(Constant)	6.144**	5.895	5.981	6.006	6.041	6.298	4.302*
Residential July	-0.908*	-1.102	-0.963	-0.859	-0.796	-0.741	1.107*

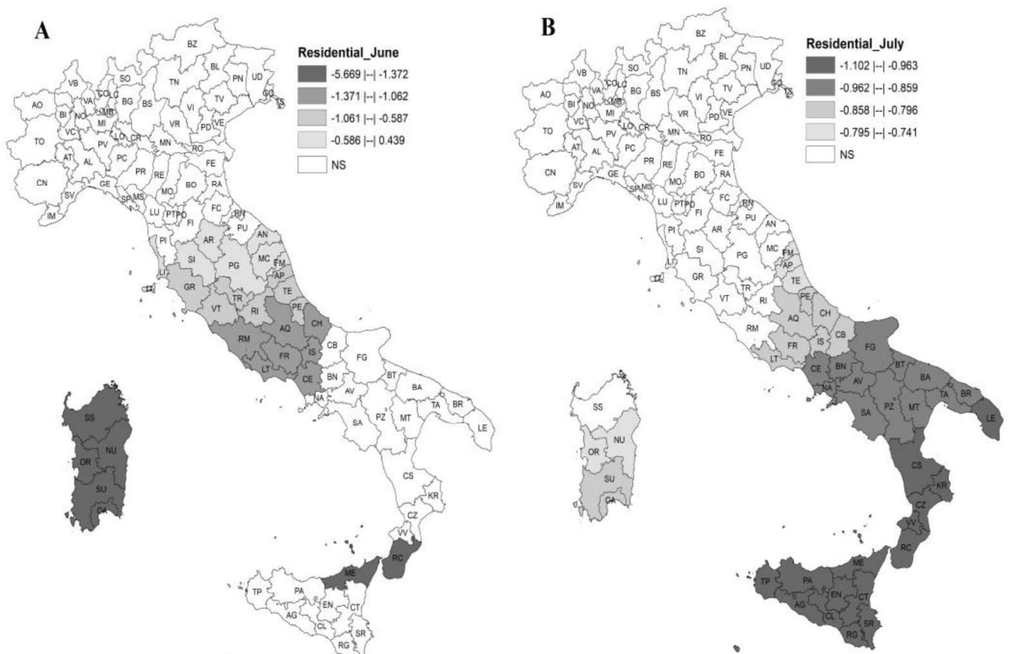
*p<0.05 **p<0.01. Both stepwise OLS and GWR (with Gaussian Kernel function) estimations are produced through STATA ver. 14.

As we can see for the June MV (model 1), the stepwise OLS model identifies the *retail and recreation* variable (mobility trends for places like restaurants, cafes, shopping centres, theme parks, museums, libraries, and movie theatres) as the best predictor. But the spatial non-stationarity test is not significant. Therefore the spatial analysis is not carried out (however, GWR estimates are shown).

In the models for the explanation of the July (model 2) and August MV (model 3) the best predictor is *residential* (mobility trends for places of residence or time spent in places of residence). In these two models the spatial non-stationarity test is significant and therefore the GWR is conducted in addition to the stepwise regression. Moreover the local coefficient mappings are shown in figure 3 for model 2 and 3 only.

In particular, the global analysis (OLS) shows that the reduction of time spent at home in the period of June (*residential*) is correlated to an increasing in the variation of mortality in July (table 2, model 2). Taking into account that isolation in Italy ended on May 4th, 2020, a time lag of about 1 month is needed to identify a relationship between excess mortality and change in human mobility. This is consistent with the amount of time over which the change in mobility affects the excess mortality. The re-opening of restaurants and in general of all activities related to leisure has (probably) an impact on the contagions and as a result on mortality in June. This impact does not show local clustering at the provincial level but the effect is across the country. July and August are traditionally characterized by holidays, with principal trips from Nord to Centre-South and in the main islands of Italy. So, the time spent at the home decreases significantly compared to the lockdown period (see figure 1, category *residential*).

Figure 3 – *Local coefficient estimates of Residential by quintiles range in June (A), July (B).*



(NS= not significant)

5. Conclusions

In this paper the relationship between MV and changes in human mobility out of the lockdown period in Italy is explored. In detail spatial analysis shows the provinces where the lagged mobility predictors have the greatest impact on MV. Early results provide evidences to support that changes in human mobility are (probably) a 'conduit' for the changes in mortality observed in the summer of 2020. This is coherent with the findings of Francetic and Munford (2021) and Basellini *et al*. (2020). Although other experiments should be done, a time lag of approximately one month needs for the relation between excess mortality and change in human mobility.

However, the findings must be considered with great caution. GCMR data do not represent a perfect random sample of the target population as smartphone and tablet users. They may differ from the general population in terms of demographic, social, and economic features. Thus the results could be affected by a sampling self-selection bias. Nevertheless, the analysis shows not only that the mobility restrictions are effective to limit the potential negative effects of the COVID-19 epidemic on mortality but also the specific setting of mobility such as mobility trends for places of residence, is crucial. Furthermore, we plan to deepen the research considering an analysis by gender and re-estimate the models for the year 2021 also. In our opinion, the results obtained are consistent with the evidence that the re-opening in the summer after the lockdown probably favoured the re-start of infections and the second epidemic wave of autumn 2020 in Italy.

Finally, the analysis framework can be useful not only to address the debate within the scientific community in order to improve the understanding of the course of the epidemic and the actual benefit of a strategy to control the spread of COVID-19, but also to assess the crucial implications for public health decision-making in the event of future such inauspicious occurrences, as current events show, unfortunately.

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SUMMARY

Mobility and Mortality in Covid-19 Epidemic: A Spatial Analysis

The COVID-19 epidemic forced authorities to implement lockdown policies to reduce the spread of the disease and, as a consequence, the excess mortality. These policies encouraged homeworking, hence reducing the number of commuters with the implicit assumption that restricting human mobility reduces the risk of infection in areas of residence, work, and other activities. Yet, the spatial relationship among different areas has been rarely addressed both in the public discourse and in early accounts of the consequences of mortality in COVID-19 time period. As shown in literature, the spatial regression models are useful to analyse phenomena with non-stationarity variability in contrast to standard regression models.

By employing spatial regression models, the findings suggest that the higher the mobility to places of residence, the higher the excess mortality. This increasing in mortality is not homogeneous throughout the Italian provinces. Specifically, the variability in the mortality on August 2020 compared to the average value on 2015-2019 period (baseline) is greater in the Central-Southern provinces, due to the movements to the residence places in July 2020.

In conclusion, the spatial interactions between mobility and COVID-19 spread could support the analysis about the relationship between excess mortality and socio-economic settings, highlighting the importance of modelling spatial variability.

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