Economic and social consequences of human mobility restrictions under COVID-19

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In response to the coronavirus disease 2019 (COVID-19) pandemic, several national governments have applied lockdown restrictions to reduce the infection rate. Here we perform a massive analysis on near–real-time Italian mobility data provided by Facebook to investigate how lockdown strategies affect economic conditions of individuals and local governments. We model the change in mobility as an exogenous shock similar to a natural disaster. We identify two ways through which mobility restrictions affect Italian citizens. First, we find that the impact of lockdown is stronger in municipalities with higher fiscal capacity. Second, we find evidence of a segregation effect, since mobility contraction is stronger in municipalities in which inequality is higher and for those where individuals have lower income per capita. Our results highlight both the social costs of lockdown and a challenge of unprecedented intensity: On the one hand, the crisis is inducing a sharp reduction of fiscal revenues for both national and local governments; on the other hand, a significant fiscal effort is needed to sustain the most fragile individuals and to mitigate the increase in poverty and inequality induced by the lockdown.

COVID-19 | economic segregation | human mobility | national lockdown

On March 9, 2020, Italy was the first European country to apply a national lockdown (1) in response to the spread of novel coronavirus disease 2019 (COVID-19). Following Italy and China, national lockdowns have been adopted by other governments, and mobility flows have been drastically reduced to decrease the transmission rate of COVID-19 (2).

Concern is arising regarding the economic consequences of lockdown and how it can disproportionally hit the weak and the poor (3). Lockdown measures have affected several production sectors, value chains, and trade exchanges, motivating G20 governments to announce fiscal interventions of about $8 trillion and massive monetary measures (4). The supply shock, in fact, is triggering deep contractions of aggregate demand, further endangering socioeconomic recovery (5).

The intensity of the sudden stop induced by the COVID-19 outbreak produces effects which are similar to those of a large-scale, extreme, natural disaster (6–11). Here, analogously to refs. 12 and 13, we model the change in mobility affecting Italian municipalities as an exogenous shock. To this aim, we leverage a deidentified large-scale collection of near–real-time data provided by Facebook platform to characterize the effect of population mobility restrictions (14). We, then, rely on official statistics at the level of municipalities, to investigate the features of those that are mostly affected.

We measure mobility variations as a proxy for the intensity of the economic downturn associated with the lockdown. As shown in ref. 2, mobility trends associated with tourism, retail, and services have experienced a sudden contraction of more than 90% in Italy during the lockdown. Against this background, we investigate the geographic distribution of the mobility shocks, in order to identify the economic conditions of the most and least affected zones. Our findings show that, on the one hand, mobility reduction induced by lockdown is stronger for municipalities with a higher fiscal capacity. On the other hand, we notice that the contraction in mobility is higher for municipalities with lower per capita income and for those with higher inequality. In the aftermath of the crisis, central governments need not only to sustain economic recovery but also to compensate the loss of local fiscal capacity and tax receipts, while channeling resources to mitigate the impact of lockdown on poverty and inequality.

Effects of Mobility Restrictions

In Fig. 1 *A* and *B*, we compare two daily snapshots of the mobility network of municipalities aggregated at the province level. After 21 d of national lockdown, we notice a striking fragmentation of the usual national mobility patterns from North to South. We characterize daily connectivity patterns (16) through network measures (17).

Significance

This paper presents a large-scale analysis of the impact of lockdown measures introduced in response to the spread of novel coronavirus disease 2019 (COVID-19) on socioeconomic conditions of Italian citizens. We leverage a massive near–real-time dataset of human mobility and we model mobility restrictions as an exogenous shock to the economy, similar to a natural disaster. We find that lockdown measures have a twofold effect: First, their impact on mobility is stronger in municipalities with higher fiscal capacity; second, they induce a segregation effect: mobility contraction is stronger in municipalities where inequality is higher and income per capita is lower. We highlight the necessity of fiscal measures that account for these effects, targeting poverty and inequality mitigation.

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The authors declare no competing interest.

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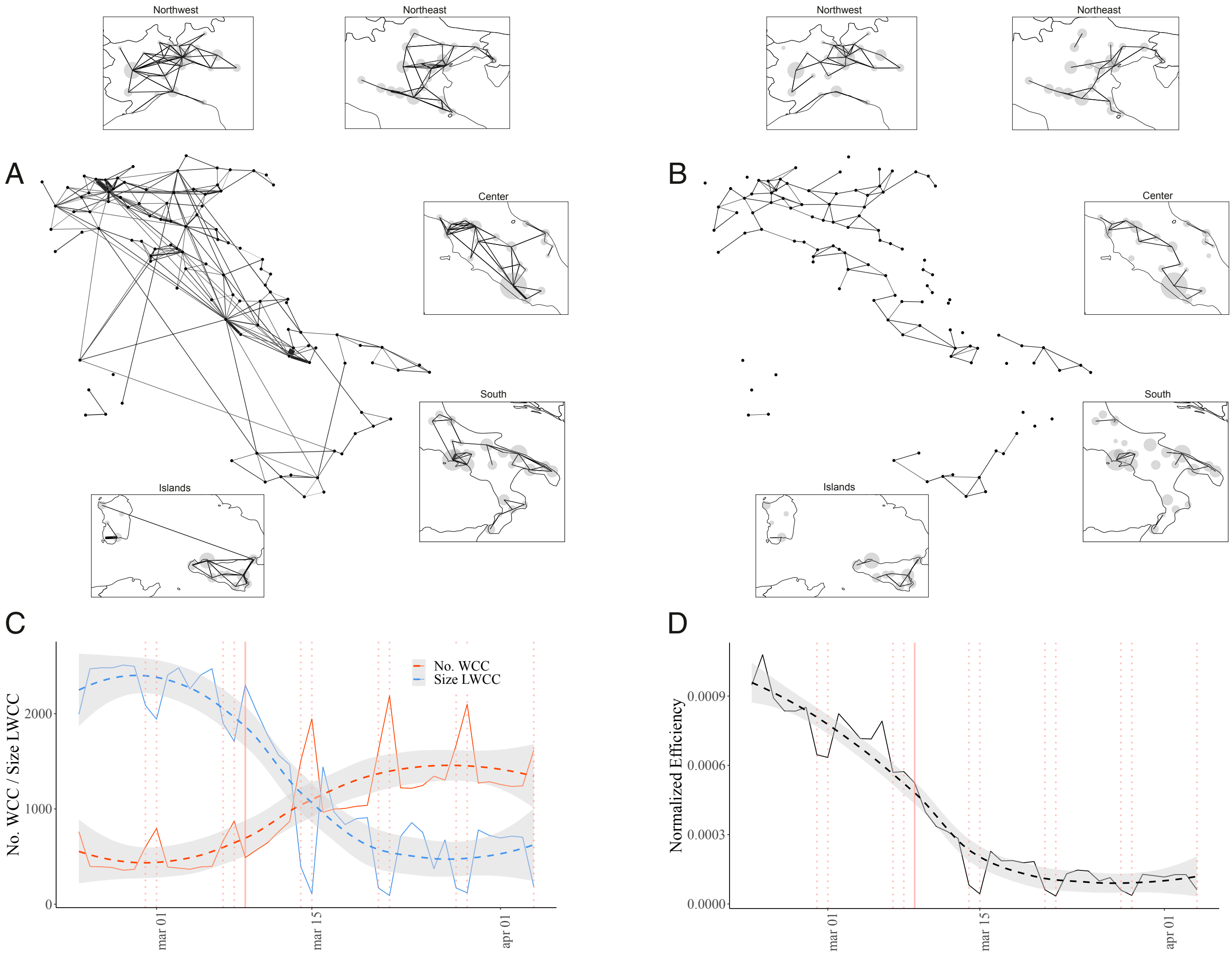

Fig. 1. Connectivity of the Italian mobility network during COVID-19 epidemic. (*A* and *B*) Snapshots of the mobility network on two Mondays before and after national lockdown (March 9), that is, on (*A*) February 24 and (*B*) March 30. Nodes represent municipalities aggregated at the province level, and they all have equal size, whereas thickness of edges is proportional to their weight. *Insets* provide an outlook on different regions, where node size is instead proportional to the population of the province. (*C*) The temporal evolution of the network connectivity in terms of number of weakly connected components (No. WCC, red) and size of the giant connected component (Size LWCC, blue), measured on daily snapshots of the mobility network from February 23 to April 4; trends are significantly increasing (M-K: $P \approx 0$; K-T: $P \approx 0$ $R = 0.64$; T-S: $R = 30.52$) and decreasing (M-K: $P \approx 0$; K-T: $P \approx 0$, $R = -0.67$; T-S: $R = -58.58$), respectively. (*D*) The temporal evolution of the global efficiency for the Italian mobility network from February 23 to April 4. Efficiency is computed according to ref. 15. We use the reciprocal of weights to model distances between nodes. The trend is significantly decreasing (M-K: $P \approx 0$; K-T: $P \approx 0$, $R = -0.75$; T-S: $R = -0.00003$). To visualize trends in *C* and *D*, we show a locally estimated scatterplot smoothing (LOESS) regression (dashed line) with 95% CI (shaded area), and highlight lockdown and weekdays with a solid and dotted vertical red lines, respectively.

In Fig. 1*C*, we analyze the temporal evolution of the number of weakly connected components and the size of the largest connected component in the overall mobility network. We identify two opposite and significant trends, increasing (Mann–Kendall [M-K]: $P \approx 0$; Kendall's Tau [K-T]: $P \approx 0$ $R = 0.64$; Theil–Sen [T-S]: $R = 30.52$) and decreasing (M-K: $P \approx 0$; K-T: $P \approx 0$, $R = -0.67$; T-S: $R = -58.58$), which document the breakdown of hubs and long-range connections.

We further assess the impact of mobility restrictions leveraging a network-based representation of mobility data and computing network efficiency (15) (*Materials and Methods*) as a proxy of the system dynamics at play. Efficiency is a global network measure that combines the information deriving from network cohesiveness and the distance between nodes to measure how efficiently information/individuals travel over the network (18). Additionally, efficiency is particularly suitable for treating graphs with multiple components which evolve over time (19). As shown in Fig. 1*D*, we observe a drastically decreasing trend of the efficiency of the network (M-K: $P \approx 0$; K-T: $P \approx 0$, $R = -0.75$; T-S: $R = -0.00003$), which confirms a pronounced drop in the overall mobility potential.

Finally, we observe significant changes in the distribution of several node centrality measures over time (*SI Appendix*, Figs. S2–S4 and Table S3), with peripheral municipalities being those most affected by the lockdown (*SI Appendix*, Fig. S5 and Table S4).

In the following assessment, we use the variation in nodal efficiency (*Material and Methods*), that is, the contribution of each node to the global network efficiency, as a proxy for the local effects of mobility restrictions. We compute the percentage relative change induced by the lockdown, by constructing mobility networks in two windows: 14 d before and after the day of intervention.

Economic Segregation from Mobility Disruption

First, we focus on average individual income, which constitutes the basis for the Italian Personal Income Tax declared annually by taxpayers.

Second, we use a municipal composite index of material and social well-being (Index of Socio-economic Deprivation) produced by the Italian Ministry of Economy and Finance, which aggregates several dimensions of material and social conditions at the municipal level (20) (*Materials and Methods*) and represents one of the determinants of municipal standard expenditure needs.

In *SI Appendix*, Fig. S6, we show the relationships between the two indexes with respect to the relative change in nodal efficiency. We observe a significant negative correlation with the Deprivation Index (Pearson: $R = -0.153$, $P \approx 0$; Spearman-Rho (S-R): $R = -0.235$, $P \approx 0$; T-S: $R = -0.064$; K-T: $R = -0.162$, $P \approx 0$) but a positive correlation with income per capita (Pearson: $R = 0.263$, $P \approx 0$; S-R: $R = 0.404$, $P \approx 0$; T-S: $R = 0.001$; K-T: $R = 0.273$, $P \approx 0$). We also notice similar and significant relationships when using other network centrality measures (*SI Appendix*, Table S3).

As a third main variable, we consider the municipal fiscal capacity, measured each year by the Italian Ministry of Economy and Finance and employed in the fiscal equalization process (21). In particular, municipalities with high fiscal capacity tend to be financially independent from the central government, while low values imply a higher reliance on transfers.

Finally, as additional regressors, we introduce a measure of municipal inequality, that is, the ratio between mean and median individual income, and an inverse measure of urban density in terms of the amount of real estate per capita.

In Fig. 2, we show the geographic distributions of the median income per capita of Italian provinces, separating the most affected (Fig. 2*A*) from the least affected (Fig. 2*B*). We report the distribution of inequality for each province with respect to the mean of all provinces. It is immediately visible that the most affected provinces have on average lower income per capita. However, the geographical distribution does not reflect a north–south division but rather a separate dynamics for the northeast of Italy with respect to the rest of the country. Some of the provinces in the northwest, such as Turin and Genoa, are present among the most affected ones. Finally, income inequality is higher than average in almost all of the least affected provinces, while, in the most affected ones, we find a sparser distribution. This observation suggests the necessity of a more detailed analysis at the municipal level to qualify these aggregated results.

Second preliminary evidence is that the joint distribution by percentiles of the variation of mobility and economic indicators is concentrated on the top and bottom percentiles (*SI Appendix*, Figs. S7 and S8). This result is important, since it shows a different relation between the extremes of the distribution of economic indicators and mobility compared with the one observed around the mean values (*SI Appendix*, Fig. S6).

Against this background, in Table 1, we show the results of a quantile regression, where the relative variation in nodal efficiency over time is regressed against a set of economic indicators with regional controls. Our quantile regression approach estimates the conditional quantile of our dependent variable over its predictors (22), allowing us thus to concentrate on the dynamics within tails of the distribution and to capture effects that, with linear methods, would be classified as nonsignificant (6). Our estimates at the top and bottom quantile of the distribution of the variation in nodal efficiency show a better fitting with respect to the ordinary least squares (OLS) reported as reference in Table 1. These results confirm and refine the observations highlighted in Fig. 2. We observe a significant and positive relation between change in mobility during the lockdown and average individual income for the bottom quantiles of the distribution ($q_{0.05} = 0.2587$, $\mathrm{SE} = 0.0253$). We study how municipalities at the lower end of the distribution of changes in mobility (10th to 20th percentiles) are distributed according to their income per capita, and we find that the reduction in connectivity and mobility is higher for municipalities with a low average individual income, while municipalities with high income per capita experience less intense changes. Moreover, at the upper end of the distribution, the relation is reversed ($q_{0.95} = -0.2489$, $\mathrm{SE} = 0.0506$). This asymmetry of the joint distribution of mobility contraction and income per capita unravels the existence of a possible segregation effect: Even though some of the wealthiest cities have experienced greater casualty rates, low-income individuals are more affected by the economic consequences of the lockdown.

When we move to the analysis of municipal characteristics, measured through deprivation and fiscal capacity, we find a different result: Municipalities that are relatively richer in terms of social indicators and fiscal capacity are those that are more affected by the loss in mobility efficiency in the aftermath of the lockdown ($q_{0.05} = 0.1686$, $\mathrm{SE} = 0.0276$ for deprivation; $q_{0.05} = -0.1461$, $\mathrm{SE} = 0.0286$ for fiscal capacity).

Two seemingly opposite patterns emerge: Individual indicators (average income) show that the poorest are more exposed to the economic consequences of the lockdown; conversely, aggregate indicators at the level of municipalities, that is, deprivation and fiscal capacity, reveal that wealthier municipalities are those more severely hit by mobility contraction induced by the lockdown.

In order to shed light on these apparently contrasting results, we investigate the relationship between inequality and the mobility contraction: We find a significant and negative relationship between the two variables at the lower end of the distribution of mobility reduction ($q_{0.2} = -0.0410$, $\mathrm{SE} = 0.0124$). This result clarifies our findings: Not only are stronger negative changes in mobility associated with low income municipalities, but they are also linked to high levels of inequality. Since inequality is calculated as the ratio between mean and median income, a municipality with higher inequality has a larger share of poor individuals, that is, citizens with income under the mean, with respect to other municipalities with comparable levels of median income per capita. In other words, we find that mobility contraction tends to be more intense for municipalities where the number of individuals with an income lower than the median is greater, even though indicators of municipal performance are good (high fiscal capacity). All in all, our results seem to indicate that Italian municipalities are facing a challenge of unprecedented intensity, since, on the one hand, they will experience a sharp reduction of the fiscal revenues generated by their tax bases and, on the other hand, they will need to produce an effort to sustain the most-fragile individuals.

Our results are not affected by the inclusion of real estate and regional controls. We find a negative relation between the number of buildings per capita and changes in mobility ($q_{0.05} = -0.1622$, $\mathrm{SE} = 0.0251$): Municipalities affected more by the contraction in mobility have more buildings per capita, hence less urban density. Moreover, by including controls for all regions, our results are not altered, showing that our findings are not driven by the regional distribution of municipalities (see *SI Appendix* for extended results, including regional controls).

On the whole, our evidence shows that the lockdown seems to produce an asymmetric impact, hitting poor individuals within municipalities with strong fiscal capacity, with weaker effects in northeast Italy.

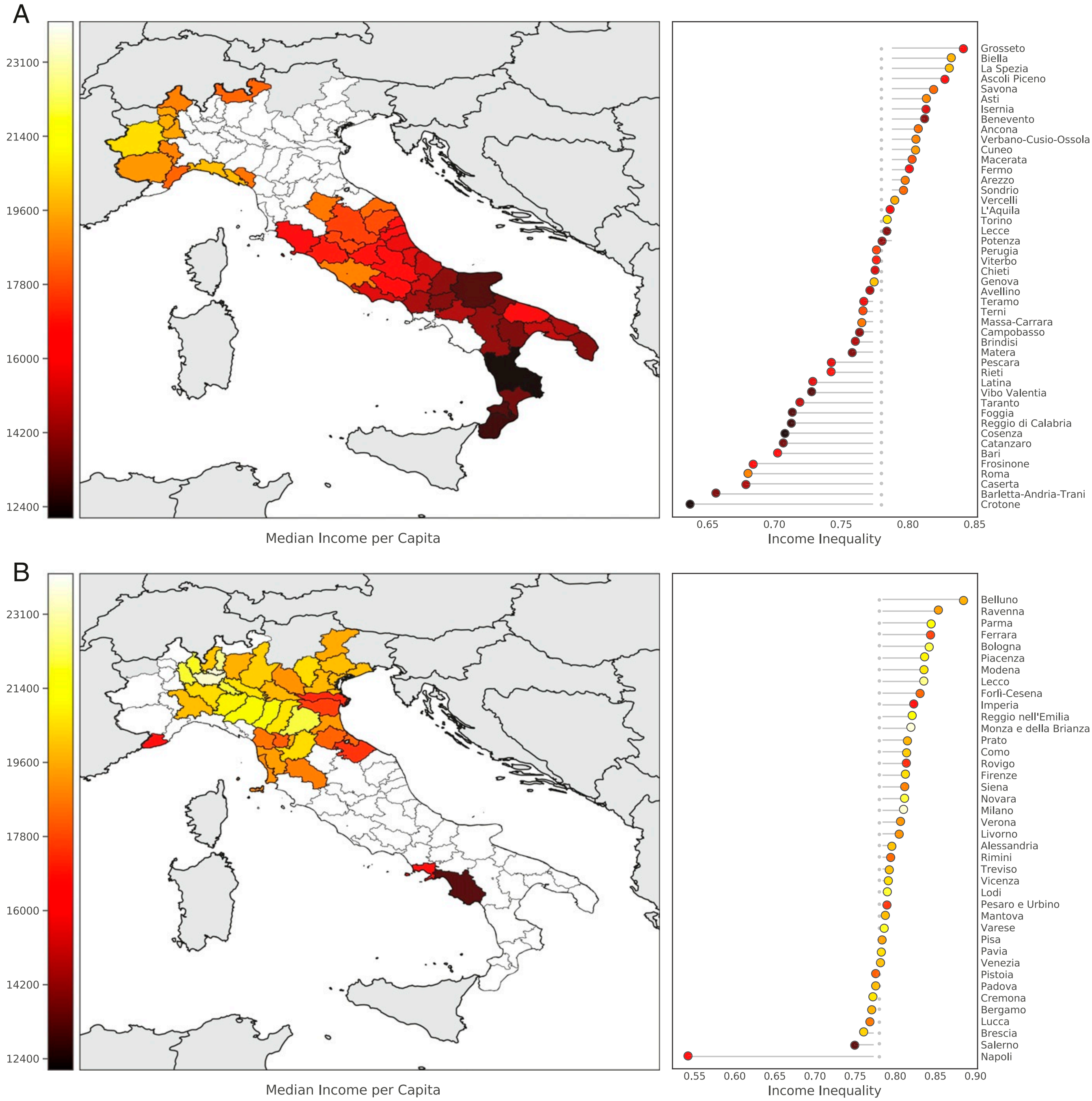

Fig. 2. Characteristics of the (*A*) most affected and (*B*) the least affected municipalities aggregated at the province level. (*Left*) Geographic distributions with colors corresponding to median income per capita in every province. (*Right*) Position of each province in the distribution of income inequality with respect to the average inequality in the sample (gray dotted line). Italian regions with no available data have been grayed out.

Conclusions

We analyze a massive mobility dataset before and after the Italian lockdown introduced to address the COVID-19 pandemic. We explore how variations in mobility relate to some fundamental economic variables, and we accordingly show that reduction in connectivity tends to be stronger for municipalities with low average individual income and high income inequality. At the same time, we notice that mobility restrictions have a higher impact on municipalities with higher fiscal capacity.

Our findings shed light on some social and economic consequences of policy measures adopted to contain the diffusion of COVID-19. First, the lockdown seems to unevenly affect the poorer fraction of the population. Second, we find that the reduction in mobility and connectivity induced by the lockdown is more pronounced for municipalities with stronger fiscal capacity. Finally, the distribution of income plays a role: Municipalities where inequality is higher experience more pronounced mobility contractions. Our results suggest an unprecedented fiscal challenge: On the one side, central and local fiscal revenues will be lower; at the same time, additional resources are needed to sustain the recovery of the weaker fraction of the population. In the absence of targeted lines of intervention, the lockdown

Table 1. Results for quantile regression of the relative difference of efficiency over time with respect to income per capita with multiple controls: social and financial distress in the municipality (deprivation and fiscal capacity), concentration of estates (real estate pc), income inequality, and regional controls

q	Intercept	Income pc	Deprivation	Fiscal capacity	Inequality	Real estate pc	(pseudo)R2
$q_{0.05}$	−0.8398***	0.2587***	0.1686***	−0.1461***	−0.0344*	−0.1622***	0.05223
	(0.0491)	(0.0253)	(0.0276)	(0.0286)	(0.0204)	(0.0251)	
$q_{0.1}$	−0.5089***	0.2871***	0.1723***	−0.1280***	−0.0315*	−0.2539***	0.17578
	(0.0456)	(0.0260)	(0.0266)	(0.0261)	(0.0177)	(0.0232)	
$q_{0.2}$	−0.2241***	0.2272***	0.1272***	−0.0972***	−0.0410***	−0.2907***	0.29896
	(0.0317)	(0.0187)	(0.0179)	(0.0242)	(0.0124)	(0.0206)	
$q_{0.8}$	0.3770***	0.0788***	0.0068	−0.0548***	0.0018	0.0868***	0.14346
	(0.0199)	(0.0121)	(0.0117)	(0.0123)	(0.0094)	(0.0133)	
$q_{0.9}$	0.8644***	−0.0962***	−0.0868***	−0.3598***	0.2099***	0.8759***	0.20012
	(0.0523)	(0.0347)	(0.0319)	(0.0335)	(0.0269)	(0.0304)	
$q_{0.95}$	1.2128***	−0.2489***	−0.1214**	−0.3844***	0.3488***	1.0334***	0.24347
	(0.0761)	(0.0542)	(0.0506)	(0.0362)	(0.0329)	(0.0345)	
OLS	0.1098*	0.0654**	0.0557*	−0.2045***	0.0737***	0.1145***	0.09001
	(0.0576)	(0.0327)	(0.0328)	(0.0404)	(0.0239)	(0.0398)	

Regression is obtained with the iterative weighted least squares method on standardized variables. Standard errors reported in parentheses are calculated via bootstrap with 1,000 iterations. Pseudo R2 are obtained via McFadden's method. Only quantiles 5 to 20 and 80 to 95 are shown. Bottom line shows OLS regression as a reference. Number of observations is 2,345. Regression coefficients for the 16 regional controls and for the median quantile are reported in *SI Appendix*. ***$P < 0.01$, **$P < 0.05$, *$P < 0.1$.

would most probably induce a further increase in poverty and inequality.

Materials and Methods

Data Availability Statement. For what concerns Facebook human mobility, all data are provided under an academic license agreement with Facebook through its "Data for Good" program (available at https://dataforgood.fb.com/tools/disease-prevention-maps/). Facebook releases data upon request to nonprofit organization and academics. For what concerns economic variables and the mobility matrix that we have used to validate the prelockdown Facebook mobility data, the data are all publicly available through I.Stat (http://dati.istat.it/), with the exception of the median income used to calculate the inequality index, which can be obtained from the Italian Ministry of Economy and Finances (MEF). For a detailed description of all of the sources, we report the appropriate references in *SI Appendix, Data*.

Human Mobility Data. We analyzed mobility between municipalities based on "Disease Prevention Maps" provided by Facebook through its "Data for Good" program (14). These maps consist of deidentified and aggregated information of Facebook users retrieved by their mobile phones with geopositioning enabled, showing movement across administrative regions (i.e., Italian municipalities, in our case). Similar to recent research (23, 24), data do not indicate numbers of individuals traveling but are constructed by Facebook with proprietary methods, which include mechanisms to ensure privacy protection, to provide an index that correlates with real movements of people (14). We collected data relative to movements between Italian municipalities from February 23 to April 4 (COVID-19 was first diagnosed in the peninsula in the night between February 20 and February 21). The resulting dataset contains approximately 800,000 distinct observations covering almost 3,000 distinct municipalities. The average number of daily users with location enabled during the observation period was approximately 3.8 million. Data are not publicly available, but they were provided by Facebook under an academic license agreement (*SI Appendix, Data*).

Network Efficiency. The efficiency is a global network measure that combines the information deriving from the network cohesiveness and the distance among the nodes, measuring how efficiently information is exchanged over the network (15), and it can be defined as the average of nodal efficiencies e_{ij} among couples of vertices of the network. Given a weighted network $G(V, E)$ with $n = |V|$ nodes and $m = |E|$ edges, the connections of G are represented by the weighted adjacency matrix W with elements $\{w_{ij}\}$, where $w_{ij} \geq 0 \ \forall\, i, j$. The global efficiency can be written by the following expression:

$$E_{glob}(G) = \frac{1}{n(n-1)} \sum_{i \neq j \in V} e_{ij} = \frac{1}{n(n-1)} \sum_{i \neq j \in G} \frac{1}{d_{ij}}, \quad [1]$$

where d_{ij} is the distance between two generic nodes i and j, defined as the length of the shortest path among such nodes. The shortest path length d_{ij} is the smallest sum of the weights w_{ij} throughout all of the possible paths in the network from i to j. When nodes i and j cannot be connected by any path, then $d_{ij} = +\infty$ and $e_{ij} = 0$. Following the methodology of ref. 15, the global efficiency $E_{glob}(G)$ is normalized in order to assume maximum value $E(G) = 1$ in the case of perfect efficiency. To normalize $E_{glob}(G)$, we consider the case of the ideal network G_{id}, that is a fully connected graph, where all nodes are connected to each other via the shortest possible distance that, in our case, corresponds to $\min(d_{ij}) = \min(w_{ij}) = w_{\min}\ \forall i, j$. The efficiency of such an ideal graph is $E_{glob}(G_{id}) = 1/w_{\min}$, and thus the normalized efficiency is $E(G)_{norm} = E_{glob}(G)/E_{glob}(G_{id})$, with range $0 \leq E(G)_{norm} \leq 1$. In this setting, the nodal efficiency, that is, the contribution of each node to the global efficiency, can be simply written as

$$e_i = \frac{1}{n-1} \sum_{j \neq i} \frac{1}{d_{ij}}, \quad [2]$$

while the normalized nodal efficiency can be written as $e_i^{norm} = e_i\, w_{\min}$. Besides the geographical distance between two nodes of the graphs, an epidemiological proximity can also be defined, considering that two locations are closer if many people move between them. To compute network efficiency, we use the reciprocal of weights on arcs to compute, accordingly, the shortest path distance between two nodes.

Model. We define t_0 as the 14-d period before lockdown and t_1 as the 14-d period after the day of intervention. We construct two networks of mobility for each of the periods t_0 and t_1, where nodes are represented by municipalities and (weighted) edges correspond to the sum of mobility traffic between them over time, as measured by Facebook. Let i be an Italian municipality in our sample; we define the relative variation in efficiency Δe_i as $(e_{i,t_1} - e_{i,t_0})/e_{i,t_0}$, where e_i is defined in Eq. **2**.

For our model, we estimate the following equation:

$$\Delta e_i = \alpha + \boldsymbol{\beta} \cdot \mathbf{x}_i + \boldsymbol{\gamma} \mathbf{z}_i, \quad [3]$$

where $\mathbf{x_i}$ is a vector of economic indicators measured at the municipal level and $\mathbf{z_i}$ represents a matrix of regional fixed effects. All economic indicators have been measured for periods preceding the start of the lockdown and are described below.

Economic Data. Economic data cover different dimensions of the local socioeconomic context of each Italian municipality, in total, 7,904 jurisdictions, representing the elementary administrative unit in Italy.

In total, our dataset includes six variables: individual average declared income, which is a proxy of the well-being of citizens; deprivation, fiscal capacity, and inequality, which provide different measures of the municipal financial and social wealth; and, finally, as a proxy of the structural features of each territory, we include the amount of real estate per capita and regional fixed effects.

Descriptive statistics and appropriate references are reported in *SI Appendix, Data*.

Declared Income. This variable is the tax base of the personal income tax declared by taxpayers in the 2018 tax return to the Revenue Agency for the 2017 financial year. The distribution at the municipal level is provided by the MEF, and both the mean and the median values are included in the dataset.

Municipal Index of Socioeconomic Deprivation. This variable is a composite index made up of five elementary indicators that cover the following dimensions: 1) education: the percentage of population older than 6 y that is illiterate or without a degree; 2) unemployment: the percentage of active population without a job; 3) housing: the percentage of rented properties over the total number of real estate properties; 4) population density: average number of components in each family; and 5) economic poverty: percentage of taxpayers with a total declared income lower than 10,000 euros.

The five elementary indicators are computed at the municipal level, then transformed in percentage deviation from the national mean, and finally aggregated together with equal weights. The aggregation methodology is reported in ref. 20. This index is one of the main determinants of municipal standard expenditure needs. The data are made available by the Italian MEF through the website https://www.opencivitas.it (a repository of all information used for the evaluation of municipal standard expenditure needs).

Municipal Fiscal Capacity. This variable is the official measure of the standard level of municipal fiscal revenues based on three main sources: property tax, local income tax, and local fees. This value, based on 2016 data (latest available information), has been computed by the Italian MEF and represents, together with standard expenditure needs, the main building block of the Italian system of municipal fiscal equalization. Official figures are made public each year through a specific decree.

Municipal Income Inequality. We measure income inequality at the municipal level, in a very simple and direct way, as the ratio between average and median values of the distribution of the declared income. Municipalities with values above 1 are those where income is less equally distributed.

Amount of Real Estate per Capita. This is the number of existing buildings of different categories divided by the number of individuals in the municipality; this variable can be interpreted as an inverse measure of population density or as a direct measure of urban sprawl. Data are available through I.Stat for the year 2016 (latest available information).

Regional Controls. Our regression sample provides a good representation of the entire set of Italian municipalities, in terms of both population size and geographical location, including 2,387 observations corresponding to 30% of Italian municipalities. Nevertheless, to exclude spatial spillover effect, we control for regional confounding factors.

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