From stay-at-home to return-to-work policies: COVID-19 mortality, mobility and furlough schemes in Italy

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Abstract

Assessing the economic impact of COVID-19 pandemic and vaccination roll-out strategies is essential for a rapid recovery. In this paper we analyze the impact of mobility contraction on employee furlough and excess deaths in Italy. We provide a link between the reduction of mobility and excess deaths, confirming that the first countrywide lockdown has been effective in curtailing the COVID-19 epidemics. Our analysis points out that a mobility contraction of 10% leads to a mortality reduction of 5% whereas it leads to an increase of 50% in Wage Guarantee Funds allowed hours. Based on our results, we propose a prioritizing policy for the administration of COVID-19 vaccines in the most advanced stage of a vaccination campaign, when healthy active population is left to be vaccinated.

keywords: COVID-19 mortality; Furlough schemes; Economic impact of lockdowns; Vaccination rollout

1 Introduction

The spread of the novel coronavirus (SARS-CoV-2) worldwide and the subsequent enforcement of strict containment measures by several national governments has severely impacted the world economy, which shrank by 4.3% in 2020 (Chetty et al., 2020, World Bank, 2021). On the supply side, social distancing measures placed workers under stay-at-home orders, shut down ‘non-essential’ activities and challenged supply chains. On the demand side the pandemic has reduced consumer spending virtually wiping out demand in entire economic sectors. A whole bunch of literature analyzes the actual effectiveness of the most restrictive policies, such as countrywide lockdown, in preventing the contagion by reducing mobility flows and discouraging social interactions (Acemoglu et al., 2020, Favero et al., 2020, Yoo and Managi, 2020). In particular, recent work has shown mobility reductions to be followed by a significant drop in the number of new COVID cases and the death toll (Farboodi et al., 2020, Glaeser et al., 2020, Warren and Skillman, 2020).
Although a stream of literature has largely investigated the epidemiological and socio-economic consequences of lockdown measures, there is still a paucity of evidence about the effect of the reduction of mobility on employment. To fill this gap, in this paper we investigate the implications of the containment policies by considering the amount of working hours allowed by the Italian government to be covered by the Wage Guarantee Fund in the aftermath of the first countrywide lockdown in 2020.

This aspect is relevant for two main reasons. On the one hand, the impact of the Covid-19 crisis on Italian workers is dramatic, with 444 thousand jobs lost in 2020. This is on top of 3.6 million furlough workers. On the other hand, the estimated expenditure for Covid-related Wage Guarantee Funds allowed hours is almost 20 billion Euros in 2020 (Commission, 2021). This is by far the main Covid induced increase of public budget expenditure in Italy. This calls for an analysis of the socio-economic consequences of the vaccination roll-out strategy in Italy, to speed up the recovery and to limit unemployment.

Vaccination strategic distribution plans generally follow the WHO guidelines (WHO, 2004) and are also consistent with the scientific literature (Medlock and Galvani, 2009, Sah et al., 2018). With regards to Europe, recently entered in force several criteria for prioritizing population according to multiple criteria related to age, work, and health vulnerability. The Italian strategic plan, released in December 2020 (della Sanità, 2020), provides a detailed definition of priorities involving the first administration phases covering the first nine months of 2021 and about 50% of the Italian population. Regarding the last phase, specific criteria have not been provided yet. On the same page, we found other EU countries. For instance, Germany identified six categories of prioritization: the first five categories have different urgency according to age and health risk, and cover about 30 million people, whereas the sixth category includes the remaining population, covering about 45 million people. Austria and Switzerland adopted similar rules, with a developing plan going up to the the second quarter of 2021. In France two final phases, namely 4 and 5, involve younger population (over 18 year old) without comorbidities, but details on allocation criteria have not been disclosed yet. On the same page is the UK plan that identifies a phase aimed at achieving coverage for the entire population, and will start after vaccinating priority groups targeting those who are at greater risk of exposure and those who provide essential public services. Ireland introduces some specifications regarding the population at lower risk assuming that priority is given to the 18-34 age group because it includes people who have more social

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1. As from 2020 employment statistics issued by ISTAT (Italian National Institute of Statistics) in February 2021. See https://www.istat.it/it/files//2021/02/Employment-and-unemployment_202012.pdf
2. As from INPS data updated on October 10, 2020. For further information see https://www.inps.it/nuovoportaleinps/default.aspx?itemdir=54304
3. The vaccination plan is going to be updated following the limitation imposed to AstraZeneca vaccine for over 55s.
4. https://www.bundesgesundheitsministerium.de
5. https://www.sozialministerium.at
6. https://www.bag.admin.ch/
7. https://solidarites-sante.gouv.fr/
8. https://assets.publishing.service.gov.uk/
9. https://www.gov.ie/en/publication/39038-provisional-vaccine-allocation-groups/
contacts. Among the priority groups, Ireland also identifies workers employed in essential sectors at high risk of exposure, going beyond the criterion of essentiality and looking at the riskiness in terms of exposure and contagion spread. The Spanish plan identifies some categories of the population and provides criteria for assessing their higher or lower priority, and among the categories of medium-high priority are still workers in essential sectors (to ensure the normal functioning of society) and people who are vulnerable because of their socio-economic conditions (e.g., those with precarious work, people in the lower income bracket, etc.). Indeed, drivers of socio-economic nature are found in the Irish and Spanish cases, that consider among the priority classes those who live in crowded neighborhoods or housing (therefore at high risk of outbreak). There is therefore the need to define further criteria for the prioritization of vaccination for people not working in essential or strategic services, that are substantially equivalent and generally represent a consistent share of the population.

To this end, here we introduce a criterion for the vaccine distribution to the share of non prioritized population, meaning the healthy and active population. We start providing additional evidence on the effectiveness of restriction to mobility for the Italian case. Results show that under the public health point of view, a ten-percent drop in mobility explains a 5 percent drop in excess deaths in the following month. Furthermore, we analyze the impact of mobility reduction on Wage Guarantee Fund (number of allowed working hours), as a proxy for the suspension of the economic activity due to Covid-19 and a proxy for the induced public expenses. Results show that a 10% drop in human mobility corresponds to a 50% increase of the Wage Guarantee Fund (WGF) expressed in full time equivalent units during the following month. Available data refer to a time window spanning from March to August 2020. We run a fixed-effects model on a monthly longitudinal dataset comprising 107 Italian provinces (NUTS3 regions). For the best performance of the methods implemented we also addressed potential endogeneity issues concerning our main variable of interest, mobility range, following an instrumental approach as in Glaeser et al. (2020).

As a further result we observe higher mobility to be associated with a greater share of essential working residents, hence we provide evidence supporting the inclusion of workers in essential sectors among the priority categories: if more people are allowed to move, since employed in essential sectors or not eligible for remote working, we expect the risk of the contagion to increase. The intervention is even more critical with respect to those essential jobs which imply a high risk of exposure. Here the main aim of reducing morbidity and mortality comes together a socio-economic rationale, as the one of limiting economic disruption.

\[\text{https://mscbs.gob.es}\]

\[\text{As previously mentioned, the Irish provisional allocation plan identifies people working in essential jobs at a high risk of exposure among the priority categories, with the rational of minimizing harm while reducing economic disruption. A lower degree of priority is associated to workers in occupations which are essential to the functioning of society (e.g. goods-producing industries) but where precautionary measures can be adopted without much difficulty. Also Spain provides the rationale to evaluate essential workers’ priority level, by taking into account economic criteria and assessing the risk of exposure and of developing severe morbidity.}\]
Concerning the advanced stage of the campaign addressing the share of non prioritized population, our proposal is to drive the allocation so that return-to-work is facilitated for the beneficiaries of wage guarantee schemes, with the expected benefit of a more efficient allocation of public funds and a reduction of potential job losses. The criterion is then compared to an alternative one based on resident working population in each province. Such comparison shows that the two alternatives lead in some cases to significantly different distribution priorities, while in other cases leading to the same priority.

This paper is organized as follows: Section 2 provides an essential literature review about the impact of mobility restriction on socio-economic outcomes, Section 3 describes the data collection whereas Section 4 provides a description of the econometric model. We present our results in Section 5 and discuss them in Section 6, where we also state our conclusions and future research directions.

2 Literature review

The analysis of the actual effectiveness of restrictive mobility policies to prevent COVID-19 infections has been addressed in a body of scientific research spanning multiple disciplines. The consequences of such policies have been examined on an international scale, and are nowadays covered by a significant and rapidly expanding literature. Regarding mobility restriction policies in the U.S. (Glaeser et al., 2020) employ data on five U.S. cities to estimate the effectiveness of lockdowns and other restrictions in limiting the spread of coronavirus disease. The authors perform a panel and a cross sectional regression of the logarithm of COVID-19 cases per capita on the percentage drop in mobility, employing the two-periods lagged value of the explanatory variable in the panel setting. To address potential endogeneity issues concerning the main regressor of interest, mobility has been instrumented by the employment-weighted average share of essential workers and by the employment-weighted average telecommuting share across industries at the zip code level. According to their main instrumental variable panel specification, when controlling for zip and week fixed effects, the authors find that a drop in mobility by 10 percent points leads to a 30 percent decline in COVID-19 cases per capita. In an additional specification of the cross sectional model, they find a positive and significant association between the logarithm of per-capita deaths and mobility changes, which is robust to the inclusion of controls when instrumenting for mobility.

Regarding Germany, Krenz and Strulik (2020) implement an instrumental variable strategy to investigate the association between COVID-19 diffusion and mobility containment at a regional level (NUTS3 regions). As an instrument for mobility they employ a metric assessing the quality of the road infrastructure in German regions, namely the average travel time on roads towards the next major urban center is used as a proxy for remoteness. The authors argue that the impact of ”road infrastructure” on the spread of the disease goes through the effect it has on mobility flows. By regressing the logarithm of COVID-19

\footnote{Data on essential industries from Minnesota and Delaware are used to this end.}
per-capita cases on delta mobility in an IV cross sectional setting, this study shows a negative and significant association between a change in mobility and COVID-19 disease cases. According to the authors’ interpretation, German regions with a higher decline in mobility on Easter Sunday are those which have accumulated the largest number of COVID-19 cases. Besides, the first stage of the IV model shows a positive relationship between mobility drops and accessibility defined as ”travel time to the next urban center”, suggesting that mobility flows declined most in those areas which are less remote (i.e. metropolitan areas).

Moving to the Italian case, Borsati et al. (2020) provide evidence on the association between public transports usage and the number of excess deaths, as transport modes have been addressed as a potential driver of the contagion in the ongoing debate. Using data at local labour markets level the authors detect a non statistically significant correlation between the propensity to use public transports and excess deaths as recorded during the first six months of 2020. They find instead a positive and significant association between the dependent variable and synthetic indices for internal and external commuting flows computed on 2011 national census data, and this result is still consistent in significance and sign when controlling for economic and demographic variables as well as for individual and time fixed effects.

Focusing on excess mortality, the work by Borri et al. (2020) explores the causal effect of lockdown policies in Italy on mortality by COVID-19 (again proxied by excess deaths) and mobility. Implementing a difference in differences model on an daily panel dataset, the authors show that a higher intensity of the lockdown is associated to a significant decrease in the number of excess deaths with respect to the whole population, and this holds true in particular for older people (in the range 40-64 and beyond). A second finding is that municipalities with a higher drop in the share of active people due to the lockdown are those showing a stronger contraction in mobility.

The analysis by Bonaccorsi et al. (2020) examines instead the socio-economic consequences of the Italian lockdown. By employing a network quantity, the node efficiency, to track changes in connectivity between municipalities 14 days after the lockdown with respect to 14 days before the lockdown, the authors argue that richer municipalities in terms of social indicators (index of material and social well-being) and fiscal capacity are those showing a stronger contraction in mobility. At the same time, however, they observe that among those municipalities experiencing a higher drop in mobility the contraction is much higher for municipalities with a lower average income and higher levels of inequality (measured as the ration between mean and median income).

Changes in mobility have been measured comparing mobility flows on Easter Sunday 2020 to an average Sunday in April 2019.

Internal commuting for local labour market (LLM) $i$ is computed as the ratio between the number of people moving between municipalities within $i$ and the population of $i$, while external commuting flows accounts for the number of people moving from $i$ to other LLMs and the number of people moving to $i$ from other LLMs, again normalized on LLM $i$ population.

According to the definition given by the authors, a municipality experiences a more intense lockdown if the reduction in the share of active population following the lockdown is above the median reduction across all municipalities located in the same province.

Temporary shutdown of non essential economic activities as from DPCM March 22, 2020.
In this expanding stream of literature, lockdown policies have been shown to explain changes in epidemiological data often through their effects on mobility, but according to the work by Goolsbee and Syverson (2021) on U.S. data, human mobility flows (especially those accounting for consumers’ visits to business locations and stores) are just partially driven by the enforcement of stay-at-home/shelter-in-place orders, as they may also arise from voluntary behavioral adjustments due to the fear of the pandemic.

Following this short literature review, we notice that although the ongoing scientific research is largely dealing with the epidemiological and socio-economic impact of the lockdown even in terms of market labour flows (Casarico and Lattanzio, 2020), we still have little evidence about the effects of lockdown policies on measures which could be taken as proxies for public expenditure and economic activity contraction.

3 Data collection and treatment

Data have been collected according to the three dimensions involved in the analysis: furlough schemes, mobility, and mortality. Furlough schemes are measured as Wage Guarantee Funds hours that have been authorized by the Italian Government, as a wage integration measure. Data are released by INPS (the Italian National Social Welfare Institution) and cover the period January-September 2020 (INPS, 2020). In addition, we considered the share of working population and the number of workers according to the six digits ATECO (numerical classification of economic activities, the Italian version of European NACE). Data have been collected from ORBIS database17. We computed for each province the share of workers employed18 in those ATECO codes not suspended by the Italian government.

Mobility data have been collected from the Facebook Data for Good program (Maas et al., 2019), whose reliability has been tested against the census commuting data collected by the Italian statistical institute in 2011 (refer to appendix A for details). Finally, as representative of the epidemic spreading, we considered the excess mortality data at municipal level collected by ISTAT (2020) expressed as the difference between the number of deaths recorded in 2020 and the average number of deaths occurred between 2015 and 2019 in the same period. As discussed in Buonanno et al. (2020), excess death toll is a reliable proxy of mortality by COVID-19. Such an assumption is needed to overcome the potential issues related to the endogeneity of testing policies (especially during the first wave of the epidemics), hospital capacity and difference in death classification at the local level. Table 1 shows that data span different time and spatial resolutions, ranging from monthly data of Wage Guarantee funds to 8-hourly data of Movement Range. With regards to the spatial aggregation variability of data, we observe a variability ranging from administrative regions of Wage Guarantee funds to municipality level of excess mortality.

The Facebook Data for Good program makes available different sets of data (Maas et al., 2019), covering both mobility flows between administrative regions and mobility

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17https://www.bvdinfo.com/en-gb/our-products/data/national/aida
18We used firm-level employment data as from 2019 fiscal year reporting.
inside administrative regions. In order to better represent the mobility contraction inside administrative regions we used the mobility range, an indicator that expresses the average contraction of people mobility inside an administrative region. Mobility between NUTS3 regions has been used to compute the network centrality (or remoteness) index of Italian provinces.

As already mentioned, we employed a measure for the amount of working hours allowed to be covered with the Wage Guarantee Fund to proxy the impact of national policies and imposed shutdowns on private sector economic activities. Right after the pandemic outbreak in Italy, the Italian government has extended by decree[^19] the use of already existing wage guarantee schemes against the pandemic crisis to strengthen employment protection. In a joint work from INPS and Bank of Italy ([INPS and d’Italia, 2020](#)), it is reported that in the months of March and April 2020 around 50% of employers in the private sector have been allowed to use wage compensation schemes according to the new rules in force. This kind of intervention turns into lower labour costs for the firm but translates into a loss for the employee: estimates by INPS-Bank of Italy ([INPS and d’Italia, 2020](#)) show a mean monthly-gross income loss of around 27%. Moreover since wage subsidies are granted by the government this leads to greater public expenditures.

The growth in requests to be allowed to wage integration schemes by the employers can be partially explained in light of an additional labour market measure issued in March, the firing freeze, that is a temporary suspension of firings. Starting from around the 12th week of 2020 (which coincides more or less with the introduction of the firing freeze and the extension of wage integration schemes) firings dropped sharply with respect to their average level in 2017-2019 ([Casarico and Lattanzio, 2020](#)); starting from week 9, a sharp decrease has been detected in the number of hirings as well.

National public policies have had a remarkable impact on labour market flows: according to recent estimates ([Viviano, 2020](#)), if measures like the extension of wage supplementation schemes together with firings freeze and financial supports for firms had never been issued there would have been 600 thousand more firings in 2020 because of the pandemic crisis.

Figure 1 shows how intense the use of the Wage Guarantee Fund has been on average over the last year. The figure shows the monthly average Wage Guarantee Fund (in terms of accumulated hours), the weekly average number of excess deaths and the weekly average

[^19]: Decree Law n. 18/2020 issued on March 17.
Table 2: Descriptive Statistics

|                      | Mean   | Std. Dev. | Min   | Max     | Obs. |
|----------------------|--------|-----------|-------|---------|------|
| W.G.F. FTE           | 14676.54 | 30937.9   | 0     | 355018.5 | 856  |
| Excess deaths        | 48.884  | 264.510   | -478.2| 5181.4  | 1070 |
| Mobility Range       | -0.172  | 0.184     | -0.661| 0.150   | 1177 |
| Betweenness          | 0.033   | 0.069     | 0     | 0.594   | 855  |
| Share Essentials     | 60.459  | 13.131    | 23.746| 79.2    | 1284 |

A drop in mobility evolution over a time window spanning from January to December 2020 (according to the availability of the data). Each time series has been normalised to maximum for the sake of scale uniformity and figure readability. As one can see, around the $9^{th}$ week mobility drops significantly (w.r.t. the baseline) while almost simultaneously the number of excess deaths shows a sharp increase reaching its peak during the $12^{th}$ week of the year (around the last ten days of March). At the end of February the first containment measures had been issued but just on a local scale, addressing those areas where new COVID-19 cases had been recorded. However, a first contraction of mobility flows and a growth in deaths can be detected. We also observe a peak in the average number of allowed working hours to be covered with the Wage Guarantee Fund in April, with about one month delay with respect to the introduction of more restrictive measures, corresponding with the national lockdown on March 12. This may be explained by the fact that the time when the employer is allowed to use the wage guarantee schemes do not correspond with the actual temporary suspension of the working activity INPS and d’Italia (2020).

While excess deaths have been computed by comparing the number of deaths in 2020 with average pre-pandemic death levels in the same time window, the amount of the Wage Guarantee Fund has not. However, the intensity in the use of the Fund in the early months of 2020 before the contagion outbreak (January and February) can be taken as a reference point and the graph shows how early levels represent just a small fraction of the peak which can be observed around week 18.

Maps in figure Appendix B instead, plot the monthly distribution of the Wage Guarantee Fund allowed hours across Italian NUTS 3 regions: darker shades point out those areas where furlough schemes (WGF hours) have been used with higher intensity in each month.

Before composing the panel, data have been checked for consistency and have been averaged/rescaled (whenever possible) in order to fit the weekly variation and the spatial aggregation of an administrative region. As a result, we obtained a longitudinal dataset comprising monthly observations on a cross section of 107 Italian provinces.

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20Prime Ministerial Decree February 23, 2020.
21Prime Ministerial Decree March 11, 2020.
Figure 1: Wage Guarantee Fund, excess deaths and mobility range over time

Note: the plot displays the trend over time of the monthly average amount of the Wage Guarantee Fund (average allowed working hours), the average number of excess deaths per week and in weekly average mobility changes. All variables are expressed in normalized units: the Wage Guarantee Fund and excess deaths have been normalized on their maximum while mobility range has been normalized on its minimum. Two-weeks moving average are reported for excess deaths and mobility range.

4 The econometric model

To explore the relationship between the dependent variables and the main explanatory variable, namely Mobility Range, we employed a linear model for longitudinal data, accounting for Italian provinces’ heterogeneity. The linear model is expressed as follows

\[ \ln(y)_{it} = \beta \text{Mob.Range}_{i(t-1)} + \delta \text{Lockdown}_t + p_{vi} + \varepsilon_{it} \]  

(1)

where \( p_{vi} \) denotes the individual-specific fixed effects, which allow to control for provinces’ time invariant unobserved characteristics. Since we assume \( p_{vi} \) to be potentially correlated with the observed regressor we implemented a fixed-effects model. The model also includes a dummy named Lockdown which takes value 1 in those months when the national lockdown was in force - March, April and May - to control for potential time-related effects due to the imposed restrictions.
Here $y_{it}$ stands for Excess Deaths or Wage Guarantee Fund, since equation (1) has been estimated using each of them as the dependent variable. In both cases the logarithm of the response variable has been regressed on a period lagged value of the explanatory variable Mobility Range. With regards to the Wage Guarantee Fund especially, a delay could occur between the time in which firms may take advantage of the wage supplementation schemes introduced against the crisis and the time in which it is officially authorized and recorded (INPS and d’Italia 2020). A time window is likely to occur, as well, before we observe a decline in the level of deaths at least partially driven by an adjustment of collective behaviours as a reaction to the spread of the virus (Borri et al 2020).

Model (1) has been then refined in order to overcome potential endogeneity issues concerning the main explanatory variable Mobility Range.

As already pointed out in previous scientific works, it is plausible to assume the endogeneity of a mobility measure with respect to variables which are strictly related to the spread of the disease like the number of COVID-19 cases or the count of deaths (Borri et al. 2020, Glaeser et al. 2020, Krenz and Strulik 2020). A potential reversed causality issue may affect the estimates, assuming that mobility flows are adjusted when people observe an increase (or decrease) in the level of deaths potentially due to the contagion. The same argument can be extended with respect to the relationship between mobility and the amount of the Wage Guarantee Fund: a fall in commuting flows can explain an increase in the Wage Guarantee Fund, since the enforcement of containment measures meant to discourage mobility traffic and limit social interactions could foster the use of wage guarantee schemes by the employer even in attempt to reduce physical proximity in the workplace. However, a temporary suspensions of working activities could itself explain a further drop in commuting flows. This could be the most intuitive way to interpret the relationship between mobility and furlough schemes but is not the only one, as mobility could impact the Wage Guarantee Fund even through different channels. If less people move because of containment rules or since they fear the contagion, we may observe a decline in the demand for goods and services by final consumers. In turn, entrepreneurs may be led to a temporary reduction of working time and to ask for wage compensation schemes in order to cope with a contraction in the demand.

To overcome potential endogeneity-issues, we employed two instruments for Mobility Range, developing different specifications of our model. The first instrumental variable (IV), the betweenness centrality (Newman 2010) of Italian NUTS3 regions, describes topological properties of the mobility network built on Facebook data movement between administrative regions. This measure is used as a proxy of the remoteness of Italian provinces, in the same

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22 Even as a potential effect of consumer substitution patterns (Goolsbee and Syverson 2021).

23 To measure the province centrality in the mentioned network we computed also the pagerank, then we studied the variation in nodal efficiency relying on mobility data as previously done by Bonaccorsi et al. (2020). We performed several trials employing each quantity alone and combined as instrumental variables in the econometric model. We finally opted not to use more than one network quantity as an instrument (e.g. when the page rank is used as an excluded instrument together with the betweenness it appears to be redundant), and we chose the betweenness to be used alone and combined with the share of essential residents.
vein as in Krenz and Strulik (2020). Even if built on mobility data, the node betweenness
provides a different information with respect to the one conveyed by mobility range: it
describes a global property of the network connecting each Italian province by looking at
the entire system. Indeed, while mobility range measures the average contraction of people
moving inside an administrative region focusing on a local scale, the betweenness centrality
looks at the whole network, in a global perspective, providing a ranking of Italian NUTS 3
regions based on their importance of bridging different regional mobility systems. Based on
this, we assume this quantity to be less or even not susceptible to changes in the number of
fatalities or in the number of Wage Guarantee Fund allowed hours occurring at a local
scale (i.e. changes referring to the single observational unit i).

The choice of the second instrument has been inspired by Glaeser et al. (2020): looking at
the provisions of Prime Ministerial Decrees issued between March and May we
computed for each Italian province the time-varying Share of Essential Residents (or Share Essentials),
that is the share of labour force which was allowed to move during the first
national lockdown since employed in economic sectors designated as essential by the Italian
government. Finally, the share of authorized employees has been multiplied by province i
2019 employment rate to proxy the share of essential workers. Following the argument
in Glaeser et al. (2020) and Krenz and Strulik (2020), we assume that the centrality of a
province in the mobility network and the share of people employed in essential industries
have an impact on excess deaths just through mobility flows. A similar argument applies
for Wage Guarantee Funds allowed hours.

The first stage and main equations for the IV model are given by

\[
\begin{align*}
\text{Mob.Range}_{it}(t-1) &= \pi IV_{i(t-1)} + \gamma \text{Lockdown}_t + pv_i + \eta_{it} \\
\ln(y)_{it} &= \beta \text{Mob.Range}_{it(t-1)} + \delta \text{Lockdown}_t + pv_i + \varepsilon_{it}
\end{align*}
\]

both stages control for individual-specific fixed effects and include the Lockdown dummy.

We estimated three specifications of the model: the first one employs only betweenness
centrality as instrumental variable, the second one includes just Share Essentials while the
third one uses both variables as instruments. To be in line with the instrumented variable
both IVs have been lagged by one month.

With respect to the Wage Guarantee Fund we mostly rely on the IV specification employing
share essentials together with centrality, or using the betweenness alone as instrumental
variable. Finally, we performed a GMM estimation of the coefficients.

\footnote{We refer to Glaeser et al. (2020) in the choice of the instrument for mobility but we computed the
measure according to a different formula.}

\footnote{Our references are Dpcm March 11, Dpcm March 22, Dpcm April 1, Dpcm April 10, Dpcm April 26
and Dpcm May 17, 2020.}

\footnote{Source of employment data is ISTAT (Italian National Institute of Statistics) Labour Force Survey.}
5 Results

Estimates in table 3 have been obtained regressing the logarithm of excess deaths on the main explanatory variable, namely mobility range, which keeps track of the change in mobility occurred in Italy during and after the first national lockdown.

Results in model [A] have been estimated on the full panel comprising all 107 Italian provinces and a time window spanning from March 2020 to October 2020. Column (1) reports fixed-effects estimates from model [1] while columns from (2) to (4) display the results for the three IV specifications of the model. To overcome potential endogeneity issues concerning our main regressor, in column (2) we instrument for mobility range with province centrality in the mobility network, while specification in column (3) employs share essentials as the external instrument, and model in column (4) uses both variables.

As previously mentioned, each specification includes the Lockdown dummy variable, which takes value 1 in those months when the first national lockdown was in force in Italy: March, April and May.

All columns report a positive and statistically significant association between a change in mobility and excess deaths in the full-length period.

Model (1) shows that excess deaths increases by 0.35 percent at time \( t \) if mobility increases by one percent in the previous month\(^{28} \). Point estimates from specification (1) should be interpreted carefully. Indeed, the magnitude of the effect grows as we instrument our main regressor, as in specifications (2)-(4), suggesting a downward bias potentially due to endogeneity issues. First stage F-statistics suggest that the instruments are actually strong.

In order to point out a potential variation over time in the effect mobility on the dependent variable all estimates have been repeated by splitting the sample in two periods, one comprising months from March to May (model [B]) when the national lockdown was in force (lockdown period), and the other including observations from June to October (model [C]). As expected, the increase in mobility led to a greater growth in deaths during the lockdown period (model [B]), when the first wave of the pandemic reached its peak in Italy, and this effect weakened in the following months (model [C]). All coefficients are significant except for model [C](2), the one instrumenting for the centrality of provinces, when referring to the post-lockdown period.

Furthermore, results in section [B] display an increase in the coefficient once we instrument the main explanatory variable, while estimates in section [C] suggest the presence of an upward bias in the baseline model [C](1).

\(^{27}\)To cope with negative values we first rescaled variable excess deaths by adding the absolute value of its minimum (i.e. 478.2) to each observation then we took the logarithm.

\(^{28}\)About the interpretation of the coefficient: since we are dealing with semi-elasticities we say that a unit increase in mobility implies a \((\beta \times 100)\)% variation in the dependent variable. ‘Mobility range’ is not expressed in percentage points, meaning that a unit change in mobility means actually a 100% change (in order to be expressed in percentage point it should be multiplied by 100). To get the effect of a one percent change in mobility on excess mortality we should divide the coefficient by 100, that is \( \frac{0.35}{100} = 0.0035 \), and then multiply again by 100 to come to an easier interpretation of the coefficient as in the main text.
Model [A] in table 4 displays results from the first stage of the IV model. The share of essential residents shows a positive and significant relationship with mobility, meaning that, as expected, an increase in the fraction of working people employed in essential industries implies a lower drop in mobility. With respect to the Betweenness centrality of provinces we observe a negative and significant coefficient instead, suggesting a higher contraction in mobility flows for provinces with a higher centrality in the national network.

Let’s now turn our attention to the relationship between drops in mobility flows and the amount of the Wage Guaranty Fund as described in table 5.

The dependent variable has been expressed in full time equivalent units for a more intuitive interpretation. The metric, originally expressed in terms of allowed working hours in a month, has been divided by the maximum number of working hours in a full-time monthly schedule (excluding week-ends and bank holidays). If we assume that each worker has been laid-off for an amount of hours close to the monthly full-time workload, the measure as above can be read as the number of full-time equivalent working employees who have been temporary suspended from work in a month. It seems reasonable actually, since in March and April 2020, each individual put under wage compensation schemes has been laid-off for an average amount of hours equal to 154, accounting for around 90% of the full-time monthly schedule (INPS and d’Italia 2020).

As for excess mortality, all models have been estimated on the full sample comprising time units from March to August (model version [A]) and on two smaller samples including the same individual units observed in subsequent time windows, that is when the national lockdown was in force (model [B] - March to May) and in the following months (model [C] - June to August).

Results from the full sample regression show a negative and significant association between Mobility Range and the dependent variable, meaning that for every one percent drop in mobility at time \((t−1)\) we observe a 4.35 percent increase in the full time equivalent Wage Guarantee Fund in the following month (that is to say an increase in the number of full-time working employees under wage guarantee schemes, given a possible interpretation of a full time equivalent unit) according to specification (2) when instrumenting by the betweenness centrality.

This suggests that the enforcement of national policies meant to prevent the contagion discouraged mobility flows and fostered the use of wage compensation schemes provided by law to support workers. The relationship between mobility and furlough schemes could additionally be explained by a change in the demand for goods and services by final consumers.

Estimates of \(\beta\) tend to decrease as we instrument our main regressor by just one or both the selected IVs (columns (2)-(4)), even though results from column (4) should be taken carefully, since we have to reject the null hypothesis from the Sargan-Hansen test of overidentifying restrictions (Hansen J statistic=4.028, p-value=0.0448).

\(^{29}\) Again, recall that the explanatory variable Mobility Range is not expressed in percentage units and should be multiplied by 100 to be so.

\(^{30}\) Decree Law No. 18/2020 of 17 March 2020
Model [B] from table [5] confirms our expectations: the impact of movement range on the dependent variable becomes stronger if we focus on the lockdown period when stricter restrictions were in force. Point estimates in model [C] show a sharp drop instead: after a gradual easing of containment measures between June and August we still see a negative association between changes in mobility and the authorized Wage Guarantee Fund but this relationship seems to be just slightly significant according to the IV specifications in columns (3) (t-statistic= −1.67, p-value= 0.097) and (4) (t-statistic= −1.87, p-value= 0.063) or no significant at all as from column (2) (t-statistic= −1.54, p-value= 0.124).

When focusing on the sub-periods (model [B] and [C]) and instrumenting by both the IVs (column (4)) we do not reject the null hypothesis from the Sargan-Hansen test.

First stage regressions results (section [A], table[6] are in line with what already observed from table[4] that is a higher drop in mobility is observed in more central provinces and for the provinces with a lower fraction of essential working residents.

Maps in figure 2 provide a graphical representation of the province-specific fixed effects estimates obtained from the main equation of the instrumental variable model (equation[3]) when instrumenting by centrality and share essentials (tables [3] and [5], section [A], column (4)).

The intensity of the color filling each territorial unit on the map is proportional to the associated individual fixed-effect coefficient: darker colors express higher coefficients. Provinces whose coefficient are not statistically significant are in grey. The baseline in both cases (panel ‘a’ and ‘b’) is the province of Agrigento.

With respect to excess deaths, panel ‘a’ in figure 2 shows that the provinces which explain a higher increase in the dependent variable in the whole period (once controlling by mobility and lockdown-related time trends) are the most affected provinces located in the north of Italy (darker colors are concentrated in the north).

The map appears to be less polarized in the case of the Wage Guarantee Fund (panel ‘b’, figure 2). Even if the observable pattern is different we still see that higher coefficients are concentrated in the north-east of the country plus some darker areas located in the north-west and central regions as in the urban areas of Turin, Milan and Rome.

Following the same approach, estimates for the province-specific fixed effects in the lockdown and post-lockdown periods only (models [B] and [C] in tables [3] and [5], specification (4)) are displayed in Figure 6, Appendix B. While fixed effects coefficients seem to be heterogeneous and geographically clustered when the lockdown was in force, we observe more homogeneous effects as the lockdown measures have been loosened in the following months.
Table 3: Excess deaths panel results

| [A] Full Sample Regression | (1) | (2) | (3) | (4) |
|----------------------------|-----|-----|-----|-----|
| Mobility range | 0.356*** | 0.714*** | 0.532*** | 0.529*** |
| (t-1) | (0.046) | (0.252) | (0.066) | (0.065) |
| Constant | 6.232*** | 6.501*** | 7.001*** | 6.225*** |
| (t-1) | (0.007) | (0.022) | (0.025) | (0.003) |
| Observations | 856 | 855 | 856 | 855 |
| Number Ids | 107 | 107 | 107 | 107 |
| Individual FE | Yes | Yes | Yes | Yes |
| Overall R² | 0.136 | 0.188 | 0.210 | 0.203 |
| Root MSE | 0.188 | 0.210 | 0.203 | 0.203 |
| First Stage F-Stat | 47.57 | 573.25 | 298.85 | 0.570 |
| Hansen J stat. | 0.570 | 0.136 | 0.188 | 0.210 |

| [B] Split sample regression (March to May) | (1) | (2) | (3) | (4) |
|------------------------------------------|-----|-----|-----|-----|
| Mobility range | 0.395*** | 0.942*** | 0.667*** | 0.653*** |
| (t-1) | (0.062) | (0.338) | (0.082) | (0.081) |
| Constant | 6.501*** | 6.501*** | 7.001*** | 6.225*** |
| (t-1) | (0.022) | (0.025) | (0.025) | (0.003) |
| Observations | 321 | 320 | 321 | 320 |
| Number Ids | 107 | 107 | 107 | 107 |
| Individual FE | Yes | Yes | Yes | Yes |
| Overall R² | 0.038 | 0.188 | 0.277 | 0.244 |
| Root MSE | 0.190 | 0.277 | 0.244 | 0.244 |
| First Stage F-Stat | 26.40 | 779.47 | 388.17 | 0.784 |
| Hansen J stat. | 0.784 | 0.136 | 0.188 | 0.210 |

| [C] Split sample regression (June to October) | (1) | (2) | (3) | (4) |
|---------------------------------------------|-----|-----|-----|-----|
| Mobility range | 0.262*** | 0.234 | 0.222*** | 0.222*** |
| (t-1) | (0.040) | (0.282) | (0.042) | (0.040) |
| Constant | 6.225*** | 6.225*** | 7.001*** | 6.225*** |
| (t-1) | (0.003) | (0.003) | (0.003) | (0.003) |
| Observations | 535 | 535 | 535 | 535 |
| Number Ids | 107 | 107 | 107 | 107 |
| Individual FE | Yes | Yes | Yes | Yes |
| Overall R² | 0.056 | 0.095 | 0.095 | 0.095 |
| Root MSE | 0.085 | 0.095 | 0.095 | 0.095 |
| First Stage F-Stat | 13.02 | 317.31 | 173.12 | 0.002 |
| Hansen J stat. | 0.002 | 0.136 | 0.188 | 0.210 |

Robust standard errors in parentheses

* \( p < 0.10 \), ** \( p < 0.05 \), *** \( p < 0.01 \)
Table 4: Excess deaths IV panel results

[A] Full Sample First Stage IV

|                        | (2)     | (3)     | (4)     |
|------------------------|---------|---------|---------|
| Mobility range_i(t-1) | -1.192*** | -0.361*** |         |
|                        | (0.173) | (0.127) |         |
| Lockdown               | -0.269*** | -0.098*** | -0.098*** |
|                        | (0.014) | (0.011) | (0.011) |
| Share essentials_i(t-1)| 0.016*** | 0.016*** |         |
|                        | (0.001) | (0.001) |         |

Observations: 855
Number Ids: 107
Root MSE: 0.166
Individual FE: Yes

[B] Full Sample Reduced form IV

|                        | (2)     | (3)     | (4)     |
|------------------------|---------|---------|---------|
| ln Excess Deaths_i(t-1)| -0.851*** | -0.418   |         |
|                        | (0.302) | (0.288) |         |
| Lockdown               | 0.163*** | 0.253*** | 0.253*** |
|                        | (0.018) | (0.025) | (0.025) |
| Share essentials_i(t-1)| 0.009*** | 0.008*** |         |
|                        | (0.001) | (0.001) |         |

Observations: 855
Number Ids: 107
Root MSE: 0.208
Individual FE: Yes

Robust standard errors in parentheses

* p < 0.10, ** p < 0.05, *** p < 0.01
### Table 5: Wage Guarantee Fund panel results

|                      | (1)       | (2)       | (3)       | (4)       |
|----------------------|-----------|-----------|-----------|-----------|
| Mobility range \(\delta_{i(t-1)}\) | -6.232*** | -4.354*** | -5.736*** | -5.675*** |
|                      | (0.208)   | (0.743)   | (0.262)   | (0.261)   |
| Lockdown             | -1.717*** | -1.265*** | -1.597*** | -1.590*** |
|                      | (0.093)   | (0.219)   | (0.125)   | (0.126)   |
| Constant             | 8.226***  |           |           |           |
|                      | (0.020)   |           |           |           |
| Observations         | 619       | 618       | 619       | 618       |
| Number Ids           | 104       | 104       | 104       | 104       |
| Individual FE        | Yes       | Yes       | Yes       | Yes       |
| Overall \(R^2\)      | 0.445     |           |           |           |
| Root MSE             | 0.880     | 1.030     | 0.969     | 0.971     |
| First Stage F-Stat.  | 42.29     | 605.02    | 310.49    |           |
| Hansen J Stat.       |           |           |           | 4.028     |

#### [A] Full Sample Regression

|                      | (1)       | (2)       | (3)       | (4)       |
|----------------------|-----------|-----------|-----------|-----------|
| Mobility range \(\delta_{i(t-1)}\) | -7.610*** | -5.188*** | -6.005*** | -5.979*** |
|                      | (0.251)   | (1.013)   | (0.286)   | (0.287)   |
| Constant             | 6.018***  |           |           |           |
|                      | (0.090)   |           |           |           |
| Observations         | 307       | 306       | 307       | 306       |
| Number Ids           | 104       | 104       | 104       | 104       |
| Individual FE        | Yes       | Yes       | Yes       | Yes       |
| Overall \(R^2\)      | 0.634     |           |           |           |
| Root MSE             | 0.905     | 1.294     | 1.194     | 1.200     |
| First Stage F-Stat.  | 26.30     | 732.26    | 364.73    |           |
| Hansen J Stat.       |           |           |           | 0.804     |

#### [B] Split sample regression (March to May)

|                      | (1)       | (2)       | (3)       | (4)       |
|----------------------|-----------|-----------|-----------|-----------|
| Mobility range \(\delta_{i(t-1)}\) | -0.875*** | -1.317    | -0.424    | -0.469    |
|                      | (0.251)   | (0.854)   | (0.255)   | (0.251)   |
| Constant             | 8.849***  |           |           |           |
|                      | (0.029)   |           |           |           |
| Observations         | 312       | 312       | 312       | 312       |
| Number Ids           | 104       | 104       | 104       | 104       |
| Individual FE        | Yes       | Yes       | Yes       | Yes       |
| Overall \(R^2\)      | 0.030     |           |           |           |
| Root MSE             | 0.387     | 0.477     | 0.478     | 0.477     |
| First Stage F-Stat.  | 10.23     | 332.91    | 179.79    |           |
| Hansen J Stat.       |           |           |           | 1.021     |

#### [C] Split sample regression (June to August)

|                      | (1)       | (2)       | (3)       | (4)       |
|----------------------|-----------|-----------|-----------|-----------|
| Mobility range \(\delta_{i(t-1)}\) | -0.875*** | -1.317    | -0.424    | -0.469    |
|                      | (0.251)   | (0.854)   | (0.255)   | (0.251)   |
| Constant             | 8.849***  |           |           |           |
|                      | (0.029)   |           |           |           |
| Observations         | 312       | 312       | 312       | 312       |
| Number Ids           | 104       | 104       | 104       | 104       |
| Individual FE        | Yes       | Yes       | Yes       | Yes       |
| Overall \(R^2\)      | 0.030     |           |           |           |
| Root MSE             | 0.387     | 0.477     | 0.478     | 0.477     |
| First Stage F-Stat.  | 10.23     | 332.91    | 179.79    |           |
| Hansen J Stat.       |           |           |           | 1.021     |

Robust standard errors in parentheses

* p < 0.10, ** p < 0.05, *** p < 0.01
Our results have two main implications for the Italian vaccine roll-out strategy. When moving to vaccinate the health and active share of the population, essential workers and workers not eligible for remote working should be prioritized, since they increase mobility thus inducing higher excess mortality. Second, based on the results of the econometric analysis we propose to prioritize those areas in which the effect of mobility on Wage Guarantee Fund is stronger. Areas are identified according to the estimates of the individual-specific fixed effects as from the full-sample IV model (specification [A](4), table 5), considering the Wage Guarantee Fund as the dependent variable. Fixed effects coefficients are graphically represented in figure 2, where panel 'b' shows which NUTS 3 regions explain a higher
Figure 2: Province-specific fixed effects estimates

(a) Excess Deaths
(b) Wage Guarantee Fund

Notes: the map shows a graphical representation of the province-specific fixed effects estimated through equation \( \ln(WGF \text{ FTE})_{it} = \beta_0 + \beta_1 \text{Mob.Range}_{it-1} + \delta \text{Lockdown}_{it} + \sum_{j=2}^{N} p_j d_{j,it} + \epsilon_{it} \), when instrumenting Mobility Range by both province centrality and the share of essential residents (IV model, specification (4), section [A], tables 3 and 5). Color intensity for each province \( i \) is proportional to coefficient \( p_j \).

increase in the Wage Guarantee Fund (FTE units). Fixed effects estimates account for time-invariant provinces’ effects like demographic and socio-economic characteristics (which reasonably remain stable in the period we consider).

The provinces that have been most in need for wages supplementation schemes have been identified according to fixed effects estimates performed on the entire period, spanning from March to August 2020, and on the lockdown time only (March to May). We assume that stricter restrictions are likely to be enforced in the months when the last steps of the campaign are about to start. We could instead refer to the estimates obtained when focusing the post-lockdown period (June to August) if we expect milder (or almost absent) restrictions to be enforced.

We compare our allocation criterion with a benchmark based on Working population\(^{31}\), i.e. the number of people employed per administrative region.

Each province \( i \) is ranked according to the two criteria explained above, and we indicate

\(^{31}\)The number of people employed in province \( i \) has been obtained by multiplying the 2019 value of the employment rate of people aged 20 to 64 as from ISTAT (Labour Force Survey), by the number of residents aged between 20 and 64.
with $R^W_i$ and $R^WGF_i$ the position of the province $i$ in the Working Population, and Wage Guarantee Fund criteria. To highlight possible inequalities we compare the criteria by subtracting WP to WGF rankings

$$\Delta^WGF_i = R^WGF_i - R^WP_i$$

where $\Delta^WGF$ is the difference in the ranking positions between $\{WGF, EM\}$ and the working force ranking. The distribution of $\Delta$ is reported in figure 3. The intensity of the color is proportional to $\Delta^WGF_i$. Areas in light colors between blue and red tones are those with a similar position in both criteria ($\Delta \sim \pm 10$), they are therefore equivalent under both criteria. Provinces in blue and dark blue shades correspond to provinces having $\Delta^WGF_i < 0$, then they would be disadvantaged in case of WP criterion. On the other hand, provinces in red and dark red shades ($\Delta > 0$), would be disadvantaged by distribution criteria based on public expenditure (WGF).
6 Final discussion

In this paper we analyse the impact of human mobility on excess mortality and the use of furlough schemes in Italy. We assume that, safe return-to-work will be possible for vaccinated workers, reactivating mobility and restoring full production capacity. This is because the negative health consequences of human mobility will be neutralized. Therefore, we propose a vaccine prioritization policy of the health and active share of the population in two stages. First, access to vaccination should be guaranteed to essential workers and the ones not eligible for remote working. Then, return-to-work should be facilitated for the beneficiaries of wage guarantee schemes. This will be beneficial both in terms of a reallocation and more efficient use of public funds and in terms of reduction of potential job losses. It is important to highlight that our recommendations refer to the last phase of the vaccination campaign, when vulnerable categories according to the national strategic plan have already been vaccinated and immunized against the virus (della Sanità, 2020).

The proposed strategy puts in advantage those workers employed in the administrative areas in which wage integration measures have been used more, allowing them to come back sooner to a safe workplace, triggering a gradual economic recovery. The expected benefit of this policy can be interpreted mostly in terms of a gradual resumption of most economic activities and in terms of potential alternative allocations of public funds. We recall that, according to the European Commission (Commission, 2021), the Italian government has committed around 19 billion euros to cover wage supplementation schemes, accounting for around 70% of the total amount committed to employment support measures. With the approval of the 2021 Italian Budget Law (Law n. 178/2020), the use of wage guarantee schemes against the COVID-19 crisis has been extended until the end of March 2021 and until the end of June 2021, in the latter case with regard only to the Derogatory Wage Guarantee Fund and the Wage Integration Fund. Further measures on employment protection are currently under discussion.

To support our proposal we explored the link between the drop in mobility and the amount of the Wage Guarantee Fund expressed in full time equivalent units, also providing evidence on the association between changes in mobility and measures related to the spread

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32 A similar argument could be extended even to those workers who lost their job because of the pandemic crisis: immunity against COVID-19 could facilitate applying for and starting a new job in a safer way.

33 The prospected scenario does not take into account potential market labour flows (especially firings) which could occur when public policies issued to increase employment protection, among which firing freeze, are lifted. The 2021 Italian Budget Law (Law n. 178/2020) has extended the firing freeze until the end of March 2021 together with the extension of wage supplementation schemes against the COVID-19 crisis. Further measures are under discussion.

34 As from the same document, since March 2020 the Italian government has committed around 100.3 billion euros in accordance with three fiscal packages as from Law Decree no. 18 from 17 March, Law Decree no. 34 from 19 May, Law Decree no. 104 from 14 August, including, among the others, measures to support firms and employment.

35 Law n. 178/2020.

36 Cassa integrazione guadagni in deroga.

37 Fondo di Integrazione Salariale, FIS.
of COVID-19 infections, proxied by the number of excess deaths.

Results highlight a negative and significant relationship between mobility changes and the amount of the Wage Guarantee Fund (in full time equivalent units) over the period March-August 2020. Moreover, we find that a 1% contraction in mobility (w.r.t. the baseline) explains a 5% growth in the amount of the Wage Guarantee Fund (FTE units) allowed in the following month. Looking at the interpretation of a full time equivalent unit, a drop in human mobility explains an increase in the number of full-time working employees enrolled in wage guarantee schemes in the following month. The association becomes stronger if restricting the analysis when the first national lockdown was in force (March to May 2020), then gets milder and less significant after mobility restrictions are loosened (June to August 2021).

Under the public health point of view, results show the existence of a positive and significant association between ‘one month-lagged’ mobility changes and the excess deaths recorded: a one percent drop in mobility (w.r.t. the baseline) explains a 0.5 percent drop in the number of excess deaths in the following month.

Our finding are in agreement with the literature, as a positive association between mobility changes and deaths has already been observed by Glaeser et al. (2020), among others. In addition, Borri et al. (2020) highlighted a significant reduction in excess deaths (especially with respect to older people) in those municipalities experiencing more restricting lockdown measures, then, the authors put in evidence how municipalities with a higher drop in the share of active people following business shutdowns are those showing a stronger contraction in mobility. Similarly, we notice that lower shares of essential working residents in an administrative region (province) are associated to a higher mobility contraction and that provinces with a higher centrality are those experiencing a higher drop in mobility flows. In line with this evidence, Krenz and Strulik (2020) detected a higher decline of mobility flows in areas which are less remote (lower travel time to the next urban center).

The empirical evidence points out an association between the share of people employed in essential industries and excess deaths going through human mobility flows. These results provides support for the inclusion of workers in essential sectors among the priority categories.

Concerning the last stage of the vaccines delivery plan, we propose a prioritization criterion addressing the beneficiaries of furlough schemes and we test it against a benchmark based on the resident working force. We notice that while in some cases the two criteria are substantially equivalent, in other cases the choice of criterion is detrimental and leads to the significant disadvantages. From the economic point of view, we suggest that a criterion based on public expenditure review yields a co-benefit due to the substitution potential of the funds saved by the WGF reduction, that could be effectively invested both in strengthening the sanitary system and in supporting the national economy.

Although we analyze the Italian case, our results are relevant for an international audience as well, since similar employment protection measures have been issued by European governments as a response to the pandemic. Short-time furlough schemes meant to support the firms affected by the crisis have been introduced or extended in Europe (Commission).
European Union member states are allowed to ask for European funds in order to cover such employment protection measures: financial support in the form of loans granted on favourable terms is provided under the SURE instrument (temporary Support to mitigate Unemployment Risks in an Emergency)\textsuperscript{38}.

As further data covering the period of the second epidemic wave and the effects of the COVID-19 crisis are expected to be released, future work will be devoted to a better characterisation of the models developed and to a further refinement of the prioritisation index.

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A Facebook and census data

In this section we test how Facebook data represent a reliable approximation of the population commuting for work and study, i.e. excluding those that do not habitually move within the provinces and between the provinces. Our idea is to test this reliability by looking at the data provided by the Italian statistical office in 2011, i.e the last census data collection in Italy.

Both data are presented in the form of a origin destination matrix, where the links express the number of commuters who travel between and within provinces. In the case of ISTAT data, people move for study or work, in all time slots, and data are averaged over a period of one year. On the other hand, Facebook data account for the people moving daily, sampled at 8 hours intervals. In order to compare data, we averaged over the whole available period the Facebook data obtaining an averaged origin destination matrix. Our hypothesis is that the temporal averaging leads to a origin destination matrix accounting for the habitual commuting of the study and workforce.

\textsuperscript{38}Italy is among those member states which will benefit the most from the allocation of the resources provided under the SURE: around 27.4 billions out of the total amount of 90.3 billion euros approved by the European Council are gradually provided to Italy. Other member states which have been allowed to receive a financial support under the SURE are Belgium (7.8 billions), Spain (21.3 billions), Poland (11.2 billions), Portugal (5.9 billions), Greece (2.7 billions), Romania (4.1 billions). For further information see https://ec.europa.eu/info/business-economy-euro/economic-and-fiscal-policy-coordination/financial-assistance-eu/funding-mechanisms-and-facilities/sure_en
Figure 4: Scatter plot of the commuting flows of ISTAT and Facebook mobility data.

Figure 5: Focus on daytime (8AM-4PM): Scatter plot of the commuting flows of ISTAT and Facebook mobility data. Fit 7.49, $R^2 = 0.97$

Figure 4 shows the plot of the weight of the links accounted in both OD matrices. From a linear fit we find that Facebook data and ISTAT data are on average 1 to 7.5 ratio, confirming the data provided by [Bonaccorsi et al. (2020)]. As a further test, we considered only the Facebook traffic recorded during the daytime (8AM-4PM), comparing it to the corresponding period of ISTAT data. Results are depicted in Figure 5, where the agreement of the two datasets is conserved. According to these results we could consider, although sampling a smaller part of the population, Facebook movement data reliable under the point of view of the characterization of the mobility of habitual commuters.
Figure 6: Province-specific fixed effects estimates: lockdown and post-lockdown periods

(a) Excess Deaths: lockdown
(b) Wage Guarantee Fund: lockdown
(c) Excess Deaths: post-lockdown
(d) Wage Guarantee Fund: post-lockdown

Notes: the map shows a graphical representation of the individual fixed effects estimated through equation
\[ \ln(y)_{it} = \beta_0 + \beta_1 \text{Mob.Range}_{i(t-1)} + \sum_{j=2}^{N} p^{i,j}d_{j,it} + \varepsilon_{it}. \] Estimates from the lockdown and post-lockdown periods are represented.
Figure 7: Monthly Wage Guarantee Fund allowed hours

(a) January

(b) February

(c) March

(d) April
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