



Running the risk: Immunity and mobility in response to a pandemic[☆]

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ABSTRACT

The relative effectiveness of non-pharmaceutical interventions, such as lockdowns and work-from-home mandates, depends on whether individuals adjust their social behavior in response to infection risk when policy restrictions are absent. Exploiting geographic variation in COVID-19 exposure during the first wave, three key results emerge. First, we find evidence that areas with relatively high excess death rates during the first wave of the pandemic had relatively low excess death rates during the second wave. Second, using granular mobility data from GPS devices, we show that the same areas saw relatively high mobility during the second wave, which may suggest that the first finding is driven by an immunity effect. Finally, the heterogeneity analysis reveals that scarring, behavioral responses, and immunization may operate with varying intensity across municipalities with different age compositions, yielding observable differences in both second-wave mobility and mortality patterns.

1. Introduction

Governments and jurisdictions responded in different ways to the COVID-19 pandemic, ranging from complete and long-lasting lockdowns and school closures to individuals taking responsibility under non-binding recommendations (Hale et al., 2020). This has led to very different economic as well as social impacts (Juranek et al., 2021; Fernández-Villaverde and Jones, 2020; Chetty et al., 2023).¹ Although an increasing body of evidence suggests that mitigation policies have curbed the growth of COVID-19 infections, it remains unclear how much of this slowdown is due to mitigation policies versus other determinants.

Laissez faire approaches rest on the assumption that citizens will adjust their behaviors, for example, individuals might practice self-distancing out of fear of infection, wear masks, or they could become more informed about the disease, its severity, and reduce their mobility when the risk of infection becomes salient.² But understanding the causal relationship between risk-taking,

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¹ For an early study on the economic effects of viral diseases see Adda (2016).

e.g., mobility, and infections and subsequent deaths is empirically difficult. On the one hand, increased mobility encapsulates more social mixing and, as such, induces an increase in infections and deaths. On the other hand, increased infections and deaths may lead people to adapt to the altered risk of infection, expressed by suppressed levels of mobility.

Our aim is to determine and quantify the importance of a behavioral response to an increased risk of COVID-19-related mortality. We do so employing a difference-in-differences framework that combines high-frequency mortality data and municipal-level mobility data, available from the Italian National Institute of Statistics (ISTAT) and from City Analytics by EnelX and HERE Technologies (EnelX henceforth), respectively. We exploit the geographical variation in COVID-19 incidence during the pandemic's initial wave, using less exposed municipalities as counterfactuals to examine the evolution in more exposed municipalities within the same region or province, absorbing any time-varying mandatory policy restrictions. We take advantage of the time dimension of the data and use an event-study design to test for the existence of differential pre-trends between treated and control municipalities.³

We leverage the granular geographical heterogeneity of daily excess death rates across Italian municipalities during the first wave of the pandemic (January to May 2020) to show that (i) communities that experienced a severe first wave faced a milder and less deadly second COVID-19 wave four months later (October to December 2020) and (ii) municipalities more exposed to the first wave of pandemic show differential patterns in risk-taking, measured by *mobility*, during the second wave of the COVID-19 pandemic.

The observed lower excess mortality during the second wave in areas more severely hit by the first wave could be attributed to different potential explanations. One possibility is that these regions might experience long-term reductions in mobility due to scarring effects, i.e., persistent changes in beliefs about the probability of extreme, negative shocks (Kozłowski et al., 2020). Alternatively, the finding can be interpreted as evidence of an immunization effect — i.e., COVID-19-related deaths during the first wave generate immunity, which translates into fewer COVID-19-related deaths during the second wave (Vinceti et al., 2021). These two potential explanations are observationally equivalent in terms of second wave mortality. However, they should have opposite implications in terms of individuals' behavior, to the extent that the latter reflects individuals' perceived risk of contagion. More specifically, if the scarring effect dominates, then areas more severely hit during the first wave should exhibit less social mixing during the second wave. On the contrary, if individuals internalize the potential immunization effect, one should expect a relatively higher degree of social mixing compared to areas with a lower first wave intensity.

We find that the first wave mortality generates immunization. One additional daily death per 1000 inhabitants during the first wave reduces daily excess death rates during the second wave by roughly one death per 10,000 inhabitants — an estimated elasticity of -0.14 . Moreover, we observe that doubling the excess death rate during the first wave induces a 4% increase in mobility during the second wave — an estimated elasticity of 0.04 . In other words, there is no sign of an overpowering scarring effect, quite the opposite, as people adjust their behavior to risk, decreasing mobility less over the second wave with respect to the counterfactual trend.

Our data allow us to examine age-specific heterogeneity by leveraging municipal age composition. Because COVID-19 mortality risk increases substantially with age, on the one hand, older individuals are naturally more vulnerable and may be less willing to trade off mortality risk for increased mobility. On the other hand, younger people typically face almost no risk and may adjust their behavior less dramatically. Our findings suggest indeed that the overall interplay among immunization, behavioral responses, and scarring is not uniform across age groups. A stronger first wave among municipalities with a larger share of young people, who are more mobile, leads to larger mortality reductions during the second wave. Consequently, the most substantial mobility adjustments appear in municipalities dominated by middle-aged residents (26 to 81), suggesting that this group is more actively balancing the benefits of increased mobility against their own risk of infection. Overall, these results are consistent with the notion that scarring, behavioral responses, and immunization operate with varying intensity across sub-populations, yielding observable differences in both second-wave mobility and mortality patterns.

Italy is the ideal setting for several reasons. It was the first Western country to be hit by COVID-19, and almost immediately introduced a complete lockdown, which limited mobility between municipalities.⁴ As a result, nearby but isolated municipalities could develop waves of different intensity. Second, the use of highly granular geographical units and high-frequency data allows us to leverage the variations arising from the incidence of the first wave. This combination of detailed geographic resolution and frequent data also facilitates the inclusion of a diverse range of fixed effects, which helps mitigate concerns regarding unobserved heterogeneity.

In particular, the richness of the data allows us to control for day and municipality fixed effects that absorb time shocks affecting all municipalities (for example, national and regional policies) and time-invariant differences in outcomes across municipalities (for example, age differences), thus focusing on within-municipality variation over time. Week-by-region fixed effects capture

² Yet, it is worth noting that until recently, the workhorse epidemiological SIR model for the spread of diseases did not account for an endogenous behavioral response to the progression of the epidemic. These are referred to as behavioral SIR (BSIR) models (Eksin et al., 2019; Eichenbaum et al., 2021; Atkeson et al., 2021; Piguillem and Shi, 2022; Guerrieri et al., 2022; Bisin and Moro, 2022; Garibaldi et al., 2020, among the most notable). Similar applications were first exploited by Philipson and Posner (1993) for the HIV epidemic. We depart from this theoretical literature by empirically investigating a reduced form relationship to identify and quantify the significance of behavioral responses absorbing any mandatory policy variability. As this theoretical literature is expansive, we are restricting ourselves to a selection of particularly relevant contributions.

³ We check if fixed effects models are misspecified (Gauthier, 2021; Callaway and Li, 2023). We test the violation of the parallel trends assumption and we exclude heterogeneous treatment effects over time and across regions by absorbing the variation due to mandatory policy, i.e., this study does not exploit lockdown implementations.

⁴ Testing for a mobility response in a country that decided on a complete lockdown is likely to generate a conservative estimate.

health-related containment measures that were changing at the weekly level under the responsibility of the 20 regional health authorities (including non-pharmaceutical interventions such as resource allocation, risk communication, social distancing, and travel restrictions).⁵

To our knowledge, no other empirical study has specifically examined how the first wave of COVID-19 influenced potential immunization and linked it to behavioral responses, such as risk taking. By addressing this gap, our paper contributes to two prominent strands of literature that use mobility data to explore the relationship between behavior and the spread of contagious diseases.

On the one hand, the research seeks to understand how behavior and restrictions on individual behavior (such as school closures, curfews, and work-from-home orders) influence the spread of diseases. Using comprehensive mobility data from Switzerland, [Persson et al. \(2021\)](#) document the effect of various non-pharmaceutical public health measures on mobility levels and their subsequent effect on the spread of COVID-19. [Carranza et al. \(2022\)](#) show that the degree of adherence to non-pharmaceutical interventions is to a large degree driven by socioeconomic status and that reduced mobility translates into fewer infections. Similarly, [Badr et al. \(2020\)](#), [Sears et al. \(2023\)](#), and [Caselli et al. \(2022\)](#) show that stay-at-home mandates and the resulting reduction in mobility had a substantial effect in suppressing the spread of COVID-19 in the US and in Italy during the early phase of the pandemic. Interestingly and consistent with an endogenous reaction to perceived infection risk and the presence of a scarring effect, the first two papers show a reduction in mobility even before the implementation of restrictions.

While these papers focus on the idea that levels of mobility can be seen as a proxy for socializing, and thus for the opportunities for a disease to spread, there are also several contributions that use interregional mobility patterns to model contagion networks and to predict spatial-temporal patterns of disease propagation. Prominent examples include [Wesolowski et al.'s \(2012\)](#) analysis of the spread of malaria in Kenya and [Jia et al. \(2020\)](#) showing how population flows out of Wuhan, captured by mobility data, can explain subsequent COVID-19 infections in the rest of China.

On the other hand, mobility data has also been employed to understand how individuals endogenously adjust their behavior to risk and perceptions of risk and how their response varies with demographics. [Argente et al. \(2022\)](#) analyze changes in mobility following text messages sent by South Korean authorities informing residents about the recent whereabouts of newly diagnosed COVID-19 cases. They document a significant reduction of mobility into city districts of Seoul with a high number of such text messages. [Ding et al. \(2020\)](#) and [Besley and Dray \(2022\)](#) show that individuals reduce their mobility levels when local cases are high, and the magnitude of this response depends on social and civic capital. Furthermore, [Gutierrez et al. \(2022\)](#) underscore the importance of perception of local risk by analyzing the impact of delays between occurred and reported deaths in Mexico on pandemic growth and responses in an online survey, while [Faia et al. \(2022\)](#) show for the US evidence of confirmation bias in belief updating about the pandemic risk. They also show the importance of such beliefs of political partisanship, which were less present in Italy. [Giulietti et al. \(2023\)](#) also document an impact of local risk perception on behavior by showing increased vaccine uptake in areas with high death rates in the period preceding the vaccine roll-out.⁶

We contribute to these strands of literature by emphasizing both the role of the internalized immunity channel and the behavioral response to risk, which outweighs the potential influence of the scarring effect. While previous literature studies behavioral response from a theoretical perspective ([Bisin and Moro, 2022](#); [Garibaldi et al., 2020](#)), or calibrates models to match it ([Farboodi et al., 2021](#)), we devise a quasi-experimental approach to analyze the relationship between risk of death and mobility. Our results are also important for the debate on the effectiveness of stringent lockdown measures in controlling the pandemic ([Piguillem and Shi, 2022](#); [Pollinger, 2023](#)). Empirically, [Cronin and Evans \(2021b\)](#) show that individuals voluntarily reduced visits to high-risk locations, thus internalizing information about health risks. Given that less than 20% of the drop in foot traffic to high-risk areas is due to public restrictions, the authors argue against broad shutdowns. In addition, [Goolsbee and Syverson \(2021\)](#) demonstrate that during the pandemic, the drop in consumer visits was primarily driven by individuals' voluntary avoidance of commerce, rather than government restrictions.⁷ Our results also relate to studies on optimal policy where individual responses might generate heterogeneous benefits for different subgroups. For example, a strict and long lockdown for older individuals can reduce deaths and allow for less strict lockdowns for lower-risk groups. Consistent with [Acemoglu et al. \(2021\)](#), we find that voluntary behavioral changes — apart from the effects of lockdowns — can achieve some objectives of mandatory policies, such as reducing contagion and deaths. Therefore, it remains relevant to investigate how government restrictions interact with behavioral adjustments and how these interactions vary across different groups. Indeed, optimal policies that differentially target risk/age groups significantly outperform uniform policies ([Acemoglu et al., 2024, 2021](#)).

More broadly, our work also relates to the theory of risk compensation ([Peltzman, 1975](#)), suggesting that people typically adjust their behavior in response to perceived levels of risk, becoming more careful where they sense greater risk and less careful if they feel more protected. Such risk compensation has already been observed in the context of e.g. road safety ([Pope and Tollison, 2010](#)),

⁵ Note that the national health service and health care decisions in Italy are regionally based. The system provides universal coverage to citizens, with public health care that is largely free of charge. Treatments that are covered by the public system and a small co-payment include tests, medications, surgeries during hospitalization, family doctor visits, and medical assistance provided by pediatricians and other specialists.

⁶ [Barrios et al. \(2021\)](#), [Durante et al. \(2021\)](#) and [Bian et al. \(2022\)](#) point to a substantial role of social and civic capital in driving mobility reductions and adherence to public health interventions. [Deiana et al. \(2022\)](#) show that compensation measures aimed at improving the fairness of a crisis policy response nudge compliance with emergency rules, reducing the risk. On the contrary, [Fetzer \(2022\)](#) finds that the UK government's large-scale subsidy program encouraging dining out during the first 2020 COVID-19 wave contributed to the increase in new COVID-19 cases, thereby accelerating the onset of the second wave.

⁷ [Gupta et al. \(2020\)](#) review the social and economic effects of COVID-19 in the US, focusing on the impacts of policy-driven and voluntary social distancing on mobility, labor markets, and public health. They discuss models for understanding social distancing and policy typologies during closures and re-openings. They also review new data and present findings on behavioral versus policy-induced shifts in mobility during the pandemic.

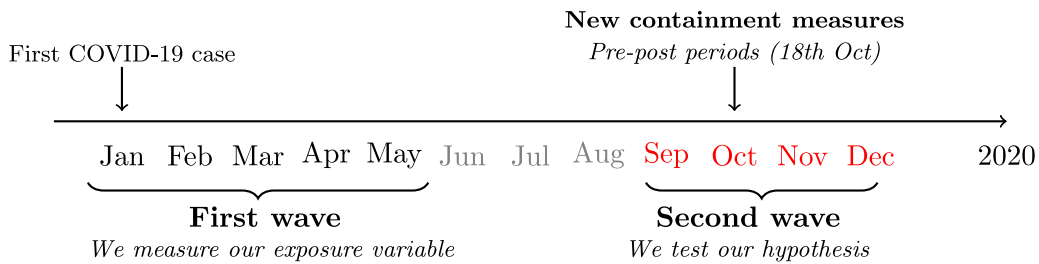


Fig. 1. Timeline.

recreational sports (Shealy et al., 2006), as well as migration (Deiana et al., 2024). Moreover, for other infectious diseases, there is survey-based research analyzing the relationship between immunity and risk-taking. In the context of Lyme disease (Brewer et al., 2007) documents increased risk-taking following vaccination. For HIV (Godlonton et al., 2016) find no evidence for increased risk-taking following an information campaign about the decreased infection risk associated with circumcision. In contrast, Holt et al. (2018) document an increase in risk-taking in the context of HIV pre-exposure prophylaxis.

The paper is organized as follows: in Section 2, we describe the background, data sources, and present some descriptive statistics. In Section 3, we present our results in the context of a conceptual framework outlining the relationships between the relevant variables and the empirical model. Section 4 concludes.

2. Setting and data

In this section, we illustrate the epidemiological and institutional context. Then, we describe the data source and the identification strategy, which is based on a difference-in-differences setup. Fig. 1 summarizes the timeline of the events.

2.1. A brief background of the COVID-19 pandemic in Italy

The first COVID-19 wave

The first two Italian cases of the pandemic were confirmed on January 30, 2020, when two Chinese tourists were hospitalized in Rome and tested positive for COVID-19. The first recorded non-travel-related COVID-19 case occurred in Codogno (Lombardy) - when a 38-year-old man from Codogno went to the emergency room with severe pneumonia. An outbreak of COVID-19 infections was subsequently detected on February 21, 2020, starting from 16 confirmed new cases in Codogno (LO), Lombardy, which increased to 60 the following day, and with the first deaths reported on February 22. Over fifty thousand inhabitants residing in 11 municipalities in Northern Italy were locked down. From then on, the health crisis worsened quickly.⁸

First, between March 8 and 9, the central government extended stay-at-home orders to all regions in the North (Emilia-Romagna, Friuli-Venezia Giulia, Lombardy, Veneto, Piedmont, and Liguria), while on March 10, 2020, the government extended the *anti* COVID-19 measures to all 20 regions. Two weeks later, the Prime Minister announced even more stringent measures, such as the closures of all non-necessary economic activities (Borri et al., 2021). The measures adopted were further extended until April 13 and then until May 3. With the end of the lockdown, on May 4, 2020, some production activities reopened, while others had to wait until May 18. The cumulative number of COVID-19 cases reported in Italy by the end of May was 232,639. The peak number of active cases was in March (113,351,) while by May the number had dropped to 22,893.

The second COVID-19 wave

With the beginning of summer, the number of people testing positive decreased, and consequently, the government eased the lockdown-type containment measures. From mid-June, the epidemiological spread started to increase again, but very slowly. The pace went up in September with schools reopening and economic activities resuming.

We set the beginning of the second wave to October 18, the date the Italian government introduced new containment measures (Decree 18 October 2020) with more stringent obligations to wear masks, social distancing, and more restrictions on access to universities, restaurant activities, private and religious ceremonies, and sports events (Manica et al., 2021).

The wearing of masks became mandatory both outside and indoors. On November 7, a curfew between 10pm and 5am was imposed, with shopping malls closed on weekends and the use of distance learning for all high schools, but otherwise, people were free to move. With one caveat, to further reduce the contagion curve, the Italian government imposed a system of physical distancing measures organized in progressively restrictive tiers (coded yellow, orange, and red) each week regionally according to real-time epidemiological risk assessments (Decree 4 November 2020).⁹ To capture behavioral changes in mobility that are not influenced by these regional restrictions, we are going to measure the mobility net of any region by week variation. We use data from 2020 through mid-December, before the start of vaccine deployment on December 27.

⁸ In these areas, the central government suspended public and private events of any nature, closed schools of any kind, as well as museums and other institutes and places of culture, and all commercial activities, excluding those for the sale of basic necessities.

⁹ Each week, a Steering Committee, comprising representatives from the Ministry of Health and regional authorities, reviewed regional pandemic data. Based on updated risk assessments, regions could be reassigned to a different zone through a Ministry of Health decree. The red zone imposed the strictest measures,

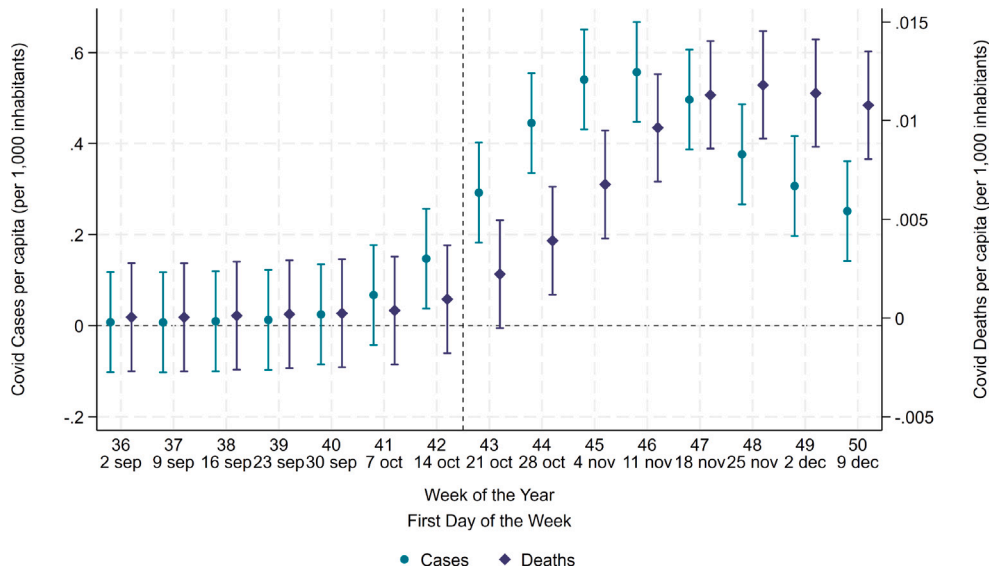


Fig. 2. COVID-19 cases and deaths.

Note: Cases represent the rate of seropositive individuals for COVID-19 per 1000 inhabitants. Excess deaths indicate the rate of deaths (presumably) due to COVID-19 per 1000 inhabitants. We present both the week of the year and the first day of each week; for example, week 36 starts on September 2, 2020, week 42 starts on October 14, 2020, and week 50 starts on December 9, 2020.

2.2. Data

The data used in this paper comes from two main sources.

We construct a measure of daily excess deaths using official municipality-level data from the National Institute of Statistics (ISTAT) for the period January–December of each year, starting in 2015 and ending in 2020. The dataset represents the main comprehensive source of epidemiological information in Italy and has full coverage of all deaths that occur over the national territory in each calendar year. While the standard procedure to release the data takes usually more than a year, during the pandemic, ISTAT sped up the dissemination of the data for all 7,903 existing municipalities. These data have previously been used to evaluate the effect of the closing of all non-essential economic activities on mortality by COVID-19 (Borri et al., 2021).¹⁰ We compute excess deaths as the difference in the daily number of deaths at the municipal-day level (m) in 2020 with respect to the municipal daily average in the five preceding years (as in Woolf et al., 2020). Using excess deaths as a proxy of COVID-19-related mortality overcomes issues related to the potential endogeneity of testing policies, hospital capacity, and death classification across municipalities.

Reassuringly, according to Fig. 2, the timeseries of excess deaths during the second wave follows the number of COVID-19 cases, but with a delay of one week. It is worth keeping this in mind, as individuals may also look at COVID-19 cases to predict future health risks.

We use measures of excess death in two ways: first, we construct our exposure variable based on the COVID-19 incidence during the first wave. The variable is based on the difference between per-capita average daily deaths during the first wave (January–May 2020) and the corresponding numbers for the years 2015 to 2019, i.e. we compute the cross-sectional daily excess death rate (D_m^1) as follows:

$$D_m^1 = \frac{1000}{152 \times N_{m,2020}} \left(\sum_d D_{m,d,2020} - \frac{1}{5} \sum_y \sum_d D_{m,d,y} \right) \quad (1)$$

for $d \in \{\text{Jan} - \text{May}\}$ and $y \in \{2015, \dots, 2019\}$

where: $N_{m,2020}$ is the municipality population on January 1st, 2020; 152 days are the days of exposure during the first wave; $D_{m,d,2020}$ is the number of deaths in municipality m in day d during January 1 to May 31; $D_{m,d,y}$ is identical to the former, but refers to years $y = 2015 \dots 2019$. We measure the daily death rate per 1000 inhabitants and for those over 50 (our main exposure variable).

We similarly define the first of the two main outcomes of interest $D_{m,d}^2$, which is the daily excess death rate during the second COVID-19 wave. However, instead of averaging over the second wave period, we compute the excess deaths for each single day

including stay-at-home orders, closure of non-essential businesses, and distance learning for all schools. In the orange zone, bars and restaurants could offer takeaways until 10 pm, and home deliveries were permitted. Yellow zones had moderate restrictions, allowing outdoor activities near homes and in-person schooling for younger grades, while the white zone indicated the lowest risk with minimal restrictions.

¹⁰ Others estimate mortality in a counterfactual scenario without COVID-19 (Depalo, 2021; Cerqua et al., 2021).

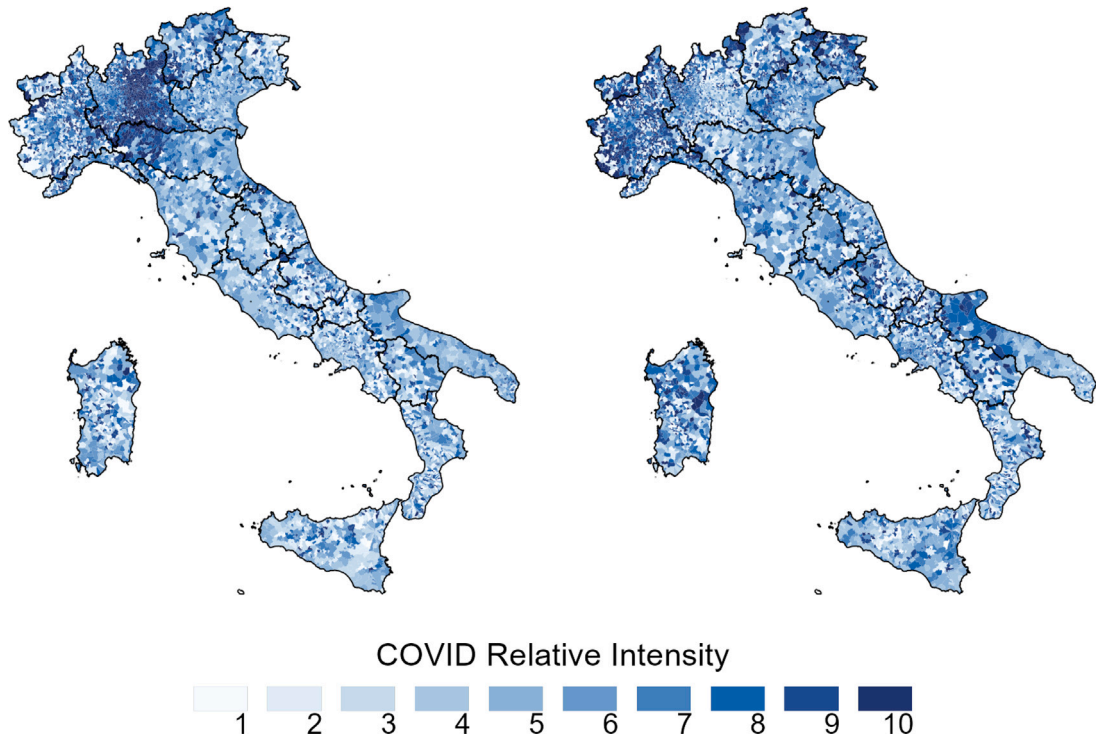


Fig. 3. Excess death rates during the first and second wave.

Note: COVID-19 relative intensity corresponds to the 10 deciles of the excess death rate wave-specific distribution. For wave 1, the variable corresponds to D_m^1 , for wave 2, the variable is computed as D_m^2 , substituting the period January–May 2020 with September–December 2020.

between September 2 and December 15, 2020:

$$D_{m,d}^2 = \frac{1000}{N_{m,2020}} \left(D_{m,d,2020} - \frac{1}{5} \sum_y D_{m,d,y} \right) \text{ for } y \in \{2015, \dots, 2019\} \quad (2)$$

Mapping the deciles of excess deaths in Wave 1 (Panel (a) of Fig. 3) shows a clear North-South divide. Despite this, we observe enough variation across the almost 8,000 municipalities to capture differences within the weekly 20 regional anti-COVID-19 health measures. The right panel shows the corresponding variation during the second wave (averaged across time). Places that were less hit during the first wave appear to be more hit during the second wave.

We combine data on mobility indicators, also at the municipal and daily level, using the City Analytics by EnelX and HERE Technologies (EnelX henceforth), which are based on anonymous aggregated data from connected vehicles, navigation maps, and systems, such as geolocation data from mobile apps. The indicator produced by EnelX measures the percent change in the mobility on the day d in municipality m from a baseline defined as the average mobility between January 13 to February 16, 2020, in the same municipality:

$$M_{m,d}^2 = \frac{\text{mobility}_{m,d} - \text{mobility}_{m,13Jan-16Feb}}{\text{mobility}_{m,13Jan-16Feb}} \quad (3)$$

The main advantage of these data, compared to alternative mobility data (such as Google or Facebook mobility data) lies in their geographic granularity. The EnelX mobility indicators are available for 7903 municipalities, while Facebook and Google mobility reports are available only for the 107 provinces. EnelX mobility data track with high precision, Facebook mobility data (Borri et al., 2021). In Appendix Fig. A.1, we show that aggregating the EnelX mobility data at the province level generates a series that resembles very closely the Google mobility report data. Regressing for each province, the daily average Google retail and recreation, grocery and pharmacy, transit stations, and workplaces mobility against the EnelX daily mobility generates a distribution of R-squared that tends to be larger than 80 percent (the average is 86 percent). Overall, the two timeseries are very similar.

2.3. Descriptive evidence

At the beginning of the pandemic, a small number of human interactions, followed by travel restrictions, determined a fairly uneven spatial distribution of COVID-19. The most famous case is the city of Bergamo and the nearby Seriana Valley. During the first COVID-19 wave, emergency departments and hospital wards in Bergamo were overflowing with patients, and triage had to be

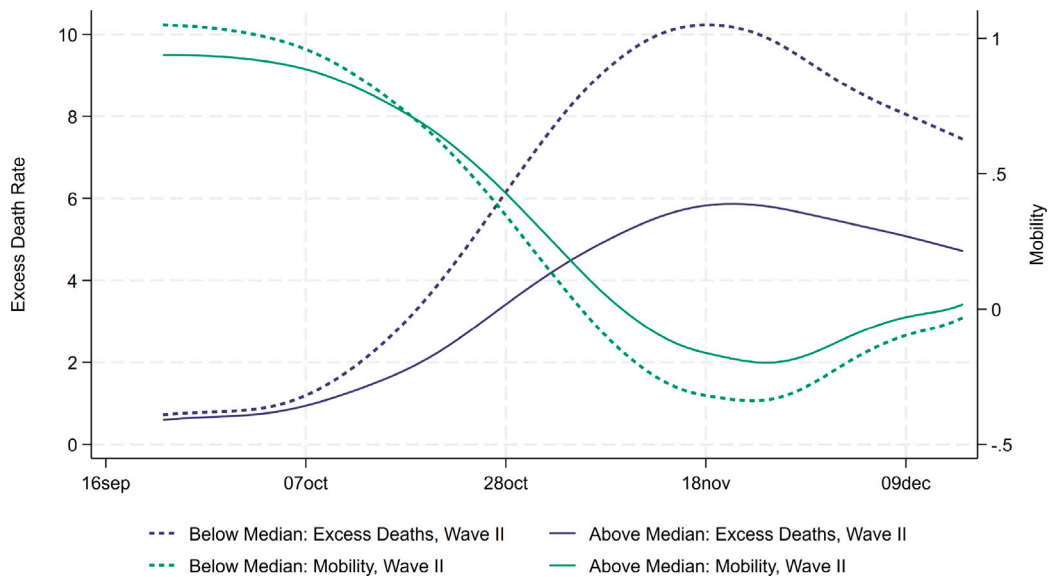


Fig. 4. Excess death rate and mobility during the second wave.

Note: COVID-19 Relative Intensity (Wave 1) groups municipalities above/below the median of the region-specific distribution of excess mortality during the first wave. The daily time series of average excess death rate (darker colors) and average mobility index (lighter colors) are re-scaled using the first three weeks of September and smoothed using local polynomial regressions. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

performed to determine who would receive treatment. Meanwhile, municipalities in nearby valleys experienced significantly lower rates of infection and mortality.

In contrast, during the second wave, the hospital wards in Bergamo were relatively empty, with sufficient capacity to treat patients from regions of Italy most severely affected. As shown by [Buonanno et al. \(2020\)](#), this pattern was observed across the Lombardy region.¹¹ Using data from all Italian municipalities, we document the same pattern. [Fig. 3](#) illustrates that areas severely impacted by the first COVID-19 wave experienced lower rates of infection and mortality during the second wave.

As a way to counter the second rapid rise in COVID-19 infections observed starting at the end of September 2020, the Italian government progressively increased restrictions aimed at promoting physical distancing. At first, restrictions were set at the regional level, while beginning on October 18th, 2020, interventions were uniformly enacted at the national level by the Minister of Health and the Technical-Scientific Committee. Yet, compared to the first lockdown, with its full-day curfew, the new curfew was taking place only at night, from 10pm to 5am. This implied that during the day, individuals were free to move and thus influence their risk of infection.¹²

In order to describe differences in mobility during the second wave that are driven by the intensity of the first wave — within each of the 20 regions — we divide municipality-level excess rates during the first wave into above and below the median rates ([Fig. 4](#)). We then compute and plot the smoothed average daily excess death rate and mobility indicator for the end of 2020 (September to December), rescaled by the corresponding averages during the first three weeks of September. There is clear evidence that municipalities hit more severely by COVID-19 during the first wave are less hit during the second one, and that individuals respond to the reduced risk by a relative increase in their mobility.

In particular, at the peak of the second wave, municipalities below the median mortality during the first wave, face a rescaled excess mortality that at the peak is twice as large when compared to the above median exposed municipalities. In response to risk, mobility falls everywhere, but less so in municipalities severely hit during the first wave. To analyze this evidence more formally, we employ the following empirical setup.

2.4. Empirical strategy

There are potentially two ways to identify the effect of mortality during the first wave on risk-taking behavior and excess death rates during the second wave. The first, in the spirit of Granger causality, uses time-series variation and the delay between mobility

¹¹ A serological study by [Perico et al. \(2020\)](#) found that 38.5% of Bergamascan workers had antibodies against COVID-19, indicating a substantial level of immunity within the population.

¹² On November 4, 2020, the Italian Minister of Health, enacted a new legislation categorizing Italian regions into four distinct zones: red, orange, yellow, and white, each representing one of three different risk scenarios.

and mortality that is due to the incubation period of the virus, and the second exploits cross-sectional variation in COVID-19 immunization during the second wave.

The main limitation of the first approach is that the behavioral test would only be valid if individuals living in a municipality are well informed about high-frequency changes in mortality risk. The second test is considerably more forgiving, as individuals living in the municipality would have several months to learn about immunity acquired in the first wave, where immunity is meant in a broad sense, as reduced risk of severe infection and may not only be driven by viral immunity but also be due to improved medical treatments that are local.¹³

We focus on the second approach but exploit the time dimension to show how the effects develop over time. This allows us to develop a two-way fixed effect event study.¹⁴ On October 18, 2020, second-wave restrictions were implemented nationally and enforced regionally, with measures tailored to varying levels of contagious risk. We define this period as the *post-period* in a standard difference-in-differences design (DD), where our main exposure variable is the excess death rate at the municipality level during the first wave (January–May 2020). This measure is aimed at capturing subsequent immunization. Our reduced forms focus on two main outcomes during the second wave of the pandemic: *daily excess death rates* and *daily mobility* (changes) at the municipality level.

Note that we do not need the geographical spread of COVID-19 infection rates during the first wave to be as good as randomly assigned, but only that more and less exposed municipalities to the pandemic follow similar patterns in mortality and mobility before the second wave. To be more precise, we estimate a linear model of excess deaths or mobility $Y_{m,d}$. Region-by-week fixed effects (ϕ_{rw}) subsume any changes in health measures determined weekly by regional health authorities, depending on the contagious risk. This is particularly relevant for Italian regions that were categorized into four distinct zones — red, orange, yellow, and white — each based on varying levels of contagion risk. Absorbing this variability, we focus on human response rather than mitigation policy changes.

$$Y_{m,d} = \psi + \phi Post_d \cdot D_m^1 + \omega_m + \eta_d + \phi_{rw} + \epsilon_{m,d} \quad (4)$$

Differences in outcomes for municipality m on the day d may in part depend on municipality-level unobservables ω_m that do not change over our 4-month time period, for example, differences in infrastructure, economic development, labor force participation, population's age structure, mortality levels that are not due to COVID-19, etc. Daily fixed effects η_d capture any changes in containment measures that occur at the country level.

Our first outcome of interest is the excess death rate, measured as the difference between the death rates in 2020 and the average in the years 2019–2015 per 100,000 ($D_{m,d}^2$). Our second outcome of interest is the daily indicator of mobility flow variations with respect to the January–February 2020 baseline period drawn from City Analytics by EnelX. The exposure variable D_m^1 , represents the municipal excess death rate for individuals aged 50 and over during the first wave of the pandemic (January 1 to May 31, 2020).¹⁵ We define a dichotomous variable $Post$ that is equal to one after the start of the second wave, that is after October 18 (week 42), i.e. when the Italian government introduced the Wave 2 containment measures. All regressions are weighted by population, and we account for potential heteroskedasticity in the errors by clustering standard errors at the municipality (m) level.

A critical assumption for our identification strategy is that municipalities more exposed to the first wave of COVID-19 and those that were less hit behave similarly in the pre-period, i.e. before the start of the second wave, to ensure that the municipalities with higher COVID-19 penetration are not endogenously related to trends in both outcomes: excess mortality and mobility in the second wave.

Event-study figures generate an eyeball test for such pre-existing trends. This implies that the average change in the comparison group represents the counterfactual change in the treatment group if there was no treatment. The event-study regressions have the following form:

$$Y_{m,d} = \psi + \sum_{\tau=37}^{50} \phi^\tau D_m^1 W_\tau + \omega_m + \eta_d + \phi_{rw} + \epsilon_{m,d}, \quad (5)$$

ϕ^τ are the week-specific coefficients of the interactions between the set of week indicators W_τ and the exposure variable D_m^1 . If the leads in the event-study analysis are not statistically different from zero, then the treated municipalities are trending similarly with respect to the untreated municipalities before the beginning of the second wave of the pandemic.

This model specification allows for 6 pre- (37th–42nd week) and 8 post-treatment effects (43rd–50th week), with respect to the baseline week 2nd–8th September, i.e., the first week after the summer break. If the leads are not statistically different from zero, we can assume that the parallel trends assumption holds. The coefficients from week 14th–20th October, instead, allow us to examine whether the treatment effect increases or stays constant over time.

In addition, we perform a series of robustness checks that include alternative sample selection, different exposure variables, additional fixed effects, clustered standard errors, and randomization inference methods to reinforce the validity of our identification strategy.

¹³ Moreover, analyzing the phenomenon solely using cross-sectional data would overlook the path dependence of the mandatory policies implemented at different times and locations.

¹⁴ We are in the context of everyone being treated at the same time, i.e. there is no staggered in the treatment assignment, so the estimation with two-way fixed effect provides correct and interpretable estimates (Roth et al., 2023).

¹⁵ As a robustness we also use the excess death rates for the entire population. Results are virtually unchanged.

Table 1
Main results.

	(1) D ² Excess deaths	(2) M ² Mobility	(3) M ² Km
D ¹ × Post	−0.094*** (0.01)	46.074*** (6.367)	41.151*** (5.553)
Cons	0.008*** (0.000)	8.346*** (0.037)	5.382*** (0.033)
Elasticity	−0.141	0.037	0.041
Municipality FE	✓	✓	✓
Day FE	✓	✓	✓
Reg × week FE	✓	✓	✓
Sample mean			
D ¹ (over 50)	.012	.012	.012
D ²	.008	.008	.008
M ²	15.026	15.026	15.026

Note: Observations are 821,656. In column (1), the outcome is the daily excess death rate per 1000 inhabitants during the second wave as in Eq. (2). In columns (2) and (3), the outcomes are the mobility index and the number of kilometers traveled in day d and municipality m as in Eq. (3). The exposure variable is D^1 , which measures the daily incidence of COVID-19 during the first wave (Jan-May) for over 50, as in Eq. (1). $Post$ that is equal to one after the start of the second wave, that is after October 18 (week 42), i.e. the date the Italian government introduced the Wave 2 containment measures. All regressions include municipality, day-fixed effects, and week-by-region dummies. Standard errors are clustered at the municipality level (7874).

* $p < .10$ ** $p < .05$ *** $p < .01$.

3. Results

3.1. Main empirical findings

To see whether the descriptive evidence is robust to more stringent constraints, we now estimate the empirical model developed in Eq. (4). Table 1 presents the main results on the relationship between previous exposure to the pandemic — summarized by the daily excess mortality of COVID-19 during the first wave D^1 — and the two outcomes of interest: excess death rate and mobility during the second wave.

In columns (1) and (2), we report the ϕ coefficient of the DD estimating Eq. (4) for, respectively, the excess mortality (D^2) and mobility (M^2) over the second wave. To get a better sense of the immunity that the first wave generates, in column (1) we regress excess mortality in the second wave on excess mortality in the first times a post Wave 2 dummy. The estimated coefficient implies that one extra daily death per 1000 inhabitants during the first wave reduces daily excess death rates during the second wave by approximately one death per 10,000 inhabitants. The corresponding elasticity — evaluated at the means of D^2 and D^1 — is equal to -0.14 , which is arguably important and large enough for individuals to notice. This result aligns with those of Vinceti et al. (2021), suggesting that, although immunity levels were below the herd immunity threshold, they may have been sufficiently high in places heavily affected by the first wave to interact with behavioral factors and thus reduce the intensity of the second wave.

In column (2), we compute the elasticity of second wave mortality with respect to the exposure variable. The estimated elasticity is 0.037. A one percent increase in the first wave death rates induces roughly a 0.04 percent increase in mobility during the second wave. With a standard deviation of D^1 being 0.045 — four times the mean — this estimated elasticity is substantial. Specifically, a one-standard-deviation increase in first-wave mortality results in a 16% increase in mobility during the second wave. In column (3), we find similar results using a different measure of mobility, also produced by EnelX, which uses the daily percentage change in the number of kilometers traveled within a given municipality with respect to the baseline period January–February 2020.

Our identification strategy relies on the assumption that more and less exposed municipalities to the COVID-19 pandemic — measured with D^1 — followed a similar path before the new restrictions were implemented. If this is the case, it allows us to use less exposed municipalities as a counterfactual for the evolution of more exposed ones. To ensure that this condition holds, we employ an event-study approach and re-estimate our main specification, incorporating leads and lags of the suspension period, as outlined in Eq. (5). To strengthen visual evidence and mitigate concerns about the validity of the common trend assumption, we rely on the dynamics of the effects.

Fig. 5 shows no evidence of differential behavior between treated and control municipalities before the new set of restrictions in week 43. In all cases (mobility and excess death rate in the second wave), there is no evidence of an anticipation effect, as the coefficients in the pre-period are never statistically different from zero. This is consistent with the parallel trend assumption, which also alleviates concerns related to scarring effects. Once the second COVID-19 wave hit, individuals living in municipalities with presumably more acquired immunity experienced reduced excess death rates and increased mobility.

The effect of first-wave mortality on second-wave deaths becomes evident immediately following the imposition of new restrictions due to rising infections from late October 2020 onward, and this effect persisted until the end of 2020. At the same

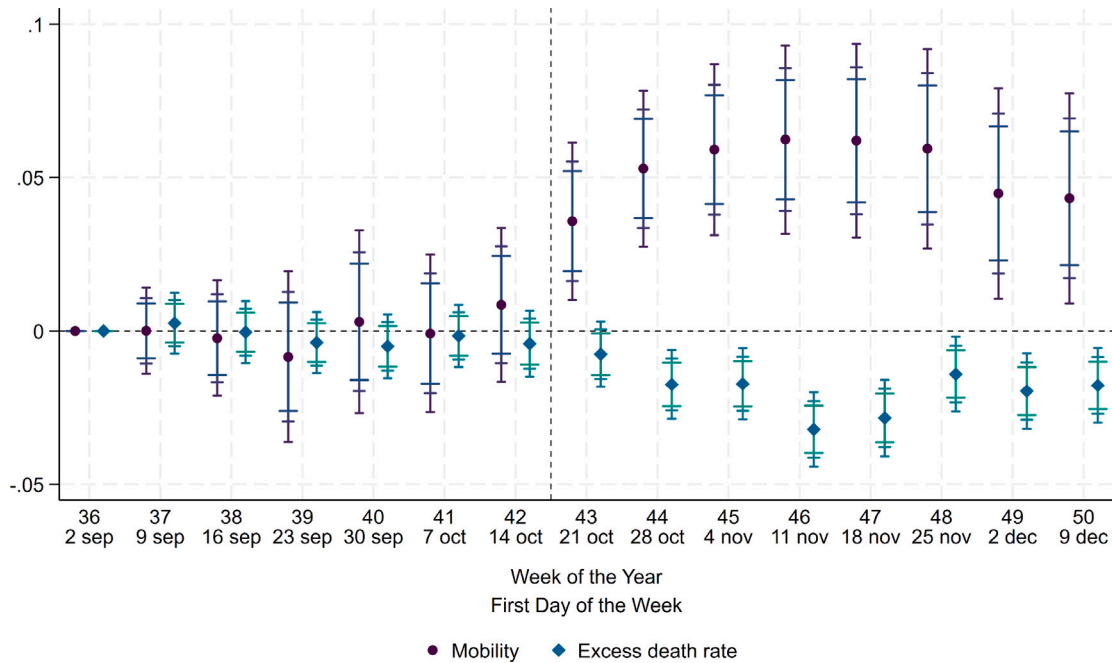


Fig. 5. Mobility and excess death rate per 1000 inhabitants.

Note: Observations are 821,656. The figure shows the dynamic effects of the results from columns (1) and (2) of Table 1. The dependent variables are the daily excess death rate per 1000 inhabitants, as specified in Eq. (2) (square), and the mobility index for the day d and municipality m , as specified in Eq. (3) (circle). The exposure variable, D^1 , measures the daily incidence of COVID-19 during the first wave (January–May) for individuals over 50, as defined in Eq. (1). All regressions include municipality and day-fixed effects, as well as week-by-region dummies. All variables are standardized. Standard errors are clustered at the municipality level. The plots display coefficients along with their corresponding 99%, 95%, and 90% confidence intervals.

time, mobility increased, indicating both an immunity effect and greater risk-taking behavior among those severely affected during the first wave.

3.2. Robustness

We perform a series of robustness tests. These include using an alternative sample selection, analyzing varying exposure variables during the first wave, incorporating additional fixed effects (such as region-by-day and province-by-week dummies), exploring the impact of different clustered standard errors, and applying randomization inference methods to assess the likelihood of spurious correlations.

These tests are summarized in Table A.1, Fig. A.3, and Fig. A.4 in Appendix A. First, we examine whether our results are robust to using a balanced panel of municipalities (for 772 out of 7,874 municipalities, we miss some observations, mostly from smaller municipalities, but these missing data do not affect the main conclusions. The first column of Table A.1 shows that the empirical findings are consistent with those in Table 1, with estimates being more precise and slightly larger in magnitude. Second, we employ a different measure of risk (D^1), using the daily excess death rate during the first wave for all age groups instead of those above age 50. Column (2) exhibits even larger effects under this alternative specification.

In a recent paper, Cronin and Evans (2021a) use the number of deaths to quantify excess mortality and life years lost during the pandemic from both COVID-19 and non-COVID-19 causes. They show that excess mortality measures may be biased estimates of COVID-19 deaths due to population trends in mortality. We replicate our main analysis using alternative definitions for both D_m^1 and D_m^2 based on a re-weighting approach similar to that proposed by Cronin and Evans (2021a).¹⁶ Reassuringly, the results in column (3) are nearly identical to the main findings, supporting the robustness of our analysis.

¹⁶ Specifically, the alternative measure of first-wave exposure is calculated as:

$$\tilde{D}_m^1 = \frac{1000}{152} \left(\frac{\sum_d D_{m,d,2020}}{N_{m,2020}} - \frac{1}{5} \sum_y \left(\frac{\sum_d D_{m,d,y}}{N_{m,y}} \right) \right)$$

for $d \in \{\text{Jan} - \text{May}\}$ and $y \in \{2015, \dots, 2019\}$

Similarly, the alternative measure of second-wave excess mortality is computed as:

$$D_{m,d}^2 = 1000 \left(\frac{D_{m,d,2020}}{N_{m,2020}} - \frac{1}{5} \sum_y \frac{D_{m,d,y}}{N_{m,y}} \right) \text{ for } y \in \{2015, \dots, 2019\}$$

In columns (4) and (5), we introduce additional fixed effects to control for residual time and geographical variability. In column (4), we include day-by-region fixed effects, yielding unchanged results. In column (5), we use province-week fixed effects, exploiting the Italian provinces as a different geographic administrative definition. Provinces represent the second-level administrative division between municipalities and regions, and many have autonomous powers. Each province has a Prefect (*Prefetto*) and a Chief of Police (*Questore*) with oversight of local law enforcement. Including province-week fixed effects captures province-level variations, resulting in smaller but still statistically significant coefficients for D^1 . Finally, we use clustering at the higher level (province), leading to minimal changes in the standard errors, further confirming the robustness of our estimates (column 6).

Fig. A.2 shows that, in the early months of the pandemic, the impact on overall mortality was due not only to deaths directly caused by COVID-19, which were initially underestimated, but also to other causes. The strain on the healthcare system during the first wave is one potential explanation for the observed discrepancy. This situation partially subsided during the second wave (ISTAT, 2022). A concern for our analysis is that the reduction in excess mortality during the second wave in places more severely hit during the first wave is the result of both an immunization mechanism and a reduction in the number of fragile individuals — those more likely to be affected by the indirect detrimental effects of the pandemic on local health systems. For this reason, the substantial mortality during the first wave may have resulted in a reduced population base for subsequent mortality.¹⁷ To mitigate these concerns, we account for selective survival between the two waves by updating the denominator $N_{m,2020}$ in our $D_{m,d}^2$ outcome measure. We replicate our main results by updating the denominator of excess mortality rates, taking into account deaths between the first and the second wave. The estimated coefficients in Fig. A.3 are virtually unchanged from the evidence provided in Fig. 5.¹⁸

Lastly, given our clustered “treatment assignment” we use randomization inference as an additional way to reject the null hypothesis of no effect. We randomly allocate D^1 across municipalities 250 times, and each time re-estimate Eq. (4). The distribution of the placebo coefficients for both the reduced forms shown in Panel (a) and (b) of Fig. A.4 are different from the coefficients estimated in the baseline regressions.

3.3. Rationalizing the empirical evidence: A conceptual framework

We offer a potential explanation for the empirical results presented earlier using a conceptual framework. For simplicity, we omit the municipality and time indices. Excess mortality during the second wave D^2 depends on contemporaneous mobility M^2 and first wave excess mortality D^1 . Similarly, mobility during the second COVID-19 wave (M^2) depends on contemporaneous excess mortality risk (D^2) as well as the excess mortality during the first wave (D^1).

The excess mortality equation follows:

$$D^2 = \alpha M^2 + \delta D^1 + u^D \quad (6)$$

The effect of mobility on mortality is measured by α . Due to increased virus circulation and contagion, mortality is likely to increase with mobility $\alpha \geq 0$. The parameter δ expresses the immunization effect, i.e. the effect of exposure in the first wave on the risk of mortality in the second wave, and is anticipated to be non-positive, $\delta \leq 0$.

The mobility equation follows:

$$M^2 = \beta D^2 + \gamma D^1 + u^M \quad (7)$$

The parameter γ measures scarring, i.e. the effect high death rates in the first wave have on behavior in the second wave and as such is thought of as being non-positive, $\gamma \leq 0$. The behavioral response of individuals to contemporaneous excess mortality is measured by β . Since individuals are likely to socialize less when the risk of infection is high, we also think of this response as being non-negative, $\beta \geq 0$.

The reduced form expression for D^2 can be written as:

$$D^2 = \alpha\beta D^2 + \alpha\gamma D^1 + \delta D^1 + \alpha u^M + u^D$$

The reduced-form coefficient from a regression of second-wave mortality on first-wave mortality is given by:

$$\pi_D = \frac{\alpha\gamma + \delta}{1 - \alpha\beta} \quad (8)$$

The two effects point in the same direction, $\alpha\gamma \leq 0$ and $\delta \leq 0$, as both the scarring effect γ (via the feedback mechanism α) and the immunization effect δ generate a reduction of mortality due to higher exposure to the first wave, as in column (1).

The main difference between these two measures and those applied in Section 2.2 is that both $\bar{D}_m^1$ and $\bar{D}_{m,d}^2$ define excess mortality using the average mortality rate in the 2015–2019 period with year-specific populations ($N_{m,y}$) as the baseline, rather than using the municipality population as of January 1, 2020.

¹⁷ If this hypothesis holds, however, one would expect to see that locations heavily impacted during the first wave would consistently record fewer deaths over the entire period, also between September and mid-October, and a corresponding decline in mobility patterns (fewer people around), which is not reflected in Fig. 5.

¹⁸ Although we are not able to re-scale our mobility measure $M_{m,d}^2$, if many people died during the first wave in a particular area, there would be fewer individuals left to contribute to mobility during the second wave. Contrary to this expectation, we find the opposite: areas hit harder during the first wave are those that show increased mobility during the second wave. Moreover, the use of region-day fixed effects should further mitigate concerns about the differential degree of strain on local health systems to the extent that they capture substantive heterogeneity in health system-related effects before and after the onset of the second wave.

Similarly, the reduced form equation of mobility is:

$$M^2 = \alpha\beta M^2 + \beta\delta D^1 + \gamma D^1 + \beta u^D + u^M$$

The reduced form coefficient in a regression of second-wave mobility on first-wave mortality is:

$$\pi_M = \frac{\beta\delta + \gamma}{1 - \alpha\beta} \quad (9)$$

Since we expect $\alpha \geq 0$ and $\beta \leq 0$, we anticipate the denominator $1 - \alpha\beta$ to be non-negative. Moreover, as argued above, we expect $\beta \leq 0$ and $\delta \leq 0$ and thus $\beta\delta \geq 0$. Thus, the sign of π_M tells us whether $\beta\delta \geq -\gamma$, that is whether the combination of immunization (δ) and behavioral response (β) has a larger impact on mobility than the absolute value of the scarring effect (γ).¹⁹

Our findings indicate that areas heavily impacted during the first wave tend to experience lower mortality rates but exhibit higher mobility levels during the second wave. Within the conceptual framework outlined, this evidence suggests that scarring effects are not predominant. Instead, individuals appear to adapt their behavior in response to risk, resulting in a smaller reduction in mobility during the second wave. The empirical evidence aligns with recent studies showing that individuals adjust their behavior based on the perception of contemporaneous levels of risk during the pandemic (Ding et al., 2020; Gutierrez et al., 2022; Faia et al., 2022; Argente et al., 2022; Eichenbaum et al., 2024).

3.4. Heterogeneous effects by age composition

The framework proposed above provides an aggregate perspective. However, the relative importance of the two identified mechanisms — the immunity-driven behavioral response and the scarring effect — likely varies across the population based on perceived levels of immunity and individual preferences for balancing risk against increased mobility. Age is a critical factor influencing these dynamics. While mortality risk is strongly age-dependent, scarring effects may be more pronounced among older individuals, and the opportunity cost of mobility is also expected to vary with age, further influencing behavioral responses.

To investigate these potential differences, we ideally would examine variations in mobility responses across age groups. However, a key limitation of our analysis is the absence of age-specific mobility data at the municipal level. To address this gap, we adopt an indirect approach by leveraging the age composition of each municipality. Specifically, we classify the population into three categories — young, middle-aged, and elderly — and introduce interaction terms in our baseline mobility specification:

$$M_{m,d}^2 = \psi + \tau_y(Post_d \cdot Y\ddot{o}ung_m) + \tau_o(Post_d \cdot \ddot{O}ld_m) + \omega_m + \eta_d + \varrho_{rw} + \epsilon_{m,d} \\ + \phi(Post_d \cdot D_m^1) + \phi_y(Post_d \cdot Y\ddot{o}ung_m \cdot D_m^1) + \phi_o(Post_d \cdot \ddot{O}ld_m \cdot D_m^1). \quad (12)$$

Here, $Y\ddot{o}ung_m$ and $\ddot{O}ld_m$ measure the shares of young and old sub-populations in municipality m , respectively, expressed as deviations from the national averages (indicated by the double dot). The coefficients of interest are ϕ_y and ϕ_o , which capture how the effect of first-wave exposure D_m^1 on second-wave mobility differs in municipalities with larger-than-average young or old populations. Since these shares are expressed in deviation form, ϕ_y and ϕ_o measure how the baseline coefficient ϕ changes when the corresponding share increases by one percentage point above the national average. Re-centering also modifies the interpretation of ϕ , which can now be viewed as the effect of first-wave exposure for municipalities with average age shares.

Since we do not have any priors on the best age cut-offs, we use a data-driven approach to estimate Eq. (12) across different cut-off values. A detailed description of the selection procedure is contained in Appendix B. As illustrated in Fig. B.1, the combination of 26 and 81 years emerges as optimal based on the highest adjusted R^2 . Fig. B.2 in Appendix B illustrates the substantial cross-sectional heterogeneity in the shares of young and old individuals across Italian municipalities.

Panel A of Table 2 presents the estimated coefficients from the mobility equation with these cut-offs, and Panel B provides the analogous results for second-wave excess mortality, D^2 .

In Panel A, the baseline effect of first-wave exposure on mobility (ϕ) is strongly positive ($\phi = 44.01$), suggesting that municipalities heavily affected in the first wave feel relatively protected and thus increase mobility in the second wave. However, this effect is dampened in municipalities with a higher share of young individuals ($\phi + \phi_y = 35.03$) and even more so in those with a larger share of elderly ($\phi + \phi_o = 27.90$). Turning to second-wave mortality in Panel B, the baseline coefficient $\phi = -0.089$ indicates a significant protective effect of first-wave exposure on second-wave mortality. This effect becomes even more negative (i.e., stronger in absolute value) in places where the young share is larger ($\phi + \phi_y = -0.102$). In contrast, in municipalities with a higher share of

¹⁹ If one is willing to assume that first-wave mortality influences mobility only through immunization, we can estimate the 2SLS coefficient. The ratio of the two coefficients corresponds to the IV parameter if the exclusion restriction holds:

$$\frac{\pi_M}{\pi_D} = \frac{(\beta\delta + \gamma)/(1 - \alpha\beta)}{(\alpha\gamma + \delta)/(1 - \alpha\beta)} = \frac{\beta\delta + \gamma}{\alpha\gamma + \delta}. \quad (10)$$

Given the sign restrictions, we have that

$$\frac{\beta\delta + \gamma}{\delta} \leq \frac{\beta\delta + \gamma}{\alpha\gamma + \delta} \leq \frac{\beta\delta}{\alpha\gamma + \delta}. \quad (11)$$

Thus, the IV parameter can, depending on α and γ , either be larger or lower than β . In the absence of scarring, $\gamma = 0$, the ratio of the two coefficients identifies the causal effect of excess mortality risk on mobility, β . But also if the mobility effect on infections is small and so is scarring, and thus $\alpha\gamma$ is close to zero, the IV parameter represents a lower bound of β .

Table 2
Estimated coefficients of the unrestricted model of mobility and mortality.

Panel A: M^2	Cut-off			
	25–80 (1)	25–81 (2)	26–80 (3)	26–81 (4)
$\phi : Post \times D^1$	44.428*** (6.214)	44.231*** (6.219)	44.213*** (6.219)	44.011*** (6.224)
$\phi_y : Post \times Young \times D^1$	−9.337*** (2.703)	−9.29*** (2.683)	−9.043*** (2.619)	−8.981*** (2.598)
$\phi_o : Post \times Old \times D^1$	−15.001*** (3.279)	−16.295*** (3.52)	−14.858*** (3.25)	−16.116*** (3.489)
<i>Linear Combination</i>				
$\phi + \phi_y$	35.091*** (6.219)	34.941*** (6.209)	35.17*** (6.235)	35.03*** (6.225)
$\phi + \phi_o$	29.426*** (6.165)	27.936*** (6.204)	29.355*** (6.177)	27.895*** (6.216)
Panel B: D^2	Cut-off			
	25–80 (1)	25–81 (2)	26–80 (3)	26–81 (4)
$\phi : Post \times D^1$	−0.087*** (0.01)	−0.088*** (0.01)	−0.088*** (0.01)	−0.089*** (0.01)
$\phi_y : Post \times Young \times D^1$	−0.016*** (0.004)	−0.015*** (0.004)	−0.014*** (0.004)	−0.013*** (0.004)
$\phi_o : Post \times Old \times D^1$	−0.001 (0.006)	0.001 (0.007)	0.000 (0.006)	0.002 (0.007)
<i>Linear Combination</i>				
$\phi + \phi_y$	−.103*** (.01)	−.103*** (.01)	−.103*** (.01)	−.103*** (.01)
$\phi + \phi_o$	−.088*** (.012)	−.087*** (.012)	−.088*** (.012)	−.087*** (.012)
Municipality FE	✓	✓	✓	✓
Day FE	✓	✓	✓	✓
Reg $\times$ week FE	✓	✓	✓	✓

Note: The table shows the estimated coefficients of the unrestricted model for the optimal combination of cut-off and close values. In Panel A the dependent variable is the mobility index for the day d and municipality m , as specified in Eq. (3). In Panel B the dependent variable is the daily excess death rate per 1000 inhabitants, as specified in Eq. (2). *Post* that is equal to one after the start of the second wave, that is after October 18 (week 42), the date the Italian government introduced the Wave 2 containment measures. We include all the double interaction terms in the model, but do not display them in the table. Standard errors are clustered at the municipality level.

* $p < .10$ ** $p < .05$ *** $p < .01$.

older residents, the interaction term is not statistically significant, implying that the estimated effect remains at the baseline level – $\phi + \phi_o = -0.087$. Increasing the share of young individuals while keeping the share of old fixed effectively reduces the middle-aged proportion, and vice versa. Since each sub-population may exhibit distinct parameter values in Eqs. (8) and (9), municipalities with a relatively higher prevalence of one group could display stronger or weaker reduced-form coefficients π_M and π_D .

Municipalities with a larger share of young individuals show a smaller upward shift in second-wave mobility following severe first-wave mortality. One explanation is that younger populations, facing lower fatality risks, generally have a weaker behavioral response, thereby tempering post-wave mobility adjustments.²⁰

In municipalities with a larger share of older individuals, the relationship between first-wave mortality and second-wave mobility is reduced even more. Older populations may exhibit stronger scarring effects.²¹ In addition, older populations may acquire less robust immunity from first-wave exposure. These two factors can reinforce one another, resulting in a further downward shift of the reduced-form coefficient π_M .²²

Despite these differences, the overall linear combination of coefficients remains positive in both cases, suggesting that the net impact of rational responses to perceived protection still leads to an aggregate rise in mobility when comparing high first-wave mortality municipalities to others.

Turning to second-wave mortality, when the share of young residents increases, the negative relationship between D^1 and D^2 is more pronounced (i.e., the effect is more negative). If a larger young population allows wider circulation of the virus in wave one (without high mortality, given the young are less vulnerable), the surviving at-risk segment may gain stronger immunity, reinforcing

²⁰ Since $\partial\pi_M/\partial\beta < 0$, a higher share of residents with a weaker behavioral response ($|\beta|$ lower) implies a reduction of π_M .

²¹ Since $\partial\pi_M/\partial\gamma > 0$, a stronger scarring effect ($|\gamma|$ higher) implies a reduction of π_M .

²² Since $\partial\pi_M/\partial\delta < 0$, a weaker immunization effect ($|\delta|$ lower) implies a reduction of π_M .

Table A.1
Robustness checks.

Panel A						
	(1)	(2)	(3)	(4)	(5)	(6)
	D ² Excess deaths					
D ¹ × Post	−0.099*** (0.01)	−0.181*** (0.022)	−0.097*** (0.01)	−0.094*** (0.01)	−0.042*** (0.011)	−0.094*** (0.017)
Cons	0.008*** (0.000)	0.008*** (0.000)	0.009*** (0.000)	0.008*** (0.000)	0.008*** (0.000)	0.008*** (0.000)
<i>Sample mean</i>						
D ¹	.012	.012	.012	.012	.012	.012
D ²	.008	.008	.008	.008	.008	.008
M ²	15.026	15.026	15.026	.008	.008	.008
Panel B						
	(1)	(2)	(3)	(4)	(5)	
	M ² Mobility					
D ¹ × Post	47.561*** (6.642)	88.844*** (13.417)	47.514*** (6.745)	46.109*** (6.374)	20.976*** (6.485)	46.074*** (8.442)
Cons	8.265*** (0.039)	8.389*** (0.034)	8.246*** (0.03)	8.346*** (0.037)	8.493*** (0.038)	8.346*** (0.049)
<i>Sample mean</i>						
D ¹	.012	.012	.012	.012	.012	.012
D ²	.008	.008	.008	.008	.008	.008
M ²	15.026	15.026	15.026	.008	.008	.008
Municipality FE	✓	✓	✓	✓	✓	✓
Day FE	✓	✓	✓	✓	✓	✓
Reg × week FE	✓	✓	✓			✓
Reg × day FE				✓		
Prov × week FE					✓	

Note: Observations are 745,710 in column (1), i.e., we select a balanced panel of municipalities (105 × 7102 municipalities). In all other columns, the observations are 821,656. The exposure variable is D^1 , which measures the daily incidence of COVID-19 during the first wave (Jan–May) for individuals over 50, as in Eq. (1). The exception are: in column (2), where we use a different exposure variable, i.e., the daily excess death rate during the first wave for all age groups, instead of the excess death rate for the population over 50 (D^1), and in column (3), where we follow the approach proposed by Cronin and Evans (2021a). The variable $Post$ is equal to one after the start of the second wave, i.e., after October 18 (week 42), the date the Italian government introduced the Wave 2 containment measures. Standard errors are clustered at the municipality level, while they are clustered at the province levels in column (5).

* $p < .10$, ** $p < .05$, *** $p < .01$.

the immunization channel.²³ On the other hand, municipalities with more young individuals may also have a weaker behavioral response ($|\beta|$ lower), which alone would reduce the magnitude of π_D .²⁴ The data suggest that the immunization channel outweighs the dampening effect of weaker behavioral responses, resulting in a net increase in $|\pi_D|$.

For municipalities with a larger share of older residents, we find no additional shift in how first-wave mortality translates into second-wave mortality. One plausible explanation is that two opposing mechanisms balance each other: (i) *stronger scarring* in older populations increases $|\pi_D|$, while (ii) *weaker immunization* reduces $|\pi_D|$.²⁵ If these effects cancel out, the net result is no overall change in municipalities with a higher old-age share.

These interpretations should be viewed as suggestive given the aggregate nature of our data, where sub-population behaviors are inferred rather than directly observed. Other unmeasured factors may also influence how different age groups adapt to the pandemic. Nonetheless, our results are consistent with the notion that scarring, behavioral responses, and immunization may operate with varying intensity across municipalities differing in age composition, yielding observable differences in both second-wave mobility and mortality patterns.

4. Conclusions

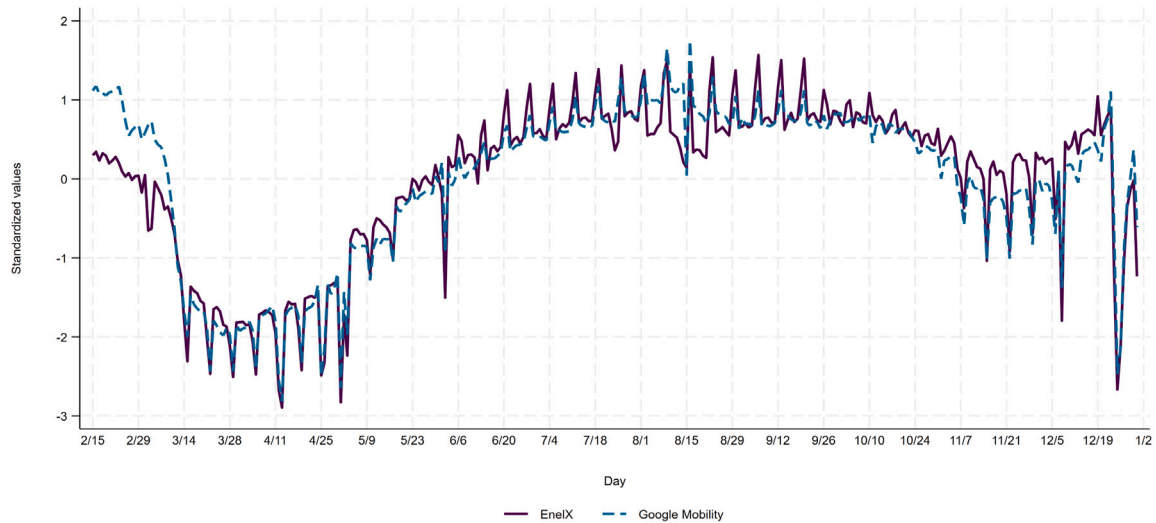
In this paper, we have established that people react to local risk of infection by reducing their level of mobility and thus their potential risk of exposure and propagation following a local increase of infections.

Using quasi-randomly distributed levels of excess death rate in the first wave of the pandemic, we study the impact on the following excess death rate and mobility during the second wave. Although we have focused on changes in mobility as an indicator

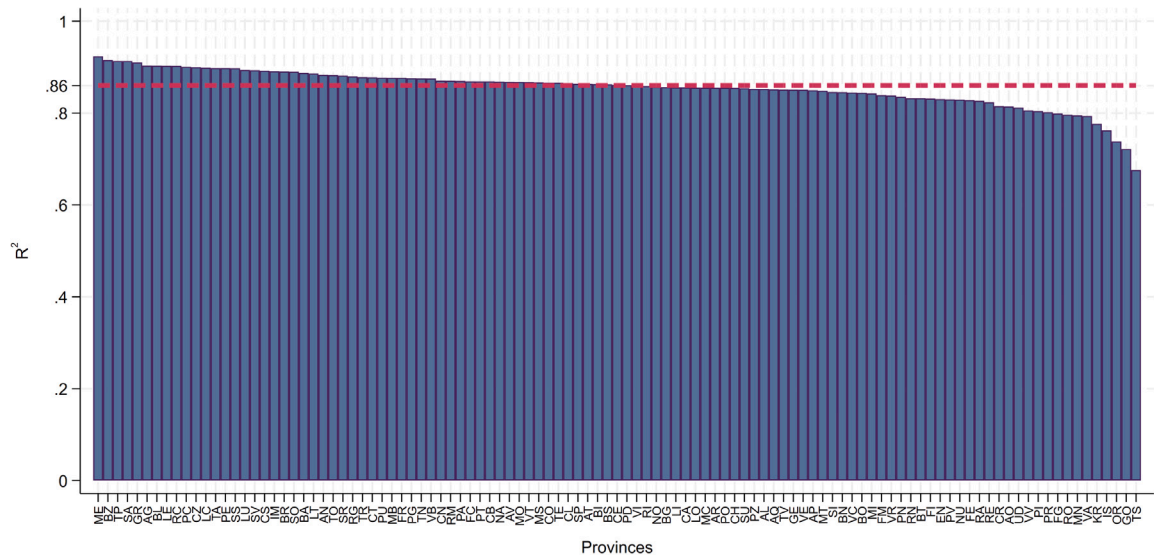
²³ Since $\partial\pi_D/\partial\delta > 0$, a stronger immunization effect ($|\delta|$ higher) implies an increase of $|\pi_D|$.

²⁴ Since $\partial\pi_D/\partial\beta < 0$, a weaker behavioral response ($|\beta|$ lower) implies a reduction of $|\pi_D|$.

²⁵ Because $\partial\pi_D/\partial\delta > 0$ and $\partial\pi_D/\partial\gamma > 0$, having $|\delta|$ decrease lowers $|\pi_D|$, whereas having $|\gamma|$ increase raises $|\pi_D|$.



(a) Time series

(b) Adjusted R^2 **Fig. A.1.** EnelX and Google Mobility Report.

Note: Figure (a) shows the daily time series of the mobility index from EnelX (solid) and Google Mobility Report (dashed line). We average retail and recreation, grocery and pharmacy, transit stations, workplace mobility variables. Data from Google is downloaded from <https://www.google.com/covid19/mobility/> and the methodological documents are from <https://support.google.com/covid19-mobility/answer/9824897?hl=en>. Last access Jan 31, 2023. Figure (b) shows the adjusted R^2 from 107 regressions, one for each province, of the two different measures of mobility: EnelX and Google. The horizontal dashed line shows the average R^2 .

of risk taking in response to local infections, it seems plausible that the observed behavioral changes also extend to other dimensions, such as wearing face masks (Mitze et al., 2020), meeting outside or visiting elderly friends and family (see, for example, Xu and Cheng, 2021). As mobility probably best captures the number of social contacts one has (extensive margin), there is likely also an effect on the quality and intensity of these contacts (intensive margin). From this point of view, the observed reduction in mobility only captures part of the story and the overall impact of behavioral changes on disease propagation is likely to be larger than the effects measured in this paper.

The observed negative response to local risk has important consequences for policymakers who want to understand the spread of diseases and how to balance between infection-reducing policies, such as shop and restaurant closures, and their implied economic

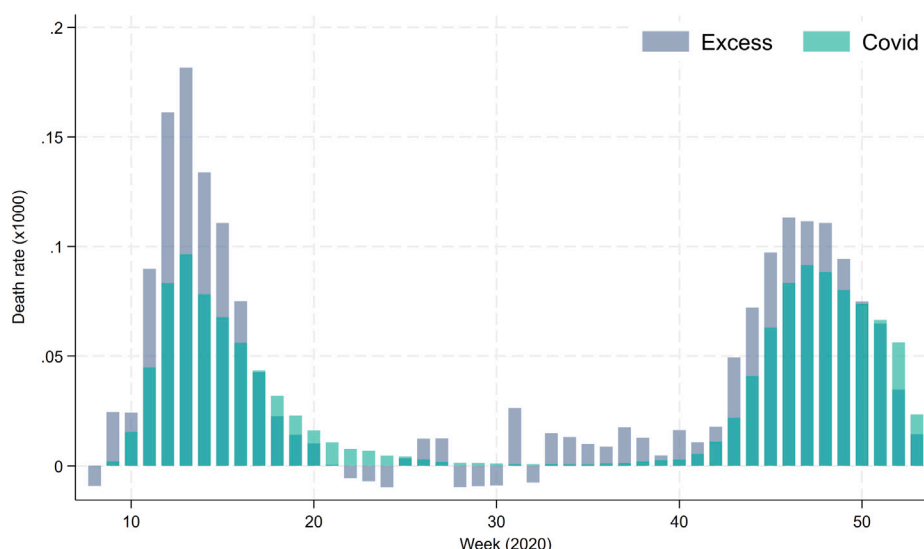


Fig. A.2. COVID-19 and Excess Deaths.

Note: The figure compares our measures of excess mortality (measured as mortality rate per 1000 inhabitants) with the mortality rate using only COVID-19 deaths during 2020. The figure reports national weekly rates. Daily data on COVID-19 deaths are available (at regional and national levels only) from the Italian National Institute of Health (ISS).

costs. Although the observed negative mobility response to local risk appears to be good news for those advocating for a more *laissez faire* approach to reducing the spread of diseases, this conclusion could be premature, as it is not clear whether people individually display optimal levels of risk reduction. Moreover, even if individuals were to display individually optimal behavior, given the apparent negative externalities of behavior on others (see, for example, [Bethune and Korinek, 2020](#)), the socially optimal level of mobility reduction is likely to be larger than the individual one and government intervention may still be warranted.

The empirical findings highlight how the age structure of a population shapes both behavioral and epidemiological responses to early pandemic exposure. Municipalities with a larger share of young residents tend to experience a more pronounced decline in second-wave mortality, likely reflecting stronger immunization dynamics following broader viral circulation during the first wave. At the same time, the mobility response in these areas — while still positive — is relatively muted, consistent with the idea that younger individuals exhibit weaker behavioral reactions to perceived risk. In contrast, municipalities with a greater proportion of older residents display a substantially reduced mobility rebound, likely driven by stronger scarring effects and weaker immunization. However, these areas do not exhibit a significantly altered mortality pattern, possibly due to offsetting behavioral and immunological forces. Overall, the findings highlight the complex interplay between immunity, behavioral adjustment, and demographic composition in determining pandemic trajectories across different communities.

From a health policy perspective, what can be done to fully leverage the observed effect? The salience of risk appears to play a central role. In Italy and other European countries, officials primarily communicated risk through the Corona traffic light system, which often covered areas with several hundred thousand inhabitants. However, as shown in this paper, people responded to changes in infection rates — likely informed by personal experience or alternative data sources — at a much more granular level. From this perspective, official risk communication should also adopt a more localized approach.

Our focus has been on the COVID-19 pandemic. However, our insights appear to be portable to other ongoing and future pandemics. For some transmissible diseases (such as Ebola and common flu) mobility seems to be a good indicator for socializing and thus risk-taking, while for others diseases (such as HIV, Syphilis, or herpes) this link appears much weaker, and other dimensions of risk-taking (such as the use of condoms or the number of sexual partners) appear to be more important. However, for most of these diseases, it appears to be plausible that individuals adapt their behavior to the risk of infection in one way or another, as documented for COVID-19 in the present study. How this happens for other pathogens appears to be an important topic for future research and understanding of how contagious diseases spread.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Tables and figures

See [Table A.1](#) and [Figs. A.1–A.4](#)

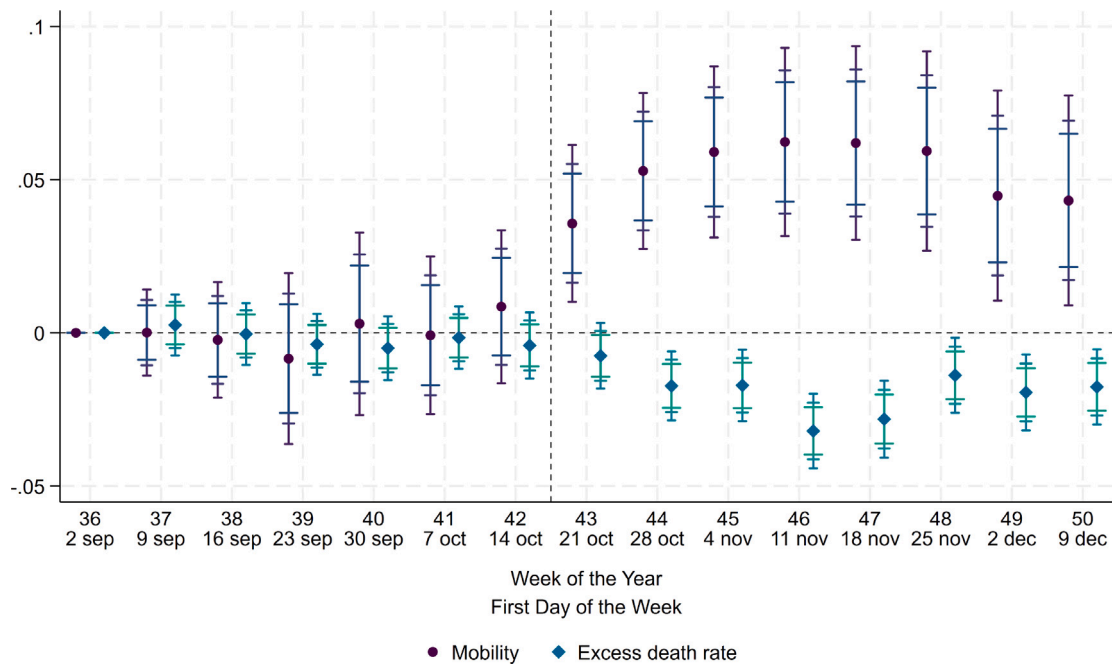


Fig. A.3. Mobility and excess death rate per 1000 inhabitants: robustness.

Note: Observations are 821,656. The figure shows the dynamic effects of the results in columns (1) and (2) of Table 1 where we adjust the population N_m . The dependent variables are the daily excess death rate per 1000 inhabitants as in Eq. (2) (square) and the mobility index in day d and municipality m as in Eq. (3) (circle), respectively. Different from Fig. 5, we calculate the denominator as the population count in 2020 minus the deaths that occurred during the first wave of the pandemic. The exposure variable is D^1 , which measures the daily incidence of COVID-19 during the first wave (Jan–May) for over 50, as in Eq. (1). All regressions include municipality, day-fixed effects, and week-by-region dummies. All variables are standardized. Standard errors are clustered at the municipality. Plots display coefficients and corresponding 99%, 95%, and 90% confidence intervals.

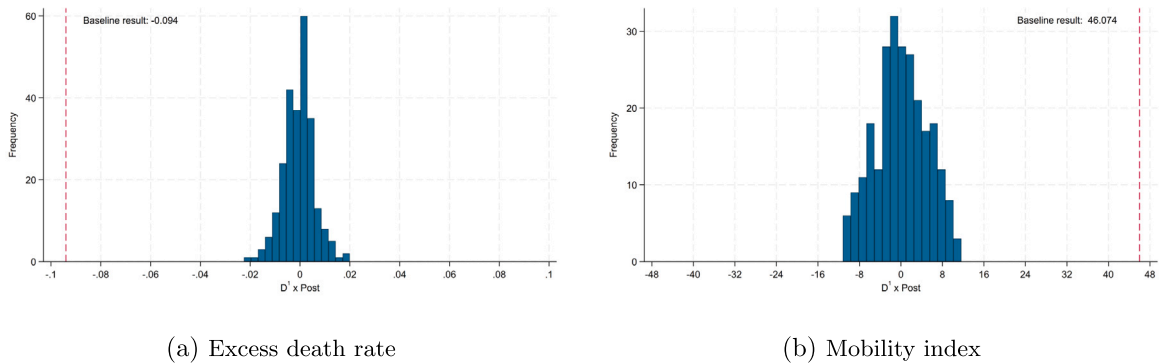


Fig. A.4. Randomization exercises.

Note: Figures (a) and (b) show the placebo for the reduced forms in columns (1) and (2) of Table 1, respectively. The falsification exercises are based on the random assignment of the exposure variable (D^1) across municipalities. We estimate the models 250 times. The coefficients estimated in columns (1) and (2) in Table 1 are -0.094 and 46.074 , respectively. All regressions include municipality, day-fixed effects, and week-by-region dummies. Standard errors are clustered at the municipality level.

Appendix B. Optimal combination of cut-offs

We take a data-driven approach and estimate Eq. (12) using various combinations of possible cut-off values, as we have no prior knowledge regarding the most suitable age cut-offs for defining the two sub-populations. More specifically, we consider values in the range 20–40 for the cut-off below (young) – τ_b – which is used to identify the share of young individuals, and 60–85 for the cut-off above (old) – τ_a . We select the optimal combination of cut-offs as the one that maximizes model fit, measured by the highest adjusted R^2 .

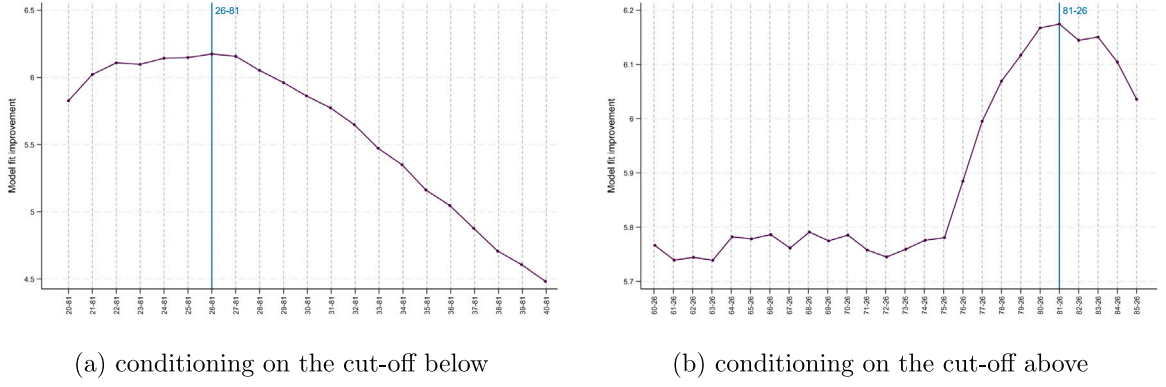


Fig. B.1. Model fit under different specifications of the cut-offs.

Note: The plot shows the value of $\tilde{R}^2$ corresponding to the best combination of cut-offs for each value of the cut-off below and above. The red vertical line corresponds to the global optimum. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

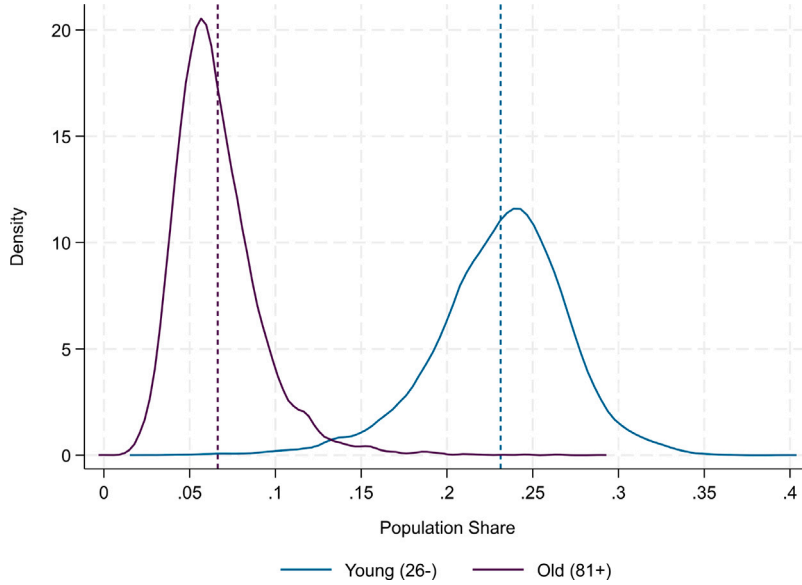


Fig. B.2. Distribution of young and old shares across Italian municipalities.

Note: The plot shows the distribution of the share of young (lighter colors) and old (darker colors) individuals across Italian municipalities. The cut-offs used to define young and old sub-populations are the optimal cut-offs identified in Fig. B.1. Dashed lines correspond to national averages. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Given that the estimating equation includes several mean-shifters — $\omega_m, \eta_d, \varrho_{rw}$ — improvements in model fit are quite small in numerical terms. For this reason, we use the relative increase in the partial R-squared:

$$Model\ Fit(\tau_b, \tau_a) = \frac{Partial\ R^2_{w\ interactions, \tau_b, \tau_a}}{Partial\ R^2_{w/o\ interactions, \tau_b, \tau_a}}, \quad (13)$$

where $Partial\ R^2_{w/o\ interactions}$ is the partial R-squared of $Post_d \times D_m^1$ (netting the full set of fixed effects), while $Partial\ R^2_{w\ interactions}$ is the partial R-squared including the full set of interactions from Eq. (12). Maximizing model fit for different cut-offs gives us $\tau_b^* = 26$ and $\tau_a^* = 81$. $Model\ Fit(\tau_b, \tau_a)$ is concave.

Fig. B.1 plots the two sections of $Model\ Fit(\tau_b, \tau_a)$ for $\tau_b^* = 26$ and $\tau_a^* = 81$, respectively. Inspecting the two plots, it is evident that the interactions deliver a sizeable increase in model fit with respect to the baseline specification. At its maximum, the relative increase in the partial R-squared is larger than 6.

Fig. B.2 shows the cross-sectional distribution of the shares of young and old individuals across Italian municipalities computed according to optimal cut-offs.

Appendix C. Supplementary data

Supplementary material related to this article can be found online at <https://doi.org/10.1016/j.euroecorev.2025.105057>.

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