INTRODUCTION

The sudden appearance of COVID-19 in early 2020 has forced governments worldwide to implement hastily arranged policies to limit the death toll from the virus, including travel restrictions, lockdowns, and business shutdowns. These measures aim to save lives by reducing the rate of new infections – “flattening the curve” – thus preventing the congestion of the health care system and ensuring that there is enough capacity to admit everyone in need (Ferguson, et al., 2020). In this paper, we investigate the effectiveness of business shutdowns, focusing on three issues in particular. First, we quantify their overall effects in reducing mortality. Second, we focus on the importance of timing – that is, when in the epidemic curve they are most effective (the when). Third, we explore how the effectiveness of business shutdowns varies depending on which particular sector of the economy is closed down (the how).

To carry out the analysis, we focus on the first wave of COVID-19 in Italy, for long one of the world’s worst affected areas. Focusing on Italy has two main advantages. The first is that the Italian government implemented a stringent business shutdown policy, affecting nearly every aspect of economic activity. This allows us to investigate the effectiveness of shutdowns in the service sector as well as in production activities. The second key advantage is the availability of highly granular daily death registry data, as well as data on socio-demographic, labor market and territorial characteristics, for thousands of municipalities. We use these data in a diff-in-diff approach, exploiting a peculiarity in the implementation of the business shutdowns...
policy that allows us to mitigate endogeneity concerns credibly. Rather than targeting specific firms in communities with high infection rates, the government ordered the closure – throughout the country and at the same time – of all firms not operating in essential sectors. By calculating the employment share in non-essential sectors, we isolate variation in how different communities were affected by the shutdowns. Because the government’s list of essential sectors was valid at the national level, such variation is exogenous to the policy itself.

Our first set of results offers strong evidence that business shutdowns can effectively curb COVID-19 mortality and, more generally, the spread of infectious diseases. We estimate that a 10% point higher share of employment in shutdown sectors is associated with about 0.4 fewer excess deaths per day per 100,000 inhabitants. To put this number in context, we perform a back-of-the-envelope calculation on the number of lives saved through business shutdowns. We estimate that business shutdowns may have reduced the death toll of the first wave of the COVID-19 epidemic in Italy by about 40%.

Our second set of results highlights the importance of timeliness. Exploiting the fact that communities were at different stages in the epidemic curve when business shutdowns were implemented – some had a high number of infections, while others had just a few – we estimate that “early” implementation increases the effectiveness of shutdowns. According to these results, up to an additional 5% of fatalities could have been prevented in just the first 2 weeks of policy implementation if shutdowns had been ordered 1 week earlier.

Our third finding is that closing down the hospitality and food service sector has the largest effects in reducing mortality. Instead, shutting down manufacturing and other production activities, while substantially reducing mobility, has only limited effects on mortality rates. These results, which are consistent with the notion that a higher degree of interpersonal contact at the workplace can facilitate the spread of infectious diseases (Lewandowski, 2020; Markowitz et al., 2019), are related to those of Magnusson et al. (2020) and Aron and Muellbauer (2020). The former match COVID-19 infection with occupational and demographic data for the full sample of the Norwegian working-age population to find that nurses, physicians, dentists, physiotherapists, bus/tram/taxi drivers, bartenders, waiters, food service attendants and stewards – who typically have close contact with other people – had 1.5–4 times the odds of catching COVID-19 when compared to everyone in their working age group. Instead, Aron and Muellbauer (2020) summarize excess deaths by occupation in England, highlighting that most of COVID-19 deaths were among people employed in the consumer-facing service sector.

Our findings and those of the studies reviewed above speak to a quickly growing literature assessing the effectiveness of non-pharmaceutical interventions (NPIs) on COVID-19 infections and mortality. We describe this literature in detail in the following section. The rest of the paper is organized as follows: Section 2 describes the dataset and presents the empirical methodology. Section 3 presents the results, while Section 4 concludes.

1.1 Literature review: The effectiveness of NPI

Early literature on the effectiveness of NPIs has borrowed from epidemiological models (such as SIR and SEIR) to solve the trade-off between minimizing the burden on the economy while reducing the number of fatalities (Atkeson, 2020; Barlow et al., 2021; Chinazzi et al., 2020; Eichenbaum et al., 2020; Jones et al., 2020; Pedersen & Meneghini, 2020). SIR and SEIR models typically assume an equal number of contacts for each individual (Khain, 2020). Our results suggest that this assumption may be problematic when determining optimal business shutdown policies, and thus highlight the advantage of using alternative methods, such as cross-country regressions, synthetic controls methods, or quasi-experimental approaches.

Cross-country variation in the type and timing of NPIs adopted across countries has allowed some studies to identify effective characteristics in reducing contagion (Alfano & Ercolano, 2021; Brauner et al., 2021; Égert et al., 2020). In line with our results, Brauner et al. (2021) find that business shutdowns, and particularly those of businesses with high infection risk, such as bars, restaurants, and nightclubs, have been effective at reducing COVID-19 transmission. Cross-country regressions have some inherent caveats: they need to be cautiously interpreted within the context of implementation, such as the presence of other NPIs, country demographics, and specific implementation details.

Most researchers have quantified the effectiveness of NPIs on slowing the spread of infectious diseases, and ultimately on mortality, by performing single country analyses. Some literature, like our paper, exploits within-country variation in the implementation of NPIs through differences-in-differences approaches or event studies (Alfano et al., 2021; Becchetti et al., 2020; Borri et al., 2021; Courtemanche et al., 2020; Fang et al., 2020; Schuppert et al., 2021). Other studies use synthetic control approaches to evaluate the effectiveness of NPIs in a single country (Bayham & Fenichel, 2020; Born et al., 2021; Cho, 2020; Juranek & Zoutman, 2020).
Both approaches lead to studies that coincide on the effectiveness of school closures and restrictions of the movement of people in limiting the spread of COVID-19. Among the studies just mentioned, only Courtemanche et al. (2020) assess the effectiveness of business shutdowns. The authors estimate the impact of government-imposed closures of some non-essential businesses on the spread of COVID-19 in the US. Their focus is on restaurants, bars, and entertainment-related businesses. Our focus is on the effects of generalized businesses shutdowns, a relatively strict and isolated approach taken by the Italian government to curb COVID-19 infections.

The case of Italy is also studied by Bongaerts et al. (2020). Their paper aligns with our first set of findings, as they conclude that business shutdowns effectively reduce mortality. They do not explore sectoral heterogeneity, however, a key point of this paper. They also consider a much shorter timeframe than ours and conduct the analysis at the municipality-rather than at the local-labor-market level. As we show, this may be problematic since many people in Italy work in a different municipality from the one in which they reside, which complicates the measurement of how many people were affected by the shutdowns at that level of disaggregation.

2 | METHODS

The sample spans from 1st January to May 15, 2020, thus covering the entire period of the first wave of the COVID-19 epidemic in Italy (see also Alicandro et al., 2020). Since this mostly affected the northern part of the country, while leaving the central and southern parts largely unscathed, the focus is on 10 most northern regions (Emilia-Romagna, Friuli-Venezia Giulia, Liguria, Lombardy, Marche, Piedmont, Tuscany, Trentino-Alto Adige, Valle d’Aosta, and Veneto). Together these make up almost 60% of Italy’s population and 95% of its fatalities during the first wave of COVID-19.

Appendix Table A1 provides descriptive statistics on the sample coverage, while the rest of this section continues by describing how we (i) construct a business shutdown variable, (ii) measure COVID-19 mortality, (iii) complement the dataset with co-factors of COVID-19 mortality, and (iv) carry out the empirical analysis.

2.1 | Business shutdowns

Figure 1 provides a chronology of the unprecedented measures taken by the Italian government to fight the first wave of the COVID-19 epidemic in 2020. Our focus is on business shutdowns, implemented on 11th and 22nd March. Did they contribute to reducing mortality? If so, by how much?

To answer these questions, we exploit variation across communities in the employment share of firms forced to shut down, which, crucially, is exogenous to the government policies. Exogeneity follows from the fact that, rather than targeting specific firms in specific communities, the government uniformly ordered the closure of all firms in certain specific sectors throughout the country. To do so, it issued a list of essential sectors valid countrywide: firms operating in those sectors could stay open, while all the others had to close down.
Our prior is that business shutdowns were more binding in labor markets with a higher employment share in non-essential sectors (those in which firms had to shut down). We therefore construct a variable measuring the employment share in firms affected by the shutdowns by matching the government’s list of essential sectors to data on the number of workers in each non-farm private sector. To do so, we source municipality-level data on the number of workers (both employees and self-employed) in each 3-digit sector from ISTAT (2017).3

Following common practice in spatial and urban economics studies (Acemoglu & Restrepo, 2020; Allcott & Keniston, 2018; Autor et al., 2013; Moretti, 2010), we pool municipalities into local labor markets. Local labor markets are areas whose borders are defined to minimize external commuting (commuting outside borders). Since in Italy many people work or study in a different municipality than the one in which they reside, carrying out the analysis at the local-labor-market-level limits possible mismatches between the extent to which individuals are affected by the government policies and the municipality where COVID-19 deaths are recorded.4 Overall, we follow 298 local labor markets, each with about 115,000 inhabitants on average.

Next, for each sector, we calculate the number of workers affected by the government policies and construct our business shutdowns variable, $BS_{it}$, according to the following formula:

$$BS_{it} = C_t \times \frac{S_C}{E_i} + P_t \times \frac{S_P}{E_i}$$

where $S_C$ ($S_P$) measures the number of workers in commercial (production) firms affected by the shutdown of non-essential activities in local labor market $i$; $E_i$ is total employment; and $C_t$ ($P_t$) is a commercial (production) activities shutdown policy dummy that takes value equal to 1 from 15 days after the introduction of the policy to 15 days after its expiration, where the 15-day lag is to account for the well-known lag between COVID-19 infection and death (Lauer, et al., 2020; Linton, et al., 2020; SARS-CoV-2 Surveillance Group, 2020).5

Our business shutdowns variable accounts for the fact that commercial and production activities were affected at different times and thus it is time-varying. When both non-essential commercial and production activities were shut, about 50% of all non-farm private sector workers were forced to stay home, on average. Importantly, there is large variation across local labor markets, with the standard deviation of the employment share in shutdown firms being about 10%. Appendix Table A2 further divides the economy into 19 broad sectors according to the NACE Rev 2 classification and lists the share of suspended employment in each.

### 2.2 | Measurement of COVID-19 mortality

Although other outcome variables, such as the incidence of COVID-19 infections and hospitalisations, are also important, our aim is to investigate the effectiveness of business shutdowns in reducing mortality, which was the ultimate objective of the policy. To measure COVID-19 mortality, we rely on the concept of excess deaths – that is, the difference between deaths for all causes during the COVID-19 epidemic and deaths that would be expected under normal circumstances (see, among others, Aron & Muellbauer, 2020 and Ciminelli & Garcia-Mandicó, 2020a).6

We start by sourcing death registry data from ISTAT (2020). The data provide municipality-level information on daily deaths for the 1st January-15th May period, from 2015 to 2020 and cover 4895 municipalities, accounting for the whole population in the 10 regions that we consider. Appendix Figure A1 plots total daily deaths for the full sample of municipalities. Next, we construct a daily mortality series (deaths per 100,000 inhabitants) at the local-labor-market-level using census population data from ISTAT.7 We then calculate excess mortality by subtracting 2016 daily deaths per 100,000 inhabitants from those in 2020. The choice of 2016 as counterfactual stems from a visual inspection of the raw death data (Appendix Figure A1) and the daily mortality series (Appendix Figure A2). We confirm this choice when using the synthetic control group method of Abadie et al. (2020) and Abadie et al. (2010), which assigns unit weight to the year 2016.8

### 2.3 | Additional data

The dataset is complemented with other variables capturing slow-moving labor market, territorial and socio-demographic characteristics that we use to control for potential co-factors of COVID-19 mortality. We also construct a digital labor index
measuring how much work can be done remotely in firms not affected by shutdowns. Moreover, since the government also ordered the closure of all educational institutions, we collect data on the number of residents enrolled at university. For variables updated at a regular frequency, we compute their means over the 2015–2019 period and treat them as time-invariant factors. For those not updated at a regular frequency, we use the most recent data available. Appendix Table A3 provides the complete list of covariates and more details on when they are measured.

Finally, to run an extension estimating the effect of business shutdowns on mobility, we source Google mobility report data. These data measure daily percent changes in mobility in different areas (workplaces, transit places, retail and recreation, as well as residential places) from February 15, 2020 onwards relative to a baseline 3rd January-6th February 2020 period, for each Italian province. We construct local-labor-market-level variables using the share of people living in different provinces within each local labor market as weights.

2.4 | Empirical specification

Using excess deaths, and the previously defined business shutdowns variable, we estimate the effects of business shutdowns on COVID-19 mortality in a diff-in-diff approach in the spirit of Rajan and Zingales (1998), exploiting differences across local labor markets in the exposure to the business shutdown policy. Differently from diff-in-diff approaches where one group receives the full treatment (treated group) and another one does not (control group), which are usually estimated through a dummy variable, our specification hinges on differences in treatment intensity across different local labor markets and is estimated through a continuous variable (the employment share in shutdown businesses). We verify the validity of the parallel trend assumption by comparing developments in excess mortality in the average local labor markets in the lower and upper half of the treatment intensity variable (Appendix Figure A3): excess mortality was following similar trends in local labor markets with a low and a high employment share in business affected by the shutdown before, and up to 15 days after, the policy implementation.10

Next, we proceed by estimating the following equation:

\[ y_{it} = \lambda BS_{it} + \sum_{k=1}^{K} \pi_k (T_i \ast X^k_i) + \mu_i + \tau_t + \epsilon_{it} \]  

(2)

where \( y_{it} \) measures excess daily deaths per 100,000 inhabitants in local labor market \( i \), at time \( t \); \( BS_{it} \) is the treatment intensity variable, measuring the employment share in shutdown activities (defined in Equation (1)); \( T_i \) is a COVID-19 dummy, taking value equal to 1 in the period after the detection of the first community case (21st February) and 0 in the period before; the \( X^k \)s are (time-invariant) local labor market characteristics included as controls; \( \mu_i \) are local labor markets fixed effects; \( \tau_t \) are time fixed effects; and \( \epsilon_{it} \) is an idiosyncratic error, clustered at the local labor market level. The \( \lambda \) coefficient measures the effect of having a higher employment share in shutdown firms on the excess mortality rate. We estimate Equation (2) through OLS with analytical population weights and standard errors clustered at the local labor market level.11

3 | RESULTS

3.1 | Overall effectiveness of business shutdowns in reducing mortality

Table 1 reports the results on the effect of business shutdowns in reducing COVID-19 mortality. Column 1 shows estimates from a parsimonious model without control variables. Columns 2–6 show estimates from extended specifications in which we gradually add other demographic, labor market and territorial characteristics as additional controls. The reported coefficients measure the changes in daily deaths per 100,000 inhabitants associated with a standard deviation increase in the variable considered, which is about 10% points for business shutdowns.

We estimate a negative and highly statistically significant coefficient for our business shutdowns variable across all specifications. A 10% points higher employment share in shutdown firms is associated with about 0.3–0.4 fewer excess deaths per day per 100,000 inhabitants, depending on the specification considered. The coefficient is −0.4 in the most comprehensive specification, including all controls, which we use as the baseline in the rest of the analysis (Column 6). Compared with an average daily excess death toll of about 1.5 deaths per 100,000 inhabitants, these results indicate that business shutdowns have meaningful effects in reducing mortality. Turning to the control variables, they all enter with the expected sign and, except in
one case, they are also highly statistically significant. A deeper discussion on the control variables is provided in Appendix B, alongside a battery of robustness checks and alternative specifications.

In short, we verify the robustness of our results to (i) relying on different methodologies for the construction of the business shutdown variable, (ii) the inclusion of other variables that could affect the extent of COVID-19 infections and deaths, (iii) the usage of mean 2015–2019 rather than 2016 mortality rate as counterfactual, and (iv) running the estimation on the full sample of Italian local labor markets rather than those in the 10 most northern regions. We also run two placebo tests as well as (i) an alternative specification in which the business shutdown variable (Equation (1)) is replaced with a dummy taking value 1 when the employment share in non-essential businesses is above 50%, and (ii) a dynamic specification in which the effect of the business shutdown policy is allowed to vary over time. Estimates from all these robustness checks and alternative specifications confirm the robustness of our baseline results and formally validate the parallel trend assumption. Finally, in Annex B we also show that carrying out the analysis at the municipality-rather than the local-labor-market-level leads to substantial measurement error in the treatment variable, thus underestimating the effectiveness of business shutdowns in reducing mortality.

3.1.1 Back-of-the-envelope calculations on prevented deaths

How many deaths can be ascribed to COVID-19? And how many deaths have been prevented by shutting non-essential businesses down? We answer these questions through some simple back-of-the-envelope calculations. We start by using the coefficients estimated through Equation (2) to calculate the number of excess deaths, in each day of the epidemic and each local labor market, according to the following formula:

\[
\hat{Y}_{it} = \left( \hat{\delta}_i + \hat{\lambda} \ast BS_{it} + \sum_{k=1}^{5} \hat{\kappa}_k \ast X^k_{it} + \hat{\mu}_i \right) \ast pop_i \tag{3}
\]

where \(\hat{Y}_{it}\) is the predicted number of excess deaths due to COVID-19 in local labor market \(i\) in day \(t\); the \(\hat{\delta}_s, \hat{\beta}_s, \hat{\lambda}, \hat{\kappa}_k\)s and \(\hat{\mu}_s\) are the coefficients estimated from Equation (2); \(BS_{it}\) is the employment share in shutdown firms; the \(X^k_{it}\)s are the control variables; \(pop_i\) is population (in 100,000). We calculate \(\hat{Y}_{it}\) using the coefficients reported in Column 6 of Table 1 and then sum each \(\hat{Y}_{it}\) over the entire period of the first wave of the COVID-19 epidemic in Italy (21st February to 15th May), and across all local
labor markets. This back-of-the-envelope calculation indicates that COVID-19 resulted in slightly more than 48,000 excess deaths—equal to almost 0.14% of the local population—during the first wave of the epidemic in the 10 regions of Italy’s north.

Next, to get a rough sense of the efficacy of business shutdown policies in reducing mortality, we calculate the number of excess deaths that would have occurred in a hypothetical scenario of no business shutdowns. To do so, we artificially set the variable $BS$ in Equation (3) equal to 0 and find that deaths would have been more than 78,000. Hence, our results suggest that business shutdowns might have reduced COVID-19 mortality by about 40%. This estimate is in line with previous work analyzing the effectiveness of non-pharmaceutical interventions (NPIs). In their seminal study, Ferguson, et al. (2020) estimate that NPIs could reduce mortality by 15%–30% in the UK, depending on the basic reproduction number and occupancy of ICU beds. Jones et al. (2020) estimate a 30% reduction in the cumulative death rate by introducing early mitigation policies and work-from-home orders, while Dave et al. (2021) find that Shelter-in-Place Orders in the United States reduced cumulative deaths by about 50% in the first 3 weeks since adoption.

Two caveats to our estimates, which also apply to previous work, are in order. First, in Italy business shutdowns coincided with the lockdown period. Hence, our results are conditional on a lockdown being in place and should not be generalized to cases in which business shutdowns are disjoint from lockdown policies. We believe, however, that our results remain relevant: over the past 2 years of the pandemic, business shutdowns have generally been implemented together with lockdowns, curfews, or other restrictions of people’s movements. A second caveat may be that some non-essential businesses would have closed even in the absence of government-mandated policies. If this were to be the case, we would be overestimating the deaths prevented through government policies. On the other hand, our back-of-the-envelope calculations assume that COVID-19 has linear effects on mortality. However, when infections are left unchecked and the healthcare system is overwhelmed, the fatality rate of COVID-19 increases (Ciminelli & Garcia-Mandícó, 2020b; Favero, 2020). In this sense, our calculation of 30,000 prevented deaths may be a lower bound of the real effects of business shutdowns on mortality.

3.2 The importance of timely interventions

Given that infections grow exponentially and feed in within households (Song et al., 2021), the effects of mitigation and suppression policies should be stronger if implemented earlier in the epidemic curve. Dave et al. (2020) and Friedson et al. (2020) show that this is indeed true for the case of lockdowns. In this section, we investigate to what extent this is valid for business shutdowns. We exploit the fact that, while the government applied the business shutdowns policy at the same time throughout the entire country, communities were at different stages in their epidemic curve when the policy was implemented – those close to the epidemic epicenter (usually defined as the towns of Codogno and Alzano Lombardo in the Lombardy region) displayed much higher COVID-19 caseloads relative to those far from it (Appendix Figure A4). Hence, the variation across local labor markets in the timing of the policy implementation relative to the stage of the epidemic can be considered exogenous to the policy itself.

We proceed by constructing a variable measuring the differences across local labor markets in the relative “timing” of the policy implementation. To do so, we calculate the cumulative number of cases reported up to the day of the adoption of the policies as a share of the local population. On average, detected cases were about 120 per 100,000 people when business shutdowns were adopted. However, there was great heterogeneity across local labor markets. Some had recorded as little as 1 case per 100,000 people, while others had almost 1700.

The relative timing of business shutdowns should be more important for the short-run effectiveness of the policy since the longer the policy is implemented, the more differences in infection rates at the time of implementation are washed out. Hence, we focus on the first two weeks of the policy implementation and restrict the sample to the 1st January-11th April period, where $d_i^1$ is two dummy variables taking value 1 for, respectively, each of the first 2 weeks of the business shutdown policy and 0 otherwise, the subscript $p$ denotes province; $Z_p$ measures cumulative cases up to the day in which the policy is implemented; $\text{pop}_p$ is population size; and the rest is as in Equation (2). We use data on cases at the provincial-level (rather than at the local-labor-market-level) since official data on detected cases are only available at this level of disaggregation.

Table 2 shows the results. Column 1 reports the results from a parsimonious specification that does not include the timing interaction terms. Column 2 reports results estimated from the full Equation (4) above, where the coefficient of the timing interaction terms is normalized to show the change in policy effectiveness associated with 100 more detected cases per 100,000
people at the time of implementation. Both specifications also include the baseline control variables, but for brevity their coefficients are not reported. The new estimates suggest that the short-run effectiveness of business shutdowns decreases with higher infection rates. In the first week of implementation, business shutdowns were about 40% less effective in local labor markets with 100 more cumulative reported cases per 100,000. In the second week, the effectiveness of the policy was still reduced in communities with higher infection rates at the time of implementation, albeit by a considerably smaller margin.

These results beg the natural question of how many more lives could have been saved had the government intervened earlier in the epidemic curve. To answer this question, we use the estimates from Column 2 of Table 2 to perform a back-of-the-envelope calculation, similarly to what done in Section 3.1. We find that intervening 7 days earlier, when cumulative cases per 100,000 inhabitants were around 20 on average, could have resulted in an additional 5% more lives saved during the first two weeks of policy implementation.

### 3.3 Heterogeneity in the effectiveness of business shutdowns across sectors

The analysis carried out so far suggests that business shutdowns are generally effective in reducing COVID-19 mortality. However, there may exist heterogeneities depending on which sectors are affected. Consumer-facing service activities can amplify contagion due to the high degree of interpersonal contact between workers and customers (Lewandowski, 2020; Markowitz et al., 2019). In this section, we extend the analysis to explore such heterogeneities, focusing in particular on four broad sectors, which were also those most impacted by the shutdowns: (i) retail trade, (ii) hospitality (food services and accommodation activities), (iii) manufacturing and construction, and (iv) office and support activities (real estate, professional and administrative and support activities). Together, these account for about 60% of overall non-farm private employment and make up for almost 80% of employment in shutdown firms (Appendix Table A2) and an even larger share of GDP (Navaretti, et al., 2020). Understanding whether there exist heterogeneities in the effectiveness of business shutdowns across these sectors would help policymakers implement targeted interventions that minimize the trade-off between the number of lives saved and the economic costs.

For the estimation, we twist Equation (2) and replace the variable $BS_t$ with sector-specific variables measuring, within each sector, the employment share in firms that are closed down. Table 3 reports the results. Columns 1–4 show estimates when considering each sector separately one at a time, while Column 5 reports estimates from a comprehensive specification including all four sectors. The coefficients report the change in daily excess deaths per 100,000 inhabitants associated with a 10% points increase in the employment share in shutdown firms within each respective sector. All specifications also include our baseline control variables (as in Column 6 of Table 1), but their coefficients are not reported for brevity.

Our results suggest that closing down hospitality effectively reduces mortality while shutting down manufacturing and construction does not. We estimate a negative (−0.4) and statistically significant coefficient from shutting down the hospitality.
sector in the restricted (Column 2) and extended specifications (Column 5). In contrast, the coefficients estimated for manufacturing and construction activities are close to zero and statistically insignificant.

The evidence on the effectiveness of shutting down retail trade and office and support activities is mixed. The coefficients estimated for retail trade are negative and meaningful but not statistically significant at standard confidence levels (Columns 1 and 5). The coefficient for office and support activities, instead, is negative but not statistically significant when the variable enters the regression independently (Column 4), whereas it is close to zero in the extended specification (Column 5). The lack of statistical significance for the retail trade shutdown coefficient might be due to the low variation of shutdown employment in the retail trade sector across local labor markets (see Appendix Table A2). The fact that the office and support activities shutdown variable lose importance in the extended specification may be because the share of employment in shutdown firms in this sector displays a fairly high correlation with the hospitality shutdown variable across local labor markets (0.46).

What could explain the effectiveness of shutting down the hospitality sector and the lack of effect from shutting down the manufacturing and construction sectors? One possibility is that the shutdowns of manufacturing and construction activities did not bind, meaning that workers still went to the workplace, notwithstanding the government’s order. In this case, the variable measuring the share of workers that stayed at home would be measured with an error. We rule out this explanation in Appendix C, where we explore the mobility effects of business shutdowns and find that the shutdown of manufacturing and construction activities substantially decreased workplace mobility and increased the time that people spent at home. Hence, the lower effectiveness of production activities shutdowns does not seem to be due to low compliance rates.

The fact that we found the shutdown of services and production activities to have similar effects in decreasing mobility but different effects in reducing mortality also suggests that the drop in mobility was not the main channel for the overall effectiveness of the policy. If it were to be the main channel, we would have found the shutdown of different sectors to have similar effects on mobility and mortality. Instead, taken together, our results offer suggestive evidence that an important channel behind the effectiveness of business shutdowns is the reduction in interpersonal contact at the workplace.

Indeed, the differential degree of occupational exposure by sector is likely to play an important factor in the spread of COVID-19. While workers in the service sector interact among themselves and with customers every day – the opposite of social distancing – for the most part, factory and office workers only interact with other workers in the same unit, and the opportunities to contract or spread the virus appear to be more limited than in the consumer-facing service sector. This can explain why we find that communities with a higher share of employment in shutdown production activities did not experience lower rates of COVID-19 mortality. These results are in line with the findings on occupational exposure to COVID-19 of Lewandowski (2020) and Aron and Muellbauer (2020). In particular, the latter uses excess mortality data for England to find that most COVID-19 deaths in the working-age population were concentrated among people employed in the consumer-facing service sector.

### Table 3: Sector-specific effects of business shutdowns

|                     | (1)     | (2)     | (3)     | (4)     | (5)     |
|---------------------|---------|---------|---------|---------|---------|
| Retail trade        | −0.24   | −0.22   |         |         |         |
|                     | (0.28)  | (0.25)  |         |         |         |
| Hospitality         | −0.45*  | −0.42*  |         |         |         |
|                     | (0.25)  | (0.25)  |         |         |         |
| Manufacturing & construction | −0.03 | −0.02  |         |         |         |
|                     | (0.11)  | (0.10)  |         |         |         |
| Office and support activities | −0.23 | −0.06  |         |         |         |
|                     | (0.14)  | (0.12)  |         |         |         |
| Observations        | 40,392  | 40,392  | 40,392  | 40,392  | 40,392  |
| Between R-squared   | 0.09    | 0.09    | 0.09    | 0.10    | 0.09    |

Note: the table reports results for the sector-specific effects of business shutdowns in reducing mortality. Columns (1)-(4) report coefficients when each sector is considered one at a time. Column (5) considers all sectors at the same time. The coefficients are estimated using the employment share, within each sector, in shutdown firms in place of the variable \( BS_{it} \) in Equation (2).

Significance levels: *\( p < 0.1 \), **\( p < 0.05 \), ***\( p < 0.01 \).
4 | DISCUSSION

The sudden appearance of COVID-19 in early 2020 has brought about large human losses in most countries worldwide, often forcing governments to implement hastily arranged policies to limit the death toll from the virus. The closure of non-essential activities (commonly referred to as business shutdowns) has been one such policy. This paper investigated its effectiveness in reducing COVID-19 mortality, focusing on the importance of acting early, and of targeting the right sectors.

Our results offer strong evidence that business shutdowns can be very effective in curbing COVID-19 mortality: we calculated that they may have reduced the death toll of COVID-19 during the first wave of the epidemic in Italy by about 40%. Implementing shutdowns early on in the epidemic curve is key to increase their effectiveness. If the policy had been introduced 7 days earlier, the death toll might have been reduced by an additional 5%. The effectiveness of shutdowns is heterogeneous across sectors. Consistent with the notion that sectors with a higher degree of interpersonal contact can facilitate the spread of infectious diseases, closing down the hospitality sector has the largest effects in reducing mortality. Shutting down the construction and manufacturing sectors – in which interpersonal contact is limited to workers in the same unit – only has mild effects.

Our analysis carries clear policy implications. From a public health perspective, governments should not hesitate to act early on and decide the closure of non-essential businesses to save lives when new outbreaks of COVID-19 and other pathogens materialize. However, since business shutdowns carry large economic costs, they should be targeted, prioritizing the closure of sectors with a high degree of interpersonal contact between workers and customers and a low propensity toward digital labor.

Our results and related policy implications should be interpreted in the context of the first wave of COVID-19 in Italy, in which strict restrictions on people's movement were in place, but where other protective measures, such as mask-wearing, frequent disinfection, and social distancing measures in public places, were not widespread (Égert et al., 2020). As these measures become the norm, the contribution of business shutdowns to reducing COVID-19 mortality may become smaller. Moreover, our study did not cover other important aspects when assessing the appropriateness of business shutdowns, including those related to the depreciation of human capital and increased mental health problems for workers forced to stay home. More research is needed to understand these costs to have a complete picture for policymakers when deciding whether to implement business shutdowns.

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CONFLICT OF INTEREST

The authors have no conflict of interest to declare.

DATA AVAILABILITY STATEMENT

Regarding replication: the data we use are open access data from the Italian National Institute for Statistics (ISTAT). We provide a detailed explanation of the data and variables used in the manuscript, as well as the relevant links for other researchers to access the data. In case of publication we would make our codes and data available, such that anyone who accesses the data can replicate our results.

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ENDNOTES

1. An exception is the work of Kaplan et al. (2020). These authors incorporate heterogeneity in contact by sector, which allow them to discuss the need for sector-specific policies.

2. However, the results are very similar when focusing on all 20 regions of Italy (see discussion and relevant results in Appendix B).

3. These data are for 2017 (the most recent year covered by ISTAT) and are available for each 3-digit sector except agriculture and public administration, which are excluded from the analysis. Since the government defined the list of essential sectors using the 5-digit sector classification, we also source country-level data on the number of workers in each 5-digit sector and construct a measure of the share of suspended employment in each 3-digit sector at the national level. We use this measure to compute the employment share in shutdown sectors in each local labor market.

4. To pool municipalities into local labor markets we use the 2011 concordance table provided by ISTAT.

5. Lauer et al. (2020) and Linton et al. (2020) study COVID-19 incubation and find a lag of about 5 days between infection and incubation. The SARS-CoV-2 Surveillance Group (2020) follows a panel of COVID-19 deaths in Italy and finds a median time of 10 days between the onset of symptoms and death. In light of these studies, we account for a minimum lag of 15 days between the implementation of the policy and its effects, but our results do not depend on this particular choice (alternative estimates available upon request).

6. This measure does not allow uncovering the COVID-19 fatality rate, but rather pools together direct and indirect COVID-19 deaths. Direct deaths refer to people dying of COVID-19, while indirect deaths refer to those dying for causes related to COVID-19, such as overcrowded hospitals. It should be noted, however, that COVID-19 may have also resulted in less deaths due to other causes, such as road accidents, accidents on the workplace and influenza. Hence, the number of indirect deaths is net of fewer deaths resulting from government social distancing policies.

7. These data provide information on the resident population in each municipality, as of first/January¹, from 2015 to 2019. We impute 2020 population by using 2019 growth rates.

8. Our results are robust to using other counterfactuals in the calculation of excess deaths, such as the average mortality between 2015 and 2019 (see Appendix B).

9. To construct the index we use data on the number of employees in each sector from ISTAT (Atlante Statistico dei Comuni, 2017) as well as sector-specific scores in the propensity toward digital labor. Such scores are assigned by Manyika et al. (2015) and are reported in Appendix Table A2. The index is constructed computing the weighted sum of employment in sectors that stayed open, using the scores of Manyika et al. (2015) as weights, and dividing it by the overall employment level (in open sectors). For the definition of open sectors, we rely on the list issued by the government. Using the scores of Dingel and Neiman (2020) leads to a very similar series.

10. Where the 15 day lag is given by the lag between COVID-19 infection and death, which was equal to about 15 days in the first wave of the pandemic (refer to Footnote 5 for more details).

11. We opt for population analytical weights due to the sensible differences in population size observed across local labor markets and because we will use the estimated coefficients to perform some back-of-the-envelope calculations on the overall mortality effects of COVID-19 (see below). Our estimates are however robust to not weighting for population (results available upon request).

12. The focus is on the first two weeks of the policy implementation, but the sample goes up to 1 month after implementation to account for the average 15 day lag between COVID-19 infection and death (see discussion in Section 2.1).

13. Using Italy's data, Navaretti et al. (2020) compute the GDP loss that would occur if each industry were to be closed for 1 year. Of the 12 industries that would cause the most significant costs, nine belong to the 5 sectors that were most affected by the shutdowns.

14. Education may affect health behavior (Galama et al., 2018) and attitudes toward social-distancing practices (Adda, 2016). Moreover, the level of education typically correlates with underlining health conditions (Case & Deaton, 2017) and patients with co-morbidities tend to have a higher chance of dying from COVID-19 (Yang, et al., 2020). Unfortunately, data on health conditions at the municipality/local-labour-market-level are not available.

15. Several studies have shown long-term exposure to particulate matters such as PM10 and PM2.5 to increase health risks (WHO, 2017), while Wu et al. (2020), Becchetti et al. (2020) and Conticini et al. (2020) have found a positive link between PM10 and COVID-19-induced mortality. Since data availability on air pollution is an issue, we use provincial-level data on the number of days in a year in which the level of PM10 is above the legal limit of 50 mg/m³ and match it to local labor markets.

16. Markowitz et al. (2019) have shown that higher employment rates are associated with a higher flu incidence, while Adda (2016) and Harris (2020) have shed light of the important role of commuting for the spread of infectious diseases. We therefore control for both these factors. We also account for the share of residents enrolled at university to control for the contemporaneous government's policy of moving higher education learning online. Finally, we control for the share of the elderly, since age is an important determinant of COVID-19 lethality (SARS-CoV-2 Surveillance Group, 2020), and for mean income because low-income agents tend to have worse health (Case & Deaton, 2017).

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APPENDIX A: ADDITIONAL TABLES AND FIGURES
This appendix contains additional tables and figures.

**FIGURE A1** Fatalities in 2020 compared to the five previous years. The figure compares daily fatalities in 2020 (solid red line) to daily fatalities in each of the five preceding years in the 10 regions considered. The blue dashed line denotes deaths in 2016, which we use as counterfactual to estimate the effects of COVID-19 on mortality (see Sections 2.2 and 2.4). The vertical maroon line denotes the day on which the first COVID-19 community case was detected, on 21st February) [Colour figure can be viewed at wileyonlinelibrary.com]

**FIGURE A2** Daily mortality trends. This figure plots mortality trends in 2020 and 2016. Taking differences between these two trends gives us a measure of excess deaths from COVID-19. The validity of our measure relies on the parallel trends assumption in mortality in 2020 and 2016 before the first locally transmitted COVID-19 case, which is confirmed in this figure. The choice of using mortality in 2016 as counterfactual is also confirmed when using the synthetic control group method of Abadie et al (2020) and Abadie et al. (2010), which assigns unit weight to the year 2016 [Colour figure can be viewed at wileyonlinelibrary.com]
FIGURE A3  Trends in excess mortality in local labor markets with a low and high employment share in shutdown businesses. This figure plots excess mortality trends in local labor markets with a low and a high employment share in businesses affected by the shutdown policy, defined as those in the lower and upper half of the business shutdown variable distribution (calculated as $SiCEi + SiPEi$, where $SiC$ and $SiP$ measure the number of workers in commercial and production firms affected by the business shutdown policy in local labor market $i$ and $Ei$ is total employment). The $x$-axis reports the days after the discovery of the first locally transmitted COVID-19 case. The blue vertical line reports the implementation date of the first business shutdown policy. The validity of our diff-in-diff approach relies on the parallel trends assumption of excess mortality before, and up to 15 days after, the implementation of the shutdown policy, which is confirmed in this figure [Colour figure can be viewed at wileyonlinelibrary.com]

FIGURE A4  Number of cases at the time of business shutdowns. The figure shows the number of confirmed COVID-19 cases, relative to the population, at the provincial level at the time in which the business shutdowns were implemented by the government [Colour figure can be viewed at wileyonlinelibrary.com]
| Region                  | # municipalities | # local labor markets | Population (in 1000) |
|-------------------------|------------------|-----------------------|----------------------|
| Emilia-Romagna          | 340              | 39                    | 4615.82              |
| Friuli Venezia Giulia   | 213              | 11                    | 1310.69              |
| Liguria                 | 244              | 14                    | 1649.38              |
| Lombardy                | 1506             | 51                    | 10,665.40            |
| Marche                  | 229              | 25                    | 1611.51              |
| Piedmont                | 1180             | 36                    | 4715.71              |
| Tuscany                 | 285              | 26                    | 1180.36              |
| Trentino-Alto Adige     | 270              | 48                    | 3803.21              |
| Valle d’Aosta           | 74               | 5                     | 147.93               |
| Veneto                  | 554              | 43                    | 5051.35              |
| Total                   | 4895             | 298                   | 34,751.36            |

*Note:* the columns “# municipalities” and “# local labor markets” report the number of municipalities and local labor markets covered in the analysis. The columns “population (in 1000)” report the population covered (in thousands).

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**Table A2** Descriptive statistics on business shutdowns by sector

| NACE Code | Employment Share | Affected YES/NO | Share affected Mean | s.d. | Min | Max | Digital Labor |
|-----------|------------------|-----------------|---------------------|------|-----|-----|--------------|
| Mining & Quarrying | B 0.13 | YES | 99.87 | 0.89 | 89.20 | 100.00 | 1 |
| Manufacturing | C 27.88 | YES | 59.51 | 17.33 | 2.10 | 97.04 | 3.5 |
| Electricity and Gas | D 0.53 | NO | / | / | 0.00 | 0.00 | 4 |
| Water supply & waste management | E 0.91 | NO | / | / | 0.00 | 0.00 | / |
| Construction | F 9.36 | YES | 64.18 | 7.85 | 39.92 | 84.70 | 2 |
| Sales of motor vehicles | 45 2.13 | YES | 19.41 | 10.47 | 0.00 | 46.69 | / |
| Wholesale trade | 46 5.48 | YES | 64.98 | 10.20 | 26.71 | 93.30 | 4 |
| Retail trade | 47 11.00 | YES | 40.82 | 3.92 | 27.40 | 53.74 | 1 |
| Transportation & storage | H 4.69 | NO | / | / | 0.00 | 0.00 | 2 |
| Hospitality | I 11.68 | YES | 94.70 | 4.25 | 82.03 | 100.00 | 1 |
| Information & communication | J 1.48 | NO | / | / | 0.00 | 0.00 | 6 |
| Financial & insurance activities | K 0.84 | NO | / | / | 0.00 | 0.00 | 5 |
| Real estate activities | L 2.12 | YES | 100.00 | 0.00 | 100.00 | 100.00 | 2 |
| Professional activities | M 5.62 | YES | 2.57 | 1.69 | 0.00 | 9.18 | 5 |
| Administrative & support activities | N 4.56 | YES | 19.78 | 13.14 | 2.35 | 66.85 | 5 |
| Education | P 0.51 | NO | / | / | 0.00 | 0.00 | 3 |
| Health | Q 4.15 | NO | / | / | 0.00 | 0.00 | 2 |
| Entertainment & recreation | R 0.95 | YES | 100.00 | 0.00 | 100.00 | 100.00 | 1 |
| Other service activities | S 2.68 | YES | 81.85 | 1.02 | 78.27 | 83.46 | 3 |

*Note:* This table divides non-farm private employment in 20 broad sectors. The first and second columns report the name and code, according to the NACE Rev 2 classification, of each sector. The third column states whether a sector is affected by the shutdowns or not. The fourth, fifth, sixth and seventh columns report the mean, standard deviation, minimum and maximum of the employment share in shutdown firms. The eighth column reports the score from the digital labor index of Manyika et al. (Digital America: A tale of the haves and have-mores, 2015). Among the manufacturing sector, 20, 21, 254, 26, 27, 28, 29, 30 and 325 industries (high-tech manufacturing) receive a score of 5, while all others (low-tech) receive a score of 3.
This appendix discusses the coefficients estimates for the covariates from the baseline specification (Column 6 of Table 1 in the main text) and results from a battery of robustness checks and alternative specifications on the overall effects of business shutdowns on COVID-19 mortality, shown in Table B1.

Starting with the discussion on the effects of covariates, Column 1 reports estimates from the baseline specification, including all controls (as in Column 6 of Table 1 in the main text). Coefficients are normalized to show the effect of an increase of one standard deviation in the covariates. A higher share of women in the working age population is by far the single most important factor reducing COVID-19 mortality. This is consistent with studies showing that women have lower mortality from COVID-19 (SARS-CoV-2 Surveillance Group, 2020). We also find a small, but not precisely estimated, mitigating role for education, proxied by the share of high school graduates. Among risk factors, we control for population density and the level of air pollution. We estimate a positive and statistically significant coefficient for the former, confirming that closer interpersonal proximity facilitates the spread of COVID-19, while our results for the latter are in line with other studies suggesting that air pollution may increase the lethality of COVID-19 (Becchetti, et al., 2021). Finally, our digital labor index measuring how much work can be done remotely in firms that stay open has a negative and highly significant coefficient, suggesting that remote working is associated with lower mortality.

We then turn to the robustness checks and alternative specifications. In Column 2, we estimate a specification in which we exclude the accommodation sector from the calculation of the business shutdown variable. In our preferred specification,

| Variable                      | Mean  | Std. Dev. | Min  | Max  | Period   | Source                                                                 |
|-------------------------------|-------|-----------|------|------|----------|-----------------------------------------------------------------------|
| Mortality rate                | 3.87  | 0.86      | 1.76 | 7.77 | 2015–2020 | Own calculations from ISTAT, dataset con i decessi giornalieri       |
| Business shutdowns           | 50.69 | 9.00      | 24.71| 78.72| 2017     | Own calculations from ISTAT, Atlante Statistico dei Comuni           |
| Share working age females     | 49.70 | 0.81      | 46.39| 51.48| 2015–2019| Own calculations from ISTAT, Indicatori Demografici                  |
| Share high school graduates   | 58.12 | 5.99      | 33.34| 71.26| 2015     | Own calculations from ISTAT, Condizioni socio-Economico              |
| Population density           | 2323.59 | 790.26   | 798.61| 5788.94| 2017 | Own calculations from ISTAT, a Misura di Comune                     |
| Days PM10 above limit        | 37.24 | 26.81     | 0.16 | 90.00| 2015–2016| Own calculations from ISTAT, Dati Ambientali nelle Cita             |
| Digital labor in active firms| 0.47  | 0.06      | 0.24 | 0.68 | 2017     | Own calculations from ISTAT, Atlante Statistico dei Comuni           |
| University closure            | 27.94 | 6.83      | 2.19 | 51.15| 2017     | Own calculations from ISTAT, a Misura di Comune                     |
| Internal commuting index     | 33.83 | 13.63     | 0.24 | 66.11| 2011     | ISTAT, Sistemi Locali del Lavoro, 2011                               |
| Share of 80+                  | 7.83  | 1.50      | 4.57 | 12.65| 2015–2019| Own calculations from ISTAT, Indicatori Demografici                  |
| Mean income                   | 14,100.95 | 1612.83 | 7630.78 | 18,745.39 | 2015–2017 | Own calculations from ISTAT, a Misura di Comune                     |
| Transits mobility             | −55.72| 5.05      | −71.63| −43.53| 2020 | Own calculations from Google mobility reports                        |
| Retail & recreation mobility  | −59.85| 2.18      | −66.18| −54.70| 2020 | Own calculations from Google mobility reports                        |
| Workplace mobility            | −43.38| 2.51      | −52.57| −38.86| 2020 | Own calculations from Google mobility reports                        |
| Residential mobility          | 20.77 | 1.24      | 18.21| 24.57| 2020 | Own calculations from Google mobility reports                        |

Note: Except if otherwise specified, all the variables that we collect are at the municipality-level. We compute their local labor market equivalent using the categorization by ISTAT. Mortality rate measures daily deaths per 100,000 inhabitants. Business shutdowns measure the employment share in shutdown firms (in %), population density measures population over inhabited land. Days PM10 above limit measures the number of days in a year in which PM10 averages above 50 mg/m³. Digital labor in active firms measure the weighted sum of employment across industries using digital labor scores as a share of total employment. University closures measures the share of people enrolled at university over the 18–25 population. Internal commuting index measures the flows across different municipalities in the same local labor market over total flows. Share 80+ measures the share of people aged 80 and above over the total population (in %). Transits, retail & recreation, workplace and residential mobility measure the percent change in visits to each of these locations relative to the baseline 3rd January-6th February 2020 period.

APPENDIX B: ROBUSTNESS CHECKS

This appendix discusses the coefficients estimates for the covariates from the baseline specification (Column 6 of Table 1 in the main text) and results from a battery of robustness checks and alternative specifications on the overall effects of business shutdowns on COVID-19 mortality, shown in Table B1.
we included the accommodation sector among shutdown commercial activities (the \( C_i \) component in Equation (1)). Our reasoning was that, although the government never formally ordered the shutdown of hotels, the accommodation sector was effectively shut since the introduction of the countrywide lockdown, as this severely restricted the movement of people and brought tourism to a halt. The new estimates suggest that including or excluding the accommodation sector does not drive the results.

Next, we run two placebo tests to verify that our estimates are not the result of spurious relationships. In the first, we replace our policy intervention dummies \( C_t \) and \( P_t \) in Equation (1) with dummies taking value equal to one in the pre-policy period and equal to 0 otherwise. In the second, we instead assign random values to the \( C_i \) and \( P_i \) variables in Equation (1). Reassuringly, the new estimated coefficients are not statistically significant, suggesting that our baseline estimates are not spurious (Columns 3 and 4). We also check that our results do not suffer from omitted variable bias and add the employment rate, an index measuring the level of internal commuting, the share of residents enrolled at university, the share of people older than 80 and the mean income as additional controls.

The new estimates on the effects of business shutdowns are very close to, and not statistically different from, our baseline (Column 1).

We then verify that the results do not depend on using 2016 as counterfactual in our calculation of excess deaths and estimate a specification in which we use average mortality over 2015–2019 as alternative counterfactual (Column 6). The results are again very similar to our baseline specification. We also estimate a standard diff-in-diff specification in which we divide

| TABLE B1 | Robustness checks and additional estimates on the effects of business shutdowns on COVID-19 mortality |
|----------|---------------------------------------------------------------------------------------------------|
|          | (1)                  | (2)                  | (3)                  | (4)                  | (5)                  | (6)                  | (7)                  | (8)                  | (9)                  |
| Business shutdowns | -0.37*** 0.11 | -0.38*** 0.11 | -0.67 0.15          | -0.38*** 0.14 | -0.42*** 0.11 | -0.55*** 0.11 | -0.35*** 0.11 | -0.15*** 0.04 |
|          | (0.11) 0.13         | (0.13) 0.15         | (0.52) 0.14         | (0.14) 0.11         | (0.11) 0.25         | (0.09) 0.04         | (0.11) 0.04         |
| Share working age females | -0.73*** 0.16 | -0.73*** 0.16 | -0.76*** 0.16 | -0.75*** 0.16 | -0.64*** 0.16 | -0.70*** 0.16 | -0.81*** 0.16 | -0.77*** 0.11 |
|          | (0.15) 0.16         | (0.16) 0.16         | (0.16) 0.16         | (0.16) 0.16         | (0.16) 0.16         | (0.16) 0.16         | (0.16) 0.11         |
| Share high school graduates | -0.23 0.18 | -0.25 0.19 | -0.11 0.15 | -0.14 0.16 | -0.35* 0.18 | -0.26 0.21 | -0.24 0.21 | 0.04 0.10 |
|          | (0.18) 0.19         | (0.19) 0.15         | (0.16) 0.16         | (0.18) 0.18         | (0.18) 0.21         | (0.10) 0.21         | (0.10) 0.09         |
| Population density | 0.32*** 0.09 | 0.31*** 0.09 | 0.34*** 0.09 | 0.34*** 0.09 | 0.31*** 0.11 | 0.33*** 0.11 | 0.53*** 0.14 | -0.03 0.06 |
|          | (0.09) 0.09         | (0.09) 0.09         | (0.09) 0.09         | (0.11) 0.09         | (0.09) 0.14         | (0.06) 0.06         | (0.05) 0.05         |
| Days PM10 above limit | 0.35*** 0.09 | 0.34*** 0.09 | 0.37*** 0.09 | 0.36*** 0.09 | 0.29*** 0.10 | 0.37*** 0.10 | 0.32*** 0.09 | 0.31*** 0.06 |
|          | (0.09) 0.09         | (0.09) 0.09         | (0.09) 0.09         | (0.10) 0.10         | (0.10) 0.09         | (0.09) 0.09         | (0.06) 0.06         |
| Digital labor in active firms | -0.39*** 0.13 | -0.32*** 0.13 | -0.35*** 0.13 | -0.33*** 0.13 | -0.41** 0.18 | -0.41*** 0.15 | -0.31*** 0.11 | 0.17* 0.09 |
|          | (0.13) 0.13         | (0.13) 0.13         | (0.13) 0.13         | (0.18) 0.15         | (0.15) 0.11         | (0.09) 0.09         | (0.08) 0.08         |
| University closures | -0.01 0.02 | 0.07 0.18 | 0.24 0.14 | 0.21 0.15 | 0.12 0.15 |
|          | (0.02)              | (0.18)              | (0.14)              | (0.15)              | (0.15)              |
| Employment rate | 0.07 0.18 | 0.24 0.14 | 0.21 0.15 | 0.12 0.15 |
| Internal commuting index | 0.07 0.18 | 0.24 0.14 | 0.21 0.15 | 0.12 0.15 |
| Share of 80+ | 0.07 0.18 | 0.24 0.14 | 0.21 0.15 | 0.12 0.15 |
| Mean income | 0.07 0.18 | 0.24 0.14 | 0.21 0.15 | 0.12 0.15 |
| Observations | 40,392 598,264 | 40,392 598,264 | 40,392 598,264 | 40,392 598,264 |
| Between R-squared | 0.11 0.10 | 0.09 0.09 | 0.08 0.09 | 0.02 0.02 |

Note: the table reports results from a battery of robustness checks and alternative specifications. Column (1) reports the baseline specification (Column 6 in Table 1). Column (2) excludes the accommodation sector. Columns (3) and (4) perform placebo tests. Column (5) reports the results from including additional controls, Column (6) reports results when using average 2015–2019 mortality as counterfactual, Column (7) report estimates obtained from a standard diff-in-diff specification in which local labor markets are divided in two groups (treated and untreated) depending on whether the share of employment in non-essential businesses is above/below 50%. Column (8) reports results estimated on the unrestricted sample of all 20 Italian regions, while Column (9) reports results obtained carrying out the analysis at the municipality-rather than the local-labor-market-level.

Significance levels: \* \( p < 0.1 \), \** \( p < 0.05 \), \*** \( p < 0.01 \).
local labor markets in two groups – a treated one, when the share of employment in shutdown businesses is higher than 50%, and an untreated one, when this share is below 50% – rather than exploiting the full extent of differences in treatment intensity (given by the share of employment in non-essential businesses). This alternative specification assumes that business shutdowns are not binding when they do not involve a large enough share of workers. Although it is not possible to directly compare our baseline results with those from this alternative specification, the new estimate is qualitatively in line with our baseline in that we estimate treated local labor markets to have a about 0.5 to 0.6 less excess deaths per day during the treatment period (Column 7).

Next, we note that our baseline results are obtained on the sample of the 10 most northern Italian regions, since that is where the virus was mostly confined to when the business shutdown policy was implemented. As a further robustness check, we estimate our baseline specification on the unrestricted sample of all 20 regions of Italy (Column 8). The results are very similar and not statistically different from our baseline.

Finally, we estimate an alternative specification in which we carry out the analysis at the municipality-rather than the local-labor-market-level. In Italy many people work or study in a different municipality than the one in which they reside. Hence, carrying out the analysis at the municipality-level may lead to measurement error in the treatment variable, measuring the employment share in firms that are shutdown. The new estimates, reported in Column 9, display a much lower coefficient for the business shutdown variable (−0.1 vs. −0.4 from our baseline specification) as well as for the population density and digital labor variables. This confirms that conducting the analysis at the municipality-level may lead to a measurement error, thus underestimating the real effect of business shutdowns on mortality.

We also perform an additional estimation in which the effectiveness of the business shutdown is allowed to vary over time by running an event study analysis. More specifically, we estimate the following regression:

\[
y_{it} = \mu_i + \tau_t + \lambda_t^i B S_i + \epsilon_{it}\tag{B.1}
\]

where \(y_{it}\) measures excess daily excess deaths per 100,000 inhabitants in local labor market \(i\), at time \(t\); \(BS_i\) measures the employment share in shutdown businesses (calculated as \(S_t^C / E_i + S_t^P / E_i\), where \(S_t^C\) and \(S_t^P\) measure the number of workers in commercial and production firms affected by the business shutdown policy in local labor market \(i\) and \(E_i\) is total employment); \(\mu_i\) are local labor markets fixed effects; \(\tau_t\) are time dummies; and \(\epsilon_{it}\) is an idiosyncratic error. The \(\lambda_t^i\) coefficients measure the effect of having a higher employment share in shutdown firms on the excess mortality rate in a given day \(t\).

We plot results from this event study analysis in Figure B1, which shows the effect of having a 1 standard deviation higher share of employment in shutdown businesses. We draw two conclusions. First, the parallel trend assumption is formally validated, as there are no significant changes in excess mortality depending on the employment share in shutdown businesses before policy implementation (blue vertical line) and in the first 15 days after. Second, after the 15-day lag, the effectiveness of the policy increases fast at the beginning, peaking about 25–30 days after implementation at about 0.5 per 100,000 less excess deaths per day in local labor markets with a 1 standard deviation higher employment share in shutdown business, and then decreases more slowly, to become not statistically different from 0 about 60 days after implementation.

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**FIGURE B1** Dynamic effects of business shutdowns. This figure plots the dynamic effect of business shutdowns, estimated from Equation (B.1). The blue solid line is given by the estimated \(\lambda_t^i\) coefficients, while the shaded area represents 90% confidence bands. Coefficients are standardized to show the effect of having a 1 standard deviation higher share of employment in shutdown businesses. The blue vertical line denotes the implementation of the first business shutdown policy [Colour figure can be viewed at wileyonlinelibrary.com]
Next, we check for another aspect that could potentially bias our results. Individuals may have spontaneously changed their behaviors, for instance limiting their mobility, due to concerns over the spread of COVID-19 before the government ordered the closure of non-essential businesses and the associated people lockdown. If spontaneous changes in behavior positively correlate with the share of workers employed in non-essential businesses (for instance, because people limited shopping and entertainment activities), our estimates on the effectiveness of business shutdowns in reducing mortality would be biased upwards.

In Table B2 below we check whether mobility patterns before the government’s lockdown differed in local labor markets with low and high shares of workers employed in non-essential sectors. We compare the mobility patterns during the period between the detection of the first community case and the government’s lockdown in local labor markets with a low (below the 50th percentile of the business shutdowns variable distribution) versus a high share of workers employed in firms affected by the business shutdowns (above the 50th percentile). The column p-value reports the p-value associated with a test for equality in the means.

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**APPENDIX C: EFFECTS OF BUSINESS SHUTDOWNS ON MOBILITY**

In this appendix we rule out one potential explanation for the strong effectiveness of shutting down the hospitality sector and the lack of effect from shutting down the manufacturing and construction sectors. The explanation that we rule out is that the shutdowns of manufacturing and construction activities did not bind, meaning that workers still went to the workplace notwithstanding the government’s order. We do so by investigating how much business shutdowns affected mobility patterns. We estimate four different regressions in which the dependent variables are daily percent changes in mobility in, respectively, workplaces, transit places, retail and recreation venues, and residential places. The explanatory variables are the sector-specific business shutdown variables, interacted with 0/1 policy dummies, as well as our baseline control variables (as in Equation (2)), time and local labor market fixed effects. Google mobility data are only available for the post-15th February period for the year 2020. Hence, the estimation sample is considerably reduced relative to our other analyses. Table C1 below reports the results. For each different dependent variable considered, the table also reports the overall effects of business shutdowns on mobility (i.e., without distinguishing by sector).

The new estimates indicate that, overall, business shutdowns reduced visits to the workplaces (Column 1), transit hubs (Column 3) as well as visits to retail and recreational venues (Column 5), while they contributed to increase the time that people spent at home (Column 7). Zooming in on sector-specific effects, the shutdown of manufacturing and construction activities substantially decreased workplace mobility (Column 2) and increased residential mobility (Column 8), as affected workers were forced to stay home. Qualitatively similar albeit quantitatively smaller effects are estimated for the shutdown of office activities. As expected, the shutdown of non-essential hospitality activities decreased visits to recreational venues and trips to transit hubs, while the closure of non-essential retail activities increased the time spent at home. Overall, these results suggest that the shutdown of non-essential services and non-essential production activities are effective in reducing mobility. Hence, the lower effectiveness of production activities (particularly manufacturing and construction) does not seem to be due to low compliance rates.
|                     | (1)        | (2)        | (3)        | (4)        | (5)        | (6)        | (7)        | (8)        |
|---------------------|------------|------------|------------|------------|------------|------------|------------|------------|
|                     | Workplace  | Workplace  | Retail &   | Retail &   | Transit    | Transit    | Residential | Residential |
| Business shutdowns  | −1.24***   | −1.32**    | −1.49**    | 0.57***    |            |            |            |            |
|                     | (0.19)     | (0.53)     | (0.64)     | (0.09)     |            |            |            |            |
| Retail trade        | −0.74      |            | 1.10       | 0.18       |            |            | 0.64*      |            |
|                     | (0.80)     |            | (0.97)     | (1.39)     |            |            | (0.33)     |            |
| Hospitality         | −0.21      |            | −2.72***   | −3.79***   | 0.12       |            |            |            |
|                     | (0.33)     |            | (0.99)     | (1.16)     | (0.18)     |            |            |            |
| Manufact. & constr. | −1.27***   |            | −0.41      | −0.53      | 0.59***    |            |            |            |
|                     | (0.18)     |            | (0.32)     | (0.40)     | (0.09)     |            |            |            |
| Office activities   | −0.72**    |            | −0.17      | −0.17      | 0.22*      |            |            |            |
|                     | (0.29)     |            | (0.25)     | (0.40)     | (0.11)     |            |            |            |
| Observations        | 22,496     | 22,496     | 22,496     | 22,496     | 22,496     | 22,406     | 22,406     | 22,406     |
| Between R-squared   | 0.18       | 0.18       | 0.16       | 0.18       | 0.21       | 0.21       | 0.24       | 0.25       |

Note: The table reports the effects of business shutdowns on mobility. Dependent variables measure daily percentage change in mobility relative to the 3rd January-6th February 2020 period. In Columns (1) and (2), (3) and (4), (5) and (6) and (7) and (8) the dependent variable measures, respectively, workplace mobility, retail and recreational mobility, transit places mobility and residential mobility. The explanatory variables are the overall and sector specific business shutdowns variables, in which the employment share in shutdown sectors is interacted with 0/1 policy dummies taking value 1 during the business shutdown period and 0 otherwise. The estimation sample goes from 15th February to May 15, 2020. The estimating equation includes time and local labor market fixed effects. Significance levels: *p < 0.1, **p < 0.05, ***p < 0.01.