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# ELECTORAL ACCOUNTABILITY AND LOCAL SUPPORT FOR NATIONAL POLICIES\*

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## Abstract

We study the provision of information by local governments that supports individual compliance with nationwide regulation, and how this provision relates to the electoral process. We use information about individual mobility (compliance with the lockdown) and Facebook posts by Italian local governments during the Covid 19 pandemic. We show that in municipalities where mayors were up for re-election, local governments provided significantly more covid-related information. This information caused a significant decrease in mobility and excess mortality. However, these effects seem to arise only in the northern regions of the country, where the impact of the pandemic was more severe.

**Keywords:** Covid, Elections, Facebook.

**JEL classification:** TBD.

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# 1 Introduction

As the first point of contact with government for ordinary citizens, local administrations play an important role in supporting the implementation of policies adopted at the national level, like traffic law, environmental regulation and taxation. Although they are not directly involved in designing and enforcing such policies, local governments are typically expected to inform individuals about these rules, stress the importance of complying, supporting and monitoring compliance. Whether local politicians have sufficient incentives to perform these tasks is, however, unclear. Complying with the rules is costly to individuals, so the costs of compliance are concentrated locally, but the benefits (e.g., from lower pollution) often exceed the local municipality's boundaries. Therefore, these benefits are not fully internalised by local politicians. Furthermore, the outcome of any effort made by a local government depends often on factors beyond its control, such as the resources provided by higher government levels. Finally, the preferences and political alignment of local politicians may differ from the national government's.

As important as the support of local governments is to the success of national policies, the economic literature does not seem to have devoted much attention to this role. Part of the reason may be that many supporting activities are "soft" in nature, such as providing information and guidance to citizens. As such, these activities are typically hard to measure. We intend to address this gap in this paper, investigating the following questions. What incentives do local politicians have to engage in activities that support compliance with national policies? How do these incentives relate to electoral accountability at the local level? How effective is the support of local government in fostering compliance and, ultimately, social welfare? A key novelty of our study is that, to proxy for the intensity of supporting activities, we use the provision of information related to national policies by local governments, that we measure from their institutional Facebook pages.

Our study is set in the context of the national lockdown during the recent Covid-19 pandemic in Italy. This context fits our study for several reasons. First, the lockdown was a nationwide policy in which local governments were expected to play a key supporting role, by monitoring and facilitating individual compliance.<sup>1</sup> While lockdowns

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<sup>1</sup>The interventions took different forms. For example the municipality of the island of Ischia was able to ban all tourists from China, Lombardy and Veneto). The municipality of Vo (near Padua) implemented testing and re-testing of entire population. Many others, like Pesaro, engaged in distributing door-to-door FFP2 masks, coordination of essential services like food distribution to vulnerable house-

Figure 1: *Covid lockdown protests in Italy*



were effective at reducing the spread of the pandemic, they also had a severe impact on the local economy and individual wellbeing. Indeed, protests and discontent about lockdowns were widespread in Italy, as in many other countries (see Figure 1). Furthermore, local governments had little direct control of the health outcomes of the pandemic, and so were not directly accountable for the (health-related) costs of non-compliance.<sup>2</sup> Finally, the Italian context is interesting because it allows us to capture how the proximity of elections affects the incentives of local governments to support national policies: elections were scheduled to take place in about a thousand municipalities in May 2020, and were postponed to September 2020 due to the lockdown.

Our analysis combines theoretical and empirical investigation. We propose a simple model of electoral competition based on the probabilistic voting approach (Lindbeck and Weibull, 1987). In the model, individuals are required to comply with restrictions on mobility imposed at the national level. Local politicians decide on the extent of information provision to their citizens. This information induces pro-social individuals to internalise the external costs of their own compliance with rules. Hence, information has a negative impact on individual utility, but, by promoting compliance, helps to improve public health. In equilibrium, politicians choose a level of information that depends on the extent of restrictions imposed by the national government. Furthermore, information decreases with the private cost imposed on individuals, but increases with health cost of more mobility. The model also suggests that local politicians tend to provide more information the larger the share of pro-social individuals in the population. Finally, from the perspective of local politicians, information is

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holds, etc.

<sup>2</sup>In Italy, regional governments manage health services, which local municipalities have no control on.



complementary to the restrictions imposed by the national government, and to the level of enforcement of such restrictions.

Our empirical analysis focuses on Italian municipalities during the first wave of the pandemic (March to September 2020). To proxy for the effort in providing information to citizens, we use novel data on Facebook posts by local municipalities on their institutional pages. Furthermore, to measure the effectiveness of this effort on compliance, we use novel information on local mobility constructed using Facebook data. We combine this information with public health indicators (number of cases and excess mortality). We show that municipalities where mayors were facing elections provided significantly more covid-related posts on Facebook, though only if located in the north of the country. There is no such effect for municipalities in the south. We interpret this result as due to the difference in the incidence of the pandemic in the two regions. We also find that the reduction in mobility at the municipality level (compliance with lockdown) was stronger in municipalities with an election scheduled than in comparable ones with no elections. To test the effect of information on mobility in a causal way, we use elections as instruments for information provision. This strategy allows us to deal with concerns about reverse causality, which may arise, for instance, because more mobility may be correlated with more cases which, in turn, may make mayors more concerned and thus inclined to provide more information. We find that more information provision caused a significant decrease in mobility. Again, this effect seems to arise only in the northern and central regions of the country, but not in the south. Moreover, we find a significant effect of information provision on reducing excess mortality. These results suggest that information provision - which is a proxy for overall intensity of support to the lockdown from the local municipalities - was effective in fostering compliance, and helped mitigating the health effects of the pandemic.

## 2 Literature

A number of papers have studied the compliance with government directives during COVID-19. As pointed out by [Besley and Dray \(2021\)](#), governments can play an important role in influencing private action during a pandemic, though political identity and demographics affect both the effectiveness of government action and the incentives of politicians to engage in costly interventions. [Bargain and Aminjonov \(2020\)](#) emphasise the role of individual and collective trust in political institutions in deter-

mining the effectiveness of government directives in controlling the pandemic, while [Goldstein and Wiedermann \(2021\)](#) and [Gabbadini et al. \(2020\)](#) focus on generalised trust as a determinant of the effectiveness of pandemic-controlling measures.

There is also a growing literature that looks at electoral competition and accountability during major crises such as a pandemic. [Ferraresi and Gucciardi \(2022\)](#) analyze voters perceptions regarding attributions of responsibility. [Picchio and Santolini \(2022\)](#) and [Cipullo and Le Moglie \(2022\)](#) study the effect of the pandemic on voter turnout using data from Italian local elections.

Finally, this paper also relates to a growing literature on the role of social media in influencing societal wellbeing and supporting collective policy goals. See, e.g., [Allcott et al. \(2020\)](#) and [Fraccaroli et al. \(2022\)](#).

### 3 Theoretical Framework

We consider two regions, north and south, denoted by  $r \in \{N, S\}$ . Each region contains a given number of identical municipalities that we normalize to one. There are two groups of voters in each municipality: the “egoistic” voters ( $j = E$ ) and the “pro-social” ones ( $j = P$ ). The population of each municipality is normalized to one, and the share of voters in each group is denoted by  $n_j^r$ , with  $r \in \{N, S\}$  and  $j \in \{E, P\}$ . Note that  $n_P^r = 1 - n_E^r$  for any  $r$ .

**Individuals.** Individuals in group  $E$  and  $P$  in region  $r$  have the following utility function

$$U_E^r(m, v) = (\alpha^r - e^r)m - \frac{m^2}{2} - \nu \bar{m}^r, \quad U_P^r(m, v) = (\alpha^r - e^r - i^r)m - \frac{m^2}{2} - \nu \bar{m}^r, \quad (1)$$

where  $m$  is the individual’s mobility during the pandemic and  $\alpha^r$  is a positive parameter capturing the marginal private benefit from mobility for individuals in region  $r$ . The individual’s cost of mobility increases with the level of enforcement of mobility restrictions,  $e^r$ , adopted by municipalities in region  $r$ . For pro-social individuals, the cost of mobility also increases in the amount of information about the pandemic provided by the municipality, because this information makes the individuals internalise some of the social cost of mobility (e.g., it makes them more mindful of the risk of spreading the virus to others). The last term in the utility function is the individual’s health damage during the pandemic (e.g., from getting infected) in region  $r$ . We assume that  $\nu > 0$ , so this damage increases in the total level of mobility in a municipality, that we

denote by  $\bar{m}^r$ . This assumption captures the relation between mobility and contagion. We assume each individual takes the total amount of mobility in her municipality (and, hence, the health damage) as given. For simplicity, the health damage in one municipality does not depend on mobility in other municipalities.

Maximizing the utility functions in (1), it is straightforward to determine the levels of mobility,  $m_j^r$ , chosen by individuals in each group:

$$m_E^r(e^r) = \alpha^r - e^r, \quad m_P^r(e^r, i^r) = \alpha^r - e^r - i^r. \quad (2)$$

Greater levels of enforcement and, for pro-social individuals, information, reduce mobility. Enforcement and information are thus substitute instruments to control mobility of the pro-social individuals. The aggregate level of mobility in the municipality is  $\bar{m}^r \equiv \sum_{j=E,P} n_j^r m_j^r$ .

Conditional on the policy variables  $e$  and  $i$ , the individuals obtain the following indirect utilities

$$V_E^r(e, i) = (\alpha^r - e^r) m_E^r(e^r) - \frac{m_E^r(e)^2}{2} - v^r(\bar{m}^r(e^r, i^r)) = \frac{(\alpha^r - e^r)^2}{2} - \nu \bar{m}^r(e^r, i^r),$$

$$V_P^r(e^r, i^r) = (\alpha^r - e^r - i^r) m_P^r(e^r) - \frac{m_P^r(e, i)^2}{2} - v^r(\bar{m}^r(e^r, i^r)) = \frac{(\alpha^r - i^r - e^r)^2}{2} - \nu \bar{m}^r(e^r, i^r).$$

**Policy and elections.** In each municipality, policy is decided by an incumbent mayor. In the basic version of the model, we assume that the level of enforcement,  $e^r$ , is exogenous. Hence, the only policy variable to be determined is the level of information,  $i^r$ . The mayor sustains a personal cost  $\gamma_i^r \frac{i^2}{2}$  when providing information level  $i$ . If an election is approaching, the mayor cares for her probability of re-election, denoted by  $\pi^r$ . Hence, the mayor's utility function is

$$U_M^r = \pi^r \cdot I_{ELEC} - \gamma_i^r \frac{i^{r^2}}{2}, \quad r = N, S, \quad (3)$$

where  $I_{ELEC}$  equals one if and only if the municipality is due to have an election, and zero otherwise.

To characterize the winning probability,  $\pi$ , we follow the probabilistic voting approach (Lindbeck and Weibull, 1987). We assume the electoral competition is between the incumbent mayor and a challenger, whose platform is exogenous to avoid inessential complications. If implemented, this platform would result in individuals in group  $j$  obtaining a utility of  $\hat{V}_j$ . We assume a voter in group  $j$  chooses the incumbent if and only if

$$V_j^r(e^r, i^r) \geq \hat{V}_j + \sigma_j + \delta, \quad r = N, S,$$

where  $\sigma$  is an idiosyncratic parameter capturing the individual's preference for the challenger, distributed uniformly among the individuals of group  $j$  on the  $\left[-\frac{1}{2\phi}; \frac{1}{2\phi}\right]$  interval (with density  $\phi$ , assumed identical in the two groups). Negative values of  $\sigma_j$  indicate a preference for the incumbent. The parameter  $\delta$  captures the challenger's overall popularity across the entire population and is a random variable distributed uniformly on the  $\left[-\frac{1}{2\psi}; \frac{1}{2\psi}\right]$  interval (with density  $\psi$ ).

Under the above assumptions, we obtain that the probability of winning for the mayor is (see proof below):

$$\pi^r = \frac{1}{2} + \psi \sum_{j=E,P} n_j^r \left( V_j^r(e^r, i^r) - \hat{V}_j \right), \quad r = N, S. \quad (4)$$

Let us now consider the choice of policy by the incumbent mayor. If there is no upcoming election ( $I_{ELEC} = 0$  in (3)), the mayor chooses  $i = 0$ , as there is no benefit in making any effort. Suppose now that there is an election coming ( $I_{ELEC} = 1$ ). The mayor chooses the following information level (proof below)

$$i^r = \max \left( \frac{(v + e - \alpha^r)(1 - n_E^r)}{\gamma_i^r/\psi - (1 - n_E^r)}, 0 \right), \quad r = N, S. \quad (5)$$

We assume the denominator in this expression is positive, otherwise the necessary (second-order) condition for an interior solution would not be satisfied. Hence, a positive level of information is provided if and only if  $v + e - \alpha^r > 0$ . Quite interestingly, a higher private benefit from mobility,  $\alpha^r$ , tends to discourage information provision. The intuition is that information raises the private cost of mobility, and the amount of mobility increases with  $\alpha^r$ . By the same token, the level of enforcement makes information more attractive to the mayor, suggesting that information and enforcement are complementary from her point of view. Furthermore, the expression shows that information increases when the health externality related to mobility is stronger, which is not surprising.

Finally, assuming a positive level of information provision, we obtain that

$$\frac{\partial i^r}{\partial n_E^r} = - \frac{(v + e - \alpha^r) \gamma_i^r / \psi}{(\gamma_i^r / \psi - (1 - n_E^r))^2} < 0, \quad r = N, S. \quad (6)$$

A smaller share of pro-social population induces less information provision, because the behavior of egoistic individuals is less sensitive to information.

### 3.1 Testable hypotheses

The theoretical analysis provides the following testable hypotheses:

- H1: Mayors up for reelection are more likely to provide pandemic-related information to their citizens, unless the external cost of mobility in a given region is very small compared to the private benefit.
- H2: The extent of information provided by a mayor in a region should increase with the external cost of mobility and with the enforcement of restrictions, and decrease with the private benefit from mobility
- H3: The extent of information provided by a mayor in a region should increase with the share of pro-social individuals
- H4: Greater information provision should cause reduced mobility, with a stronger effect the larger the share of pro-social individuals

## 4 Context and Data

### 4.1 Context

#### 4.1.1 The Covid pandemic in Italy

Italy was the first European country to be severely hit by the COVID-19 pandemic. Importantly, even though the entire country was significantly affected, the incidence of the pandemic in the country was not geographically uniform. The pandemic was far more severe in the north of the country than it was in the south, as can be seen from Figures 2 and 3. We have pandemic-related information for each municipality: excess mortality and covid cases at the provincial level.

#### 4.1.2 Institutional context and local elections

A national lockdown was established in Italy from March 2020. The lockdown lasted until June, and the restrictions were gradually relaxed until the second wave of the pandemic started in October 2020. See Figure 4 for a timeline of the restrictions. The lockdown was imposed by the central government and enforced by the national police. As one may expect, the lockdown resulted in a strong reduction in mobility all over the country. Figure 5 represents this reduction. The measure of mobility is based on the Human Mobility Index (HMI), which we observe at the municipality level. We also have information about mobility restrictions (imposed by the central government) at the provincial level.

Figure 2: *Covid Cases per 1000 inhabitants during the first wave (March to September 2020)*

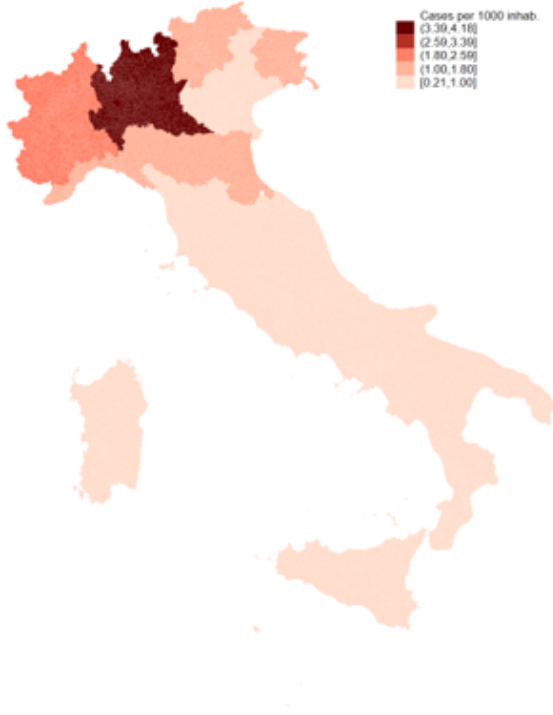
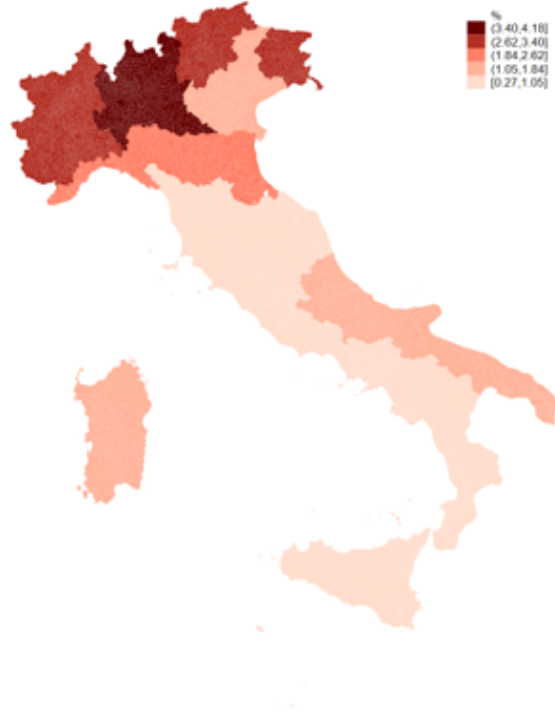


Figure 3: *Excess mortality in 2020 compared to the previous five years average*



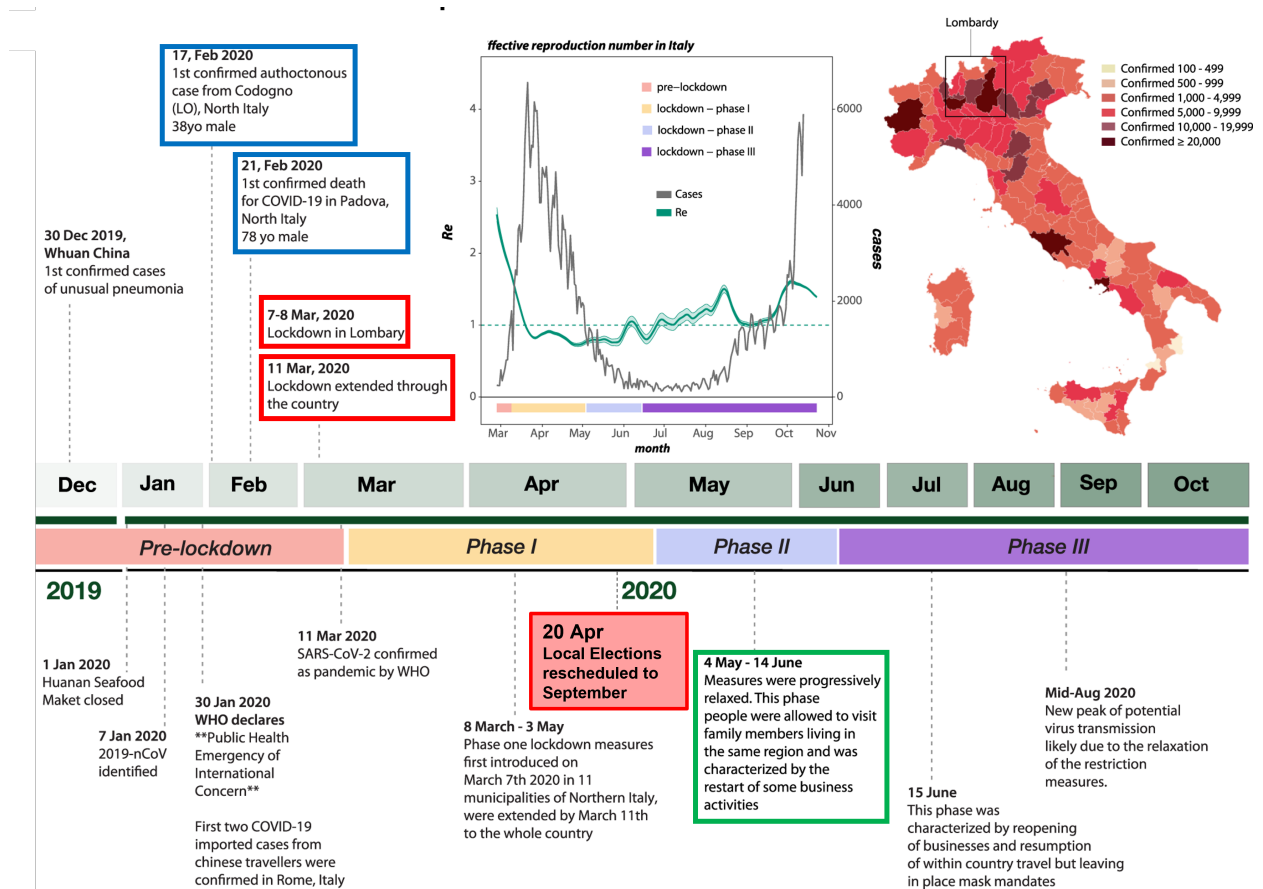
Municipal elections were to be held in 1184 municipalities (15% of the total) in May 2020. They were postponed to September 2020 (Central Government Decree of the 20th April) due to the pandemic. See Figure 6 for the timeline of events related to elections and the lockdown, and Figure 7 for the geographic distribution of municipalities under election. We observe these municipalities for 37 weeks, from March 2020 to September 2020. For each municipality, we have information about the electoral competition (election dummy, term limit, incumbent margin of victory in previous elections) as well as demographic information (population density, deprivation, population above 75). This information is time-invariant.

## 4.2 Data

### 4.2.1 Dataset structure

We briefly summarize our data sources here. Figure 8 summarises our sources of data. We have information about the development of the pandemic, namely number of cases and excess mortality, at the provincial level and measured weekly. We also have information about individual mobility (HMI), measured at the municipality level and

Figure 4: Covid restrictions timeline





daily. This information will provide our main proxy for compliance with the national lockdown.

We also have information about characteristics of each municipality. Specifically, we have information about municipality demographics, economic performance and four three measures of social capital (turnout in the 2013 constitutional referendum, payment of TV licenses in 2007, blood donations). See Appendix B for more information. Finally, we have information about the outcome of the 2020 elections in these municipalities. This information is time-invariant.

A key part of our dataset is information about the institutional facebook pages of 365 municipalities, about their facebook page, regarding posts related to covid, number of words related to covid and the ratio between covid related posts and total posts. This information is collected among January 1st up to 20th September 2020, at a daily level (collapsed by week). See Figure 9 for an example of such posts. We utilise two dictionaries with terms collected from such posts: a restricted dictionary with terms that seem most directly related to pandemic policy, and an expanded dictionary. See Appendix C for a complete description of such dictionaries. We construct three indicators from each dictionary, that we shall use as different proxies for information provision on Facebook by the given municipality:

- No. of covid related posts
- No. of covid related words
- Covid related posts / Total posts

Currently, we have information about the HMI and Facebook page activity for 365 municipalities. 185 of these municipalities faced an election in our period of observation election (of which, 73 are located in the North of the country), and 180 did not (67 of which in the north). These municipalities will be used as a (matched) control group, see below.

## 5 Empirical analysis

### 5.1 Empirical strategy

We exploit information about a panel of municipalities observed at the weekly level for a period of 37 weeks (March to September 2020). We match municipalities facing



elections to those that do not by creating a synthetic control group, creating a panel of weekly observations where the unit is a matched municipality  $i$  at week  $t$  (Iacus et al., 2012).

We estimate the effect of Facebook COVID-related activity on a weekly panel of matched municipalities, based on the following model:

$$Y_{ipt} = \beta_1 Facebook_{it} + \beta_2 Cases_{pt} + \beta_3 Fines_{pt} + X_i' \gamma + t + r + v_i + e_{it}. \quad (7)$$

The dependent variables in equation (7),  $Y_{ipt}$ , are either the HMI index (which is our proxy for individual compliance with the lockdown), or excess mortality (which is our proxy of welfare/health effects), at time  $t$  for municipality  $i$  in province  $p$ . Our main explanatory variable is the municipality's activity on Facebook, as measured by one of the three indexes presented above. We also include control for the number of covid cases per hospital beds and for the number of fines (both at the provincial level), as a proxy for the extent of enforcement of the mobility restrictions. The vector of time-invariant municipality-level controls,  $X_i$ , includes information about political characteristics (election, term limit, incumbent margin of victory in previous elections), social capital, population density, deprivation and population above 75.

A possible concern is that the variable  $Facebook_{it}$  is endogenous. For example, a municipality may be more active on Facebook to increase awareness of the dangers of the pandemic because its citizens tend not to comply with the rules and so mobility is high. To deal with this concern, we implement an instrumental variable strategy. We instrument  $Facebook_{it}$  with dummies capturing whether municipality  $i$  faced an election, a dummy capturing whether municipality  $i$  is located in the north of the country, a dummy equal to one after the introduction of the lockdown (March 2020), and their interaction. To understand this strategy, consider that, as suggested by our theory model, the presence of an election should affect the extent of information provision activity by municipalities, without having a direct effect on mobility. However, the extent and direction of this effect may depend on conditions including the extent of health externality, and the incidence of the pandemic, at the local level. As Figures 2, 3 and 4 suggest, at the time of the introduction of the lockdown, conditions were already such that the north of the country would see a significantly higher incidence of the pandemic than in the south.

Finally, we are going to estimate the model separately in two phases of the pandemic. Specifically, we are going to estimate the model comparing the period before the lockdown to the period right after the lockdown, until May 2020. This was defined as "Phase 1" of the pandemic. In a separate estimation, we are going to compare

the period before the lockdown to "Phase 2" of the pandemic, i.e. between June and September 2020. See Figure 4. The rationale for this choice is that the national restrictions in Phase 1 were much stricter, and essentially all economic activity was entirely shut down. Practically all mobility was ruled out and, due to the closures, individual incentives not to comply were very limited. This implies that the local municipalities had very little scope for intervening and affecting compliance. By contrast, a gradual reopening of economic activities was put in place in Phase 2, but individuals still had to comply with significant restrictions. In that phase, there was significantly more scope for municipalities to affect compliance.

## 5.2 Descriptive statistics

Figures 11, 10 and 12 present the distribution of our key explanatory variables over time, distinguishing municipalities between those that had an election and those that did not. These figures show a clearly different pattern between municipalities located in the north of the country and those located in the south. Similarly, municipalities under election have higher Facebook activity conditional on being in the north of the country, whereas municipalities in the south show less activity conditional on being under election.

Figures 13 and 14 present the temporal distribution of our dependent variables, mobility and excess mortality. The distribution of mobility changes present a similar difference between north and south in terms of the different behaviour of municipalities under election and not. Again, conditional on being located in the north, we observe a significant reduction in mobility in municipalities under election. By contrast, we do not see a significant difference in municipalities in the south.

The distribution of excess mortality, however, does not exhibit substantial differences between municipalities with and without elections, regardless of whether the municipality is located in the south or north.

## 5.3 Results

We present the results of the empirical analysis distinguishing between two phases of the first wave of the pandemic. Phase 1, from January to May 2020, and Phase 2, from June to September 2020. Figure 15 provides the OLS results for Phase 1. This table does not show a clear pattern of effects of municipality Facebook activity on the dependent variables. Figure 16 presents the results of the IV analysis for phase

1. The upper panel of the table, referring to the first-stage estimates, indicates that our main instrument (the triple interaction) seems to have a fairly inconsistent effect on municipalities Facebook activity. Furthermore, the instrument seems to have an effect on the main dependent variables (mobility and mortality). When looking at the second-stage results (bottom panel of the table), we again do not see a consistent pattern in terms of the effect of Facebook activity on the dependent variables. For example, the signs vary among the different measures of Facebook activity. Overall, the results regarding the effect of elections on Facebook activity, and the effect of this activity on mobility and mortality in Phase 1 seem fairly inconclusive. This is not surprising, given, as we mentioned previously, that the first phase of the lockdown was characterised by the most stringent restrictions on economic activity and mobility at the national level, so the scope for local government intervention was quite small.

The results regarding Phase 2 of the lockdown are presented next. The OLS table (Figure 17) again provides fairly inconsistent results, as one may expect due to the probably endogeneity of Facebook activity. Figure 18, presenting the IV results, provide a much more consistent picture overall. The upper panel of the table, showing the first-stage regressions, shows that, for all our measures of Facebook activity, municipalities under election and in the north were consistently more active than the other on Facebook. Furthermore, given Facebook activity, these municipalities do not exhibit a consistently different mobility or mortality than the others. Both these results support the validity of our instruments. The second-stage results consistently indicate, for all measures of Facebook activity, that this activity had overall a negative effect on mobility, seemingly fostering compliance with the lockdown. We also find a negative effect on mortality, though this effect is not statistically significant. These results suggest that information provision - which is a proxy for overall intensity of support to the lockdown from the local municipalities - was effective in fostering compliance, and helped mitigating the health effects of the pandemic.

## 6 Conclusions

We have studied the provision of information by local governments that supports individual compliance with nationwide regulation, and how this provision relates to the electoral process. We use information about individual mobility (compliance with the lockdown) and Facebook posts by Italian local governments during the Covid 19 pandemic. The analysis has shown that in municipalities where mayors were up for

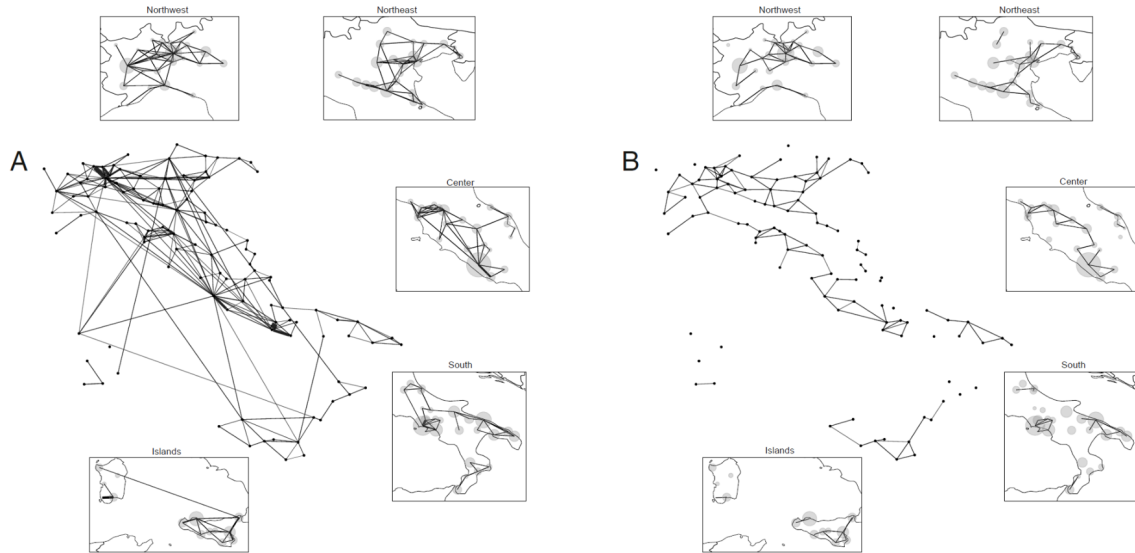
re-election, local governments provided significantly more covid-related information. This information caused a significant decrease in mobility and excess mortality. However, these effects seem to arise only in the northern regions of the country, where the impact of the pandemic was more severe.

## References

- Allcott, H., Braghieri, L., Eichmeyer, S., and Gentzkow, M. (2020). "The welfare effects of social media." *American Economic Review*, 110(3), 629–76.
- Bargain, O., and Aminjonov, U. (2020). "Trust and compliance to public health policies in times of covid-19." *Journal of Public Economics*, 192, 104316.
- Besley, T., and Dray, S. (2021). "Institutions, trust and responsiveness: Patterns of government and private action during the covid-19 pandemic." *LSE Public Policy Review*, 1.
- Cipullo, D., and Le Moglie, M. (2022). "To vote, or not to vote? electoral campaigns and the spread of covid-19." *European Journal of Political Economy*, 72, 102118.
- Ferraresi, M., and Gucciardi, G. (2022). "Political alignment, centralisation, and the sense of government unpreparedness during the covid-19 pandemic." *European Journal of Political Economy*, 73, 102144.
- Fracaroli, N., Druker, N., and Blyth, M. (2022). "Political anger.", available at: [https://watson.brown.edu/files/watson/imce/news/ResearchBriefs/2022/Anger\\_\\_\\_Politics%20%2810%29.pdf](https://watson.brown.edu/files/watson/imce/news/ResearchBriefs/2022/Anger___Politics%20%2810%29.pdf).
- Gabbiadini, A., Baldissarri, C., Durante, F., Valtorta, R. R., De Rosa, M., and Gallucci, M. (2020). "Together apart: The mitigating role of digital communication technologies on negative affect during the covid-19 outbreak in italy." *Frontiers in Psychology*, 11.
- Goldstein, A., and Wiedermann, J. (2021). "Trust me, mask up: Experimental evidence on social trust and responsiveness to covid-19 mitigation policies.", available at SSRN: <https://ssrn.com/abstract=3835934>.
- Iacus, S. M., King, G., and Porro, G. (2012). "Causal inference without balance checking: Coarsened exact matching." *Political Analysis*, 20(1), 1–24.

- Lindbeck, A., and Weibull, J. (1987). “Balanced-budget redistribution as the outcome of political competition.” *Public Choice*, 52(3), 273–297.
- Picchio, M., and Santolini, R. (2022). “The COVID-19 pandemic’s effects on voter turnout.” *European Journal of Political Economy*, 73, 102161.

Figure 5: *Human Mobility Restrictions*



Note: Near real time data on Human Mobility provided by Facebook at municipal level. Connectivity of the Italian mobility network during COVID-19 epidemic. (A and B) Snapshots of the mobility network on two Mondays before and after national lockdown (March 9), that is, on (A) February 24 and (B) March 30. Nodes represent municipalities aggregated at the province level, and they all have equal size, whereas thickness of edges is proportional to their weight. Insets provide an outlook on different regions, where node size is instead proportional to the population of the province.

Figure 6: *Timeline of elections and lockdown*

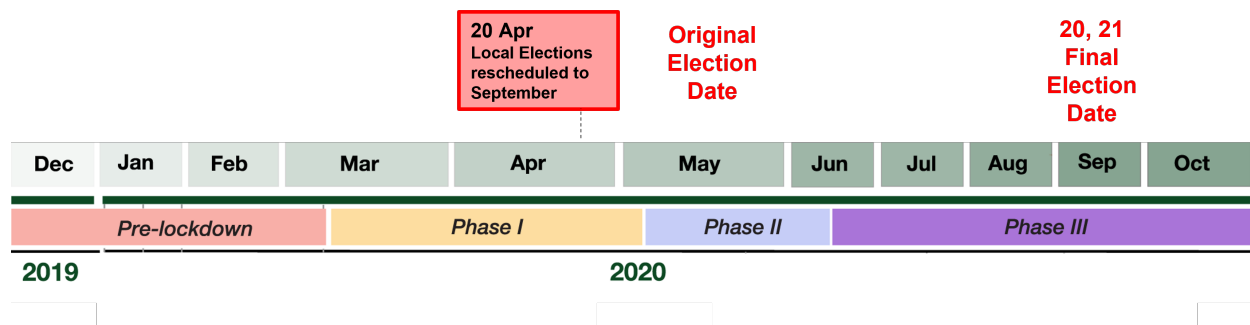


Figure 7: *Municipalities under election by region*

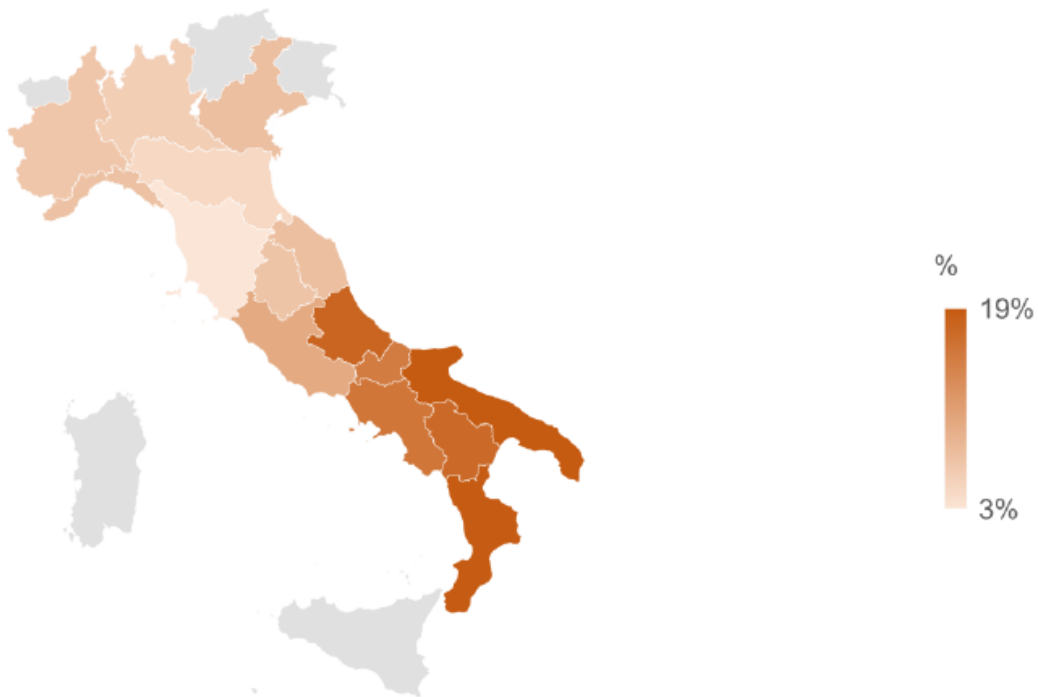


Figure 8: *Summary of data sources*

Pandemic Related Information	Number of Cases	Province	Administrative Data	Weekly
	Excess Mortality	Province	Administrative Data	Weekly
	Human Mobility	Municipality	Facebook	Weekly
Facebook Activity on Municipality Page	Posts, Links, Images	Municipality	Facebook	Daily
	Likes	Municipality	Facebook	Daily
	Reactions	Municipality	Facebook	Daily
	Followers	Municipality	Facebook	Time-Invariant
Municipality Characteristics	Demographics	Municipality	Administrative Data	Time-Invariant
	Performance	Municipality	Administrative Data	Time-Invariant
	Politics	Municipality	Administrative Data	Time-Invariant
	Socio-Economics	Municipality	Administrative Data	Time-Invariant
	Social Capital	Municipality	Administrative Data	Time-Invariant

Figure 9: *An example of FB post by a municipality*

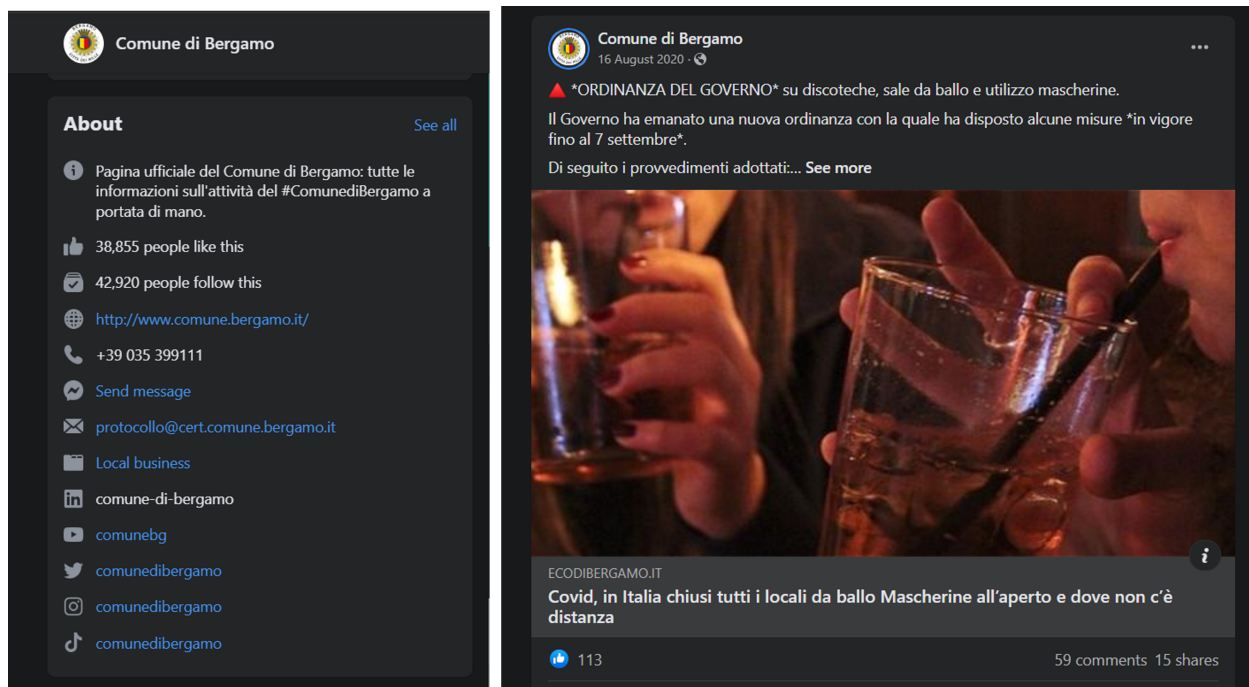


Figure 10: Temporal distribution, n. of covid related words

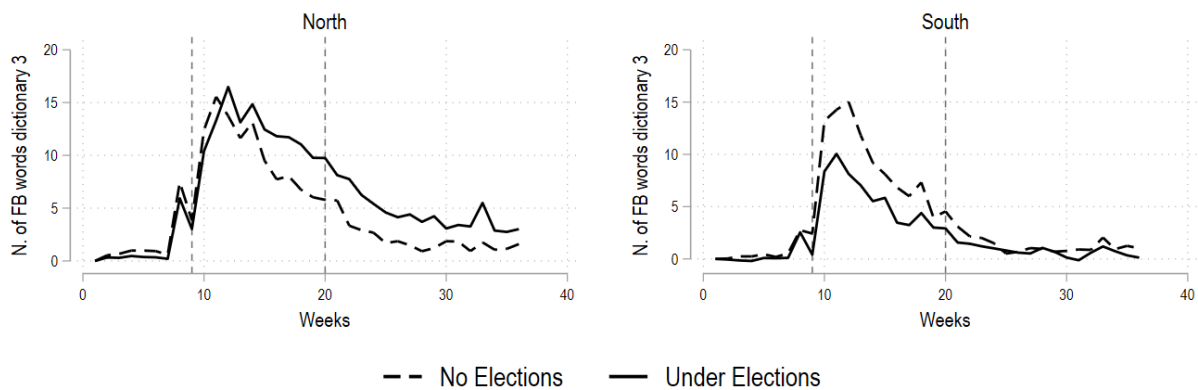


Figure 11: Temporal distribution, n. of covid related posts

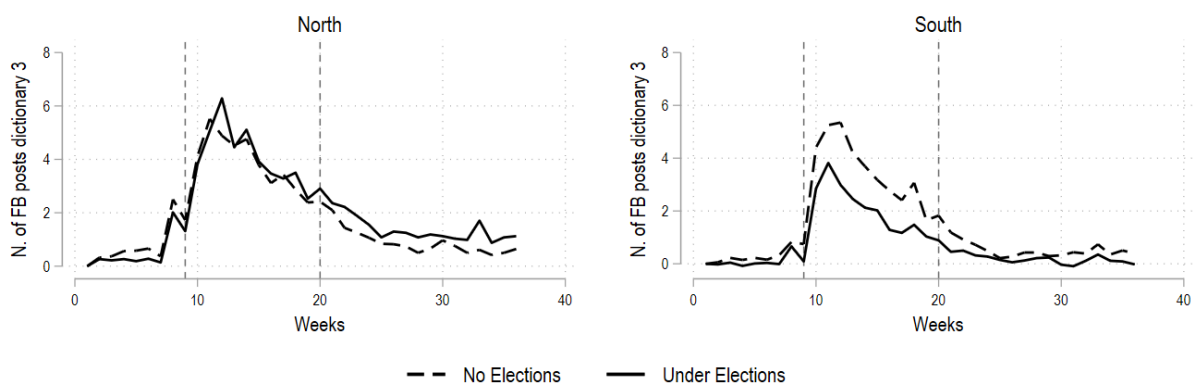




Figure 12: Temporal distribution, share of covid related posts

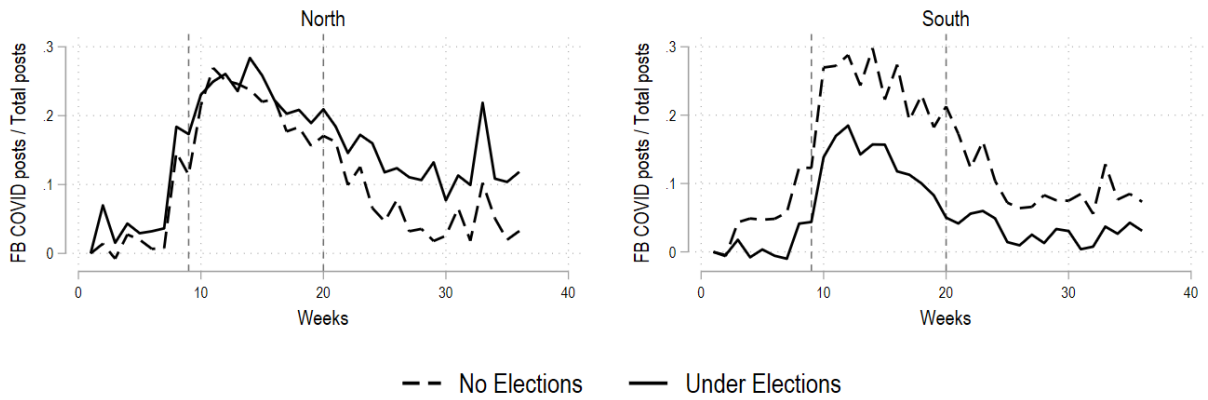


Figure 13: Temporal distribution, mobility

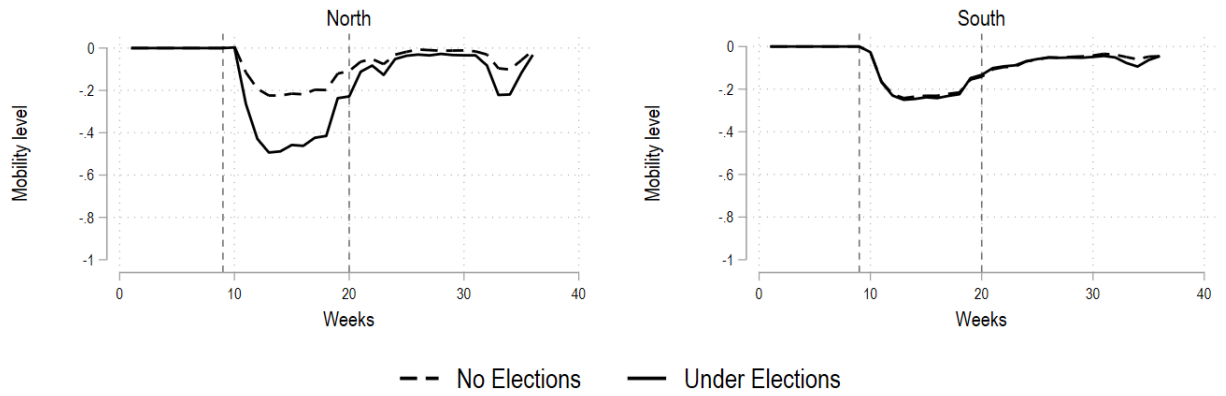


Figure 14: Temporal distribution, excess mortality

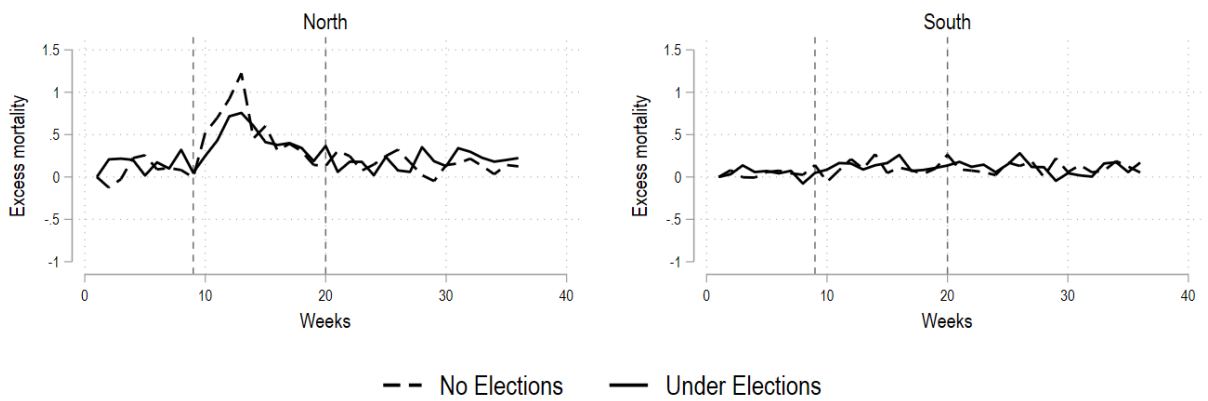


Figure 15: OLS results, Phase 1

Y = Human Mobility, weekly panel, Random Effect model estimated with F-GLS

	covid posts / total posts		no. of covid related posts		no. of covid related words	
	[1]	[2]	[3]	[4]	[5]	[6]
	<i>Restrected Dictionary</i>	<i>Larger Dictionary</i>	<i>Restrected Dictionary</i>	<i>Larger Dictionary</i>	<i>Restrected Dictionary</i>	<i>Larger Dictionary</i>
Facebook activity	-0.0230 [0.318]	-0.0517*** [0.009]	0.000160 [0.911]	-0.00144 [0.228]	0.000386 [0.372]	-0.000304 [0.423]
Controls, Week and Reg. dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5338	5338	5338	5338	5338	5338

p-values in brackets, \*\* p&lt;0.10, \*\* p&lt;0.05, \*\*\* p&lt;0.01"

Y = Excess Mortality, weekly panel, Random Effect model estimated with F-GLS

	covid posts / total posts		no. of covid related posts		no. of covid related words	
	[1]	[2]	[3]	[4]	[5]	[6]
	<i>Restrected Dictionary</i>	<i>Larger Dictionary</i>	<i>Restrected Dictionary</i>	<i>Larger Dictionary</i>	<i>Restrected Dictionary</i>	<i>Larger Dictionary</i>
Facebook activity	0.0276 [0.637]	0.0130 [0.777]	-0.00652* [0.067]	-0.00614** [0.028]	-0.00202* [0.062]	-0.00244*** [0.008]
Controls, Week and Reg. dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5338	5338	5338	5338	5338	5338

p-values in brackets, \*\* p&lt;0.10, \*\* p&lt;0.05, \*\*\* p&lt;0.01"

Figure 16: IV results, Phase 1

	FIRST STAGE						Outcome variables	
	Covid posts / Total posts		Covid related posts		Covid related words		[7] <i>Mobility</i>	[8] <i>Excess mortality</i>
	[1]	[2]	[3]	[4]	[5]	[6]		
	<i>Restrected Dictionary</i>	<i>Larger Dictionary</i>	<i>Restrected Dictionary</i>	<i>Larger Dictionary</i>	<i>Restrected Dictionary</i>	<i>Larger Dictionary</i>		
Under election (treatment)	-0.00974 [0.313]	-0.0385* [0.066]	-0.0109 [0.926]	-0.138 [0.494]	-0.00465 [0.990]	-0.282 [0.596]	-0.0320 [0.723]	-0.00815 [0.832]
NORD Dummy	-0.0104 [0.825]	-0.00106 [0.989]	-0.372 [0.647]	-0.296 [0.800]	-1.242 [0.647]	0.308 [0.919]	-0.224 [0.235]	-0.0833 [0.310]
After lockdown (post)	0.201*** [0.000]	0.195*** [0.000]	2.963*** [0.000]	3.489*** [0.000]	8.075*** [0.000]	9.221*** [0.000]	-0.207*** [0.000]	-0.0214 [0.447]
Treatment X Post	-0.0838*** [0.003]	-0.0609** [0.045]	-1.364*** [0.008]	-1.191* [0.063]	-3.901** [0.014]	-3.071 [0.115]	0.00349 [0.959]	0.0569 [0.159]
NORD Dummy X Post	-0.0176 [0.590]	0.00949 [0.787]	-0.259 [0.692]	0.148 [0.848]	-0.371 [0.857]	-0.0214 [0.993]	0.0699 [0.318]	0.287*** [0.004]
Treatment X NORD Dummy	0.000892 [0.953]	-0.00817 [0.809]	-0.0614 [0.792]	-0.291 [0.468]	-0.310 [0.672]	-0.311 [0.757]	0.247* [0.090]	0.0287 [0.644]
Treatment X NORD Dummy X Post	0.0304 [0.481]	0.0177 [0.708]	1.496 [0.110]	1.462 [0.202]	4.817 [0.115]	5.155 [0.166]	-0.217* [0.055]	-0.224* [0.070]
Observations	5338	5338	5338	5338	5338	5338	5338	5338
Controls, Week and Reg. dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SECOND STAGE (F-GLS, RE)								
Dep: Human Mobility								
Facebook activity	0.872*** [0.000]	0.595** [0.035]	-0.0284* [0.061]	-0.0596*** [0.001]	-0.0162*** [0.003]	-0.0297*** [0.000]		
Dep: Excess Mortality								
Facebook activity	0.0471 [0.916]	0.384 [0.300]	-0.0259 [0.443]	0.00836 [0.793]	-0.00905 [0.439]	-0.00777 [0.527]		
Controls, Week and Reg. dummies	Yes	Yes	Yes	Yes	Yes	Yes		
Observations	5338	5338	5338	5338	5338	5338		

p-values in brackets, \*\* p&lt;0.10, \*\* p&lt;0.05, \*\*\* p&lt;0.01"

Figure 17: OLS results, Phase 2

Y = Human Mobility, weekly panel, Random Effect model estimated with F-GLS

	covid posts / total posts		no. of covid related posts		no. of covid related words	
	[1]	[2]	[3]	[4]	[5]	[6]
	<i>Restrected Dictionary</i>	<i>Larger Dictionary</i>	<i>Restrected Dictionary</i>	<i>Larger Dictionary</i>	<i>Restrected Dictionary</i>	<i>Larger Dictionary</i>
Facebook activity	0.00907 [0.392]	-0.00812 [0.348]	0.00315** [0.030]	0.00240** [0.043]	0.000790* [0.071]	0.000806** [0.024]
Controls, Week and Reg. dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7536	7536	7536	7536	7536	7536

p-values in brackets, \*\* p&lt;0.10, \*\* p&lt;0.05, \*\*\* p&lt;0.01"

Y = Excess Mortality, weekly panel, Random Effect model estimated with F-GLS

	covid posts / total posts		no. of covid related posts		no. of covid related words	
	[1]	[2]	[3]	[4]	[5]	[6]
	<i>Restrected Dictionary</i>	<i>Larger Dictionary</i>	<i>Restrected Dictionary</i>	<i>Larger Dictionary</i>	<i>Restrected Dictionary</i>	<i>Larger Dictionary</i>
Facebook activity	0.0239 [0.578]	-0.00121 [0.970]	0.00113 [0.827]	-0.00168 [0.660]	0.000311 [0.837]	-0.000432 [0.715]
Controls, Week and Reg. dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7536	7536	7536	7536	7536	7536

p-values in brackets, \*\* p&lt;0.10, \*\* p&lt;0.05, \*\*\* p&lt;0.01"

Figure 18: OLS results, Phase 2

	FIRST STAGE						Outcome variables	
	Covid posts / Total posts		Covid related posts		Covid related words		Mobility	Excess mortality
	[1]	[2]	[3]	[4]	[5]	[6]		
	<i>Restrected Dictionary</i>	<i>Larger Dictionary</i>	<i>Restrected Dictionary</i>	<i>Larger Dictionary</i>	<i>Restrected Dictionary</i>	<i>Larger Dictionary</i>		
Under election (treatment)	-0.00606 [0.508]	-0.0368* [0.071]	0.0121 [0.864]	-0.113 [0.467]	0.0575 [0.810]	-0.174 [0.608]	-0.0401 [0.653]	-0.000971 [0.980]
NORD Dummy	-0.0127 [0.659]	0.0144 [0.803]	-0.00483 [0.986]	0.210 [0.736]	0.402 [0.657]	0.668 [0.626]	-0.304 [0.179]	-0.0323 [0.428]
After lockdown (post)	0.0478*** [0.000]	0.0301** [0.012]	0.221*** [0.001]	0.154* [0.068]	0.276 [0.178]	0.391* [0.100]	-0.0650** [0.045]	0.0321 [0.258]
Treatment X Post	-0.0231 [0.106]	-0.0164 [0.339]	-0.103 [0.285]	-0.0898 [0.403]	-0.217 [0.446]	-0.0397 [0.927]	-0.00158 [0.968]	0.0170 [0.698]
NORD Dummy X Post	-0.0280** [0.028]	-0.0186 [0.258]	-0.216* [0.051]	-0.207 [0.140]	-0.976*** [0.003]	-0.507 [0.160]	0.0248 [0.488]	0.0197 [0.684]
Treatment X NORD Dummy	-0.00228 [0.870]	-0.00661 [0.839]	-0.0931 [0.541]	-0.305 [0.341]	-0.393 [0.452]	-0.433 [0.554]	0.217 [0.124]	0.0266 [0.650]
Treatment X NORD Dummy X Post	0.0671*** [0.005]	0.0433 [0.103]	0.779** [0.019]	0.821** [0.020]	2.956** [0.025]	2.998** [0.049]	-0.0366 [0.450]	-0.0656 [0.344]
Observations	7536	7536	7536	7536	7536	7536	7536	7536
Controls, Week and Reg. dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	SECOND STAGE (F-GLS, RE)							
	Dep: Human Mobility							
	[1]	[2]	[3]	[4]	[5]	[6]		
	<i>Restrected Dictionary</i>	<i>Larger Dictionary</i>	<i>Restrected Dictionary</i>	<i>Larger Dictionary</i>	<i>Restrected Dictionary</i>	<i>Larger Dictionary</i>		
Facebook activity	-0.549** [0.022]	-0.801* [0.078]	-0.0428*** [0.005]	-0.0395*** [0.006]	-0.0119*** [0.003]	-0.00927*** [0.006]		
	Dep: Excess Mortality							
	[1]	[2]	[3]	[4]	[5]	[6]		
	<i>Restrected Dictionary</i>	<i>Larger Dictionary</i>	<i>Restrected Dictionary</i>	<i>Larger Dictionary</i>	<i>Restrected Dictionary</i>	<i>Larger Dictionary</i>		
	<i>Restrected Dictionary</i>	<i>Larger Dictionary</i>	<i>Restrected Dictionary</i>	<i>Larger Dictionary</i>	<i>Restrected Dictionary</i>	<i>Larger Dictionary</i>		
Facebook activity	-0.655 [0.272]	-0.231 [0.540]	-0.0470 [0.313]	-0.0649 [0.241]	-0.0113 [0.343]	-0.0115 [0.312]		
Controls, Week and Reg. dummies	Yes	Yes	Yes	Yes	Yes	Yes		
Observations	7536	7536	7536	7536	7536	7536		

p-values in brackets, \*\* p&lt;0.10, \*\* p&lt;0.05, \*\*\* p&lt;0.01"

# Appendix

## A Proofs

### Probability of winning

Let  $\bar{\sigma}_j$  be the value of  $\sigma_j$  such that a voter in group  $j$  is indifferent between the mayor and the challenger. We have  $\bar{\sigma}_j = V_j^r(e, i) - \hat{V}_j - \delta$ . All voters in group  $j$  such that  $\sigma_j \leq \bar{\sigma}_j$  prefer the incumbent. Hence, under our assumptions, the share of voters in group  $j$  that chooses the incumbent given  $e, i$  and the realization of  $\delta$  is

$$S_j^r = \left( V_j^r(e, i) - \hat{V}_j - \delta + \frac{1}{2\phi_j} \right)$$

so that the total share of votes of the incumbent is

$$S^r = \sum_{j=E,P} n_j^r \phi_j \left( V_j^r(e, i) - \hat{V}_j - \delta + \frac{1}{2\phi_j} \right). \quad (8)$$

Given the above expression, we can calculate the probability of winning of the incumbent, conditional on  $e$  and  $i$ . We have

$$\pi = Pr \left[ S^r \geq \frac{1}{2} \right] = Pr \left[ \sum_{j=E,P} n_j^r \phi_j \left( V_j^r(e, i) - \hat{V}_j \right) \geq \delta \sum_{j=E,P} n_j^r \phi_j \right].$$

Given the distribution of  $\delta$ , and setting  $\phi_j = \phi$  we get that

$$\pi = Pr \left[ \frac{\sum_{j=E,P} n_j^r \phi_j \left( V_j^r(e, i) - \hat{V}_j \right)}{\phi} \geq \delta \right] = \frac{1}{2} + \psi \sum_{j=E,P} n_j^r \left( V_j^r(e, i) - \hat{V}_j \right). \quad (9)$$

### Equilibrium policy variables

Maximizing (3) and applying the envelope theorem, the equilibrium value  $i$  in a given municipality in region  $r$  with elections satisfies the following FOCs:

$$\psi \left[ -n_E^r v \frac{\partial m^r}{\partial i} + n_P^r \left( -m_P^r - v \frac{\partial m^r}{\partial i} \right) \right] - \gamma_i^r i = 0 \quad (10)$$

Noting from (2) that  $\frac{\partial m_E^r}{\partial i} = 0$  and  $\frac{\partial m_P^r}{\partial i} = -1$ , we have that  $\frac{\partial m^r}{\partial i} = -n_P^r$ . Replacing in the above equation and using the expressions for  $m_E^r$  and  $m_P^r$  provided in (2), we can rewrite the above FOC as

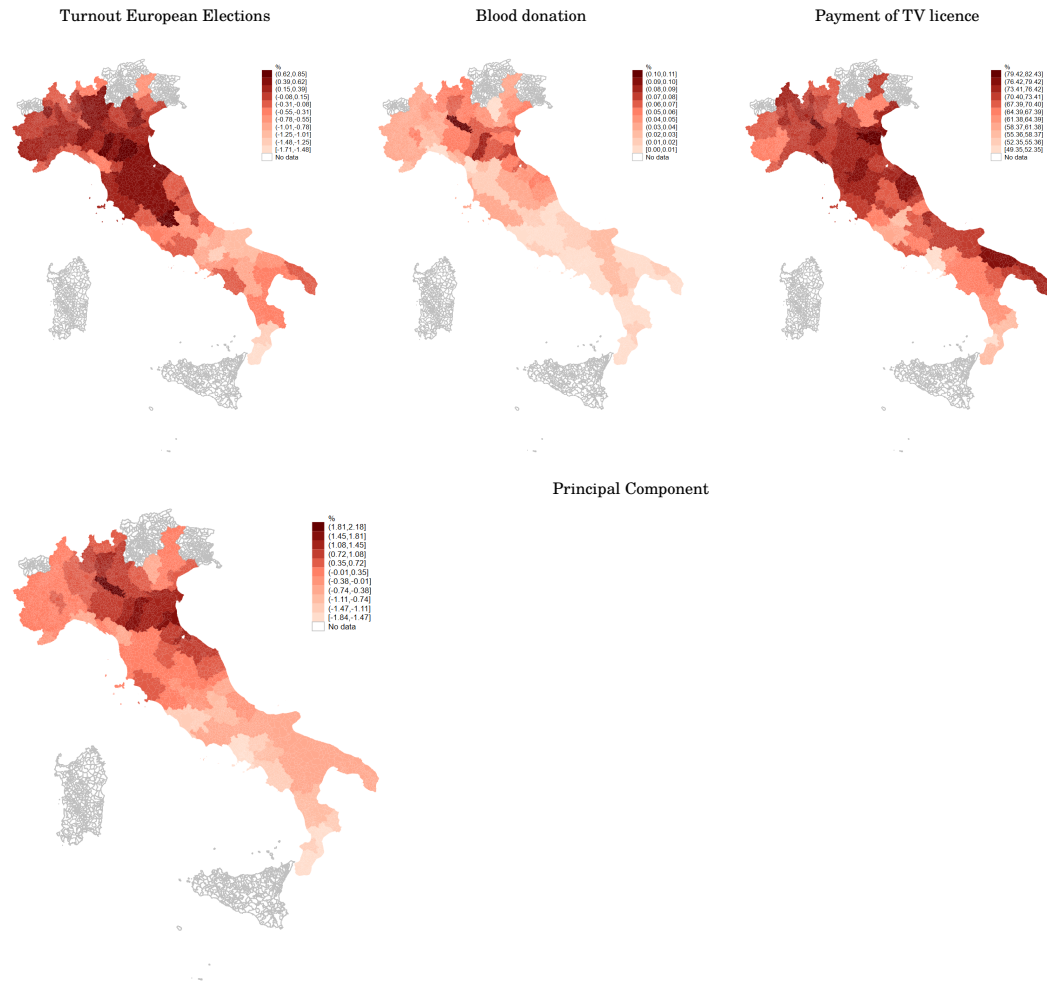
$$\psi [n_E^r v n_P^r + n_P^r (-(\alpha - e - i) + v n_P^r)] - \gamma_i^r i = 0 \quad (11)$$

Using the fact that  $n_P^r = 1 - n_E^r$ , this equation can be rewritten as

$$\psi \left[ (1 - n_E^r) (-\alpha + e + i + v) \right] - \gamma_i^r i = 0 \quad (12)$$

It is immediately checked that the second order condition for a maximum holds if and only if  $\gamma_i^r/\psi - (1 - n_E^r) > 0$ . Assuming this condition holds and solving the above equation for  $i$  we obtain (5).

## B Social Capital Indicators



## C Pandemic Dictionaries

Two types of dictionary

- Restricted dictionary: corona, coronavirus, covid, lockdown, contagi, contagio, contagiare, contagiati, anticovid, contenimento, distanziamento, quarantena,

quarantene, pandemia, nuovocoronavirus, sars, virus, epidemia, epidemiologica, epidemiologico, emergenzacoronavirus

- Larger dictionary: casa, casi, contatti, contatto, dispositivi, decedute, deceduti, decessi, decesso, decreti, decreto, defunti, disinfezione, distanti, distanza, distanze, dpcm, emergenza, emergenze, emergenziale, febbre, guarite, guariti, guarito, guarigione, guarigioni, infermieri, infezione, limitazione, limitazioni, malati, malattia, malattie, medici, medicina, medicinali, medico, ministeriale, ministeriali, ministero, ministri, ministro, ospedale, ospedali, ospedaliera, ospedaliera, ospedaliero, ospedalizzati, pervenire, prevenzione, positivi, positivo, positiva, positive, positività , protezionecivile, proteggere, protezione, protocolli, protocollo, rapidi, rapido, ricoverata, ricoverate, ricoverati, ricoverato, ricoveri, ricovero, ripartire, salute,,sanificazione, sanita, sanitari, sanitaria, sanitarie, sanitÃ , sanitario, sanzioni, sintomi, test, trasmissione, videoconferenza, volontari, volontaria, volontariato, volontario, zona, zone

## **D Self-declaration travel document during the lockdown**

**AUTODICHIARAZIONE AI SENSI DEGLI ARTT. 46 E 47 D.P.R. N. 445/2000**

Il/La sottoscritto/a \_\_\_\_\_, nato/a il \_\_\_\_/\_\_\_\_/\_\_\_\_  
a \_\_\_\_\_ (\_\_\_\_), residente in \_\_\_\_\_  
(\_\_\_\_), via \_\_\_\_\_ e domiciliato/a in \_\_\_\_\_  
(\_\_\_\_), via \_\_\_\_\_, identificato/a a mezzo \_\_\_\_\_  
nr. \_\_\_\_\_, rilasciato da \_\_\_\_\_  
in data \_\_\_\_/\_\_\_\_/\_\_\_\_, utenza telefonica \_\_\_\_\_, consapevole delle conseguenze penali  
previste in caso di dichiarazioni mendaci a pubblico ufficiale (art. 495 c.p.)

**DICHIARA SOTTO LA PROPRIA RESPONSABILITÀ**

- di essere a conoscenza delle misure normative di contenimento del contagio da COVID-19 vigenti alla data odierna, concernenti le limitazioni alla possibilità di spostamento delle persone fisiche all'interno del territorio nazionale;
- di essere a conoscenza delle altre misure e limitazioni previste da ordinanze o altri provvedimenti amministrativi adottati dal Presidente della Regione o dal Sindaco ai sensi delle vigenti normative;
- di essere a conoscenza delle sanzioni previste dall'art. 4 del decreto-legge 25 marzo 2020, n. 19, e dall'art. 2 del decreto-legge 16 maggio 2020, n. 33;
- che lo spostamento è determinato da:
  - ☐ - comprovate esigenze lavorative;
  - ☐ - motivi di salute;
  - ☐ - altri motivi ammessi dalle vigenti normative ovvero dai predetti decreti, ordinanze e altri provvedimenti che definiscono le misure di prevenzione della diffusione del contagio;  
(specificare il motivo che determina lo spostamento):  
\_\_\_\_\_  
\_\_\_\_\_;

- che lo spostamento è iniziato da (indicare l'indirizzo da cui è iniziato)  
\_\_\_\_\_  
\_\_\_\_\_;

- con destinazione (indicare l'indirizzo di destinazione)  
\_\_\_\_\_  
\_\_\_\_\_;

- in merito allo spostamento, dichiara inoltre che:  
\_\_\_\_\_  
\_\_\_\_\_.

\_\_\_\_\_  
Data, ora e luogo del controllo  
Firma del dichiarante

L'Operatore di Polizia