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Two Approaches to Saving the Economy: Micro-Level Effects of Covid-19 Lockdowns in Italy

Zsombor Cseres-Gergely

Valentin Kecht

Julia Le Blanc

Luca Onorante

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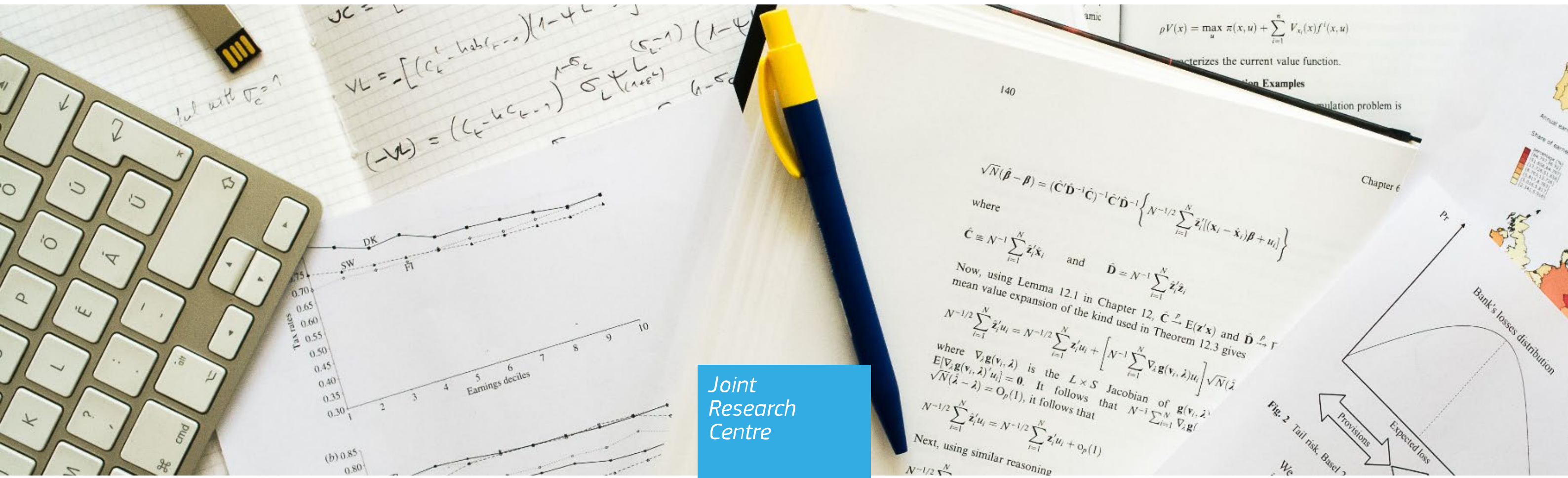

Joint Research Centre

Contact information
Name: Luca Onorante
Email: luca.onorante@ec.europa.eu

EU Science Hub
https://joint-research-centre.ec.europa.eu

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Two Approaches to Saving the Economy: Micro-Level Effects of Covid-19 Lockdowns in Italy
Executive Summary

In response to the two waves of Covid-19 in 2020, the Italian government implemented a general lockdown in March, but geographically targeted policies during fall. We exploit this natural experiment to compare the effects of the two policies in a difference-in-differences design, leveraging a unique database combining traditional, municipality-level and big data at weekly frequency. We find that the general lockdown of the first wave strongly reduced mobility at a high price in terms of employment, while the targeted policies during the second wave induced a lower decrease in mobility and little additional economic cost. We also study the role of pre-existing municipality characteristics and labour market policies in shaping these responses. Our results suggest that working from home and short-term work schemes buffered the adverse consequences of the drop in economic activity on the labour market. Both mechanisms, however, acted more strongly in high-income areas and among white collar workers, exacerbating existing inequalities.

This paper addresses several related questions. First, what was the effect of the two lockdown approaches on mobility, and did they affect communities heterogeneously? Second, was it economically less costly to impose targeted compared to general lockdowns and, relatedly, which factors cushioned the resulting adverse effects on the Italian labour market? Third, to what extent did the implemented short-term work schemes buffer the negative employment effect, and where? Finally, what was the overall effect of these policies on inequality?

Our analysis reveals that the general lockdown implemented in Spring 2020 caused large reductions in mobility and employment, whereas the targeted approach during the second wave inflicted comparatively little additional economic costs.

At the same time, we report sizeable heterogeneities in all these effects along socioeconomic lines. The drop in economic activity was less pronounced in high-income communities with higher shares of teleworkable jobs and mitigated by governmental intervention in the form of STW schemes. Both factors shielded employees more effectively from loosing their jobs in more affluent municipalities, implying that the Covid-19 crises likely worsened existing geographical inequalities and the historical North/South divide.

These findings offer important insights for policy-makers. First, we show that working from home effectively protected employees from job losses. In light of the largely positive effects of working from home or hybrid working, which include benefits in terms of job retention, job satisfaction, and worker productivity, improving the digital and legal infrastructure that allows working from home will be key to enhancing economic resilience to future pandemics and systemic disruptions in general. Second, and although both targeted and general lockdown policies provided good levels of protection, our results suggest that local approaches are less harmful to the economy while sufficient in controlling virus transmission. Factoring in the existing literature, one can therefore conclude that lockdowns should be imposed *quickly and locally.* Finally, we highlight the importance of taking appropriate labour market measures to cushion the consequences of the economic fallout on the labour force, preferably complementing with traditional unemployment insurance or other support payments to ensure an even support for all societal groups.

Two Approaches to Saving the Economy: Micro-Level Effects of Covid-19 Lockdowns in Italy

Zsombor Cseres-Gergely[a], Valentin Kecht[b], Julia Le Blanc[a], Luca Onorante [1a]

[a]*European Commission - Joint Research Centre, Via E. Fermi, Ispra, 21027, Italy*
[b]*Department of Economics, University of Bonn, Kaiserstrasse 1, Bonn, 53113, Germany*

Abstract

In response to the two waves of Covid-19 in 2020, the Italian government implemented a general lockdown in March, but geographically targeted policies during fall. We exploit this natural experiment to compare the effects of the two policies in a difference-in-differences design, leveraging a unique database combining traditional, municipality-level and big data at weekly frequency. We find that the general lockdown of the first wave strongly reduced mobility at a high price in terms of employment, while the targeted policies during the second wave induced a lower decrease in mobility and little additional economic cost. We also study the role of pre-existing municipality characteristics and labour market policies in shaping these responses. Our results suggest that working from home and short-term working schemes buffered the adverse consequences of the drop in economic activity on the labour market. Both mechanisms, however, acted more strongly in high-income areas and among white collar workers, further exacerbating existing inequalities.

Keywords: Covid-19, human mobility, lockdowns, big data, differences-in-differences
JEL: I12, I18, H12, D04, C33, H51

[1]Corresponding author: Onorante (`e-mail`: luca.onorante@ec.europa.eu). The views expressed in this paper are solely those of the authors and should not, under any circumstance, be regarded as stating an official position of the European Commission. We would like to thank Michele Vespe, Francesco Sermi, Joachim Winter, and unit B6 of the JRC for their valuable comments and help with the data. We are grateful to the participants of internal seminars at the JRC and the University of Salzburg for the numerous comments that significantly improved the paper.

1. Introduction

Given the absence of vaccines, the first year of the Covid-19 crises was largely managed through social distancing measures, often in form of partial or complete lockdowns. Italy was exposed to two waves – one in spring and one in fall 2020 – which were combatted in substantially different ways: during the first wave, a general lockdown was imposed in the whole country. Throughout the second wave, Italy used a lockdown approach with a very high degree of spatial differentiation. The stringency of these lockdown policies was regulated by a "traffic light system", which was primarily dictated by local Covid-19 incidences. Attempting to balance the health and economic costs, this system was aimed at preventing the collapse of the healthcare system while minimizing economic damage.

This paper addresses several related questions. First, what was the effect of the two lockdown approaches on mobility, and did they affect communities heterogeneously? Second, was it economically less costly to impose targeted compared to general lockdowns and, relatedly, which factors cushioned the resulting adverse effects on the Italian labour market? Third, to what extent did the implemented short-term working schemes buffer the negative employment effect, and where? Finally, what was the overall effect of these policies on inequality?

We study these questions by combining difference-in-differences approaches with a unique, geographically disaggregated database comprising: (*i*) weekly data on lockdown measures at the municipality level, (*ii*) a high-frequency database of mobility within and across municipalities, provided by Italian telecom operators and processed by the Joint Research Centre, (*iii*) a large dataset of socioeconomic characteristics for each municipality, drawing on the Italian Institute of Statistics (ISTAT) and housing market websites, (*iv*) disaggregated indicators on employment and short-term working schemes (STW).

Using these data, we offer three sets of results: First, this study is among the few systematic ex-post comparisons of global vs. local lockdown measures prior to the availability of vaccines. Our results indicate that the lockdown-induced losses in economic activity and employment were sizeable during the first wave, however, the effects during the second wave were moderate or insignificant. Mobility reduced by 45% and 22% for the first and second wave, respectively, while employment decreased by 6.4% during the first wave and did not change significantly during the second one. We argue that this pattern can be ascribed both to the different approaches in the lockdown measures and to the adjustment of the economy to the pandemic situation.

Second, the granularity of our data allows us to study socioeconomic heterogeneity in these effects. While we observe the largest mobility reductions in the most privileged municipalities – as proxied by income, wealth, unemployment or teleworkability –, these areas see the smallest reductions in employment. During the interval between the two waves, heterogeneities were even more pronounced for mobility but shrunk for employment.

Third, we document a hike in STW uptake during the first wave, which attenuates throughout the year. We show that STW receipt was much higher in more privileged municipalities and helped buffer the impact of the negative economic shocks on employment. Hence, STW schemes proved useful in preserving matches between employers and employees, but did so in a non-equal manner, as municipalities with higher levels of poverty and unemployment were proportionally less supported.

Taken together, we find that the general lockdown of the first wave strongly reduced mobility at a high price in terms of employment, while the targeted policies during the second wave led to a lower reduction in mobility and inflicted little additional economic cost. Moreover, our results indicate that working from home and STW schemes buffered the adverse consequences of the drop in economic activity on the labour market. Yet, both mechanisms acted more strongly in high-income areas and among white collar workers. Therefore, existing differences mapped into further increases in the existing geographic inequality, in particular the salient North/South divide.

The paper is structured as follows: The remainder of this section summarizes the related literature. Sections 2 and 3 describe and visualise the data. In Section 4, we present the results on the mobility effects of Covid-19. Section 5 examines the impact on the labour market, and section 6 analyses the link between short-term working schemes and employment. Section 7 concludes.

Literature. We contribute to the literature exploiting cellphone mobility data to study the Covid-19 crises. These data have not only been used to track economic activity in real time (see for instance Sampi Bravo and Jooste, 2020), but also to analyse social distancing patterns (for a survey, see Brodeur *et al.*, 2021). This latter strand of literature has highlighted the crucial role of both compliance with lockdown policies and voluntary measures (see, e.g. Abouk and Heydari, 2021; Gupta *et al.*, 2020; Brzezinski *et al.*, 2020). In terms of economic determinants, most papers have found lower levels of compliance with lockdowns to be associated with poverty, less flexible work arrangements, lower incomes and economic dislocation (Chiou and Tucker, 2020; Coven and Gupta, 2020; Wright *et al.*, 2020; Papageorge *et al.*, 2021). One exception is Bonaccorsi *et al.* (2020), who detect a stronger mobility reduction in Italian municipalities with lower levels of income during the first lockdown.

Turning to the economic consequences of the pandemic, a number of studies, with a particular focus on the United States (Coibion *et al.*, 2020a,b; Rojas *et al.*, 2020) and South Korea (Aum *et al.*, 2021a,b), documents that both lockdown-induced and voluntary social distancing have led to increased unemployment. Drops in employment and income were higher in industries and occupations with lower capacity to work from home and for younger and less educated individuals (Adams-Prassl *et al.*, 2020; Alipour *et al.*, 2021).

Lastly, this paper adds to the literature on the role of STW in preventing drops in employment during recessions (for a discussion during the Covid-19 pandemic, see Giupponi *et al.*, 2022). In particular, several recent studies have established a strong causal link between STW and employment (Kopp and Siegenthaler, 2021; Giupponi and Landais, 2018; Cahuc *et al.*, 2021). We confirm these results by exploiting regional variation in a quasi-experimental setup.

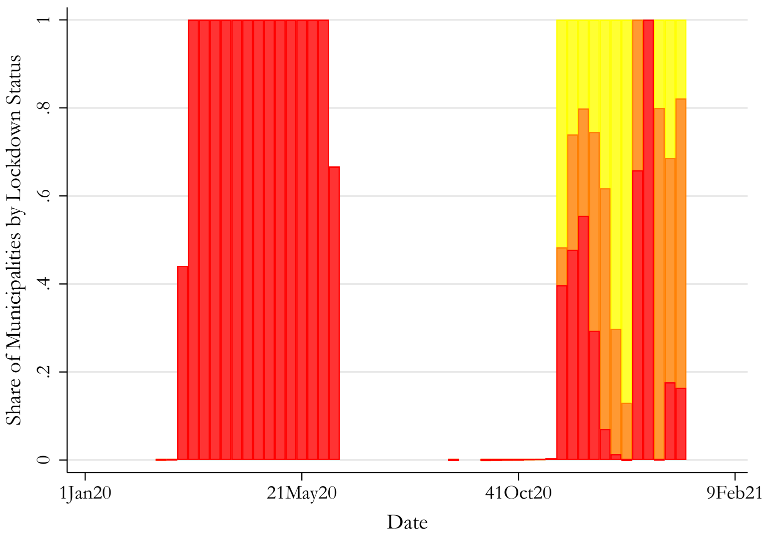
2. Data

Lockdown Measures. We manually compiled a weekly database of lockdown and restriction measures for each Italian municipality. To allow for consistent coding across Covid-19 waves and lockdowns, we adopt the very general four-color code introduced on 15 November 2020, comprising four different colors (ascending stringency): white, yellow, orange and red.[2] Restriction measures were decreed at different levels. Regions and sub-regional levels of government were able to change the national rules in that they could impose more stringent measures.

[2]For further details, see Appendix A.1

Figure 1 provides a graphical representation of the share of municipalities by confinement status throughout 2020. The two different approaches to combating the first and the second wave are clearly visible. During the first wave, a strict lockdown was first introduced in selected communities, then in additional provinces, before quickly being extended to northern Italy and to the whole country. We code this stringent, across-the-board lockdown as a red zone. The second lockdown phase sees Italian communities divided in the four colours. Given that there are close to 8000 municipalities in Italy and that the colour was not only determined by the pandemic situation in each municipality but also subject to the authorities' discretion, the data contain considerable variation for econometric analysis.

Figure 1: Weekly Share of Municipalities by Lockdown Status



Notes: Plots the share of municipalities by lockdown status (white/yellow/orange/red) at weekly frequency.

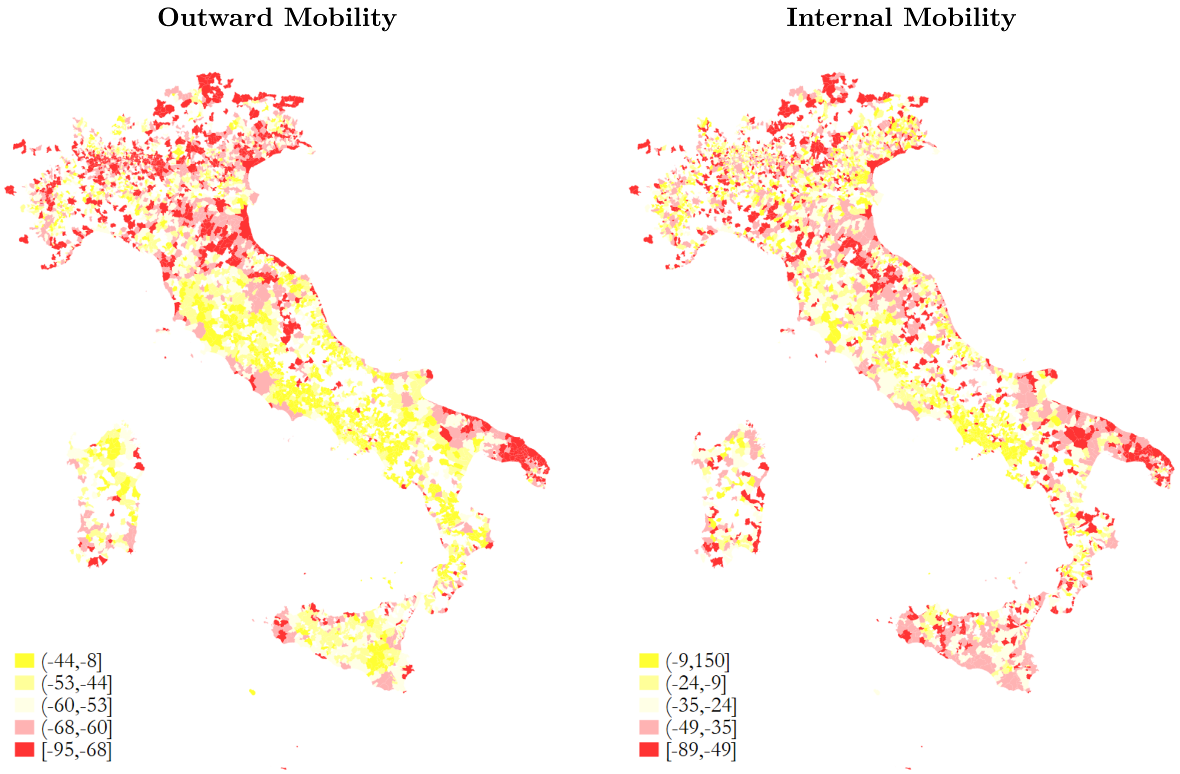
Mobility Data. Mobility data come from a unique draw on mobile phones' anonymised and aggregated position data documented in detail in Iacus *et al.* (2020) and in Santamaria *et al.* (2020).[3] Our mobility indicators aggregate mobile phone position data to the week-municipality level, thereby allowing for comparisons of mobility patterns across different municipalities and time. Our data distinguish between different types of movement – internal, inwards and outwards – depending on the direction of travel. The final dataset consists of an unbalanced panel covering all weeks between January 2020 to January 2021.

Figure 2 shows the percentage difference in movements between week 6 and week 13 of 2020, with the left (right) panel plotting outward (internal) mobility. The week starting on 3 February (week 6) was the last week without public news about a possible lockdown anywhere in Italy. By week 13, the lockdown in Northern Italy was fully in place, and both types of mobility had decreased substantially compared to pre-lockdown values, in particular in the North. In more Southern areas of Italy, mobility dropped significantly but not to the same extent as in the North.

Labour Market Data. In addition to mobility, our analysis examines the consequences of Covid-19 on the Italian labour market. We consider two types of outcomes. First, we impute municipality-level employment at quarterly frequency, using the sectoral distribution of workers in each municipality and the quarterly growth rates of sectoral employment for

[3]For further details on the mobility data, see also Appendix A.2.

Figure 2: Mobility over Time – Week 13 versus Week 6 (2020)



Notes: Percentage change in average municipality-level weekly mobility, week 6 versus week 13 of 2020.

Italy. To correctly measure municipality-level employment, this measures hinges on the assumption that sectoral employment dynamics were equal across the country.

Second, we exploit take-up rates of short-term work (STW). Decree-Law no. 18 of 17 March 2020, the so-called "Cura Italia", introduced support allowances for workers whose activities were affected by the economic downturn driven by Covid-19. These STW schemes were administered by the National Institute of Social Security (INPS), the main social security institution of the Italian public pension system. The payment of temporary allowances supported the revenue of workers while allowing them to remain employed throughout the pandemic. The data are available at the month-province level from 2009 onward.

Municipality Characteristics. In order to account for structural differences across municipalities, we collect a number of covariates. From the Italian statistical office, we draw information on average income, population and overall income tax revenue per income bracket, employment per sector in the municipality, educational level of residents as measured by their highest degree obtained, the age structure, among others.[4]

From these data we construct additional indicators for each municipality. For example we develop a municipal indicator of poverty. Using sectoral employment combined with the sector-specific information from Adams-Prassl *et al.* (2022), we also calculate a municipality-level teleworkability index measuring the share of jobs that can be executed from home, following the approach pioneered in Dingel and Neiman (2020).

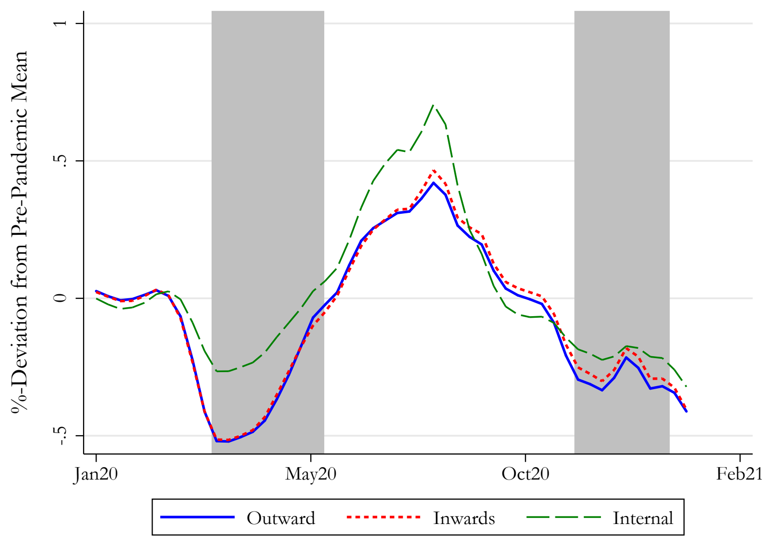
[4]For details, see Appendix A.4.

Indicators on wealth are not available at higher levels of spatial disaggregation. To approximate wealth at the municipality level, we use housing market information as a proxy for existing wealth levels in different parts of Italy, exploiting the fact that homeownership in Italy is high at 72.4%.[5] We include the average asking prices for real estate sale and rent for each Italian municipality recuperated from real estate databases. The data refer to March 2020, the very beginning of the pandemic, which can be considered pre-existing conditions that were unaffected by Covid-19. While these data overweight housing wealth, systematic biases across the country are unlikely, suggesting that this information approximates relative wealth levels reasonably well.

3. Descriptives

We start by plotting the evolution of the mobility measures over time, expressed in percentage deviations from the pre-pandemic means for Italy (Figure 3). The shaded areas indicate the two lockdown periods. Outward and inward mobility are highly correlated (correlation coefficient > 0.99).[6] Both show a large decrease during the first lockdown, a rebound during summer when restrictions were lifted, and a smaller decrease in mobility during the second wave, suggesting that the overall effect of the traffic-light system led to more precisely targeted policies. The third measure, mobility within municipalities, is less correlated with inwards and outwards mobility (at 0.60 and 0.61, respectively). This pattern suggests that internal or local mobility at least partly substituted outside mobility during lockdowns.

Figure 3: Mobility over Time



Notes: Average weekly mobility by type, deviations with respect to the pre-pandemic per capita averages for Italy and smoothed with a local polynomial with bandwidth 0.8. The shaded areas indicate the lockdown periods.

As the raw data present ample evidence of a lockdown-induced reduction in mobility, we now assess the dynamic responses to the announcement of orange or red zones *during the second wave*. In particular, we estimate an event study to (*i*) analyse whether the reduction is gradual or abrupt, and (*ii*) identify if we observe increases in mobility prior

[5] Source: Eurostat

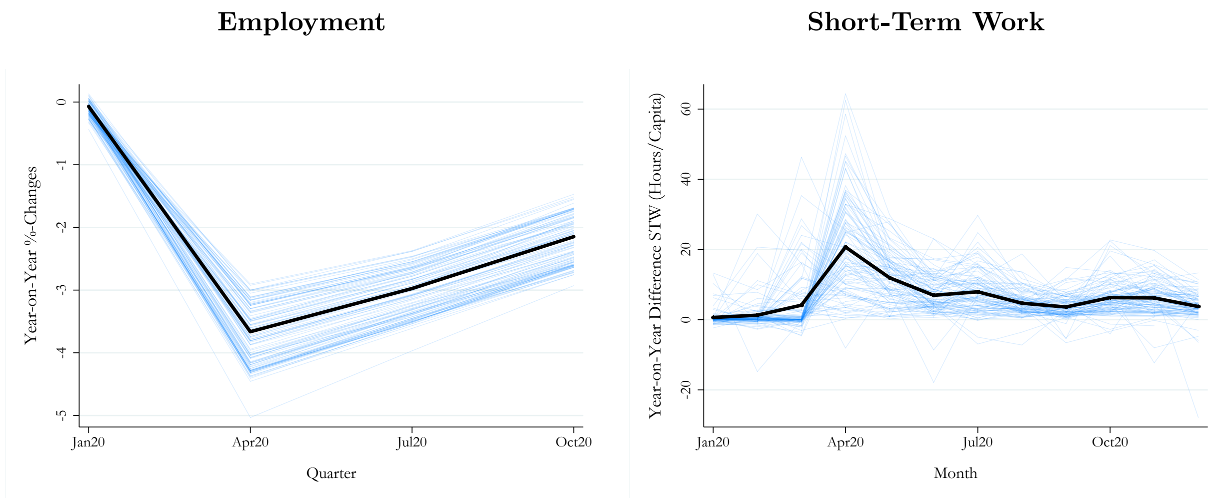
[6] Since our measure of outward mobility has a higher coverage, we henceforth drop inward mobility from the analysis.

to the onset of a lockdown, e.g. due to front-loaded activities that are impossible during lockdowns.[7].

Figures Appendix B2 and Appendix B3 report the results of the event study for outward and internal mobility, respectively. Both outward and internal mobility decrease strongly and abruptly when an orange zone is implemented, with non-significant and small anticipation effects. Entering a red zone, per contra, causes a more gradual decline in mobility. Moreover, we observe small increases in mobility between the entry into force of the lockdown and its announcement, as agents are increasing their movements in order to front-load necessary activities or to travel to other places before the lockdown. The evidence is robust to the inclusion of different geographic and time fixed effects.

Next, we plot our labour market indicators, employment and STW, in Figure 4. To rule out seasonal patterns, the variables are expressed with respect to the corresponding quarter in 2019. In the beginning of the year, both variables are close to the values from 2019. During the first quarter, we observe a sharp decrease (increase) for employment (STW) and a slow convergence back to zero for both indicators. For both variables, the thin blue lines reflect sizeable differences in response across geographic units.

Figure 4: Labour Market Indicators over Time



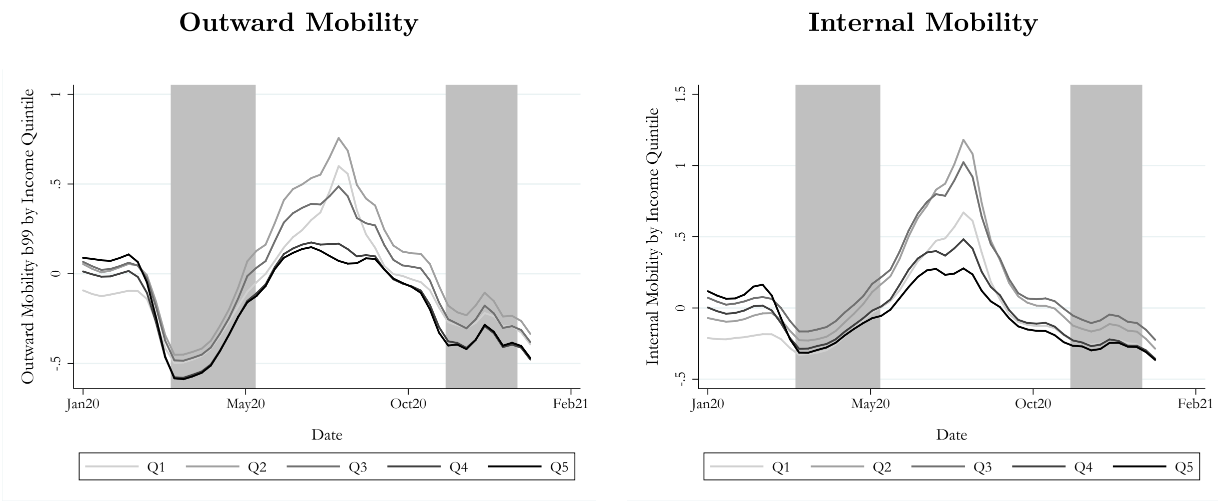
Notes: The left panel shows employment (in percentage deviations from the corresponding quarter in 2019), the right panel reports short-term work in hours per capita and in absolute differences with respect to 2019. The thin blue lines indicate province-level means, the black lines show the means for Italy.

Before turning to the econometric analysis, we highlight the importance of economic factors in determining mobility patterns (e.g. Wright *et al.*, 2020; Papageorge *et al.*, 2021). Figure 5 plots the average weekly mobility by income quintile, revealing systematic differences between poorer and richer municipalities. Individuals in the wealthiest quintile are able to decrease their mobility faster during the first lockdown and voluntarily remain at low levels of mobility even in absence of lockdowns. Municipalities in the lower quintiles, instead, show a stronger increase during the summer and a slower mobility reduction during the second lockdown.[8] Similar socioeconomic heterogeneity is observable for our labour market indicators of interest (Appendix B4).

[7]For the econometric specification, see Appendix D

[8]Figure Appendix B1 confirms that this evidence is robust to controlling for a number of covariates.

Figure 5: Mobility over Time by Income



Notes: Average weekly mobility by income quintile, deviations with respect to the pre-pandemic per capita average for Italy and smoothed with a local polynomial with bandwidth 0.8. The shaded areas indicate the lockdown periods.

4. Lockdown Effects on Mobility

In this section we analyse the relationship between different lockdown measures and mobility, establishing the following results:

1. We estimate the size of the lockdown-induced mobility reduction separately for each wave. The coefficients for the first and second wave lockdowns are at 45% and 22%, respectively. This implies that the second lockdown had a relatively smaller additional effect given equal restrictions, as people found ways to circumvent provisions and were less determined to follow the social distancing measures. We label this the *lockdown fatigue effect*.

2. We then provide evidence in favor of the observation that easing of the restrictions in summer 2020 did not lead to a full recovery. Compared to pre-pandemic levels, mobility in absence of lockdowns was 17% lower during summer 2020. We call this the *adaptation effect*.

3. Finally, we extend our framework to studying heterogeneity in both effects along socioeconomic covariates. The analysis not only reveals large differences between socioeconomic groups but also shows that the covariates matter to a varying extent for lockdown fatigue and the adaptation effect.

All regressions in this section are structured as follows: observations are indexed by municipality i, week w, month m, quarter q, region r, and province k. We use municipality level data at weekly frequency. The outcome variables are defined per capita and in percentage deviations from the pre-pandemic average in 2020 for Italy. Our preferred specification includes fixed effects for each municipality, γ_i, and for each month, δ_m.

We control for $Cases_{k,w}$, the number of new cases in a province k during week w, measured by 1000 inhabitants. This variable is included at provincial level for two reasons: first, it is unlikely that agents' behavior is affected by Covid cases in the same town because these are not publicly communicated; second, cases by town largely depend on whether a hospital is present or not, while the figures by province describe the local sanitary situation more accurately.

The estimated coefficients identify the causal effects of interest under a standard parallel trend assumption. Standard errors are double-clustered by municipality and region-month. Municipality clusters take into account autocorrelation and idiosyncrasies, region-month clustering considers the spatial dimension (lockdowns in adjacent provinces affect own outward mobility) and seasonal patterns. The region-month clustering has the additional advantage that the number of clusters equals 20x12, which is large enough to ensure asymptotic unbiasedness of clustered standard errors.

4.1. The Lockdown Fatigue Effect

We start by examining the lockdown-induced mobility reduction during the two waves, documenting the *lockdown fatigue effect.* To this end, we regress mobility on dummy variables for the lockdown colour of the municipality, separating orange and red, controlling for Covid cases and varying sets of fixed effects:

$$Mobility_{i,w} = \alpha_1\, Orange_{i,w} + \alpha_2\, Red_{i,w} + \beta\, Cases_{k,w} + \gamma_i + \delta_m + \epsilon_{i,w} \tag{1}$$

Tables 1 and 2 show the results from estimating Equation 1, separately for the first and second wave, for both outward and internal mobility. Once month (or region-month) fixed effects are included, we exclude the dummy for yellow zones, that is we treat yellow zones as white ones. This is because there are no white zones during the end of the year, i.e. there is no contemporaneous non-lockdown counterfactual otherwise.

Table 1 shows the results from regressions of outward mobility on the lockdown measures. For the first wave, column (1) shows that, in absence of further controls, both the lockdown dummies and Covid-19 cases are important predictors of mobility. Column (2) adds municipality fixed effects. Since the dependent variable is in percent changes with respect to the pre-pandemic situation, the coefficients remain largely unaffected by the unit fixed effects. Columns (3) and (4) assess the robustness with respect to two different sets of time fixed effects. Across the board it appears that the lockdown measures significantly reduced mobility in the first wave, and the incidences of Covid-19 determined an important, additional change in behavior as citizens chose to move less and reduce their exposure to the pandemic.

The right panel of the table reports the results for the second wave, distinguishing between yellow, orange, and red zones. Columns (5) and (6) show that all three provisions had significantly negative effects on mobility. From column (7) onward, we include month and month-region fixed effects in the regressions, leading to a sharp decrease in the absolute size of the coefficients on the lockdown dummies. For the reason noted above, columns (8) and (9) group the control status of white and yellow zones together. The estimated coefficients are non-significantly smaller, implying that this choice does not substantially alter the coefficients on the lockdown dummies.

It is important to point out the conceptual differences between regressions with and without time fixed effects. As observed in Figure 3, mobility dropped sharply at the onset of the two lockdown periods. In contrast, mobility towards the end of the first lockdown approached pre-lockdown levels. Since there is no variation in lockdown exposure during some periods of both waves, time fixed effects in practice eliminate these months from the estimation. If the time fixed effects are not included, we estimate averages over the entire respective lockdown periods, whereas the inclusion of time fixed effects implies that the treatment effects are identified over the parts of the lockdowns with strong variation in the treatment.

For the first wave, this implies that columns (1) and (2) estimate the lockdown effect throughout the first wave, while columns (3) and (4) focus on the onset of the pandemic. Accordingly, the estimated coefficient doubles roughly in size to around 41%. For the second wave, this pattern is reversed. In absence of time fixed effects, the mobility reduction is high at around 45%. The fixed effects in columns (7) to (9) allow us to purge the secular decline in mobility, and the estimated mobility reduction is at 22% for both orange and red zones.

These results complement Caselli *et al.* (2022), who use a regression-discontinuity design to estimate a lockdown-induced mobility reduction of 7%. Given negative spillover effects across areas, their results are likely to constitute a lower bound for the treatment effect. We prefer our difference-in-differences approach in this section as it can be equivalently applied to the economic outcome variables, which we only observe at lower levels of disaggregation.[9]

Finally, Table 2 shows the same set of results for internal mobility. During the first wave the negative effect on mobility of red zones was still sizeable but smaller at around 28%. Similar results hold for the second wave: all the colours have the expected negative sign and most of them are significant. The main difference is that the Covid-19 cases, while still mostly relevant, seem to have a smaller and largely insignificant impact. This evidence squares with the interpretation of local mobility being, at least in part, a substitute for outside mobility during lockdowns.

Table 1: Lockdown Effect on Outward Mobility

	First Wave				Second Wave				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Out	Out	Out	Out	Out	Out	Out	Out	Out
Yellow Zone					-0.336***	-0.285***	-0.068***		
					0.058	0.035	0.021		
Orange Zone					-0.483***	-0.504***	-0.251***	-0.198***	-0.222***
					0.047	0.032	0.021	0.028	0.022
Red Zone	-0.255***	-0.237***	-0.412***	-0.428***	-0.439***	-0.446***	-0.249***	-0.199***	-0.220***
	0.049	0.028	0.033	0.034	0.047	0.034	0.019	0.024	0.021
Covid Cases	-0.254***	-0.343***	-0.127***	-0.103***	-0.041***	-0.047***	-0.018**	-0.019**	-0.019***
	0.051	0.067	0.037	0.037	0.011	0.009	0.008	0.008	0.007
FE-Mun.		X	X	X		X	X	X	X
FE-Month			X				X	X	
FE-Reg-Month				X					X
R^2	0.061	0.778	0.800	0.810	0.058	0.739	0.749	0.749	0.760
Obs.	180960	180942	180942	180942	245469	245461	245461	245461	245461

Notes: Dependent variable: Outward mobility per capita, in percentage deviations from the pre-pandemic average in 2020 for Italy. Standard errors are double-clustered by municipality and region-month. Covid cases are at provincial level per capita.

[9]Strictly speaking, the coefficients are based on the two-way fixed effects (TWFE) estimator employed in a DiD setting. De Chaisemartin and d'Haultfoeuille (2020) highlight that TWFE regressions identify weighted averages of average treatment effects (ATE). Their main concern is that the weights can be negative, possibly producing an estimand of the opposite sign of the individual ATEs. A number of papers have proposed diagnostic tests for the identifying assumptions (Jakiela (2021), Roth *et al.* (2022)) and alternative estimators for settings with binary treatment and staggered roll-out (e.g. Callaway and Sant'Anna (2021), Borusyak and Jaravel (2017)). Using the estimator from Callaway and Sant'Anna (2021), the estimated lockdown-induced mobility reduction for the first and second wave is at 46% (s.e. 5%) and 23% (s.e. 0.7%), respectively, which are very close to our baseline estimates for outward mobility.

Table 2: Lockdown Effect on Internal Mobility

	First Wave				Second Wave				
	(1) Int	(2) Int	(3) Int	(4) Int	(5) Int	(6) Int	(7) Int	(8) Int	(9) Int
Yellow Zone					-0.300***	-0.403***	-0.109***		
					0.087	0.073	0.034		
Orange Zone					-0.414***	-0.494***	-0.140***	-0.058	-0.128***
					0.096	0.060	0.028	0.044	0.020
Red Zone	-0.036	-0.060*	-0.281***	-0.279***	-0.361***	-0.389***	-0.118***	-0.037	-0.098***
	0.075	0.035	0.042	0.041	0.097	0.067	0.036	0.048	0.021
Covid Cases	-0.329***	-0.251***	-0.048	-0.081*	-0.075***	-0.042**	0.020	0.019	-0.001
	0.065	0.071	0.046	0.048	0.019	0.017	0.013	0.013	0.011
FE-Mun.		X	X	X		X	X	X	X
FE-Month			X				X	X	
FE-Reg-Month				X					X
R^2	0.012	0.736	0.743	0.766	0.018	0.565	0.575	0.575	0.592
Obs.	119558	119373	119373	119373	172943	172768	172768	172768	172768

Notes: Dependent variable: Internal mobility per capita, in percentage deviations from the pre-pandemic average in 2020 for Italy. Standard errors are double-clustered by municipality and region-month. Covid cases are at provincial level per capita.

4.2. The Adaptation Effect

We now consolidate the wave-specific regressions in a common framework. Despite identifying similar lockdown effects, this approach has substantial value added for this study: First, the regressions allow us to test for differences between the two waves. Comparing the period between the two lockdowns to the pre-pandemic situation, we find evidence for the *adaptation effect*. Second, we further build on this framework when examining socioeconomic heterogeneity. We estimate the following equation on the pooled sample:

$$\begin{aligned} Mobility_{i,w} = {} & \alpha_1\, Lockdown_{i,w} + \alpha_2 Wave\, 2_w + \alpha_3 (Lockdown_{i,w} \times Wave\, 2_w) \\ & + \beta\, Cases_{k,w} + \gamma_i + \delta_m + \epsilon_{i,w}, \end{aligned} \tag{2}$$

where all variables and indices are defined as in the previous section. $Wave\, 2_w$ is a dummy which takes a value of one after the end of the first nation-wide lockdown, and zero before. $Lockdown_{i,w}$ equals one if a municipality is either in an orange or red zone, and zero otherwise. This allows us to reduce the dimensionality problem associated with estimating large numbers of parameters. In light of the results from the previous section, which showed that lockdown effects are similar for orange and red zones, this assumption is rather innocuous.

The interpretation of the estimated coefficients is straightforward: α_1 estimates the lockdown-induced mobility reduction during the first wave. The coefficient α_2 compares the pre-Covid period with the period without lockdown during summer 2020. α_3 is the coefficient comparing the first with the second lockdown. We also report estimates for $(\alpha_2 + \alpha_3)$, which directly test for the difference between the lockdown effects during the first and the second wave.

Table 3 shows the results for the different sets of fixed effects. Columns (1) to (4) refer to outward mobility, while columns (5) to (8) contain the estimated coefficients for internal mobility. Overall, the results are consistent with our previous result that mobility reductions were substantial during both lockdowns. As expected, our preferred specifications (3) and (6) provide evidence in favor of the *adaptation effect*: the estimated values for α_2 imply that individuals lowered their outward (internal) mobility by about 17% (11%) during summer 2020 compared to the pre-pandemic mean.

Finally, note that the estimated values for $(\alpha_2 + \alpha_3)$ are highly significant and positive. Therefore, the lockdown-induced mobility reduction was by about 9% (15%) smaller during the second wave of the pandemic. Taken together, these results lend support to the idea that mobility attenuated throughout 2020, as individuals got accustomed to overall lower levels of mobility.

Table 3: Comparison First Vs. Second Wave

	(1) Out	(2) Out	(3) Out	(4) Out	(5) Int	(6) Int	(7) Int	(8) Int
Lockdown	-0.339***	-0.345***	-0.452***	-0.455***	-0.135	-0.134**	-0.340***	-0.330***
	0.045	0.033	0.028	0.028	0.072	0.043	0.046	0.043
Wave 2	0.119**	0.133***	-0.171***	-0.169***	0.210*	0.263***	-0.112**	-0.074*
	0.043	0.025	0.025	0.023	0.082	0.049	0.041	0.036
Lockdown × Wave 2	-0.163*	-0.192***	0.260***	0.247***	-0.356**	-0.356***	0.265***	0.216***
	0.063	0.045	0.036	0.036	0.114	0.068	0.061	0.050
Covid Cases			-0.027***	-0.023***			-0.010	-0.020
			0.007	0.007			0.011	0.010
$\alpha_2 + \alpha_3$	-0.044	-0.059*	0.089***	0.079***	-0.146**	-0.092**	0.153***	0.142***
	0.042	0.035	0.028	0.029	0.070	0.043	0.046	0.043
FE-Mun.		X	X	X		X	X	X
FE-Month			X				X	X
FE-Reg-Month				X				
R^2	0.052	0.695	0.723	0.735	0.012	0.518	0.533	0.554
Obs.	426429	426421	426421	426421	292501	292327	292327	292327

Notes: Dependent variable: Outward mobility (columns 1-4) and internal mobility (columns 5-9), both per capita and measured in percentage deviations from the pre-pandemic average in 2020 for Italy. Standard errors are double-clustered by municipality and region-month. Covid cases are at provincial level per capita.

4.3. Heterogeneity

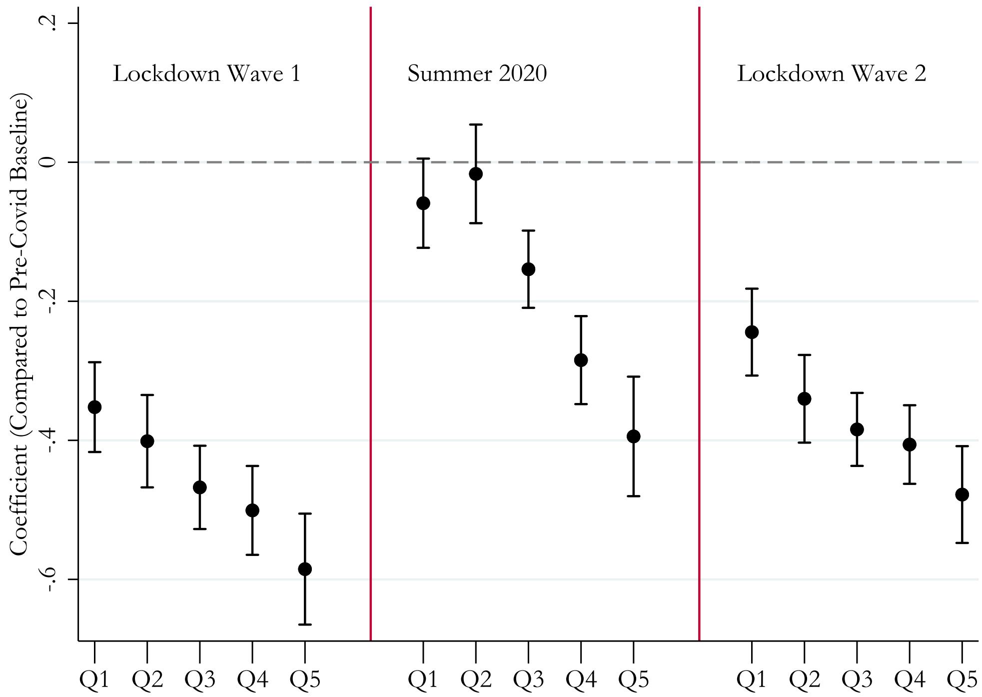
This section shows the results obtained by introducing socioeconomic heterogeneity to Equation 2. To this aim, we add interaction terms to model (4) of Table 3 in the following way:

$$\begin{aligned} Mobility_{i,w} = & \sum_h D_i^h \left[\tilde{\alpha}_1^h \, Lockdown_{i,w} + \tilde{\alpha}_2^h Wave\,2_w + \tilde{\alpha}_3^h (Lockdown_{i,w} \times Wave\,2_w)\right] \\ & + \beta\, Cases_{k,w} + \gamma_i + \delta_m + \epsilon_{i,w} \end{aligned} \tag{3}$$

where D_i^h are dummy variables indicating the quantile of a municipality in terms of average income.

Figure 6 reports the *cumulative effect by quintile* with respect to the pre-Covid scenario for each sub-period, allowing us to establish a set of stylised facts about heterogeneity in the mobility response to the pandemic. First, the differences with respect to socioeconomic covariates are large. During both lockdown periods, municipalities in the highest income quintile reduced mobility by almost twice as much as the ones in the lowest quintile. Interestingly, during summer 2020, in absence of lockdown mandates, municipalities in the lowest two quintiles almost returned to pre-pandemic levels of mobility, while the municipalities in the highest quintile still see about 39% lower mobility compared to the baseline period. Second, the differences across income groups persist throughout the first year of the pandemic. During the lockdown periods, the difference between the first and the fifth quintile is at about 23 p.p., which even increases during the non-lockdown interval. Third, the plots of the group-specific coefficients against their ranks exhibit a roughly linear shape.

Figure 6: Heterogeneity in Mobility Response by Income



Notes: Shows the results from estimating Equation 3 with outward mobility as dependent variable. Coefficients are shown alongside 95% confidence intervals. The reported coefficients are (from left to right): $\{\tilde{\alpha}_1^h\}_{h=1}^5$, $\{\tilde{\alpha}_2^h\}_{h=1}^5$ and $\{\tilde{\alpha}_1^h+\tilde{\alpha}_2^h+\tilde{\alpha}_3^h\}_{h=1}^5$. Municipality and month-fixed effects are included. Standard errors are double-clustered by municipality and region-month.

We proceed by repeating this analysis separately for a number of covariates. To synthesise the presentation of the results we only interact dummies indicating above-median levels of the respective variable. Note that we run the regression separately for each covariate and do not include the other variables in the regressions. As shown in Armillei *et al.* (2021) in the context of Italian municipalities, most socioeconomic variables commonly associated with the spread of Covid-19 are highly correlated with each other, making it difficult to claim causality. Instead, this exercise hence aims at showing which variables are associated with the largest variation in mobility responses.

The results for the three periods considered are shown in Table 4, including both the coefficients and the respective standard errors. The signs of the coefficients are largely in line with expectations, indicating for instance more pronounced mobility reductions for municipalities with higher incomes and wealth, a bigger share of residents with higher education, and lower shares of unemployment. As to their magnitude, we can broadly classify the covariates in two groups. One consists of wealth as proxied by house and rent prices. Both variables are associated with substantial heterogeneity during the lockdowns and relatively small differences during the non-lockdown period. All other variables adhere to the second group, exhibiting a converse pattern with larger discrepancies during summer 2020 compared to the two lockdowns. This group includes most prominently average income and the share of people with teleworkable jobs, but also the shares of elderly, individuals with low incomes or tertiary education. Taken together, we find that the determinants of social distancing have differed strongly over time, depending on whether lockdown policies were in place or not. In the next section we analyse the economic implications of these findings.

Table 4: Heterogeneity in Mobility Response by Covariates

	Lockdown Wave 1		Summer 2020		Lockdown Wave 2	
	b	se	b	se	b	se
Average Income	-0.09	0.04	-0.30	0.04	-0.10	0.04
House Price	-0.12	0.02	-0.07	0.02	-0.15	0.02
Rent Price	-0.10	0.02	-0.00	0.03	-0.11	0.03
Unemployment Share	0.01	0.03	0.09	0.04	0.05	0.03
Tertiary Degree	-0.05	0.01	-0.09	0.02	-0.05	0.02
ICT Sector	0.01	0.02	-0.16	0.02	0.02	0.02
Share above Age 65	0.03	0.02	0.21	0.02	0.02	0.02
Poverty Share	0.05	0.04	0.33	0.06	0.10	0.04
Working From Home	0.07	0.03	-0.24	0.04	0.09	0.03

Notes: Shows regression results per group of coefficients resulting from estimating Equation 3 with outward mobility as dependent variable and different covariates (for an illustration, see Figure 6). Instead of quintiles, we only use dummy variables indicating above-median levels of the respective variable. The estimates refer to the marginal effects of these dummies, compared to the pre-pandemic baseline. Municipality and month-fixed effects are included. Standard errors are double-clustered by municipality and region-month.

5. Lockdown Effects on the Economy

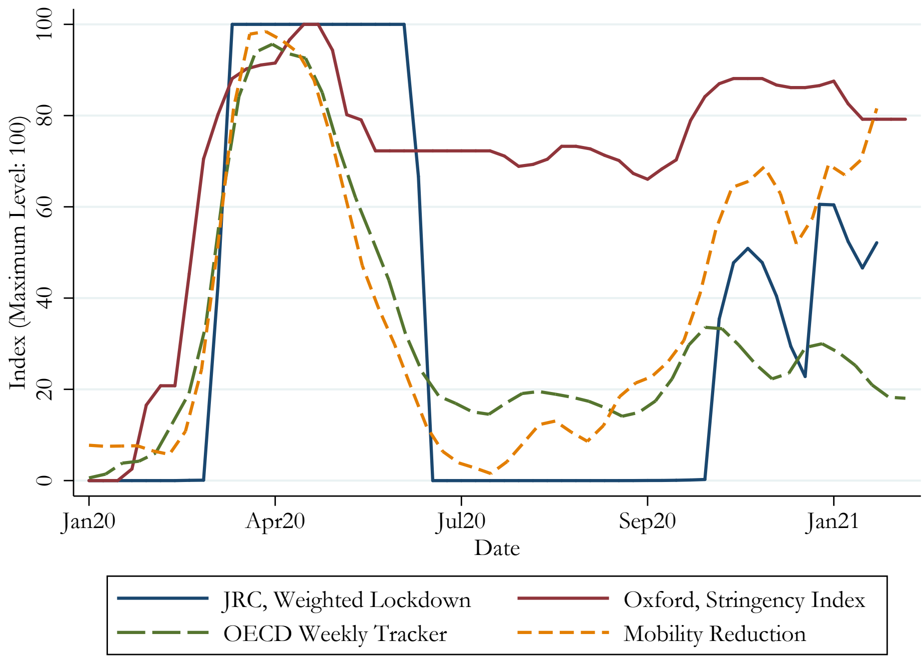
The previous section has documented that lockdown measures lead to substantial reductions in mobility. Since social distancing reduces interpersonal transmission risks related to Covid-19 (Viner *et al.*, 2020; Anderson *et al.*, 2020; Bai *et al.*, 2020), lockdown mandates slow the spread of the virus (Hsiang *et al.*, 2020). These measures, however, come at a substantial economic cost.

This section investigates whether the two different approaches to lockdown implementation have incurred different economic costs in Italy. Both proved efficient towards the disease and avoided (or solved) the overburdening of the health care system. However, the first lockdown was taken under high uncertainty, influenced by the information from the Northern provinces of the country where the virus was very lethal and difficult to control. The second was targeted using better epidemiological information and with the explicit goal of preserving economic activity to the maximum extent possible.

There are three aspects in the relationship between restrictions and economic activity that policymakers should take into account. The first is whether it is possible to target restrictions such that they sufficiently restrain the diffusion of the virus without paralyzing the economy. The natural experiment considered in this paper allows us to compare two different ways to ensure health safety and healthcare sustainability. Figure 7 shows that while lockdown stringency remained overall high (red line), higher levels of mobility were preserved throughout the second wave (orange dotted line). This was mainly due to the use of the traffic light system (blue line), which avoided stringent lockdowns when the pandemic situation was under control.

The second aspect follows from the consideration that modern decentralized economies work as networks, and as such they have a high degree of resilience to partial, even severe, lockdowns. The looser and diversified lockdowns during the second wave may have produced a lower economic cost. The green line of Figure 7, reproducing a rescaled version

Figure 7: Predicting Economic Activity using Mobility



Notes: The figure plots several weekly series during 2020 and the beginning of 2021, rescaled to the range 0 to 100: (*i*) The JRC lockdown index refers to municipality-level lockdown dummies, multiplied with the estimated wave-specific coefficients from Table 1 (columns (3) and (7)) and aggregated using population weights; (*ii*) a stringency index for governmental restriction, sourced from the Covid-19 government response tracker (Hale *et al.*, 2021); (*iii*) the OECD weekly tracker of economic activity[a]; (*iv*) the population-weighted inverse of our mobility data.

[a]For details, see https://www.oecd.org/economy/weekly-tracker-of-gdp-growth/

of the OECD Weekly Tracker for Italy, suggests that, compared to the first lockdown, (rescaled) output loss was less than proportional during the second wave.

A third aspect is the distributional one, inequality. Communities do not react equally to economic shocks, but their characteristics matter. One salient example has been the extent to which communities have a labour market structure concentrated on activities that can be executed from home. As we have shown in the previous section (Table 4), these heterogeneities map into large differences in mobility across socioeconomic groups, in particular in absence of lockdowns. In this section, we demonstrate that socioeconomic characteristics also imply differences in the economic impact, with consequences for both overall costs and inequality. If poorer regions and communities pay higher economic costs, geographic inequality is bound to increase. Given considerable inequality between the North and the South of the country, policymakers in Italy should be particularly attentive to this channel.

There is ample and growing evidence that mobility is a strong predictor of economic activity in the context of Covid-19. For instance, Sampi Bravo and Jooste (2020) use the "Google Mobility Index" to nowcast monthly industrial production growth rates in selected economies in Latin America and the Caribbean, while recent contributions of Spelta and Pagnottoni (2021) and Barbaglia *et al.* (2022) focus on European economies. These works have established a robust relationship between the economy and mobility, which they exploit for nowcasting. In this paper, we take the opposite approach: starting from mobility and employment data, we assess whether lockdowns affect the economy, check whether containment measures implied different economic costs in the two waves, and whether they acted unequally across communities, possibly increasing geographic inequality.

5.1. Employment: Was the Second Wave Less Costly?

We now examine the effects of lockdowns on municipality-level employment at quarterly frequency.[10] The analysis mirrors the approach taken in the previous section, with the important difference that we do not have a DiD-setting in the strict sense. This is due to the lack of contemporaneous control groups, which comes from the low frequency of the outcome variable. Relying on the variation over time (quarters), we estimate the association of changes in employment with the stringency and length of the lockdown measures, conditional on municipality-fixed effects and Covid-19 cases.

Analogously to Section 4.1, we start by estimating a version of Equation 1 with employment as the outcome variable of interest. To rule out seasonal patterns, employment is defined relative to the corresponding quarter in 2019. The sample includes the four quarters of 2020. The results are shown in Table 5, separately for the first wave (columns (1) and (2)) and the second wave (columns (3) and (4)). For the first wave, we find that a lockdown of 3 months reduced employment in Italy by about 6.4%. Focusing on the second wave, the results are very small and none of the estimated coefficients is significant above the 90% level. Reassuringly, we estimate negative lockdown effects for orange and red zones.

Table 5: Lockdown Effects on Employment

	First Wave		Second Wave		Comparison	
	(1) Empl.	(2) Empl.	(3) Empl.	(4) Empl.	(5) Empl.	(6) Empl.
Yellow Zone			-0.159	0.386	-0.212	0.339
			0.300	0.236	0.285	0.245
Orange Zone			-0.355	-0.337*	-0.376	-0.339
			0.408	0.198	0.405	0.231
Red Zone	-6.262***	-6.408***	-0.181	-0.606	-6.156***	-6.269***
	0.141	0.142	0.677	0.407	0.188	0.146
Wave 2					-4.234***	-4.289***
					0.110	0.119
Red Zone × Wave 2					5.920***	5.844***
					0.707	0.387
Covid Cases	1.228***	0.273	0.288***	0.303***	0.311***	0.263***
	0.274	0.506	0.060	0.041	0.059	0.042
FE-Mun.		X		X		X
R^2	0.799	0.943	0.060	0.814	0.572	0.879
Obs.	15370	15326	23097	23078	38467	38452

Notes: The regressions are run at the municipality-quarter level. Employment is measured in year-to-year percentage changes with respect to 2019. Standard errors are clustered by municipality and region-quarter. Covid cases are per capita at provincial level.

As in Section 4.2, we then directly compare the two waves by running a version of Equation 2 on the full sample. The results are shown in columns (5) and (6) of Table 5.

[10]We prefer to use employment to unemployment for two reasons. The first is of substance, as official unemployment measures exclude demotivated people who are not actively searching for a job. The second reason is that unemployment rates are only available at annual frequency at sub-regional levels, while we are able to compile synthetic quarterly employment rates at municipality level.

Yellow and orange zones do not seem to have a significantly negative effect on employment compared to the non-lockdown scenario. The dummy for the second wave enters with a coefficient of about -4.3%, implying that employment slightly recovered during the non-lockdown period in summer 2020. Finally, the coefficient on the marginal effect of the second lockdown is at around 6%. Therefore, the overall lockdown effect during the second wave compared to the pre-pandemic scenario is about 4.7%. These results suggest that the second-wave lockdowns did not have additional adverse effects on employment, at least in the short run. Put differently, the traffic light system was able to achieve its sanitary goals without any further (substantial) costs for the economy.

5.2. Employment: Geographic Inequality

We now analyse whether socioeconomic characteristics were associated with heterogeneity in the economic impact of the containment measures. Following the approach from Section 4.3, we estimate a version of Equation 3 with quarterly employment as our outcome variable, and interact dummies for several covariates of interest. The regressions control for municipality-level fixed effects and province-level cases of Covid-19.

We start by inspecting heterogeneous effects with respect to quintiles of average income. The *cumulative* coefficients with respect to the pre-pandemic period are depicted in Figure 8. The results indicate that poorer municipalities have suffered from larger reductions in employment compared to municipalities in the higher quintiles. Yet, compared to the heterogeneity in the mobility reduction, the drop in employment exhibits smaller differences with respect to municipalities' characteristics. For instance, for the first lockdown, employment in the first quintile declines only by 15% more in comparison to the fourth quintile. These differences attenuate during the non-lockdown period to slightly increase again during the second wave lockdowns.

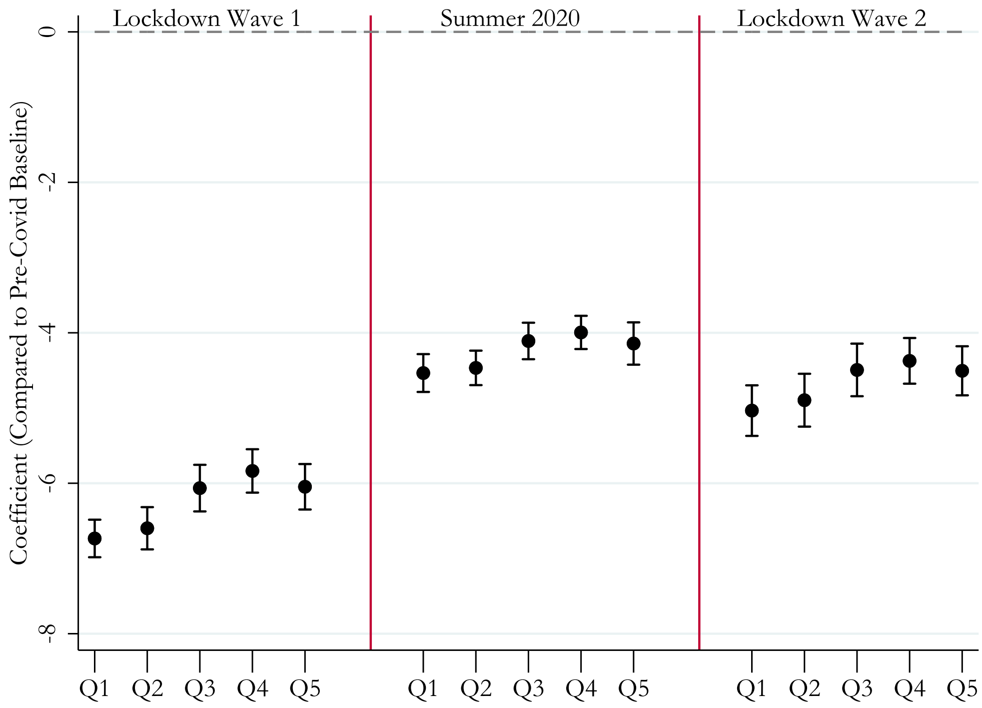
As before, we repeat this exercise with dummies referring to above-median values in a number of covariates. Results are shown in Table 6. Positive (negative) values in the table indicate that higher value in the covariates are associated with smaller (larger) drops in employment compared to the pre-pandemic baseline.

Several aspects are worth highlighting. First, contrasting the previous analysis, employment is strongly and positively affected by our indicator measuring working from home capacity. For the first lockdown, we estimate a predicted difference of 1.8 p.p. between above- and below-median values of this variable. This difference shrinks to 1.0 p.p. during the non-lockdown period and roughly doubles again during the second lockdown. Thus, working from home effectively shielded individuals from job-losses throughout 2020. We observe similar patterns for unemployment and poverty shares as well as income, albeit much less pronounced. Second, as opposed to the analysis on mobility, heterogeneity for most variables is most pronounced during the lockdown periods, with a slight decrease during summer. Finally, somewhat counterintuitively, the estimated coefficients on wealth and education are negative. One possible explanation of this result could be the voluntary reduction in the labour force in the wealthiest communities, in line with the hypothesis and growing evidence on the *Great Resignation* in Italy.[11]

The heterogeneity analyses suggest that pre-existing conditions, such as income or teleworkability, played a key role in buffering the adverse effects of the drop in economic

[11] `https://www.lavoce.info/archives/90466/si-apre-la-stagione-delle-grandi-dimissioni/`

Figure 8: Heterogeneity in Lockdown Effect on Employment By Income



Notes: Shows the results from estimating Equation 3 with employment as dependent variable. Coefficients are shown alongside 95% confidence intervals. The reported coefficients are (from left to right)$\{\tilde{\alpha}_1^h\}_{h=1}^5$, $\{\tilde{\alpha}_2^h\}_{h=1}^5$ and $\{\tilde{\alpha}_1^h + \tilde{\alpha}_2^h + \tilde{\alpha}_3^h\}_{h=1}^5$. Municipality fixed effects are included. Standard errors are double-clustered by municipality and region-quarter.

activity on employment levels. They also suggest that poorer communities have been hit most, thereby increasing geographic inequality.

Table 6: Heterogeneity in Employment Response by Covariates

	Lockdown Wave 1		Summer 2020		Lockdown Wave 2	
	b	se	b	se	b	se
Average Income	0.65	0.13	0.40	0.12	0.47	0.15
House Price	-0.25	0.14	-0.19	0.11	-0.31	0.15
Rent Price	0.04	0.16	0.03	0.13	-0.11	0.16
Unemployment Share	-0.97	0.14	-0.61	0.12	-0.76	0.15
Tertiary Degree	-0.42	0.08	-0.30	0.07	-0.33	0.08
ICT Sector	-0.30	0.05	-0.23	0.05	-0.17	0.06
Share above Age 65	0.03	0.17	0.10	0.13	0.10	0.15
Poverty Share	-0.99	0.12	-0.62	0.11	-0.80	0.14
Working From Home	1.75	0.07	1.01	0.06	1.85	0.10

Notes: Shows regression results per group of coefficients resulting from estimating Equation 3 with employment as dependent variable and different covariates (for an illustration, see Figure 8). Instead of quintiles, we only use dummy variables indicating above-median levels of the respective variable. The estimates refer to the marginal effects of these dummies, compared to the pre-pandemic baseline. Municipality fixed effects are included. Standard errors are double-clustered by municipality and region-quarter.

5.3. Short-Term Work Arrangements Supported Those That Lost Employment...

So far, we have documented a substantial drop in economic activity proxied by mobility, and, to a lesser extent, employment. Given that a number of support schemes were put into place, governmental policies could have played a significant countercyclical role. Before exploring this latter channel in Section 6, we conduct the same analysis as for mobility and employment, using short-term work (STW) as our outcome of interest. This variable, compiled at province-month level, is measured in hours per working age population, and expressed in absolute year-to-year changes with respect to 2019.

Table 7 shows the estimated lockdown effects on STW. As before, columns (1) to (4) display the regressions on lockdown dummies, separately for each wave and with and without unit fixed effects. For the first wave, we find a lockdown-related hike in STW of around 12.3 hours per working-age individual compared to the previous year. This estimated coefficient slightly increases to around 13.2 once conditioning on province fixed effects (column (2)). During the second lockdown (column (4)), STW *decreases* compared to the interval without lockdowns. This drop in STW is more pronounced for provinces that see less restrictive measures. For instance, a one-month yellow-zone regime allowed the authorities to scale back the benefits by about 3.1 hours, whereas the reduction in red zones was only at 2 hours and insignificant at conventional levels.

Table 7: Lockdown Effect on Short-Term Work

	First Wave		Second Wave		Comparison	
	(1) STW	(2) STW	(3) STW	(4) STW	(5) STW	(6) STW
Yellow Zone			-4.365***	-3.064***	-4.934***	-2.845***
			0.875	0.616	0.921	0.726
Orange Zone			-2.273**	-2.502***	-2.453***	-2.443**
			0.913	0.819	0.899	1.036
Red Zone	12.320***	13.159***	-3.880***	-2.043	13.605***	13.794***
	1.704	1.635	1.302	1.252	1.719	1.611
Wave 2					5.042***	5.286***
					0.727	0.755
Red Zone × Wave 2					-18.305***	-15.545***
					2.286	2.094
Covid Cases	0.434*	0.198	0.082***	0.042**	0.102***	0.036*
	0.243	0.237	0.015	0.017	0.019	0.020
FE-Prov.		X		X		X
R^2	0.316	0.422	0.073	0.444	0.279	0.417
Obs.	616	616	710	710	1326	1326

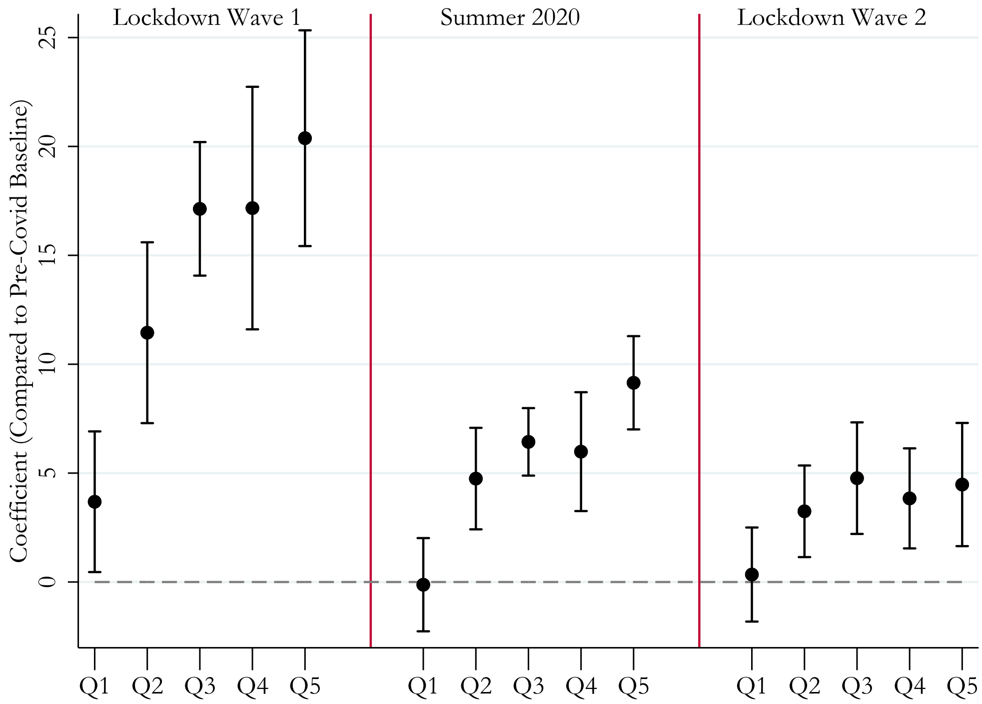
Notes: The regressions are run at the province-month level with STW as dependent variable. STW is measured in hours per working age population, and expressed in absolute year-to-year changes with respect to 2019. Standard errors are clustered at provincial level. Covid cases are per capita at provincial level.

The estimates from the comparison of the two waves over the full sample (columns (5) and (6)) confirm this pattern. Focusing on specification (6), we find again an increase of around 13.8 hours during the first lockdown. This estimates declines to 5.3 hours during the non-lockdown period, and further decreases to around 3.5 hours during the second lockdown. Note that the estimated coefficients on yellow and orange zones retain their negative sign, indicating that lighter lockdown forms were indeed associated with lower levels of STW.

5.4. ... But Did Not Reduce Inequality

We build on Equation 3 to explore heterogeneity in STW uptake along socioeconomic lines. Equivalent to before, Figure 9 plots the cumulative increase in STW by income quintile and period, compared to the pre-pandemic situation. For the first lockdown, we observe tremendous differences across provinces. In the first quintile, the increase is significant at about 3.7 hours; yet, this coefficient is dwarfed by the hike of 20.4 hours we find in the fifth quintile. In line with the results from Table 7, we find a drop in the overall level of STW during summer 2020. Yet, the degree of heterogeneity across quintiles remains substantial. The provinces in the first quintile return to pre-pandemic levels of STW, whereas the fifth quintile still remains at an elevated level of 9.1 hours. Finally, for the second lockdown, we find a similar but attenuated pattern.

Figure 9: Heterogeneity in Lockdown Effect on Short-Term Work By Income



Notes: Shows the results from estimating Equation 3 with Short-Term Work as dependent variable. Coefficients are shown alongside 95% confidence intervals. The reported coefficients are (from left to right)$\{\tilde{\alpha}_1^h\}_{h=1}^5$, $\{\tilde{\alpha}_2^h\}_{h=1}^5$ and $\{\tilde{\alpha}_1^h + \tilde{\alpha}_2^h + \tilde{\alpha}_3^h\}_{h=1}^5$. The regression controls for province-level fixed effects and Covid-19 cases. Standard errors are clustered at provincial level.

We conclude this section by reporting the degree of heterogeneity separately by covariate of interest in Table 8. We consistently find more economically advanced provinces to profit more from STW. This finding is intuitive, given that the absolute drop in economic activity was largest in these provinces. In terms of magnitudes, the estimated coefficients are consistent across all covariates: heterogeneity is large during the first lockdown and decreases throughout the later periods. The largest degree of heterogeneity is induced by the teleworkability index, followed by the unemployment share and average income. These results suggest that STW buffered the adverse effects of the negative economic shocks on employment, but in a non-equal manner, as poorer municipalities and those where unemployment was higher were proportionally *less* supported. This result is in line with (Giupponi *et al.*, 2022), who find that – in contrast to traditional unemployment insurance – STW mainly protects individuals with higher incomes and better self-insurance options. The next section analyses the link between STW and employment in more detail.

Our focus, also due to data availability, is on geographical inequality. However, disaggregate data on STW support for white- and blue-collars allow for additional explorations across these groups of workers. Appendix C reports separate regressions for STW given to white- and blue- collars and shows that, for a given level of lockdown and pandemic level, STWs have been disproportionately flowing to white-collar workers, despite the fact that blue collars constitute about 60% of the workforce (Berson *et al.*, 2020).

Table 8: Heterogeneity in Short-Term Work by Covariates

	Lockdown Wave 1		Summer 2020		Lockdown Wave 2	
	b	se	b	se	b	se
Average Income	9.76	2.39	4.58	1.20	2.63	1.19
House Price	6.45	2.31	4.03	1.25	1.85	1.15
Rent Price	4.81	2.26	2.04	1.20	0.04	1.01
Unemployment Share	-10.75	2.43	-4.46	1.20	-2.68	1.16
Tertiary Degree	3.07	2.33	2.25	1.23	1.56	1.17
ICT Sector	2.32	2.26	1.50	1.18	0.89	0.99
Share above Age 65	3.89	2.31	1.60	1.32	1.06	1.22
Poverty Share	-9.70	2.55	-4.36	1.23	-2.21	1.23
Working From Home	11.02	2.06	5.32	1.13	3.75	1.15

Notes: Shows regression results per group of coefficients resulting from estimating Equation 3 with Short-Term Work as dependent variable and different covariates (for an illustration, see Figure 9). Instead of quintiles, we only use dummy variables indicating above-median levels of the respective variable. The estimates refer to the marginal effects of these dummies, compared to the pre-pandemic baseline. Province fixed effects are included. Standard errors are clustered at the province level.

6. Short-Term Work Buffered Further Drops in Employment

Having documented the trajectories of economic activity and governmental response throughout 2020, we now explore their interaction. Our results suggest that STW schemes had a relevant role in cushioning the Covid-induced decrease in employment.

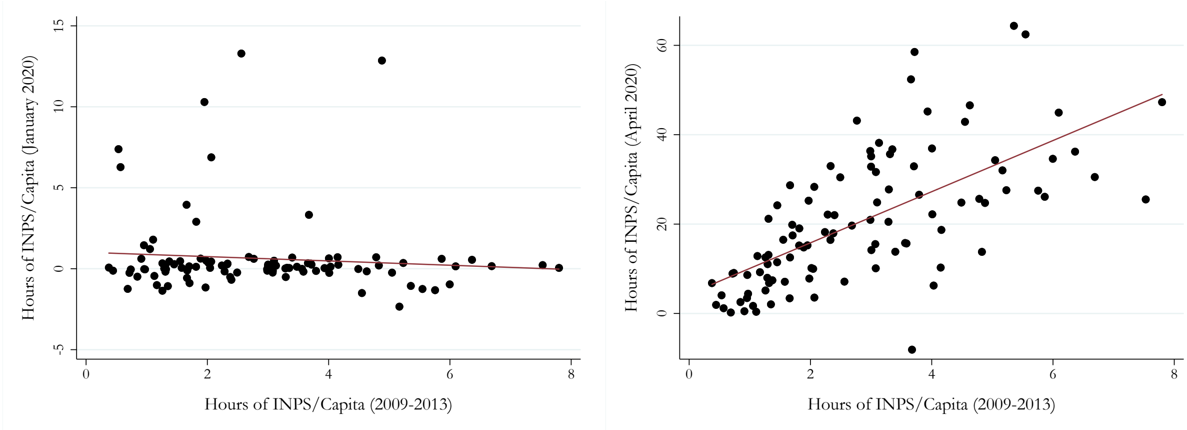
The key challenge towards identifying the effect of interest is an endogeneity problem. STW uptake is an equilibrium outcome, which is higher the more severe the reduction in economic activity and, relatedly, the drop in employment seen by a province. A simple regression of employment on STW receipt is therefore prone to reverse causality and related endogeneity issues. Column (1) in Table 9 shows the unconditional correlation between employment and STW. The negative sign underscores the endogeneity of the contemporaneous STW measure, as one would expect STW to have a positive impact on employment.

To alleviate this endogeneity concern, we construct the following Bartik-instrument: as the latent condition, we exploit historical STW receipt at the province level, denoted by $\overline{stw}_k^{2009-2013}$. We use average values over the years 2009-2013 to reduce noise. On one side, this allows us to obtain an indicator of how intensely each province was previously supported by STW, including during the financial crisis and the Euro crisis, and therefore of the potential intensity of the intervention during the Covid-19 pandemic. On the other side, historical values in STW are not affected by the Covid-related decline in employment, ruling out reverse causality. To track the employment effects of STW over time, we then interact this variable with the lockdown- and wave-dummies used before. This approach, econometrically very similar to our previous analysis, follows in spirit Nakamura and Steinsson (2014) as well as Hellwig (2021).

We first provide descriptive evidence on the functioning of the Bartik-instrument. Figure 10 plots per-capita hours of STW in 2020 (in year-on-year differences compared to

2019) against their historical average for the years 2009-2013. The left panel uses data for January 2020 as a placebo, showing that STW was around zero compared to 2019 and uncorrelated with previous values. In April 2020 (right panel), one can observe a strong positive correlation between the two variables ($R^2 = 0.43$) which implies that the past average of STW is highly predictive of the contemporaneous dynamics.

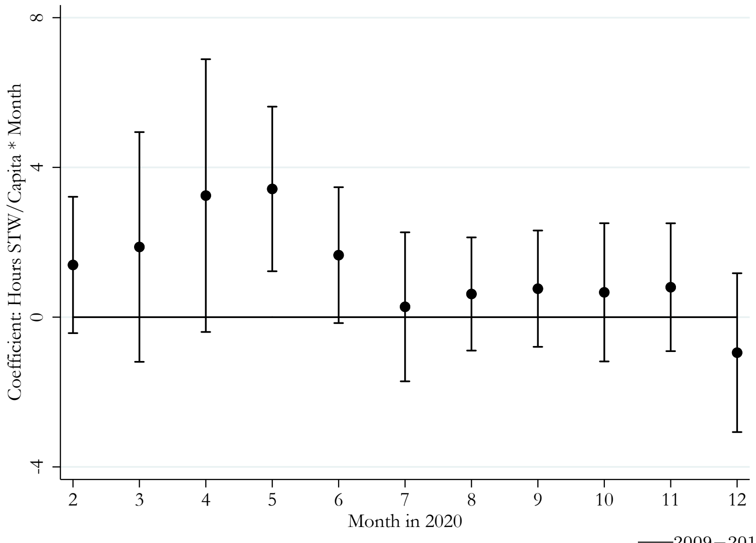
Figure 10: Hours of STW per Capita 2020 vs. Historical Average (2009-2013)



Notes: The figure plots province-level hours of STW/capita in 2020 (left panel: January; right panel: April) against their historical average (2009-2013).

In order to explore the mechanics of the Bartik-instrument more systematically, we regress STW uptake in 2020 on month dummies, both alone and interacted with historical values of STW. The regression controls also for province fixed effects. The coefficients obtained from the interaction terms are reported in Figure 11. Consistent with the previous observation, pre-pandemic levels of STW receipt are not associated with historical values, which only become highly predictive during the first lockdown. In particular, the coefficient on the interaction terms for May 2020 become significant at conventional levels. Afterwards, the significant effects vanish again, once conditioning on month and province fixed effects.

Figure 11: Monthly Correlation of STW in 2020 and Historical Averages of STW 2009-2013



Notes: Shows coefficients from regressions of stw_k on month dummies interacted with $\overline{stw}_k^{2009-2013}$, controlling for month and province fixed effects, alongside 95% confidence intervals. Standard errors are clustered at the province level.

With this reasoning in mind, the regression of interest reads

$$\begin{aligned} empl_{iq} &= [\alpha_1\, Lockdown_{i,q} + \alpha_2 Wave\,2_q + \alpha_3(Lockdown_{i,q} \times Wave\,2_q)] \\ &\quad + \overline{stw}_k^{2009-2013} \times [\alpha_4\, Lockdown_{i,q} + \alpha_5 Wave\,2_q + \alpha_6(Lockdown_{i,q} \times Wave\,2_q)] \\ &\quad + \beta\, Cases_{k,q} + \gamma_i + \delta_q + \epsilon_{i,q} \end{aligned} \tag{4}$$

where $empl_{iq}$ denotes quarterly employment at the municipality level. The indices stand for province k, quarter q and municipality i, respectively. As argued above, the approach relies on the existence of a latent correlation between contemporaneous and historical values, which is switched on and off by the indicators for lockdowns and waves. In this way, we isolate the plausibly exogeneous treatment variation based on differential effects of the Covid-induced common shock on units with different predetermined characteristics. Columns (2) and (3) in Table 9 support this view by reporting the results of regressions of $empl_{iq}$ on $\overline{stw}_k^{2009-2013}$ (without and with quarter fixed effects): in line with theory, the reported coefficients are now positive and highly significant.[12]

Column (4) of Table 9 proceeds by presenting the main results obtained from estimating Equation 4. The marginal effect for the first lockdown is highly significant at 0.27. Given the average value of 3.2 for $\overline{stw}_k^{2009-2013}$, this suggests that STW increased employment on average by about 0.89 p.p. during the first lockdown, equalling 13% of the observed drop in the outcome variable. Similar but smaller effects are observed during the non-lockdown period during summer 2020 and the second lockdown.

As a robustness check, column (5) adds all previously considered covariates to the regression, each interacted with $Wave\,2$, $Lockdown$ and $Wave\,2 \times\ Lockdown$. While the estimated coefficients become substantially smaller, the estimated coefficients for the first lockdown and the baseline coefficient for the second wave remain highly significant at conventional levels. In light of the large number of fixed effects and control variables, this is a remarkable finding. As a final specification, in column (6) we include $\overline{stw}_k^{2009-2013}$ and all other covariates as dummies, with one indicating above-median values of the respective variable. The overall pattern is consistent with the previous results.

Lastly, we reproduce parts of this analysis while distinguishing between blue- and white-collar workers (Figure Appendix B5 and Table Appendix C3). Overall, the results indicate that most of the aggregate associations detected were primarily driven by STW among blue-collar workers. It is worth highlighting that this finding does not contradict our previous conclusion that the drop in employment and the increase in STW were most pronounced in more privileged regions. The reason is that the exercise in this section is a counterfactual one, that is we estimate the hypothetical drop in unemployment in absence of the STW scheme instead of actual STW uptake.

7. Conclusions

Since the onset of the Covid-19 pandemic, a host of papers has studied the sanitary and economic consequences of different public health measures. Using a granular dataset of high-frequency indicators, we contribute to this literature by providing a systematic

[12] We refrain from instrumenting contemporaneous STW uptake with its historical counterpart. This is because identification of the IV estimate requires the additional exclusion restriction that the instrument exclusively acts through current STW. For instance, this assumption would be violated if there are other, correlated support schemes in place during the Covid-19 pandemic.

Table 9: Short-Term Work as an Automatic Stabilizer

	(1) Empl.	(2) Empl.	(3) Empl.	(4) Empl.	(5) Empl.	(6) Empl.
stw_k	-0.063***					
	0.014					
$\overline{stw}_k^{2009-2013}$		0.133*	0.164***			
		0.072	0.035			
Lockdown $\times$ $\overline{stw}_k^{2009-2013}$				0.266***	0.045***	0.333***
				0.028	0.014	0.045
Wave 2 $\times$ $\overline{stw}_k^{2009-2013}$				0.173***	0.026**	0.229***
				0.022	0.011	0.033
Wave 2 $\times$ Lockdown $\times$ $\overline{stw}_k^{2009-2013}$				-0.192***	-0.013	-0.246***
				0.029	0.018	0.063
FE-Mun.				X	X	X
FE-Quarter			X	X	X	X
Controls					X	X
R^2	0.069	0.025	0.445	0.911	0.945	0.935
Obs.	37380	37380	37380	37365	36698	36698

Notes: The regressions are run at the municipality-quarter level. Employment is measured in year-to-year percentage changes with respect to 2019. Standard errors are clustered by municipality and region-quarter. All regressions control for Covid cases per capita at provincial level. Columns (1) to (3) include raw correlations of employment with $\overline{stw}_k^{2009-2013}$. Columns (4) to (6) show results from estimating versions of Equation 4, reporting coefficients α_4, α_5 and α_6. Columns (2) to (5) include all explanatory variables in linear terms, in column (6) all explanatory variables are coded as dummies (=1 indicating above-median values, and 0 otherwise). Control variables are: average income, house price per square meter, rent price per square meter, unemployment share, share of people with tertiary degrees, share of people employed in the ICT sector, share of people above age 65, share of poor people, share of people that can work from home; each variable is included in interactions with $Wave\,2$, *lockdown* and $Wave\,2 \times$ *Lockdown*.

comparison of the effects of different lockdown approaches on the Italian economy. Our analysis reveals that the general lockdown implemented in Spring 2020 caused large reductions in mobility and employment, whereas the targeted approach during the second wave inflicted comparatively little additional economic costs. We document the adjustment of the economy to the pandemic situation and report sizeable heterogeneities in all these effects along socioeconomic lines.

The drop in economic activity was less pronounced in high-income communities with higher shares of teleworkable jobs and mitigated by governmental intervention in the form of STW schemes. Both factors shielded employees more effectively from loosing their jobs in more affluent municipalities, implying that the Covid-19 crises likely worsened existing geographical inequalities and the historical North/South divide.

These findings offer important insights for policy-makers. First, we show that working from home effectively protected employees from job losses. In light of the largely positive effects of working from home or hybrid working, which include benefits in terms of job retention, job satisfaction, and worker productivity (Aksoy *et al.*, 2022; Bloom *et al.*, 2022), improving the digital and legal infrastructure that allows working from home will be key to enhancing economic resilience to future pandemics and systemic disruptions in general.

Second, this paper adds to the evidence on the effectiveness of lockdown policies in reducing interpersonal contact. Even though both targeted and general lockdown policies provided good levels of protection, our results suggest that local approaches are less harmful to the economy while sufficient in controlling virus transmission. Factoring in the existing literature, one can therefore conclude that lockdowns should be imposed *quickly and locally* (Lewis, 2022).

Finally, we have also highlighted the importance of taking appropriate labour market measures to cushion the consequences of the economic fallout on the labour force. STW prevented job losses among some groups of individuals and allowed businesses to retain their employees throughout the crises, ensuring a swift economic rebound. However, given its focus on employed/high-income individuals and communities, STW should be complemented with traditional unemployment insurance or other support payments to ensure an even support for all societal groups. What is more, STW tends to hamper reallocation of resources, possibly preventing economic reorganization in response to systemic crises (Giupponi *et al.*, 2022). Hence, despite their importance during recessions, STW schemes should only be considered a temporary measure.

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Appendix

Appendix A. Data Sources

Appendix A.1. Lockdown Measures

We compile a complete dataset on lockdown measures for the second wave after the introduction of the four-colour "traffic light" system in Italy on November 15, 2020, including:

- White zones, with no restriction except the requirement of wearing a mask in closed places and schools;
- Yellow zones, classified as having a “moderate” risk. The essential rules are: the obligation to wear a mask when leaving the house and the prohibition to leave the house between 10 pm and 5 am (except for reasons related to work, health or necessity). The closure of shopping centers on public holidays and the day before holidays, with the exception of food shops, pharmacies and newsstands. Exhibitions, museums and bingo halls are also closed. Public transport can only run at 50% reduced capacity. Schools are in distance learning from high school onward. Movements both within and outside the municipality are permitted, and it is also allowed to reach another region as long as it is also yellow. Outdoor sports or physical activities are allowed, even in equipped areas and public parks; sports clubs remain open, but the use of changing rooms is prohibited. Swimming pools and gyms remain closed.
- Orange zones, classified as having an “elevated” risk. Additional lockdown measures are in place. Nobody is allowed to enter or leave their region or municipality, except for work, health or other urgent reasons. Food service activities, including cafes, restaurants, pubs, ice cream shops, are suspended, while delivery and takeaway restaurants are allowed to operate. Food service activities at rest stops along highways, in hospitals, and in airports may continue. Individual exercise is exclusively allowed in the municipality of residence.
- Red zones, classified as having the “maximum” risk of contagion, and where further restrictions apply. Movements are prohibited also within the region except for work, health or other urgent reasons. Schools are mostly closed (some exceptions are allowed for primary schools). Commercial activities and markets are suspended, with the exception of those selling foodstuffs and basic necessities. Newsstands, tobacco shops, and pharmacies remain open. Outdoor sports clubs and centers are closed. Individual exercise is exclusively allowed outdoors in the vicinity of one’s residence and with the use of a mask.

Due to their severity, we classify the first-wave lockdowns as red zones.

Our main data source is the Coronanet-project database described in Cheng *et al.* (2020), complemented with information from wikipedia.org.

Appendix A.2. Mobility Data

There are two Mobile Network Operators (MNOs) providing cellphone mobility data in the form of an Origin-Destination Matrix (ODMs) for Italy: Vodafone, at the province level and TIM, at the census enumeration district-level (namely ACE). We use the latter in order to exploit the higher spatial resolution, however, two caveats with respect to TIM's ODMs need to be born in mind. First, the data contain only movements starting and ending within an hour of the starting location, implying that most long-distance movements will be excluded from the data. Second, the data might cover a selected population. For each municipality, our original series contains three weekdays: Tuesdays (describing average mid-week working day behaviour), Saturday nights from 19h onward (measuring pure leisure mobility), and Sundays (represent non-working days). To obtain a smooth dataset with few missing data points and to retain confidentiality, we aggregate the original hourly ODMs in time to weekly frequency and in space to municipalities. Moreover, we express all values in %-deviations from the unweighted average mobility over all municipalities before the first lockdown, allowing to compare mobility in the cross-section, over space and time, while avoiding to disclose exact data values.

Our final dataset consists of a weekly unbalanced panel covering all weeks in 2020 and weeks 1 to 4 in 2021. We calculate three distinct indicators from the ODMs: (1) outgoing mobility from the spatial unit, (2) incoming mobility to the spatial unit, and (3) mobility within the spatial unit. For each of the variables, we are able to merge any mobility information for 7765, 7537 and 6299 out of the 7904 municipalities in Italy, respectively. For outward mobility, only 4% of all observations are missing, while for inward (internal) mobility, this figure is substantially higher at 15% (44%). This is because whenever the number of movements between two cells falls below a given confidentiality threshold, the MNO discards this number, resulting in empty observations. This is one of the standard safeguard procedures applied by the data providers. Due to its lower coverage and high correlation with outward mobility (0.9965), we drop the indicator of inward mobility from the analysis.

Appendix A.3. Labour Market Data

Employment. We construct employment at the municipality-quarter level from two sources: the number of employees by sector and municipality in 2019, and the nationwide quarterly growth rates in employment by sector throughout 2020. We apply the latter growth rates to the municipality-level data for each sector, and aggregate over all sectors. Hence, the validity of this measure rests on the assumption that all sectors exhibited the same growth rates across the whole country.

Short-term work. The Italian National Institute of Social Security (INPS) provides data on the hours of short-term work receipt by month and province, distinguishing between blue- and white-collar workers. The data span the period from 2009 to 2021.

Appendix A.4. Municipality Characteristics

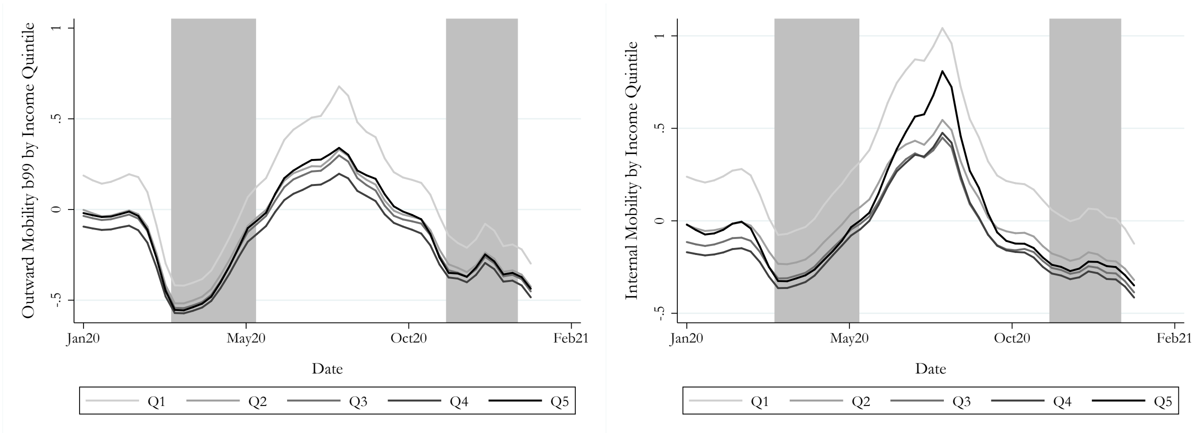
Table Appendix A10: Municipality Characteristics

Variable Name	**Source(s)**	**Description**
Average Income	ISTAT	Average income computed by dividing the number of taxpayers over their total income. Calculated from data on the total number of taxpayers and total taxes paid, both by income bracket.
House Price	immobiliare.it	Average house price per sqm (March 2020)
Rent Price	immobiliare.it	Average rent price per sqm (March 2020)
Unemployment Share	ISTAT	Calculated as the number of individuals between age 25 and 64 divided over the total number of people in that age group. Obtained from data on activity status.
Tertiary Degree	ISTAT	Share of individuals with a university degree in the age group between 25 and 64.
ICT Sector	ISTAT	Share of individuals working in the ICT sector (sector J). Obtained from employment data by sector.
Share above Age 65	ISTAT	Calculated as number of people above age 65 divided by overall population. Based on population data by age group.
Poverty Share	ISTAT	Share of individuals with a taxable annual income below 10,000€. Calculated from data on the total number of taxpayers and total taxes paid, both by income bracket.
Working From Home	ISTAT, Adams-Prassl *et al.* (2022)	Share of individuals with jobs that can be performed from home. Calculated by taking a weighted sum of sectoral employment, with weights based on sectoral data on teleworkability from the UK (Adams-Prassl *et al.*, 2022).

Notes: Description and sources of municipality characteristics. All information refer to 2019, unless indicated otherwise.

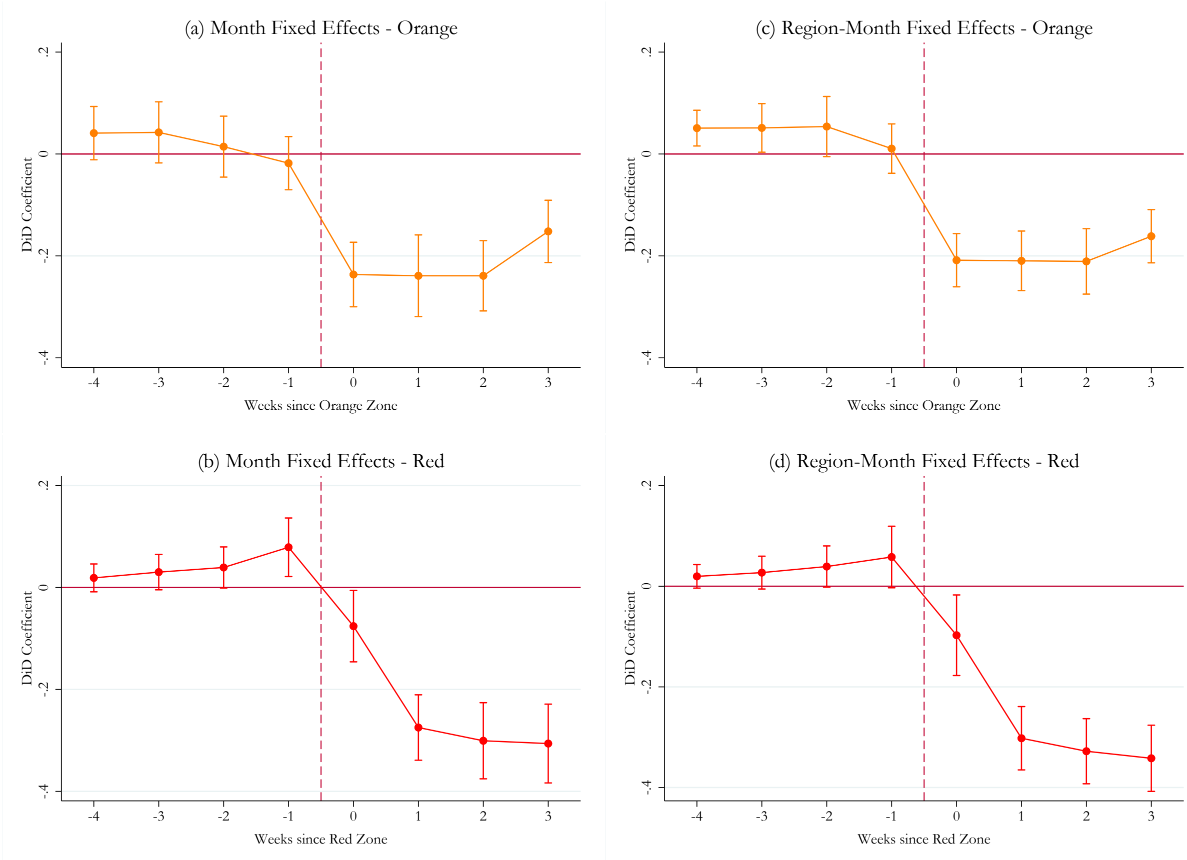
Appendix B. Figures

Figure Appendix B1: Mobility over Time by Income, Residuals



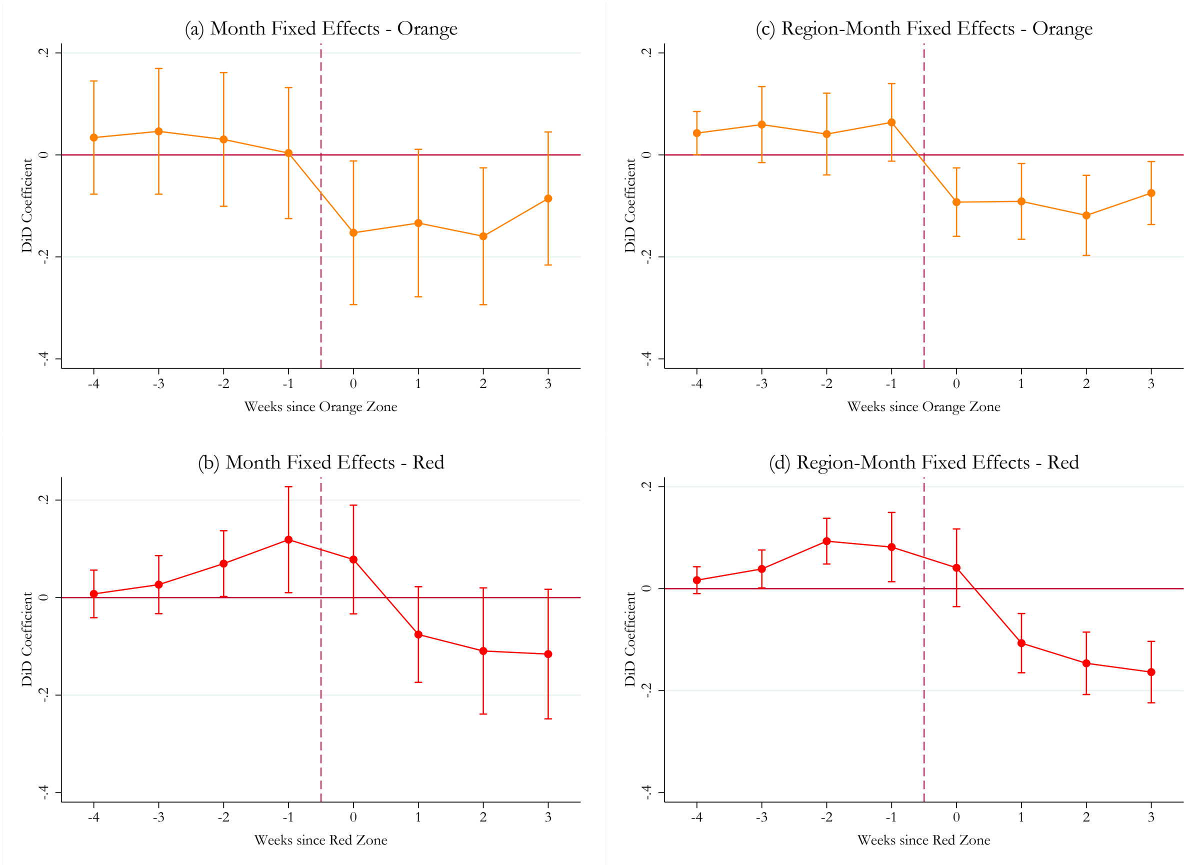
Notes: Average weekly mobility by income quintile, deviations with respect to the pre-pandemic per capita average for Italy and smoothed with a local polynomial with bandwidth 0.8. Income quintiles refer to residuals from regressions on house prices, rent prices, unemployment, the share of people with a tertiary degree, the share of people working in the ICT sector, the poverty share, and the share of people with teleworkable jobs . The shaded areas indicate lockdowns.

Figure Appendix B2: Event Study, White/Yellow to Orange or Red Zone - Outward Mobility



Notes: Dependent variable: Outward mobility per capita. The left and the right two panels are obtained from two separate regressions, which compare orange/red zones against white/yellow zones. Coefficients are shown alongside 95% confidence intervals. Explanatory variables: dummies indicating weeks until municipality enters an orange/red zone from a white/yellow zone (if change during week, the observation has been assigned to the more stringent color code for the whole week). Controls: fixed effects for municipalities as well as month (panels a) and b)) or region-month (panels c) and d)). Covid cases are at provincial level per capita. Assumption: yellow = white, allowing to construct a contemporaneous counterfactual during November and December. Baseline: all white/yellow zones.

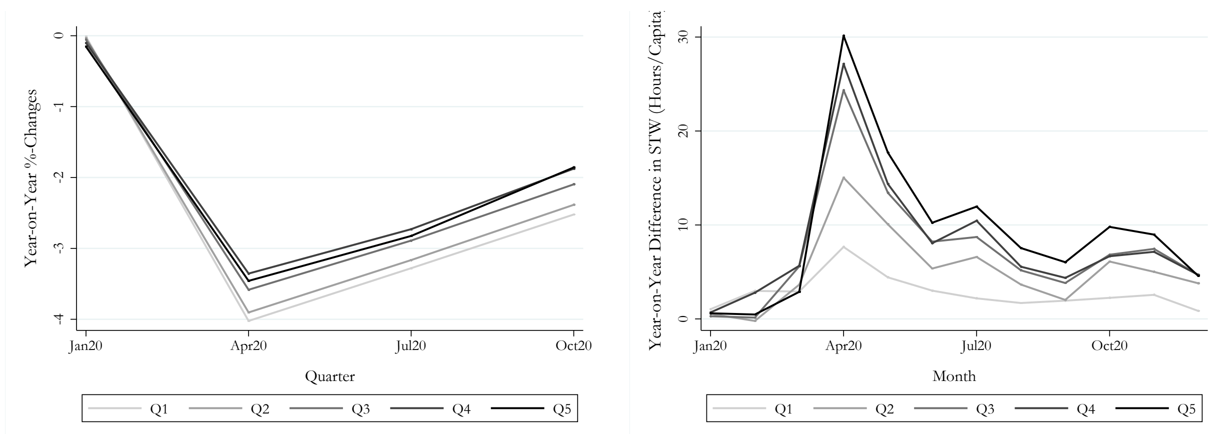
Figure Appendix B3: Event Study, White/Yellow to Orange or Red Zone - Internal Mobility



Dependent variable: Internal mobility per capita. The left and the right two panels are obtained from two separate regressions, which compare orange/red zones against white/yellow zones. Coefficients are shown alongside 95% CIs. Explanatory variables: dummies indicating weeks until municipality enters an orange/red zone from a white/yellow zone (if change during week, the observation has been assigned to the more stringent color code for the whole week). Controls: fixed effects for municipalities as well as month (panels a) and b)) or region-month (panels c) and d)). Covid cases are at provincial level per capita. Assumption: yellow = white, allowing to construct a contemporaneous counterfactual during November and December. Baseline: all white/yellow zones.

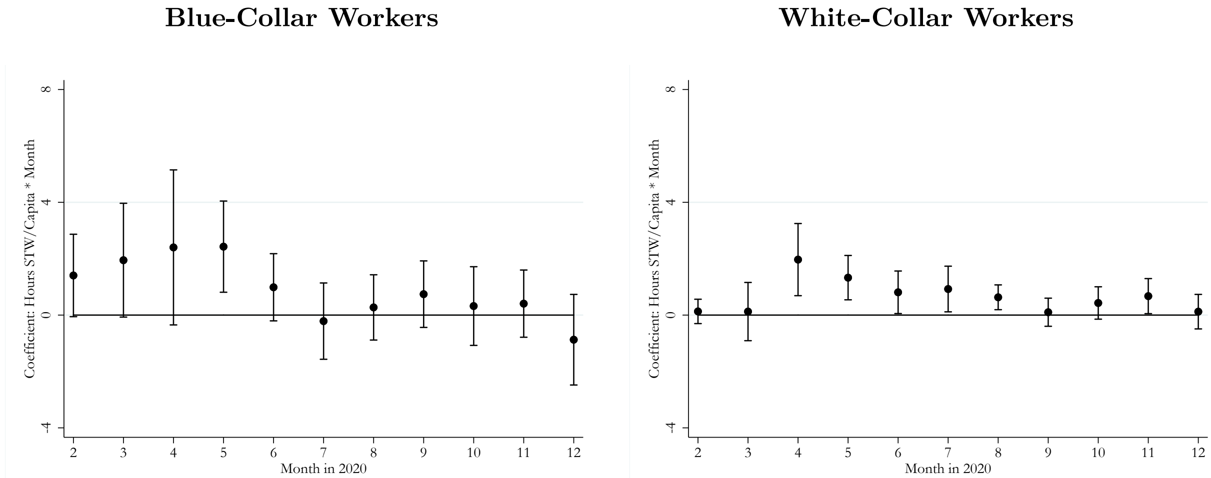
Figure Appendix B4: Labour Market Indicators over Time by Income

Employment **Short-Term Work**



Notes: The left panel shows employment (in percentage deviations from the corresponding quarter in 2019), the right panel reports short-term work in hours per capita and in absolute differences with respect to 2019; both variables are expressed by income quintile.

Figure Appendix B5: Monthly Correlation of STW in 2020 and Historical Averages of STW 2009-2013, Blue- vs. White-Collar Workers



Notes: Shows coefficients from regressions of stw_k on month dummies interacted with $\overline{stw}_k^{2009-2013}$, controlling for month and province fixed effects, alongside 95% confidence intervals. Standard errors are clustered at the province level.

Appendix C. Tables

Table Appendix C1: Lockdown Effect on Short-Term Work (Blue-Collar Workers)

	First Wave		Second Wave		Comparison	
	(1) STW	(2) STW	(3) STW	(4) STW	(5) STW	(6) STW
Yellow Zone			-1.756***	-1.095***	-1.938***	-0.889***
			0.333	0.226	0.351	0.272
Orange Zone			-1.080***	-1.073***	-1.138***	-1.057***
			0.340	0.298	0.334	0.374
Red Zone	3.897***	4.363***	-1.590***	-0.687	4.307***	4.396***
	0.608	0.553	0.552	0.485	0.590	0.523
Wave 2					1.853***	1.983***
					0.269	0.267
Red Zone × Wave 2					-6.159***	-4.937***
					0.845	0.735
Covid Cases	0.149*	0.018	0.036***	0.015**	0.043***	0.011
	0.082	0.074	0.007	0.007	0.008	0.007
FE-Prov.		X		X		X
R^2	0.300	0.479	0.082	0.560	0.245	0.478
Obs.	615	615	710	710	1325	1325

The regressions are run at the province-month level with STW as dependent variable. STW for blue-collar workers is measured in hours per working age population, and expressed in absolute year-to-year changes with respect to 2019. Standard errors are double-clustered by province and region-month. Covid cases are per capita at provincial level.

Table Appendix C2: Lockdown Effect on Short-Term Work (White-Collar Workers)

	First Wave		Second Wave		Comparison	
	(1) STW	(2) STW	(3) STW	(4) STW	(5) STW	(6) STW
Yellow Zone			-2.609***	-1.968***	-2.996***	-1.956***
			0.611	0.442	0.639	0.502
Orange Zone			-1.193*	-1.429**	-1.315**	-1.386**
			0.637	0.545	0.631	0.687
Red Zone	8.451***	8.821***	-2.290***	-1.356*	9.325***	9.422***
	1.157	1.141	0.826	0.810	1.174	1.130
Wave 2					3.197***	3.316***
					0.483	0.510
Red Zone × Wave 2					-12.174***	-10.632***
					1.527	1.428
Covid Cases	0.285*	0.180	0.046***	0.027**	0.059***	0.025*
	0.163	0.166	0.010	0.011	0.012	0.013
FE-Prov.		X		X		X
R^2	0.298	0.385	0.055	0.381	0.271	0.380
Obs.	616	616	710	710	1326	1326

The regressions are run at the province-month level with STW as dependent variable. STW for white-collar workers is measured in hours per working age population, and expressed in absolute year-to-year changes with respect to 2019. Standard errors are double-clustered by province and region-month. Covid cases are per capita at provincial level.

Table Appendix C3: Short-Term Work as Automatic Stabilizers, Blue- vs. White-Collar Workers

	(1) Empl.	(2) Empl.	(3) Empl.	(4) Empl.	(5) Empl.	(6) Empl.
$stw_{k,blue}$	-0.109***					
	0.033					
$stw_{k,white}$	0.017					
	0.051					
$\overline{stw}_{k,blue}^{2009-2013}$		0.174*	0.195***			
		0.092	0.058			
$\overline{stw}_{k,white}^{2009-2013}$		0.004	0.069			
		0.234	0.158			
Lockdown $\times$ $\overline{stw}_{k,blue}^{2009-2013}$				0.392***	0.067**	0.268***
				0.054	0.027	0.068
Lockdown $\times$ $\overline{stw}_{k,white}^{2009-2013}$				-0.126	-0.020	0.070
				0.165	0.055	0.061
Wave 2 $\times$ $\overline{stw}_{k,blue}^{2009-2013}$				0.259***	0.063***	0.162***
				0.042	0.021	0.050
Wave 2 $\times$ $\overline{stw}_{k,white}^{2009-2013}$				-0.096	-0.091**	0.049
				0.125	0.043	0.045
Wave 2 $\times$ Lockdown $\times$ $\overline{stw}_{k,blue}^{2009-2013}$				-0.319***	-0.103***	-0.148*
				0.059	0.037	0.084
Wave 2 $\times$ Lockdown $\times$ $\overline{stw}_{k,white}^{2009-2013}$				0.203	0.265***	-0.029
				0.175	0.079	0.068
FE-Mun.				X	X	X
FE-Quarter			X	X	X	X
Controls					X	X
R^2	0.074	0.025	0.445	0.911	0.945	0.935
Obs.	37360	37380	37380	37365	36698	36698

Notes: The regressions are run at the municipality-quarter level. Employment is measured in year-to-year percentage changes with respect to 2019. Standard errors are clustered by municipality and region-quarter. All regressions control for Covid cases per capita at provincial level. Columns (1) to (3) include raw correlations of employment with $\overline{stw}_{k}^{2009-2013}$. Columns (4) to (6) show results from estimating versions of Equation 4, reporting coefficients α_4, α_5 and α_6. Columns (2) to (5) include all explanatory variables in linear terms, in column (6) all explanatory variables are coded as dummies (=1 indicating above-median values, and 0 otherwise). Control variables are: average income, house price per square meter, rent price per square meter, unemployment share, share of people with tertiary degrees, share of people employed in the ICT sector, share of people above age 65, share of poor people, share of people that can work from home; each variable is included in interactions with $Wave\,2$, $Lockdown$ and $Wave\,2 \times\ Lockdown$.

Appendix D. Event-Study

We identify the shape of the reduction by means of the following estimation, following the approach recommended in Goodman-Bacon (2018) and Goodman-Bacon and Marcus (2020), among others:

$$Mobility_{i,w} = \sum_{h=-4}^{3} \alpha_1^h \, Orange_{i,w+h} + \sum_{h=-4}^{3} \alpha_2^h \, Red_{i,w+h} + \beta \, Cases_{k,w} + \gamma_i + \delta_{r,m} + \epsilon_{i,w} \tag{D.1}$$

where $Orange_{i,w+h}$ ($Red_{i,w+h}$) is an indicator equal to one for a province becoming an orange (red) zone in h weeks or h weeks ago. The sample contains all municipalities in white or yellow zones, and municipalities up to 3 weeks in their orange/red lockdowns. After a maximum of 3 weeks in an orange or red zone, a municipalities exits the sample, but may re-enter once it becomes a white or yellow zone again. We focus on the second wave, as this part of the sample contains sufficient variation in the data to identify dynamic responses. Figures Appendix B2 and Appendix B3 depict the two series $\sum_{h=-4}^{3} \alpha_1^h$ and $\sum_{h=-4}^{3} \alpha_2^h$.

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