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QUESTIONING THE SPATIAL ASSOCIATION BETWEEN THE SPREAD OF COVID-19 AND TRANSIT USAGE IN ITALY

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Questioning the spatial association between the spread of COVID-19 and transit usage in Italy

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Abstract

Within the much broader framework of global interest, the dilemma concerning the real impact of mode of transport on the spread of COVID-19 has been a priority for transport stakeholders and policy-makers. How dangerous is it to move around a certain territory? Does the danger depend on the mode of transport? By considering a novel and detailed dataset at the level of local labour markets, we analysed the spatial association between the propensity to use public transport and excess mortality in Italy attributable to the spread of COVID-19. We found that places characterised by larger commuting flows exhibit higher excess mortality, but observed no significant spatial association between excess mortality and transit usage. Our results were obtained by considering a wide range of heterogeneity in the estimation of quantile regressions across a variety of specifications. Although we do not provide a definitive answer concerning the risk associated with transit use, our analysis suggests that mobility, not modal choice, should be considered a main driver of the contagion.

Keywords: COVID-19, Public transport, Commuting, Quantile regression, Italy

JEL Classification Numbers: H41, I18, J61, R41

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1. Introduction

Mobility and population density are among the most distinguishing features of contemporary cities, at least in the most developed parts of the world. The outbreak of COVID-19 is now threatening this development model, since policy-makers are attempting to curb the spread of the epidemic using, among other options, social distancing and restrictions on mobility. The effectiveness of these measures has been extensively examined, and there is consensus regarding their importance in reducing the speed of diffusion of the virus (Hsiang et al., 2020; Li et al., 2020). However, policies designed to contain virus transmissions are very heterogeneous, since they may involve (among others): school closures, workplace closures, cancellations of public events, restrictions on gathering size, closures of public transport, stay-at-home requirements

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and restrictions on internal movements (Hale et al., 2020). Public transport, in particular, has suffered capacity restrictions designed to both reduce individual mobility and support social distancing, though empirical evidence on the transmission of the virus through public transport networks is very limited.

In this article, we aim to contribute to the ongoing policy debate by investigating the spatial association between transit[1] usage and the diffusion of COVID- 19 in Italy, one of the countries most severely hit by the first wave of the pandemic.

Despite growing evidence of the crucial role played by mobility and a wide public debate on the criticalities of supply constraints and their economic impact on transport firms, there is no evidence supporting a relationship between public transport use and the spread of COVID-19. To investigate the association between transit use and the diffusion of the disease, we consider a novel dataset on excess mortality at the level of local labour markets (LLMs), since the spatial extent of these territorial units is based on the geography of commuting flows[2]. Indeed, such "functional regions" (i.e., aggregations of multiple neighbouring municipalities) are defined as "self-contained" labour markets in which approximately 75% of residents also work within the market borders, such that the resident population coincides as closely as possible with the working population, and only a minority of individuals commute to and from the area (De Blasio and Di Addario, 2005). Thus, the boundaries of the LLMs do not reflect any administrative principles; rather, they are shaped by social and economic relations, which makes them very informative for analysing overall mobility patterns as a whole (Monte, 2020).

The spread of COVID-19 is measured by daily excess mortality between 1 January and 30 June 2020, a range spanning from nearly two months before to nearly two months after the most critical part of the pandemic cycle. Then, we measure transit usage using on data from the latest country-wide assessment of mobility for Italy, conducted in 2011. Our methodology combines these variables in a model estimated with panel quantile regressions to allow for the wide heterogeneity of the impacts of mobility and transit usage on the spatial diffusion of the virus.

Our findings point to a statistically weak association between COVID-19 diffusion and transit usage. In particular, we did not find that places in which commuters were more prone to use public transport were more severely affected by the epidemic. Regardless of the type of transport use, however, our empirical analysis does confirm that the primary contributor to the first wave of the pandemic was the intensity of people's movements. Although we cannot exclude that virus transmissions may occur on public transport, our findings suggest that policies aiming to contain the diffusion of the virus should address mobility *per se*, not necessarily individuals' choice of transport mode.

The remainder of the article is organised as follows. Section 2 analyses the literature. Section

[1] Note that throughout the rest of the article, we refer to transit as a synonym of public transport.

[2] For instance, the number of Italian LLMs decreased from 784 in 1991 to 686 in 2001 and, then, to 611 in 2011, in accordance with the commuting flows recorded by national censuses.

3 briefly summarises the timeline of the COVID-19 crisis in Italy. Section 4 describes the data used in the analysis. Section 5 discusses the empirical strategy and our main results and presents some robustness checks. Section 6 concludes.

2. Review of the literature

The relationship between transit usage and the diffusion of COVID-19 has not yet been thoroughly investigated in the literature. For obvious reasons, contributions to COVID-19 research are all recent and are appearing frequently and consistently within the major scientific journals.

Thus far, one strand of research has investigated whether travel behaviours have changed during the pandemic, with findings generally answering this research question in the positive. De Vos (2020) prediction that travel demand would drop dramatically and people would travel less on public transport was quickly confirmed. For instance, in the city of Chicago, Shamshiripour et al. (2020) found an unsurprising increased tendency to work from home during the pandemic and a change in the perceived risk of using various travel modes. Their results showed that personal vehicles had the lowest perceived risk of exposure, while transit the highest[3]. Similar perceptions were also detected in the Netherlands (de Haas et al., 2020), where people exhibited more positive feelings towards cars and far more negative feelings towards collective means of transport. Huge drops in transit use have been reported in some Spanish cities, such as Santander (Aloi et al., 2020) and A Coruña (Orro et al., 2020). A similar shift from public transport to individual modes has been observed in New York and across the UK, with travelers shifting particularly towards bike-sharing systems (Teixeira and Lopes, 2020) and driving (Hadjidemetriou et al., 2020), respectively. Such dynamics have been more pronounced in compact urban cities, where Hamidi and Zandiatashbar (2020) found a higher reduction in trips to grocery stores and transit stations in the US.

To the best of our knowledge, there have been only two attempts to correlate transit usage with COVID-19 infections: First, Sá (2020) found that areas in England and Wales in which larger shares of the population use public transport experienced more COVID-19 infections (but not higher mortality rates) per 100 000 inhabitants. Second, Lei et al. (2020) developed a model indicating that when the loading level decreases to 10% of the average level, possible infections in most cases are less than 1, proving the effectiveness of current urban rail transit passenger control strength.

In parallel, another strand of research has investigated the impact of lockdown restrictions on mobility as a whole - and, in turn, on the diffusion of the contagion - by relying on various geolocation and mobile phone data sources. In particular, Fang et al. (2020) identified that the lockdown of the Chinese city of Wuhan reduced its inflows by 77% and its outflows by 56%, while

[3] Usually, and in the absence of pandemics, public transport is rated much more positively than car driving when it comes to safety issues (Woods and Masthoff, 2017).

Glaeser et al. (2020) estimated for four major US cities a 20% average reduction in COVID-19 cases for every 10% drop in mobility.

In the Italian context, Pepe et al. (2020) studied the change in the structure of provinces' origin-destination matrix before and after the nation-wide lockdown and estimated that mobility restrictions cut total trips in half. In an analysis of intercity and local mobility patterns during the outbreak, Beria and Lunkar (2020) found a trend towards relocation from cities to urban belts, while Caselli et al. (2020) estimated that the lockdown reduced mobility among local labour markets by 7%.

In addition, several studies have shown that both human mobility and the structure of the network of commuting flows played a crucial role in spreading the disease: Cintia et al. (2020) highlighted a striking relationship between the negative variation of mobility flows and the net reproduction number (R_t) of the virus in all Italian regions; Iacus et al. (2020) showed that mobility can explain from 50 to 90% of excess mortality across Italian provinces; while Borsati et al. (2020) found that if commuting patterns between municipalities had been 90% of the real ones, Italy would have suffered approximately 2 300 fewer fatalities during the most critical part of the pandemic. However, a comprehensive analysis of the spatial association between transit and the diffusion of COVID-19 has not yet been conducted.

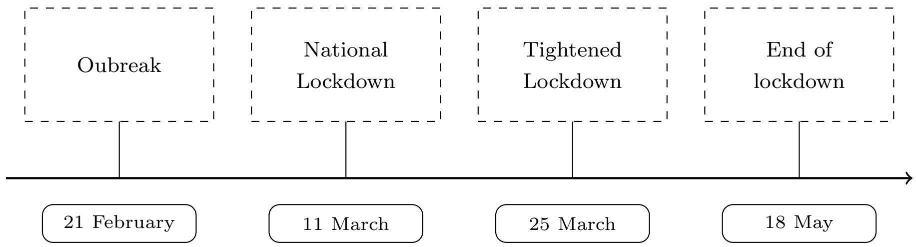
In this article, we try to connect these two strands of the literature by investigating whether places characterised by a greater propensity to use public transport have been more severely affected by the pandemic.

3. COVID-19 in Italy

Our empirical analysis focuses on Italy, the first Western country to be deeply affected by the diffusion of COVID-19. Thus, Italy is the ideal scenario for investigating whether transit usage in a country whose government and citizens were unprepared to face the pandemic contributed to the initial spread of the disease. In other words, while policymakers and residents of other European countries were influenced by emerging data and the Italian case, the travel behaviours of people in Italy were not biased by events elsewhere.

The timeline of the COVID-19 crisis in Italy (summarised in Figure 1) has been as follows: the first two COVID-19 cases were officially detected on 30 January, after a Chinese couple travelled from Wuhan to Milan, Verona, Parma, and Florence. The first cases of secondary transmission were identified near Codogno and Vo' (two municipalities in Lombardy and Veneto, respectively) on 21 February. On 23 February, two days later, the Italian government enforced mobility restrictions into and from these areas (DPCM1, 2020). On 4 March, all schools and universities were closed (DPCM2, 2020). On 8 March, a lockdown was imposed for the country's first relevant "red zone" (DPCM3, 2020): that is, the whole of the Lombardy region and 14 additional provinces within the Emilia-Romagna, Marche, Piedmont, and Veneto regions. A few days later, on 11 March, this lockdown was extended to the whole nation (DPCM4, 2020). As a result, many business activities open to the public, such as restaurants and retail stores, were forced to close, and people were advised to stay home. Between 22 March and 25 March, the lockdown was further tightened through a shutting down of all non-essential economic activities and a prohibition on any movement of people on Italian soil, with few exceptions (e.g., for work or health; DPCM5, 2020; DPCM6, 2020). This marked the so-called "phase 1" of the epidemic, which gradually ended between 4 May and 18 May.

Figure 1: Timeline of events, by date



Notes: The figure shows the timeline of the main events occurring during the first wave of the pandemic in Italy. *Source*: Authors' own elaboration.

4. Data

To investigate the association between public transport usage and the spatial diffusion of COVID-19 in Italy, we rely on two main data sources: the Italian National Institute of Statistics (ISTAT) and the Italian Institute for Environmental Protection and Research (ISPRA). We describe the variables used in the empirical analysis in the following section.

4.1. Measuring the spread of COVID-19 through excess mortality

We measure the spread of the pandemic using excess mortality, rather than the official number of COVID-19 cases, because excess mortality has some important and desirable features.

First, these data are available at the municipal level, while case data are available only at the province level. Hence, the data on excess mortality are more granular and, thus, more suitable for aggregation at the LMM level. LLMs are defined by ISTAT as travel-to-work areas, making them gravitational areas by nature.

Second, the use of excess mortality partially eliminates the risk of measurement errors and endogeneity issues related to the identification of COVID-19 patients, such as the spatial heterogeneity in screening procedures and testing capacities[4].

[4]Between 25 May and 15 July 2020, the Italian Ministry of Health and ISTAT conducted an epidemiological investigation to estimate the percentage of the population that probably contracted the infection by sampling 150 000 individuals throughout the entirety of Italy. The results (based on 64 660 serological tests) show that the number of people who contracted the virus was equal to 2.5% of the population: six times more than the official COVID-19 cases detected during the pandemic cycle (ISTAT, 2020).

Third, the use of excess mortality allows for the capture of possible COVID-19-related fatalities even before 21 February, when the first Italian cases were identified[5]. Similarly, the excess mortality measure is conceptually superior to the official COVID-19 fatalities because the latter depend on hospitals' differing classifications (Buonanno et al., 2020; Galeotti and Surico, 2020) and are likely to underestimate the true increase in mortality, since a substantial number of people died without being tested[6] (Bartoszek et al., 2020; Ciminelli and Garcia-Mandicó, 2020).

Lastly, excess mortality allows us to consider not only the direct effects of the spread of the virus, expressed by the loss of lives of individuals who have contracted the infection, but also its indirect effects, expressed by the loss of lives of individuals untreated due to the lack of opportunities for hospitalisation caused by hospital congestion.

For all 7 903 Italian municipalities, we obtained data released by ISTAT on 22 October 2020 reporting the daily number of fatalities during the first six months of 2020 and the average daily fatalities during the same periods for 2015 through 2019 (referred to as the "baseline" throughout the rest of the article). Then, we aggregated these data at the LLM level and defined our outcome of interest as the increase in fatalities recorded every day between 1 January and 30 June 2020, compared to the same day in the baseline:

$$mortality\_growth_{it} = \frac{fatalities_{it}^{2020} - fatalities_{it}^{baseline}}{fatalities_{it}^{baseline}} \tag{1}$$

where i denotes the LLM and t denotes the day. Figure 2 plots the evolution of excess mortality during our period of analysis, showing that Italy was most severely hit by the pandemic during March and April. It also illustrates how the lockdown restrictions were essential in flattening the curve, reducing mortality growth to nearly the pre-pandemic level by June.

4.2. Measuring pre-existing transit usage and commuting

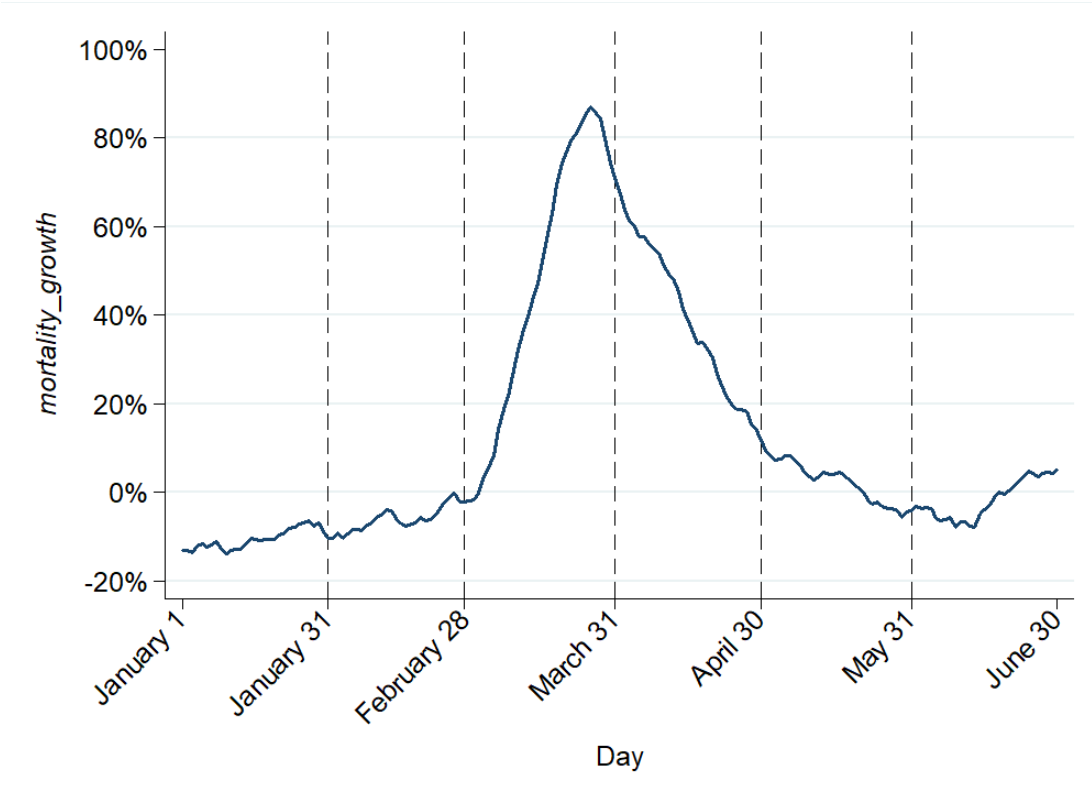
To measure areas' different pre-existing levels of public transport usage, we drew on Italy's latest official country-wide assessment of mobility, which was conducted during the 2011 national census. For each Italian municipality, the variable describes the share of the total population who moved daily by collective means of transport for the purposes of labour or study. Our transit index ($transit$) at the LMM level is defined as the average of such shares for all municipalities in the same LLM, weighted by population. In other words, this index measures the propensity for public transport usage within each functional region.

However, in the context of a pandemic, whether and how intensively people move might be more important than the type of transport used. Indeed, a growing number of studies have

[5] By analysing the first three complete genomes of SARS-CoV-2, Zehender et al. (2020) reported that the virus was present in Italy weeks before the first reported case.

[6] As reported by INPS (2020), during the first quarter of 2020, Italy suffered 46 909 more deaths than the average number of fatalities during the same periods from 2015 to 2019. By comparison, the Department of Civil Protection declared an official count of 27 938 COVID-19 fatalities. It is plausible that the majority of the remaining 18 971 fatalities were also caused by the spread of the disease.

Figure 2: Evolution of *mortality_growth* in Italy, by day



Notes: Since 2020 is a leap year, we excluded February 29 from the dataset to ensure full comparability between 2020 and the baseline data. *Source*: Authors' own elaboration.

shown that human mobility significantly contributed to the initial spread of the disease (Cintia et al., 2020; Glaeser et al., 2020; Iacus et al., 2020) and that more connected places face more severe epidemiological risk (Borsati et al., 2020). This is why several national governments imposed unprecedented lockdown restrictions and social distancing measures to better control virus transmissions.

We aim to disentangle the possible role of transit from other confounding factors by considering the structural characteristics of labour markets' commuting flows. To this end, we aggregate the latest municipality-to-municipality origin–destination matrix (ODs) - provided by the same country-wide mobility assessment[7] - into LLM-to-LLM ODs, in which each node represents an Italian local labour market. Then, following the most recent literature, we compute two synthetic indices that describe the network of commuting flows from different perspectives. The

[7]Gatto et al. (2020) provide evidence that the 2011 commuting flows are still informative of the current ones, as the spatial patterns of workers and students mobility seem to be remarkably preserved over such a long time interval.

first index is defined as the ratio between self-flows, or the total number of people p_{ii} moving between municipalities within the same LLM for reasons of work or study, and the population of the area:

$$internal\_commuting_i = \frac{p_{ii}}{population_i} \tag{2}$$

Given that, by definition, our territorial units are self-contained labour markets within which the resident population coincides as closely as possible with the working population (as explained in Section 1), this index measures the intensity of an LLM's internal mobility. Accordingly, we define each LLM's overall degree of external mobility by computing both its out-flows, or the total number of people p_{ij} moving from their residential LLM i to any other LMM j for the same reasons of work or study, and its in-flows, or the total number of people p_{ji} moving to LMM i from any other LMM j. Then, our second index is the sum of the previous incoming and outgoing flows over the population of the area:

$$external\_commuting_i = \frac{\sum_{j=1}^{n}(p_{ij} + p_{ji})}{population_i} \tag{3}$$

In other words, this second index is a proxy of the openness of each LLM, expressed by the share of the population exposed to the possible import of the virus from elsewhere.

4.3. Control variables

In our econometric analysis, we control for several other variables, in line with the recent literature explaining the spatial diffusion of the disease (e.g., Bisin and Moro, 2020; Desmet and Wacziarg, 2020). To this end, we capture relevant geographic and demographic characteristics potentially correlated with both excess mortality and transit by including the average altitude of the municipalities in the LLM (*altitude*), the share of coastal municipalities in the LLM (*coastal*), the log of the LLM's population density (*ln_density*), and a proxy of physical proximity for each territorial unit, defined as the average number of square meters per inhabitant in occupied dwellings ($house\_m^2\_pc$).

Then, given that the COVID-19 fatality rate is positively correlated with a higher presence of elderly people (Knittel and Ozaltun, 2020), that nursing homes and hospitals were the first epicentres of the pandemic (Alacevich et al., 2020; Barnett and Grabowski, 2020), and that pollution can be an important co-determinant of COVID-19-related fatalities[8] (Becchetti et al., 2020; Coker et al., 2020; Conticini et al., 2020; Wu et al., 2020), we also control for three measures of vulnerability to the pandemic at the LLM level: the population share older than 75[9] years

[8]Several studies in the medical literature show that individuals living in highly polluted areas have a reduced capacity to react to respiratory diseases and pneumonias (Pope III and Dockery, 2006).

[9]By controlling for the incidence of elderly people on the total population, we partially control for the share of inactive population within each LLM.

old (*share_over*75), the number of hospital beds per 1 000 inhabitants (*hospital_beds*), and the PM10, defined as the average values of μg/m^3 (*pm*10).

Finally, we account for differences in LLMs' economic structure by including a dummy variable that takes the value of 1 if an LLM is defined as an industrial district[10] (*district*), and 0 otherwise, since previous studies show that work-related mobility and social interactions within industrial clusters are very high (Gordon and McCann, 2000; OECD, 2002; Majocchi and Presutti, 2009).

All data are publicly available[11]. Table 1 reports standard descriptive statistics and reference years for the variables used in the empirical analysis.

Table 1: Descriptive statistics

	Mean	SD	Minimum	Maximum	Observations	Year
mortality_growth	0.233	1.612	-1.000	34.000	105 948	2020
transit	0.101	0.033	0.030	0.298	110 591	2011
internal_commuting	0.360	0.059	0.052	0.556	110591	2011
external_commuting	0.167	0.072	0.026	0.824	110591	2011
altitude[a]	370.557	285.930	1.000	1 518.736	110 591	2011
coastal	0.262	0.375	0.000	1.000	110 591	2011
ln_density[b]	4.738	1.105	2.186	8.555	110591	2019
house_m^2*_pc*[c]	41.530	4.087	28.989	53.873	110 591	2011
*share_over*75	0.113	0.023	0.056	0.189	110 591	2011
hospital_beds[d]	1.582	2.370	0.000	21.911	110 591	2017
*pm*10[e]	26.690	7.508	14.000	46.000	110 591	2017
district	0.231	0.421	0.000	1.000	110 591	2011

Notes: The number of Italian municipalities decreased from 8 092 in 2011 to 7 903 in 2020. Hence, before aggregating municipality data at the LLM level, we precisely combined data by considering all of the administrative variations occurring in Italy during these 9 years, such as the establishment of new municipalities and the suppression of others. We ended up with 611 LLM observed for 181 days.

Unit of measurement: [a] meters, [b] log of population per km^2, [c] m^2 per inhabitant, [d] per 1 000 inhabitants, [e] μg/m^3.

4.4. Descriptive evidence

We now briefly describe the spatial patterns of our main variables of interest. Figure 3a plots the spatial evolution of the average *mortality_growth* in March 2020, when Italy was

[10] Industrial districts are LLM mainly composed by small- and medium-sized enterprises specializing in the same economic activity.

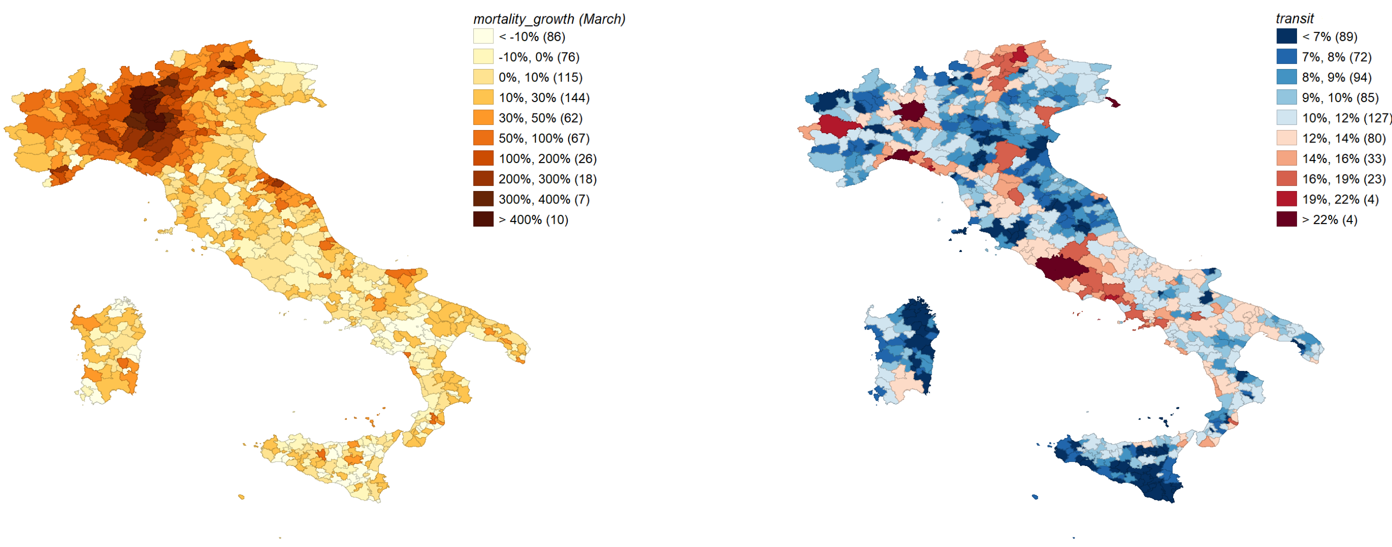
[11] *mortality_growth* data are retrieved from `https://www.istat.it/it/archivio/240401`. *transit*, *house_m*^{2}*_pc*, and *share_over*75 data are retrieved from `http://ottomilacensus.istat.it/`. *internal_commuting* and *external_commuting* data are retrieved from `https://www.istat.it/it/archivio/157423`. *altitude*, *coastal*, and *ln_density* data are retrieved from `https://www.istat.it/it/archivio/156224`. *hospital_beds* data are retrieved from `http://dati.istat.it/`. *pm*10 data are retrieved from `https://www.isprambiente.gov.it/it/pubblicazioni/stato-dellambiente/xiv-rapporto-qualita-dell2019ambiente-urbano-edizione-2018`. *district* data are retrieved from `https://www.istat.it/it/archivio/150320`.

most severely hit by the pandemic (see Figure C.1 for the same map for the other included months). COVID-19-related fatalities appear to be spatially clustered in the northern part of Italy, particularly in the Lombardy region and across the Po Valley area. However, Figure 3b shows that many of the LLMs with high levels of public transport usage are also scattered in the centre and south of Italy. Indeed, except for Milan and its hinterland, the lack of a visual correlation between *mortality_growth* and *transit* is striking, suggesting that places where workers and students are more prone to commute by collective means of transport have not experienced systematically more severe effect of the pandemic.

Figure 3: Descriptive evidence, by LLM

(a) Average *mortality_growth* in March

(b) *transit*



Source: Authors' own elaboration.

5. Empirical analysis

5.1. Econometric model

To identify whether transit played a significant role in the initial spread of COVID-19 during the first wave of the pandemic, we estimate the following equation:

$$\begin{aligned} mortality\_growth_{it} = \beta_0 + \beta_m transit_i \times \delta_m + \gamma_m internal\_commuting_i \times \delta_m \\ + \eta_m external\_commuting_i \times \delta_m + \omega_m Z_i \times \delta_m + \alpha_i + \delta_t + \epsilon_{it} \end{aligned} \tag{4}$$

where $mortality\_growth_{it}$ measures the increase in fatalities in LLM i on day t, compared to the same period during the baseline. On the right-hand side, $transit_i$, $internal\_commuting_i$, and $external\_commuting_i$ are mobility indices capturing the LMM's pre-existing public transport usage and commuting flow characteristics. Given that such indices are time-invariant, they are interacted with a vector of time dummies (δ_m) representing the first six months of 2020. Excluding January as the pre-outbreak period, the vectors of coefficients β_m, γ_m, and η_m capture the impacts of our main explanatory variables on excess mortality over the various phases of the pandemic, expressed by the different months. This model is in line with those proposed by other recent studies, such as Durante et al. (2020) and Borsati et al. (2020).

Then, $Z_i \times \delta_m$ are the set of previously described geographic, demographic, vulnerability and economic controls, also interacted with month dummies. In addition, α_i and δ_t are full sets of LMM and day fixed effects, respectively, where the LMM dummies absorb all the time-invariant differences among the territorial units, such as the provision of public transport services and the quality of the related infrastructural network, and the daily dummies account for the nationwide common evolution of excess mortality induced by seasonal trends or government policies, such as mobility restrictions and economic lockdowns. Finally, ϵ_{it} are heteroskedasticity- and autocorrelation-consistent standard errors (Andrews, 1991) clustered at the LLM level.

In the following, we present results of estimations of the previous equation both as classical least squares with fixed effects and by using quantile regressions that allow for considerable heterogeneity in the magnitude of parameters.

5.2. Estimation results

In this section, we report regression results for Equation 4 from different perspectives. The empirical analysis proceeds as follows: First, we examine the correlation between the average *mortality_growth* during the first six months of 2020 and our time-invariant explanatory variables using simple cross-sectional regressions (Table 2). Second, we exploit the longitudinal dimension of our excess mortality data by adding the daily time component and interacting all the explanatory variables with month dummies (Table 3). In so doing, we capture relevant unobserved heterogeneity through fixed effects regressions and analyse the association between excess mortality and the predictors over the various phases of the pandemic cycle. Third, we perform panel data quantile regressions to investigate any variation in the coefficients of our explanatory variables over the conditional quantiles of the *mortality_growth* distribution[12] (Figures 4–6 and Table 4).

In Table 2, column 1 includes only our main explanatory variable of interest (i.e., public transport usage), while column 2 adds both the internal and external commuting indices. Then, columns 3 and 4 progressively include all previously described sets of control variables. Although we should not interpret the estimates deriving from such simple cross-sectional specifications in depth, it is immediately clear that none of the coefficients associated with *transit* are statistically significant, while those associated with *internal_commuting* and *external_commuting*

[12]In statistics, a quantile defines a particular part of a dataset by determining the number of values in a distribution above or below a certain limit.

are positively and strongly correlated with excess mortality. Moreover, the latter preserve their sign and significance throughout the columns, exhibiting lower magnitudes as the specifications become less parsimonious. At first glance, these findings suggest that the contribution of public transport usage to the spread of COVID-19 during the first wave of the pandemic is far from obvious, while the movement of people, expressed by the network of commuting flows, seems to be a determining factor.

Table 2: Transit usage and mortality growth (cross-sectional analysis)

	mortality_growth (half-yearly)			
	(1)	(2)	(3)	(4)
transit	-0.043	-0.155	-0.178	-0.008
	(0.223)	(0.191)	(0.217)	(0.226)
internal_commuting		1.223***	0.947***	0.616***
		(0.142)	(0.142)	(0.137)
external_commuting		1.070***	0.972***	0.553***
		(0.158)	(0.167)	(0.129)
altitude			0.000**	0.000***
			(0.000)	(0.000)
coastal			-0.048**	0.012
			(0.025)	(0.024)
ln_density			0.031**	-0.004
			(0.013)	(0.013)
$house\_m^2\_pc$			0.004*	0.002
			(0.002)	(0.002)
$share\_over75$				-1.130***
				(0.425)
hospital_beds				0.004
				(0.003)
$pm10$				0.012***
				(0.002)
district				0.067**
				(0.028)
constant	0.078***	-0.530***	-0.757***	-0.555***
	(0.026)	(0.055)	(0.121)	(0.122)
Observations	611	611	611	611
R^2	0.00	0.16	0.18	0.29

Notes: All specifications present OLS estimates. The dependent variable is the average *mortality_growth* occurred during the first six months of 2020 (i.e., the whole period of analysis). Significance values: ***p<0.01, **p<0.05, *p<0.10.

In Table 3, we corroborate our preliminary findings by analysing the explanatory variables around monthly time-breaks. More precisely, we augment all the previous specifications with the set of interactions between covariates and month dummies[13]. Accordingly, all columns include the full sets of LMM and day fixed effects to better control for time-invariant characteristics potentially correlated with both excess mortality and the predictors. Since no large-scale mobility restrictions were enforced until 8 March, and since the incubation plus confirmation time

[13]Since our explanatory variables are time-invariant, their main effects are omitted from all specifications due to collinearity with LMM fixed effects.

of COVID-19 is approximately 12 to 15 days (Bartscher et al., 2020; Lauer et al., 2020), we should expect transit usage to increase COVID-19-related fatalities (through an acceleration of on-board infections) between March and April. However, the coefficients associated with *transit* are no statistically significant for all months and specifications.

Thus, we find no evidence that LLMs in which commuters are more likely to use public transport experienced greater excess mortality during the most critical part of the pandemic

Table 3: Transit usage and mortality growth (panel data analysis – part 1)

	mortality_growth			
	(1)	(2)	(3)	(4)
$transit \times February$	0.077	0.076	0.206	0.207
	(0.381)	(0.386)	(0.400)	(0.428)
$transit \times March$	-0.945	-1.070	-1.273	-0.976
	(0.907)	(0.830)	(0.970)	(0.930)
$transit \times April$	-0.336	-0.537	-0.158	-0.079
	(0.699)	(0.637)	(0.663)	(0.681)
$transit \times May$	0.576	0.489	0.116	0.036
	(0.445)	(0.448)	(0.502)	(0.530)
$transit \times June$	-0.181	-0.199	-0.425	-0.507
	(0.458)	(0.461)	(0.505)	(0.527)
$internal\_commuting \times February$		0.188	0.229	0.134
		(0.230)	(0.272)	(0.273)
$internal\_commuting \times March$		3.600***	2.183***	1.126*
		(0.662)	(0.618)	(0.611)
$internal\_commuting \times April$		2.871***	2.236***	1.815***
		(0.433)	(0.527)	(0.496)
$internal\_commuting \times May$		0.657**	0.304	0.246
		(0.286)	(0.356)	(0.350)
$internal\_commuting \times June$		0.287	0.059	0.058
		(0.269)	(0.342)	(0.342)
$external\_commuting \times February$		0.251	0.282	0.287
		(0.190)	(0.210)	(0.218)
$external\_commuting \times March$		4.468***	3.821***	2.261***
		(0.824)	(0.845)	(0.607)
$external\_commuting \times April$		2.652***	2.280***	1.627***
		(0.433)	(0.481)	(0.443)
$external\_commuting \times May$		0.263	0.213	0.159
		(0.220)	(0.267)	(0.278)
$external\_commuting \times June$		0.287	0.156	0.205
		(0.201)	(0.222)	(0.230)
constant	0.247***	-0.432***	-0.970***	-0.789***
	(0.035)	(0.096)	(0.210)	(0.208)
LLM FE	✓	✓	✓	✓
Day FE	✓	✓	✓	✓
Geographic controls × δ_m	✕	✕	✓	✓
Demographic controls × δ_m	✕	✕	✓	✓
Vulnerability controls × δ_m	✕	✕	✕	✓
Economic controls × δ_m	✕	✕	✕	✓
Observations	105 948	105 948	105 948	105 948
R^2	0.06	0.07	0.07	0.08

Notes: All specifications present OLS estimates and include LLM and day fixed effects. Standard errors clustered at the LLM level are in parentheses. Significance values: ***p<0.01, **p<0.05, *p<0.10.

cycle. Conversely, the coefficients associated with the two commuting indices in those months remain consistent in both sign and significance, even when plugging in controls. Notably, moving from the most parsimonious specification in column 2 to the most extended in column 4 decreases their magnitude without substantially increasing the standard error. This pattern suggests that the additional covariates are powerful predictors of variations in *mortality_growth* as they capture important components of variability (see Table B.1 for regression results for all control variables).

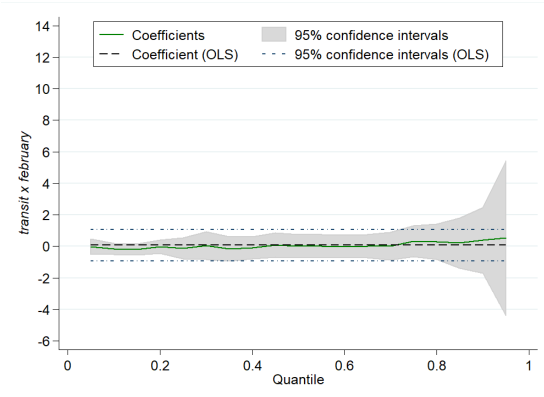
We further explore the results obtained thus far by estimating panel data quantile regressions for the specification in column 2 of Table 3 (Graham et al., 2015). By leaving aside the control variables, we aim to examine a relationship that is as "clean" as possible between excess mortality and our mobility indices at different points of the conditional distribution of *mortality_growth*. In other words, we test whether public transport might be a determining factor for at least certain low, medium or high levels of our outcome of interest. Indeed, one of the desirable features of a quantile regression is that it is less sensitive to outliers and skewness than the standard OLS method.

To this end, Figures 4–6 plot the estimated coefficients associated with all the interactions among *transit*, *internal_commuting*, and *external_commuting* and the month dummies over quantiles. In more detail, the green lines plot these coefficients with 95% confidence intervals from the 0.05^{th} quantile (representing the lowest levels of excess mortality) to the 0.95^{th} quantile (representing the highest levels of excess mortality), while horizontal lines plot OLS estimates with 95% confidence intervals. Interestingly, the magnitudes of the coefficients at various quantiles related to *transit* (Figure 4) do not differ considerably from the OLS coefficients in any month included in our period of analysis. On the other hand, during the period when Italy was most severely hit by the pandemic, Figures 5b–5c and Figures 6b–6c show how the magnitudes of the coefficients related to internal and external commuting vary over quantiles, especially in March, when both trends approximate an exponential growth towards the right tail of the *mortality_growth* distribution.

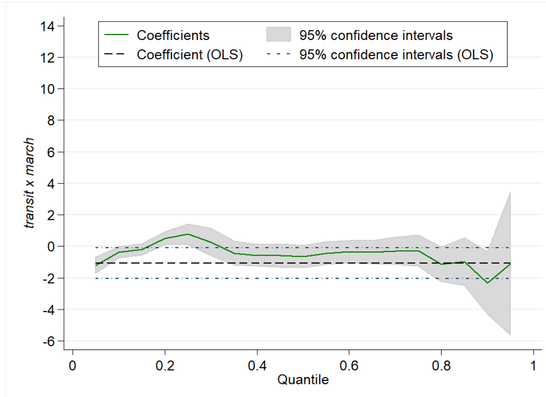
To shed light on the statistical significance of some of these coefficients, Table 4 reports the point estimates for the 0.10^{th}, 0.30^{th}, 0.50^{th}, 0.70^{th}, and 0.90^{th} quantiles of the distribution. Once again, the coefficients associated with *transit* are no significant for all months and quantiles, while those associated with *internal_commuting* and *external_commuting* remain positively and strongly correlated with excess mortality. By focusing solely on March and April and moving from the lowest to the highest quantile, we can see how the magnitudes of these latter coefficients exhibit an increasing trend that is particularly pronounced for the very high levels of excess mortality. In line with the findings of studies conducted elsewhere, such empirical evidence confirms that the structure of the network of commuting flows plays an important role in increasing the epidemiological risks for more connected places. For the sake of completeness, Figures A.1–A.3 and Table A.1 report the same set of coefficients related to panel data quantile regressions for the specification in column 4 of Table 3, which is the most complete one in relation to our data.

Figure 4: Plots of quantile regression coefficients related to *transit*, by month

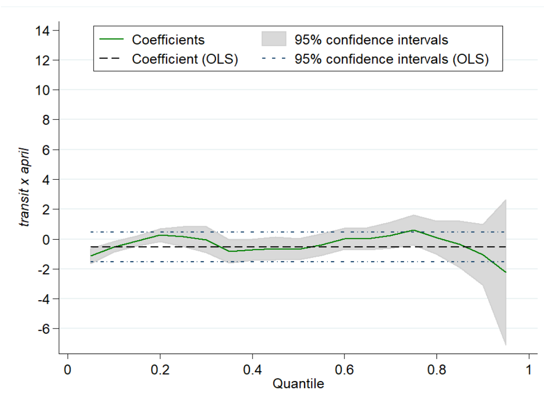
(a) February



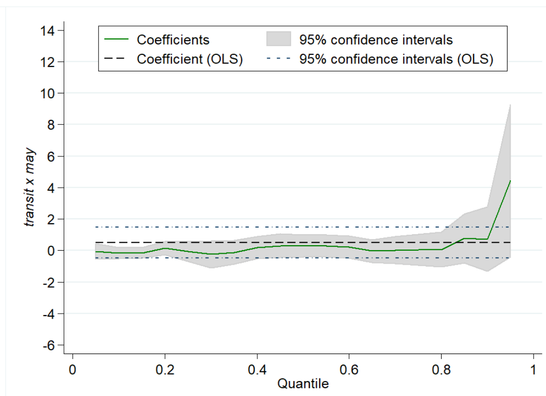
(b) March



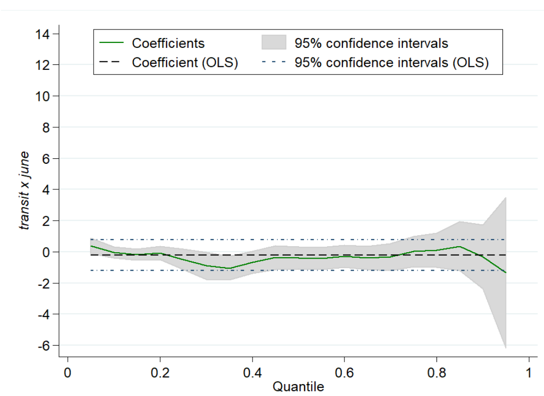
(c) April



(d) May



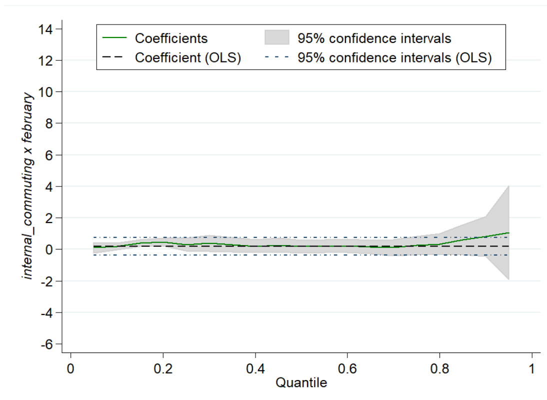
(e) June



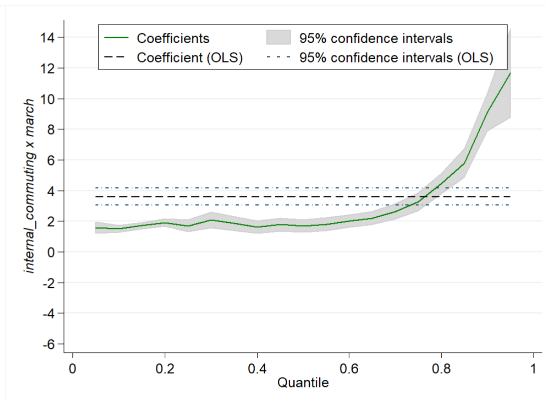
Notes: Panel data quantile regressions for the specification in column 2 of Table 3.

Figure 5: Plots of quantile regression coefficients related to *internal_commuting*, by month

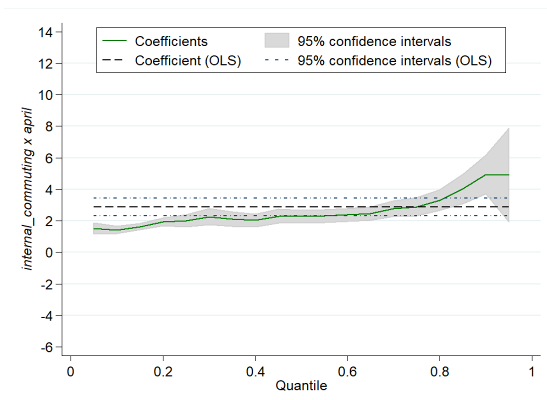
(a) February



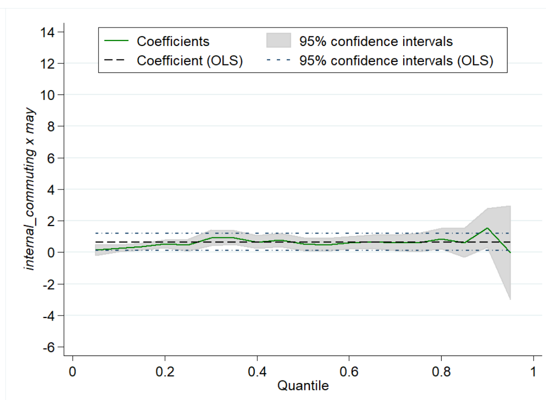
(b) March



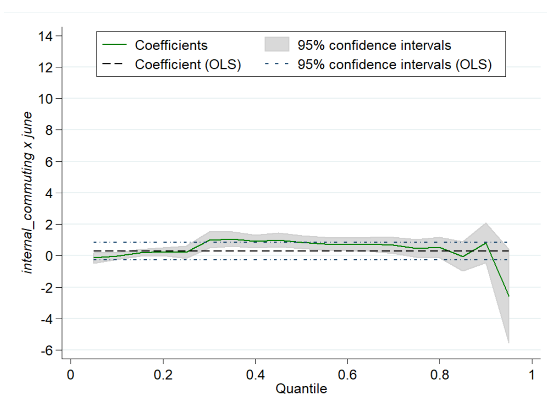
(c) April



(d) May



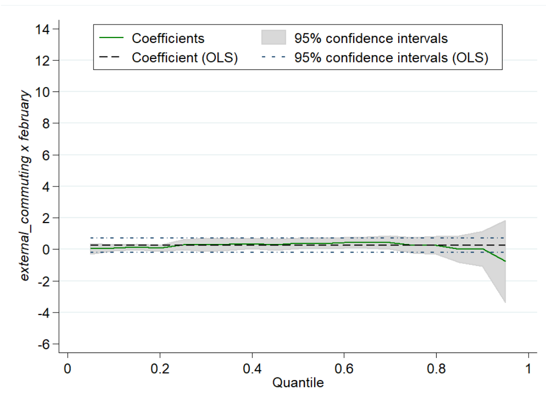
(e) June



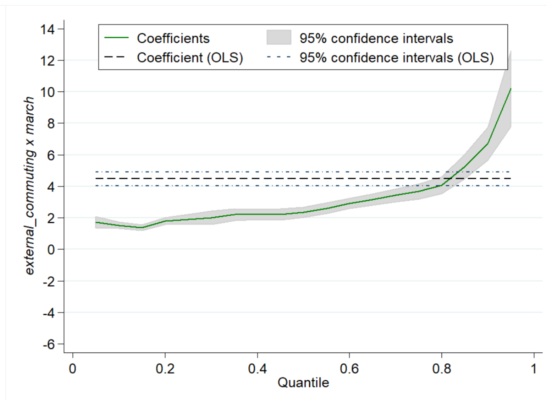
Notes: Panel data quantile regressions for the specification in column 2 of Table 3.

Figure 6: Plots of quantile regression coefficients related to *external_commuting*, by month

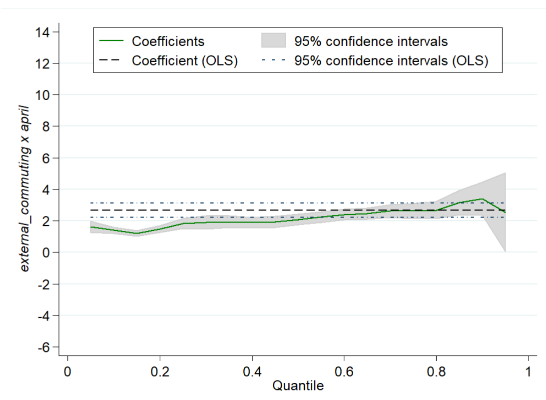
(a) February



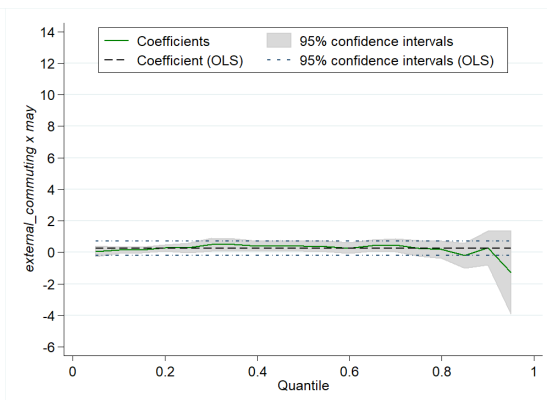
(b) March



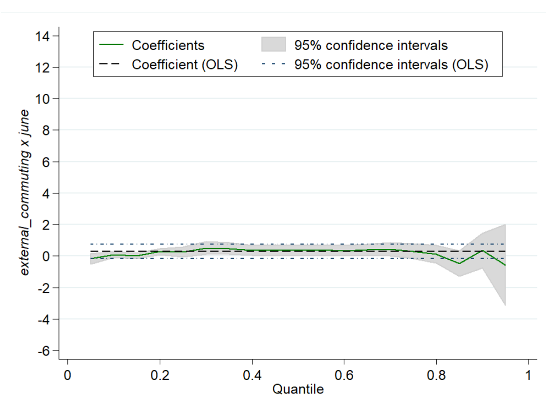
(c) April



(d) May



(e) June



Notes: Panel data quantile regressions for the specification in column 2 of Table 3.

Table 4: Transit usage and mortality growth (quantile regressions analysis – part 1)

	mortality_growth				
	(1)	(2)	(3)	(4)	(5)
Quantiles:	0.10	0.30	0.50	0.70	0.90
transit × *February*	-0.160	0.039	0.013	0.010	0.385
	(0.180)	(0.444)	(0.253)	(0.379)	(1.098)
transit × *March*	-0.381	0.259	-0.664	-0.289	-2.313
	(0.400)	(0.643)	(0.511)	(0.751)	(2.202)
transit × *April*	-0.518	-0.041	-0.675	0.252	-1.050
	(0.339)	(0.692)	(0.545)	(0.727)	(1.857)
transit × *May*	-0.172	-0.243	0.297	0.027	0.717
	(0.178)	(0.558)	(0.288)	(0.365)	(1.150)
transit × *June*	-0.052	-0.900	-0.379	-0.335	-0.336
	(0.196)	(0.589)	(0.290)	(0.424)	(1.253)
internal_commuting × *February*	0.193*	0.390*	0.178	0.103	0.819
	(0.114)	(0.199)	(0.186)	(0.234)	(0.595)
internal_commuting × *March*	1.504***	2.068***	1.694***	2.639***	9.116***
	(0.285)	(0.371)	(0.413)	(0.579)	(1.545)
internal_commuting × *April*	1.425***	2.257***	2.265***	2.782***	4.936***
	(0.246)	(0.364)	(0.347)	(0.430)	(1.181)
internal_commuting × *May*	0.263**	0.916***	0.519**	0.592**	1.561**
	(0.129)	(0.276)	(0.221)	(0.260)	(0.665)
internal_commuting × *June*	-0.013	1.002***	0.859***	0.663**	0.815
	(0.134)	(0.260)	(0.206)	(0.280)	(0.632)
external_commuting × *February*	0.097	0.283**	0.386**	0.438**	0.037
	(0.106)	(0.132)	(0.162)	(0.205)	(0.540)
external_commuting × *March*	1.518***	1.999***	2.352***	3.421***	6.716***
	(0.254)	(0.300)	(0.495)	(0.578)	(1.222)
external_commuting × *April*	1.403***	1.891***	2.079***	2.618***	3.401***
	(0.222)	(0.296)	(0.386)	(0.440)	(0.912)
external_commuting × *May*	0.137	0.490***	0.389**	0.447**	0.278
	(0.122)	(0.181)	(0.175)	(0.200)	(0.532)
external_commuting × *June*	0.097	0.511***	0.349**	0.429*	0.346
	(0.133)	(0.162)	(0.164)	(0.222)	(0.404)
constant	-1.251***	-0.787***	-0.282***	0.216***	1.451***
	(0.015)	(0.024)	(0.012)	(0.005)	(0.032)
LLM FE	✓	✓	✓	✓	✓
Day FE	✓	✓	✓	✓	✓
Geographic controls × δ_m	✕	✕	✕	✕	✕
Demographic controls × δ_m	✕	✕	✕	✕	✕
Vulnerability controls × δ_m	✕	✕	✕	✕	✕
Economic controls × δ_m	✕	✕	✕	✕	✕
Observations	105 948	105 948	105 948	105 948	105 948
Pseudo R^2	0.03	0.03	0.03	0.04	0.04

Notes: Panel data quantile regressions for the specification in column 2 of Table 3. Standard errors clustered at the LLM level following the Parente and Silva (2016) procedure are in parentheses. Significance values: ***p<0.01, **p<0.05, *p<0.10.

Overall, though we cannot rule out the possibility of virus transmission on public transport, the statistically weak association between COVID-19-related fatalities and transit usage provided here shows that places in which commuters are more prone to use public transport were not affected by higher excess mortality during the studied period. At the same time, our findings suggest that what matters most is whether people move, not how they move.

5.3. Robustness checks

In the following section, we briefly describe robustness checks designed to corroborate our empirical findings. First, though the full set of LMM fixed effects absorbs all the time-invariant differences between the territorial units, we are aware that our transit index may not be able to fully capture some qualitative characteristics of public transport services that could be relevant in the context of a pandemic, such as passenger density (Haywood et al., 2017). Indeed, in addition to utilisation rate, the crowding in public transport could also be a determining factor for virus transmissions. To test whether the aforementioned dynamic played a role in the initial spread of COVID-19, we define a proxy of transit density by calculating, within each LLM, the total number of people commuting by collective means of transport per square kilometre:

$$transit\_density_i = \frac{transit_i \times p_{ii}}{surface_i} \tag{5}$$

where $transit_i$ is our previous index of interest measuring the propensity to use public transport, p_{ii} indicates the total number of workers and students moving between municipalities of the same LLM (expressed by Equation 2), while $surface_i$ measures the area of each territorial unit (in square kilometres). Then, we estimate Equation 4 by replacing *transit* with the log[14] of this new explanatory variable. As shown by Table 5, the coefficients associated with *transit_density* are positively correlated with excess mortality in the most parsimonious specification (i.e., column 1), but their significance disappears as soon as control variables are included. Consistently with the main estimates provided by Table 3, such statistically weak association lend our empirical findings additional reliability.

Second, so far, we have analysed the relationship between our explanatory variables and the diffusion of COVID-19 by interacting all the covariates with a vector of time dummies (δ_m) representing the first six months of 2020. However, a reasonable concern is whether the analysis around monthly time-breaks might be the most appropriate for investigating the role of transit usage over the pandemic cycle. Therefore, we estimate an alternative specification to Equation 4 by interacting all the predictors with a new vector of time dummies (δ_p) defined by the timeline of the COVID-19 crisis and the related government policy responses. More precisely, and in accordance with the main events summarised in Figure 1, we analyse the explanatory variables around five periods: i) pre-outbreak (until 20 February), which is the excluded period; ii) post-outbreak and pre-lockdown (21 February to 10 March), iii) lockdown (11 March to 24 March); iv) tighter lockdown (25 March to 17 May); and v) post-lockdown (18 May onwards). Regression results provided in Table 6 show that the coefficients associated with *transit* are, once again, no statistically significant throughout all periods and specifications, while the coefficients associated with *internal_commuting* and *external_commuting* are very consistent with those provided in Table 3, meaning that the choice of time intervals is not driving our estimates.

[14]Given the skewness of *transit_density*, we log transform the variable to obtain more symmetrically distributed residuals.

Table 5: Transit usage and mortality growth (*transit_density*)

	mortality_growth			
	(1)	(2)	(3)	(4)
log(*transit_density*) × *February*	-0.000	-0.009	0.016	0.018
	(0.013)	(0.014)	(0.029)	(0.032)
log(*transit_density*) × *March*	0.125***	0.006	0.090	0.027
	(0.039)	(0.037)	(0.085)	(0.073)
log(*transit_density*) × *April*	0.058***	-0.035	0.012	-0.016
	(0.021)	(0.024)	(0.053)	(0.049)
log(*transit_density*) × *May*	0.041***	0.031*	0.025	0.019
	(0.015)	(0.016)	(0.034)	(0.036)
log(*transit_density*) × *June*	0.032**	0.029*	0.023	0.022
	(0.014)	(0.016)	(0.032)	(0.034)
internal_commuting × *February*		0.257	0.183	0.089
		(0.252)	(0.289)	(0.291)
internal_commuting × *March*		3.494***	1.921***	1.021
		(0.595)	(0.619)	(0.646)
internal_commuting × *April*		3.106***	2.204***	1.858***
		(0.477)	(0.539)	(0.513)
internal_commuting × *May*		0.448	0.231	0.191
		(0.318)	(0.362)	(0.359)
internal_commuting × *June*		0.053	-0.008	-0.021
		(0.300)	(0.354)	(0.357)
external_commuting × *February*		0.280	0.260	0.271
		(0.189)	(0.206)	(0.215)
external_commuting × *March*		4.463***	3.718***	2.212***
		(0.836)	(0.837)	(0.606)
external_commuting × *April*		2.787***	2.268***	1.645***
		(0.466)	(0.490)	(0.452)
external_commuting × *May*		0.143	0.180	0.138
		(0.219)	(0.261)	(0.275)
external_commuting × *June*		0.185	0.132	0.170
		(0.196)	(0.214)	(0.225)
constant	0.206***	-0.439***	-0.888***	-0.760***
	(0.008)	(0.094)	(0.234)	(0.223)
LLM FE	✓	✓	✓	✓
Day FE	✓	✓	✓	✓
Geographic controls × δ_m	✕	✕	✓	✓
Demographic controls × δ_m	✕	✕	✓	✓
Vulnerability controls × δ_m	✕	✕	✕	✓
Economic controls × δ_m	✕	✕	✕	✓
Observations	105 948	105 948	105 948	105 948
R^2	0.06	0.07	0.07	0.08

Notes: All specifications present OLS estimates and include LLM and day fixed effects. Standard errors clustered at the LLM level are in parentheses. Significance values: ***p<0.01, **p<0.05, *p<0.10.

6. Conclusions

The COVID-19 pandemic is causing serious challenges and dramatic changes that may permanently affect our lives in contemporary societies. Social distancing, mobility restrictions and mask usage are all common features of everyday life at the time of this writing. Within this critical framework, transport services have been subjected to several restrictions and policy discussions seeking to reduce the speed of contagion spread while maintaining a vital level of

Table 6: Transit usage and mortality growth (δ_p)

	mortality_growth			
	(1)	(2)	(3)	(4)
transit × 21 Feb–10 Mar	0.314	0.303	0.324	0.342
	(0.476)	(0.478)	(0.533)	(0.531)
transit × 11 Mar–24 Mar	-1.321	-1.463	-1.489	-1.219
	(1.085)	(1.020)	(1.218)	(1.177)
transit × 25 Mar–17 May	-0.248	-0.444	-0.383	-0.250
	(0.606)	(0.555)	(0.590)	(0.596)
transit × 18 May–onwards	-0.088	-0.109	-0.463	-0.508
	(0.352)	(0.359)	(0.390)	(0.404)
internal_commuting × 21 Feb–10 Mar		0.528*	0.313	0.164
		(0.297)	(0.361)	(0.362)
internal_commuting × 11 Mar–24 Mar		4.416***	2.680***	1.288*
		(0.834)	(0.765)	(0.778)
internal_commuting × 25 Mar–17 May		2.619***	1.983***	1.575***
		(0.376)	(0.433)	(0.403)
internal_commuting × 18 May–onwards		0.176	-0.096	-0.091
		(0.211)	(0.256)	(0.260)
external_commuting × 21 Feb–10 Mar		0.716***	0.588**	0.324
		(0.268)	(0.292)	(0.264)
external_commuting × 11 Mar–24 Mar		5.458***	4.514***	2.450***
		(1.021)	(1.007)	(0.697)
external_commuting × 25 Mar–17 May		2.345***	2.096***	1.411***
		(0.406)	(0.455)	(0.398)
external_commuting × 18 May–onwards		0.109	0.015	0.016
		(0.151)	(0.169)	(0.174)
constant	0.250***	-0.386***	-0.761***	-0.578***
	(0.030)	(0.080)	(0.173)	(0.170)
LLM FE	✓	✓	✓	✓
Day FE	✓	✓	✓	✓
Geographic controls × δ_p	✕	✕	✓	✓
Demographic controls × δ_p	✕	✕	✓	✓
Vulnerability controls × δ_p	✕	✕	✕	✓
Economic controls × δ_p	✕	✕	✕	✓
Observations	105 948	105 948	105 948	105 948
R^2	0.06	0.07	0.07	0.08

Notes: All specifications present OLS estimates and include LLM and day fixed effects. Standard errors clustered at the LLM level are in parentheses. Significance values: ***p<0.01, **p<0.05, *p<0.10.

connectivity within and among territories.

This paper has focused on the centre of these debates: transit services. In particular, we considered an Italian dataset relating excess mortality in all local labour markets with propensity to use public transport and found no significant statistical correlation. In other words, we showed that the locations where transit was most used were not disproportionally affected by the virus. In contrast, we detected a statistically significant association between the spread of COVID-19 and mobility, measured by commuting flows.

Our findings suggest that it is the undertaking of a journey, not the transit mode used, that is a significant vehicle for virus diffusion. This conclusion could have consequences for current transport policy. Social distancing rules have already had repercussions for the overall capacity of the different transport systems, and further adaptations are expected in terms of, among others, demand reduction and supply profitability. These will, in turn, affect users' transit behaviours and choice of transit mode, within wider and more unpredictable temporal horizons.

Public transport, which is one of the pillars of sustainable transport, is also the form of transport most endangered by this new pandemic paradigm. The principles of effectiveness, which were central even before the emergency, now face new and more binding constraints that threaten their economic sustainability. This could even lead to the empty core problem (Button, 2005), a phenomenon well-known to air transport companies that could be extended, *mutatis mutandis*, to all transport modes within a partially privatised market. Steps typical of this process include the need to increase transport capacity, an increase in costs, service unsustainability, bankruptcies and, ultimately, a reduction in competitiveness of the whole system. It is important to guarantee support for the surviving transport companies during this transition phase to ensure both the plurality of supply and the retention of acceptable levels of competition.

Declaration of interest

We have no conflicts of interest to disclose.

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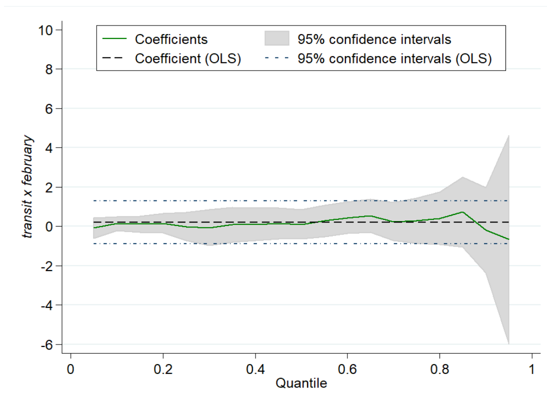
Appendices

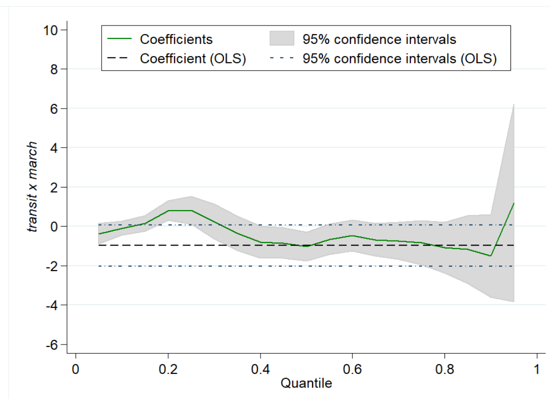
Appendix A Quantile regressions

Figure A.1: Plots of quantile regression coefficients related to *transit*, by month

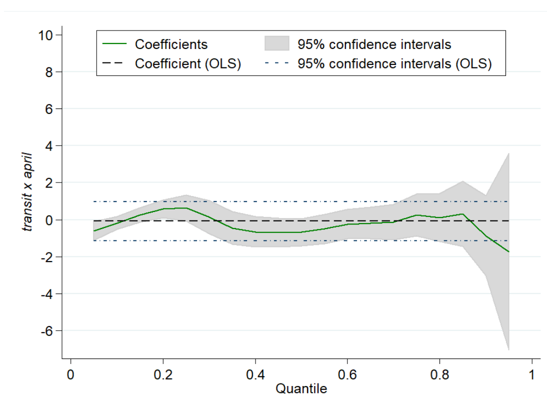
(a) February



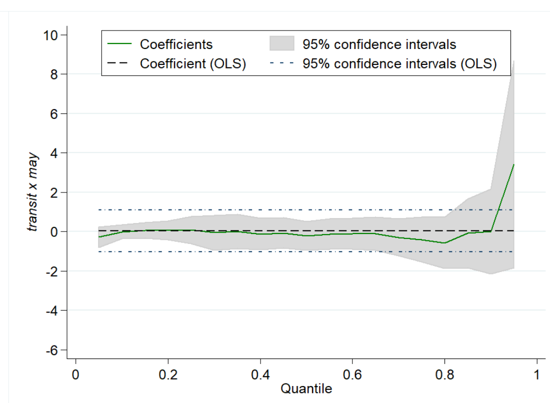
(b) March



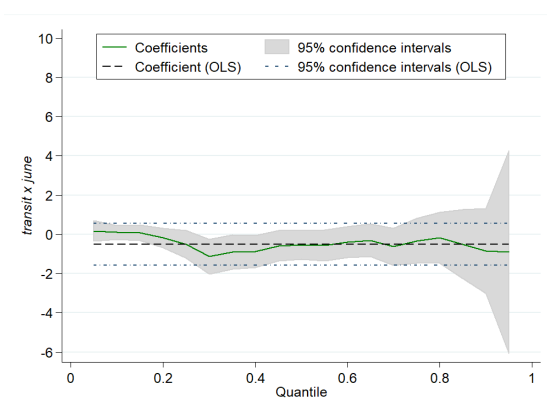
(c) April



(d) May



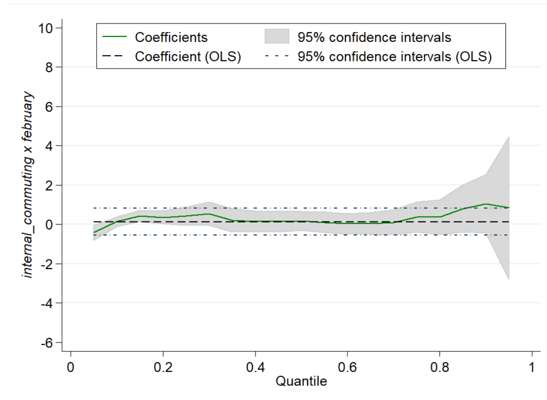
(e) June



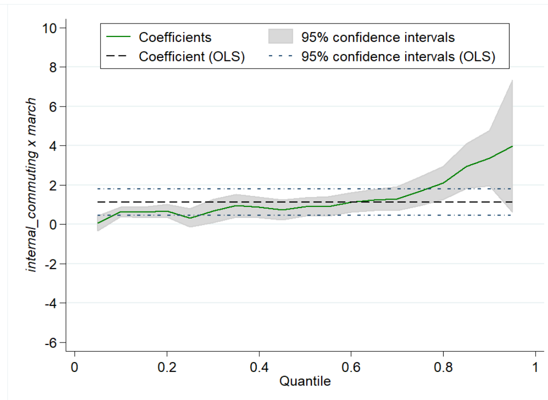
Notes: Panel data quantile regressions for the specification in column 4 of Table 3.

Figure A.2: Plots of quantile regression coefficients related to *internal_commuting*, by month

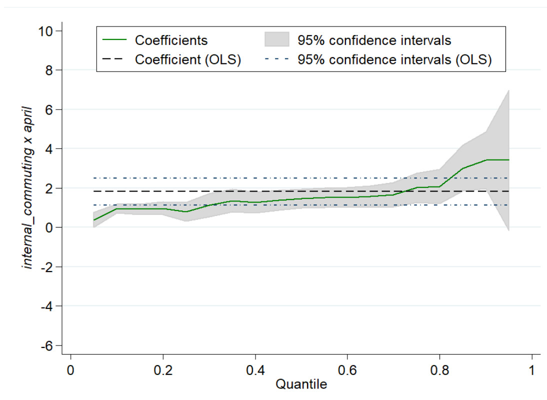
(a) February



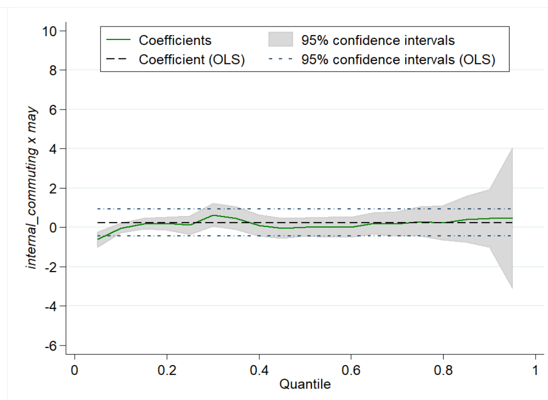
(b) March



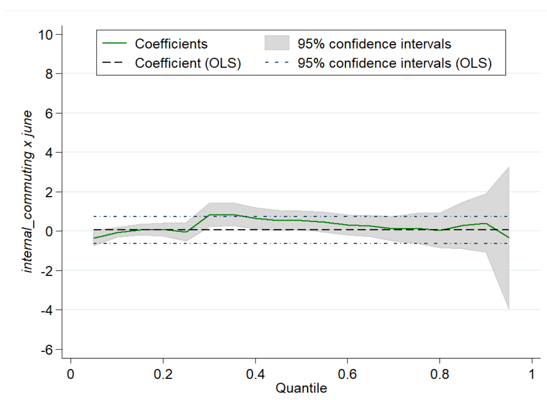
(c) April



(d) May



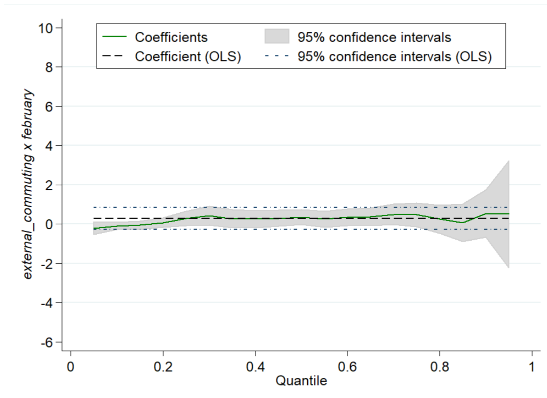
(e) June



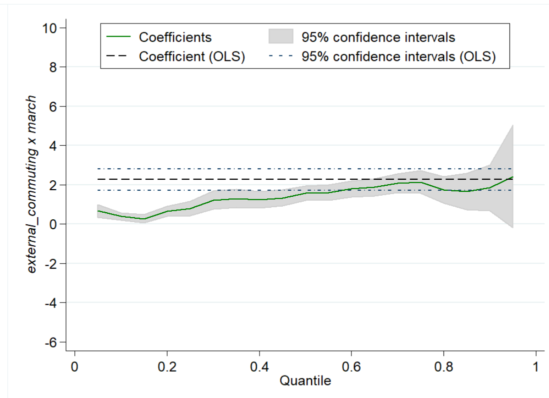
Notes: Panel data quantile regressions for the specification in column 4 of Table 3.

Figure A.3: Plots of quantile regression coefficients related to *external_commuting*, by month

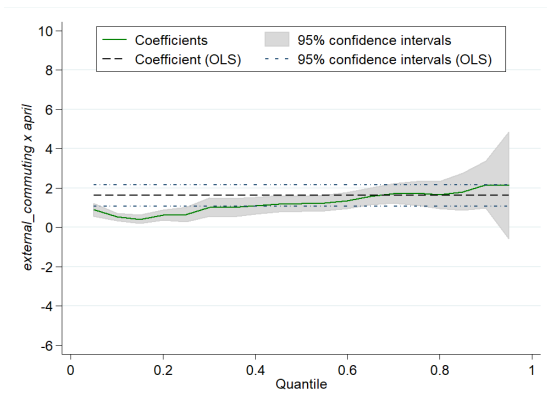
(a) February



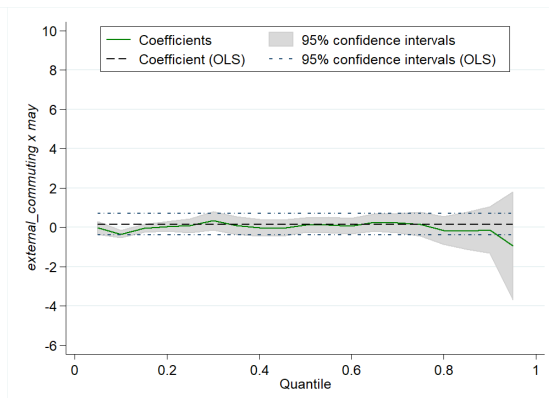
(b) March



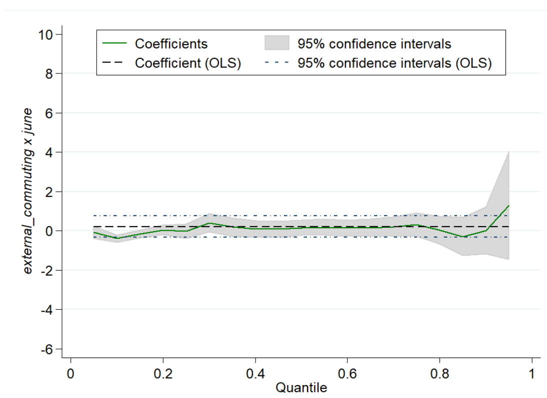
(c) April



(d) May



(e) June



Notes: Panel data quantile regressions for the specification in column 4 of Table 3.

Table A.1: Transit usage and mortality growth (quantile regressions analysis – part 2)

	mortality_growth				
	(1)	(2)	(3)	(4)	(5)
Quantiles:	0.10	0.30	0.50	0.70	0.90
$transit \times February$	0.140	-0.060	0.107	0.236	-0.196
	(0.277)	(0.457)	(0.339)	(0.422)	(1.183)
$transit \times March$	-0.096	0.241	-1.022*	-0.731	-1.506
	(0.507)	(0.674)	(0.602)	(0.753)	(2.146)
$transit \times April$	-0.184	0.136	-0.680	-0.134	-0.870
	(0.407)	(0.612)	(0.515)	(0.721)	(1.662)
$transit \times May$	-0.011	-0.053	-0.204	-0.285	0.016
	(0.279)	(0.504)	(0.343)	(0.451)	(1.337)
$transit \times June$	0.095	-1.142*	-0.549	-0.637	-0.851
	(0.305)	(0.616)	(0.367)	(0.464)	(1.465)
$internal\_commuting \times February$	0.137	0.544*	0.188	0.096	1.047
	(0.167)	(0.293)	(0.249)	(0.293)	(0.934)
$internal\_commuting \times March$	0.647*	0.685	0.899**	1.300**	3.355**
	(0.342)	(0.419)	(0.402)	(0.520)	(1.465)
$internal\_commuting \times April$	0.960***	1.134***	1.468***	1.647***	3.409***
	(0.306)	(0.386)	(0.338)	(0.475)	(1.240)
$internal\_commuting \times May$	-0.036	0.636*	0.019	0.168	0.462
	(0.200)	(0.348)	(0.255)	(0.301)	(0.859)
$internal\_commuting \times June$	-0.063	0.828**	0.555**	0.118	0.409
	(0.191)	(0.378)	(0.239)	(0.304)	(0.977)
$external\_commuting \times February$	-0.096	0.435**	0.355*	0.499**	0.539
	(0.168)	(0.209)	(0.199)	(0.211)	(0.524)
$external\_commuting \times March$	0.388*	1.217***	1.586***	2.079***	1.844*
	(0.229)	(0.342)	(0.398)	(0.533)	(1.067)
$external\_commuting \times April$	0.530**	1.027***	1.199***	1.727***	2.169***
	(0.237)	(0.327)	(0.270)	(0.338)	(0.742)
$external\_commuting \times May$	-0.350	0.333	0.117	0.222	-0.131
	(0.230)	(0.295)	(0.199)	(0.203)	(0.673)
$external\_commuting \times June$	-0.387**	0.407	0.164	0.219	0.021
	(0.193)	(0.322)	(0.176)	(0.202)	(0.580)
$constant$	-1.249***	-0.787***	-0.280***	0.218***	1.445***
	(0.015)	(0.025)	(0.012)	(0.005)	(0.033)
LLM FE	✓	✓	✓	✓	✓
Day FE	✓	✓	✓	✓	✓
Geographic controls × δ_m	✓	✓	✓	✓	✓
Demographic controls × δ_m	✓	✓	✓	✓	✓
Vulnerability controls × δ_m	✓	✓	✓	✓	✓
Economic controls × δ_m	✓	✓	✓	✓	✓
Observations	105 948	105 948	105 948	105 948	105 948
Pseudo R^2	0.04	0.04	0.04	0.04	0.04

Notes: Panel data quantile regressions for the specification in column 4 of Table 3. Standard errors clustered at the LLM level following the Parente and Silva (2016) procedure are in parentheses. Significance values: ***p<0.01, **p<0.05, *p<0.10.

Appendix B Additional Tables

Table B.1: Transit usage and mortality growth (panel data analysis – part 2)

	mortality_growth			
	(1)	(2)	(3)	(4)
$transit \times February$	0.077	0.076	0.206	0.207
	(0.381)	(0.386)	(0.400)	(0.428)
$transit \times March$	-0.945	-1.070	-1.273	-0.976
	(0.907)	(0.830)	(0.970)	(0.930)
$transit \times April$	-0.336	-0.537	-0.158	-0.079
	(0.699)	(0.637)	(0.663)	(0.681)
$transit \times May$	0.576	0.489	0.116	0.036
	(0.445)	(0.448)	(0.502)	(0.530)
$transit \times June$	-0.181	-0.199	-0.425	-0.507
	(0.458)	(0.461)	(0.505)	(0.527)
$internal\_commuting \times February$		0.188	0.229	0.134
		(0.230)	(0.272)	(0.273)
$internal\_commuting \times March$		3.600***	2.183***	1.126*
		(0.662)	(0.618)	(0.611)
$internal\_commuting \times April$		2.871***	2.236***	1.815***
		(0.433)	(0.527)	(0.496)
$internal\_commuting \times May$		0.657**	0.304	0.246
		(0.286)	(0.356)	(0.350)
$internal\_commuting \times June$		0.287	0.059	0.058
		(0.269)	(0.342)	(0.342)
$external\_commuting \times February$		0.251	0.282	0.287
		(0.190)	(0.210)	(0.218)
$external\_commuting \times March$		4.468***	3.821***	2.261***
		(0.824)	(0.845)	(0.607)
$external\_commuting \times April$		2.652***	2.280***	1.627***
		(0.433)	(0.481)	(0.443)
$external\_commuting \times May$		0.263	0.213	0.159
		(0.220)	(0.267)	(0.278)
$external\_commuting \times June$		0.287	0.156	0.205
		(0.201)	(0.222)	(0.230)
$altitude \times February$			0.000	0.000
			(0.000)	(0.000)
$altitude \times March$			0.001*	0.001**
			(0.000)	(0.000)
$altitude \times April$			0.000**	0.000**
			(0.000)	(0.000)
$altitude \times May$			0.000**	0.000**
			(0.000)	(0.000)
$altitude \times June$			0.000	-0.000
			(0.000)	(0.000)
$coastal \times February$			0.047	0.032
			(0.051)	(0.053)
$coastal \times March$			-0.265**	0.009
			(0.116)	(0.113)
$coastal \times April$			-0.098	0.017
			(0.078)	(0.080)
$coastal \times May$			0.080	0.087
			(0.058)	(0.060)
$coastal \times June$			-0.014	-0.024
			(0.062)	(0.067)
$ln\_density \times February$			0.001	-0.002
			(0.020)	(0.021)
$ln\_density \times March$			0.155**	0.012

Continued on next page

Table B.1 – continued from previous page

	mortality_growth			
	(1)	(2)	(3)	(4)
			(0.061)	(0.058)
$ln\_density \times April$			0.062*	-0.002
			(0.035)	(0.037)
$ln\_density \times May$			0.078***	0.066**
			(0.026)	(0.026)
$ln\_density \times June$			0.037	0.037
			(0.024)	(0.025)
$house\_m^2\_pc \times February$			0.007	0.011*
			(0.004)	(0.006)
$house\_m^2\_pc \times March$			0.018*	-0.004
			(0.010)	(0.011)
$house\_m^2\_pc \times April$			0.023***	0.013*
			(0.007)	(0.008)
$house\_m^2\_pc \times May$			0.010*	0.008
			(0.005)	(0.006)
$house\_m^2\_pc \times June$			0.000	0.001
			(0.004)	(0.006)
$share\_over75 \times February$				-1.013
				(0.994)
$share\_over75 \times March$				-1.427
				(1.940)
$share\_over75 \times April$				-0.603
				(1.386)
$share\_over75 \times May$				-0.058
				(1.137)
$share\_over75 \times June$				0.088
				(1.036)
$hospital\_beds \times February$				0.011
				(0.008)
$hospital\_beds \times March$				0.019
				(0.012)
$hospital\_beds \times April$				0.006
				(0.009)
$hospital\_beds \times May$				0.007
				(0.006)
$hospital\_beds \times June$				0.007
				(0.007)
$pm10 \times February$				-0.000
				(0.002)
$pm10 \times March$				0.053***
				(0.008)
$pm10 \times April$				0.025***
				(0.004)
$pm10 \times May$				0.005*
				(0.003)
$pm10 \times June$				0.000
				(0.003)
$district \times February$				-0.044
				(0.032)
$district \times March$				0.224
				(0.136)
$district \times April$				0.060
				(0.067)
$district \times May$				-0.040
				(0.041)
$district \times June$				-0.039

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Table B.1 – continued from previous page

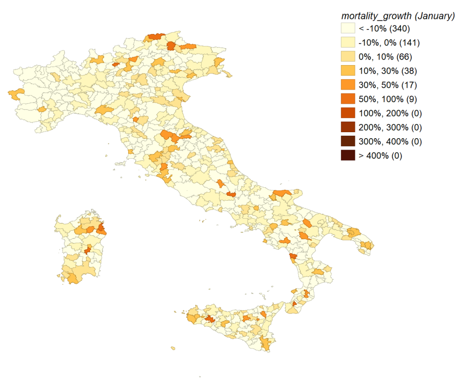
	mortality_growth			
	(1)	(2)	(3)	(4)
				(0.037)
constant	0.247***	-0.432***	-0.970***	-0.789***
	(0.035)	(0.096)	(0.210)	(0.208)
LLM FE	✓	✓	✓	✓
Day FE	✓	✓	✓	✓
Observations	105 948	105 948	105 948	105 948
R^2	0.06	0.07	0.07	0.08

Notes: All specifications present OLS estimates and include LLM and day fixed effects. Standard errors clustered at the LLM level are in parentheses. Significance values: ***p<0.01, **p<0.05, *p<0.10.

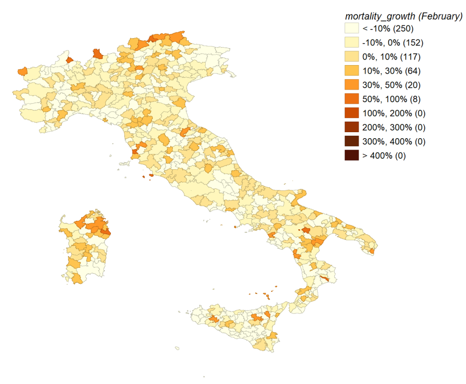
Appendix C Additional Figures

Figure C.1: *mortality_growth*, by monthly averages and LLM

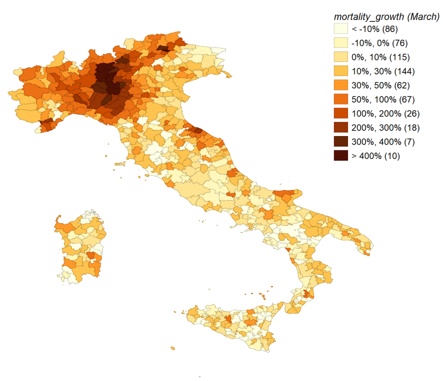
(a) January



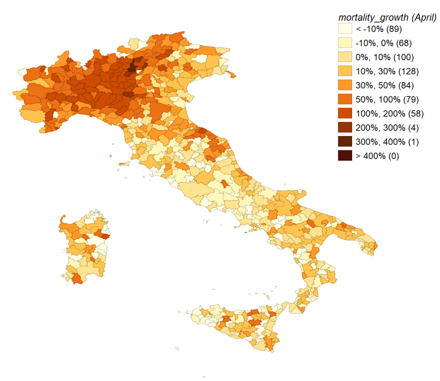
(b) February



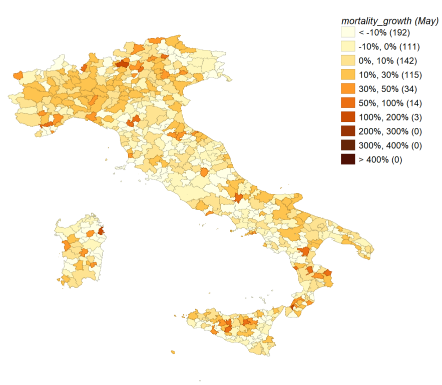
(c) March



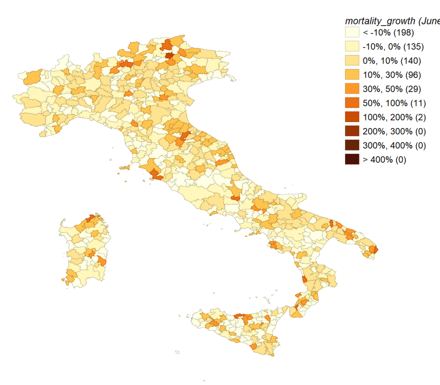
(d) April



(e) May



(f) June



Source: Authors' own elaboration.

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