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Research paper

Questioning the spatial association between the initial 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 pre-pandemic propensity to use public transport and excess mortality in Italy attributable to the initial spread of COVID-19. We found that places characterised by larger commuting flows exhibit higher excess mortality during the first wave of the pandemic, 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 initial contagion.

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 (Askitas et al., 2021; 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 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, leading to significant changes in the

planning of transit services (as extensively reviewed by Gkiotsalitis & Cats, 2021) and new demand management methods (Hörcher et al., 2021). In this article, we aim to contribute to the ongoing policy debate by investigating the spatial association between transit¹ usage and the initial 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 a lack of evidence supporting public transport use as a key driver for the initial spread of COVID-19. To investigate the association between transit use and the initial 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

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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.

possible with the working population (De Blasio & 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 and more comparable 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 first pandemic cycle. Then, we measure transit usage relying 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 initial spatial diffusion of the virus.

Our findings point to a statistically weak association between COVID-19 diffusion and “pre-existing” 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 first wave of 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 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 initial 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 were associated with different attitudes towards COVID-19 (Bergantino et al., 2021; Scorrano & Danielis, 2021; da Silva et al., 2021) and if they 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, Shamsheeripour 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. Substantial 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), as well as in the three most populated Swedish regions (Jenelius & Cebeauer, 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 & Lopes, 2020) and driving (Hadjidemetriou et al., 2020), respectively. Such dynamics have been more pronounced in compact urban cities, where Hamidi and

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 & Masthoff, 2017).

Zandiatashbar (2020) found a higher reduction in trips to grocery stores and transit stations in the US.

To the best of our knowledge, there are few attempts to empirically correlate transit usage with the initial takeoff of COVID-19 infections on a substantial scale. Among them, Buja et al. (2020) found that the spread of COVID-19 was positively correlated with the per capita public transport of Northern Italy provinces capital towns, 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, while Wielechowski et al. (2020) found a statistically weak relationship between mobility changes in public transport and new COVID-19 cases in Poland. Conversely, other studies focused on mass transit systems of specific metropolitan areas (such as the Spanish’s and the New York City’s subway systems analysed by Paez et al., 2021, Harris, 2020 and Fathi-Kazerooni et al., 2020), or on simulated models (e.g., Lei et al., 2020; Zhou & Koutsopoulos, 2020).

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 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, Caselli et al. (2020) estimated that the lockdown reduced mobility among local labour markets by 7%, while Fazio et al. (2021) showed through an agent-based model that mobility restrictions specifically applicable to areas that can be characterized as high-risk would be almost as effective as those at national level.

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; Carteni et al. (2020) pointed out how Italian regional COVID-19 cases were related to the mobility habits performed around three weeks before, Iacus et al. (2020) showed that mobility can explain from 50 to 90% of excess mortality across Italian provinces; while Borsati et al. (2022) 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 initial diffusion of COVID-19 in Italy 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 first wave of 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 in the 2020 (summarised in Fig. 1) has been as follows: the first two COVID-19 cases were

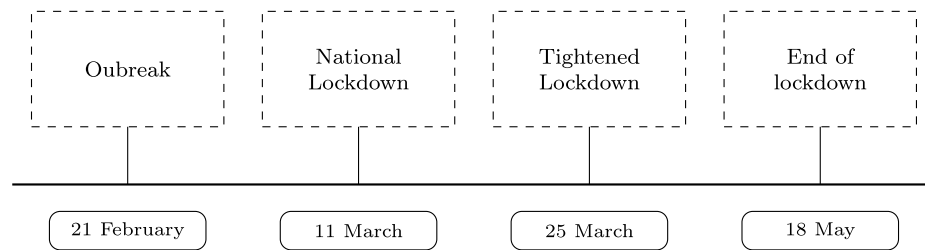


Fig. 1. Timeline of events in Italy 2020, by date

Notes: The figure shows the timeline of the main events occurring during the first wave of the pandemic in Italy 2020. *Source:* Authors' own elaboration.

officially detected on 30 January in Rome, after a Chinese couple travelled from Wuhan to Milan, Verona, Parma, Florence, and the Italian capital. The first cases of secondary transmission were identified near Codogno, Castiglione d'Adda, Casalpusterlengo, and Vo' (i.e., municipalities in Lombardy and Veneto regions) on 21 February (Romagnani et al., 2020). 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.

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 LLM 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 methodological differences in the identification of COVID-19 patients, such as the

spatial heterogeneity in screening procedures and testing capacities.⁴

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 & Surico, 2020) and are likely to underestimate the true increase in mortality, since a substantial number of people died without being tested⁶ (Bartoszek et al., 2020; Ciminelli & 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:

$$mortality_growth_{it} = \frac{fatalities_{it}^{2020} - fatalities_{it}^{baseline}}{fatalities_{it}^{baseline}} \quad (1)$$

where i denotes the LLM and t denotes the day. Fig. 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

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).

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.

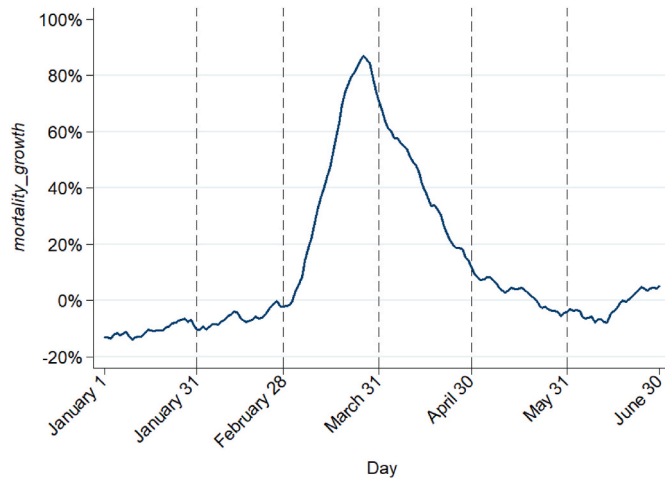


Fig. 2. Evolution of *mortality_growth* in Italy 2020, by day
Notes: Since 2020 is a leap year, we excluded February 29 from the dataset to ensure full comparability between 2020 and the baseline data. *Source:* Authors' own elaboration.

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 LLM 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.⁷

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 shown that human mobility significantly contributed to the initial spread of the disease (Cintia et al., 2020; Iacus et al., 2020) and that more connected places face more severe epidemiological risk (Borsati et al., 2022). 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 assessment⁸ - 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 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:

$$internal_commuting_i = \frac{p_{ii}}{population_i} \quad (2)$$

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,

⁷ By so doing, we differ substantially from other articles in the literature that measure public transport usage either as categorical variables specifically identifying only higher-order transit systems (e.g., Paez et al., 2021) or by approximating public transport demand at the area level using just capital towns data (e.g., Buja et al., 2020).

⁸ 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.

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 LLM j for the same reasons of work or study, and its in-flows, or the total number of people p_{ji} moving to LLM i from any other LLM j . Then, our second index is the sum of the previous incoming and outgoing flows over the population of the area:

$$external_commuting_i = \frac{\sum_{j=1}^n (p_{ij} + p_{ji})}{population_i} \quad (3)$$

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 & Moro, 2020; Desmet & Wacziarg, 2020; Pluchino et al., 2021). 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_m2_pc*).

Then, given that the COVID-19 fatality rate is positively correlated with a higher presence of elderly people (Knittel & Ozaltun, 2020), that nursing homes and hospitals were the first epicentres of the pandemic (Alacevich et al., 2020; Barnett & Grabowski, 2020), and that pollution can be an important co-determinant of COVID-19-related fatalities⁹ (Becchetti et al., 2020; Carteni 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 75¹⁰ years old (*share_over75*), the number of hospital beds per 1 000 inhabitants (*hospital_beds*), and the PM10, defined as the average values of $\mu\text{g}/\text{m}^3$ (*pm10*).

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 district¹¹ (*district*), and 0 otherwise, since previous studies show that work-related mobility and social interactions within industrial clusters are very high (Gordon & McCann, 2000; Majocchi & Presutti, 2009; OECD, 2002).

All data are publicly available.¹² Table 1 reports standard descriptive statistics and reference years for the variables used in the empirical analysis.

⁹ 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).

¹⁰ By controlling for the incidence of elderly people on the total population, we partially control for the share of inactive population within each LLM.

¹¹ Industrial districts are LLM mainly composed by small- and medium-sized enterprises specializing in the same economic activity.

¹² *mortality_growth* data are retrieved from <https://www.istat.it/it/archivio/240401>. *transit*, *house_m2_pc*, and *share_over75* 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/>. *pm10* data are retrieved from <https://www.isprambiente.gov.it/it/pubblicazioni/stato-della-ambiente/xiv-rapporto-qualita-dell2019ambiente-urbano-edizione-2018>. *district* data are retrieved from <https://www.istat.it/it/archivio/150320>. The final dataset used in this empirical analysis is available at <https://data.mendeley.com/datasets/fmhxsv2p59/1>.

Table 1
Descriptive statistics.

	Mean	SD	Minimum	Maximum	Observations	Year
<i>mortality_growth</i>	0.233	1.612	-1.000	34.000	105 948	2020
<i>transit</i>	0.101	0.033	0.030	0.298	110 591	2011
<i>internal_commuting</i>	0.360	0.059	0.052	0.556	110 591	2011
<i>external_commuting</i>	0.167	0.072	0.026	0.824	110 591	2011
<i>altitude</i> ^a	370.557	285.930	1.000	1 518.736	110 591	2011
<i>coastal</i>	0.262	0.375	0.000	1.000	110 591	2011
<i>ln_density</i> ^b	4.738	1.105	2.186	8.555	110 591	2019
<i>house_m²_pc</i> ^c	41.530	4.087	28.989	53.873	110 591	2011
<i>share_over75</i>	0.113	0.023	0.056	0.189	110 591	2011
<i>hospital_beds</i> ^d	1.582	2.370	0.000	21.911	110 591	2017
<i>pm10</i> ^e	26.690	7.508	14.000	46.000	110 591	2017
<i>district</i>	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 LLMs observed for 181 days.

Unit of measurement: [a] meters, [b] log of population per km², [c] m² per inhabitant, [d] per 1 000 inhabitants, [e] µg/m³.

4.4. Descriptive evidence

We now briefly describe the spatial patterns of our main variables of interest. Fig. 3a plots the spatial evolution of the average *mortality_growth* in March 2020, when Italy was most severely hit by the pandemic (see Fig. 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, Fig. 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 people are more prone to commute by collective means of transport have not experienced systematically more severe effect of the first wave of the pandemic.

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:

$$mortality_growth_{it} = \beta_0 + \beta_m transit_i \times \delta_m + \gamma_m internal_commuting_i \times \delta_m + \eta_m external_commuting_i \times \delta_m + \omega_m Z_i \times \delta_m + \alpha_i + \delta_i + \epsilon_{it} \quad (4)$$

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 LLM’s pre-existing public transport usage and commuting flow characteristics. Given that such indices are time-invariant, they are interacted with a vector of monthly dummies (*δ_m*) where *m* represents each of 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. (2021) and Borsati et al. (2022).

Then, *Z_i × δ_m* are the set of previously described geographic, demographic, vulnerability and economic controls, also interacted with

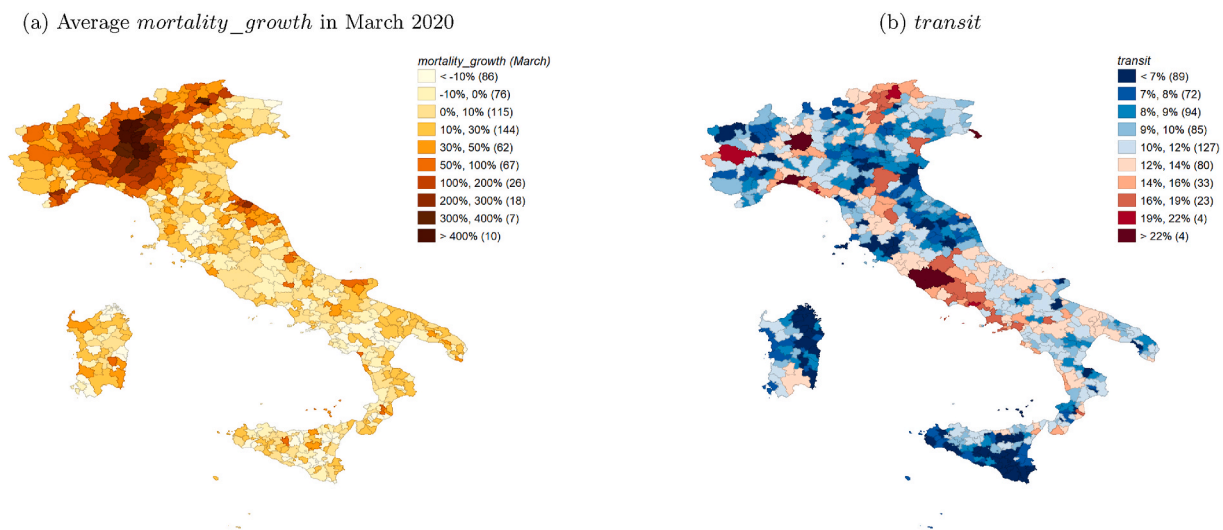


Fig. 3. Descriptive evidence, by LLM

Notes: the number of LLMs belonging to each percentage range are in parentheses. Source: Authors’ own elaboration.

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

	mortality_growth (half-yearly)				
	(1)	(2)	(3)	(4)	(5)
<i>transit</i>	-0.043 (0.223)	-0.155 (0.191)	-0.178 (0.217)	-0.008 (0.226)	-0.022 (0.216)
<i>internal_commuting</i>		1.223*** (0.142)	0.947*** (0.142)	0.616*** (0.137)	0.598*** (0.133)
<i>external_commuting</i>		1.070*** (0.158)	0.972*** (0.167)	0.553*** (0.129)	0.547*** (0.130)
<i>altitude</i>			0.000** (0.000)	0.000*** (0.000)	0.000*** (0.000)
<i>coastal</i>			-0.048** (0.025)	0.012 (0.024)	0.011 (0.024)
<i>ln_density</i>			0.031** (0.013)	-0.004 (0.013)	
<i>density</i> ²					-0.000 (0.000)
<i>house_m²_pc</i>			0.004* (0.002)	0.002 (0.002)	0.002 (0.002)
<i>share_over75</i>				-1.130*** (0.425)	-1.106*** (0.418)
<i>hospital_beds</i>				0.004 (0.003)	0.004 (0.003)
<i>pm10</i>				0.012*** (0.002)	0.012*** (0.002)
<i>district</i>				0.067** (0.028)	0.067** (0.028)
<i>constant</i>	0.078*** (0.026)	-0.530*** (0.055)	-0.757*** (0.121)	-0.555*** (0.122)	-0.578*** (0.103)
Observations	611	611	611	611	611
R ²	0.00	0.16	0.18	0.29	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.

month dummies. In addition, α_i and δ_t are full sets of LLM and day fixed effects, respectively, where the LLM 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 ordinary least squares (OLS) 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* distribution¹³ (Figs. 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, while column 5 substitutes the log of the LLM's population density with a polynomial transformation. 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,¹⁴ while those associated with *internal_commuting* and *external_commuting* 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.

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.¹⁵ Accordingly, all columns include the full sets of LLM and day fixed effects to better control for time-invariant characteristics potentially correlated with both excess

¹³ 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.

¹⁴ Estimates are robust to the inclusion of spatial autoregressive terms.

¹⁵ Since our explanatory variables are time-invariant, their main effects are omitted from all specifications due to collinearity with LLM fixed effects.

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

	<i>mortality_growth</i>			
	(1)	(2)	(3)	(4)
<i>transit</i> × February	0.077 (0.381)	0.076 (0.386)	0.206 (0.400)	0.207 (0.428)
<i>transit</i> × March	-0.945 (0.907)	-1.070 (0.830)	-1.273 (0.970)	-0.976 (0.930)
<i>transit</i> × April	-0.336 (0.699)	-0.537 (0.637)	-0.158 (0.663)	-0.079 (0.681)
<i>transit</i> × May	0.576 (0.445)	0.489 (0.448)	0.116 (0.502)	0.036 (0.530)
<i>transit</i> × June	-0.181 (0.458)	-0.199 (0.461)	-0.425 (0.505)	-0.507 (0.527)
<i>internal_commuting</i> × February		0.188 (0.230)	0.229 (0.272)	0.134 (0.273)
<i>internal_commuting</i> × March		3.600*** (0.662)	2.183*** (0.618)	1.126* (0.611)
<i>internal_commuting</i> × April		2.871*** (0.433)	2.236*** (0.527)	1.815*** (0.496)
<i>internal_commuting</i> × May		0.657** (0.286)	0.304 (0.356)	0.246 (0.350)
<i>internal_commuting</i> × June		0.287 (0.269)	0.059 (0.342)	0.058 (0.342)
<i>external_commuting</i> × February		0.251 (0.190)	0.282 (0.210)	0.287 (0.218)
<i>external_commuting</i> × March		4.468*** (0.824)	3.821*** (0.845)	2.261*** (0.607)
<i>external_commuting</i> × April		2.652*** (0.433)	2.280*** (0.481)	1.627*** (0.443)
<i>external_commuting</i> × May		0.263 (0.220)	0.213 (0.267)	0.159 (0.278)
<i>external_commuting</i> × June		0.287 (0.201)	0.156 (0.222)	0.205 (0.230)
constant	0.247*** (0.035)	-0.432*** (0.096)	-0.970*** (0.210)	-0.789*** (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.

mortality and the predictors. Given that no large-scale mobility restrictions were enforced until 8 March and that reported COVID-19 fatalities tend to occur around 18–21 days after infection (Yang 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 not 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 first pandemic 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, Figs. 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 0.05th quantile (representing the lowest levels of excess mortality) to the 0.95th 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* (Fig. 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 first wave of the pandemic, Fig. 5b–c and Fig. 6b–c shows 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 0.10th, 0.30th, 0.50th, 0.70th, and 0.90th 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.

Overall, though we cannot rule out the possibility of virus transmission on public transport, the statistically weak association between COVID-19-related fatalities and “pre-existing” transit usage provided here shows that places in which commuters were 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 LLM 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

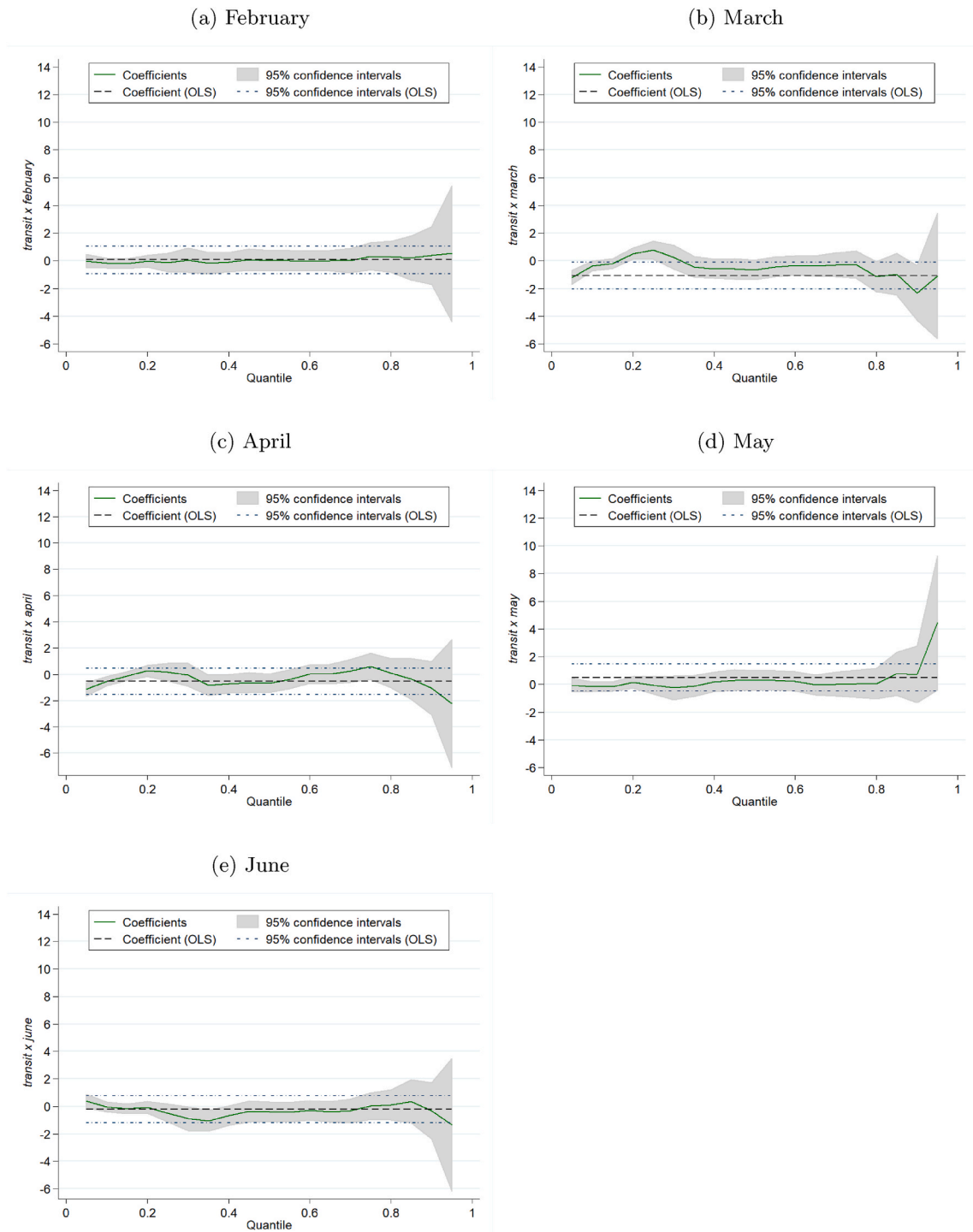


Fig. 4. Plots of quantile regression coefficients related to *transit*, by month
 Notes: Panel data quantile regressions for the specification in column 2 of Table 3.

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^{16} 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

¹⁶ Given the skewness of *transit_density*, we log transform the variable to obtain more symmetrically distributed residuals.

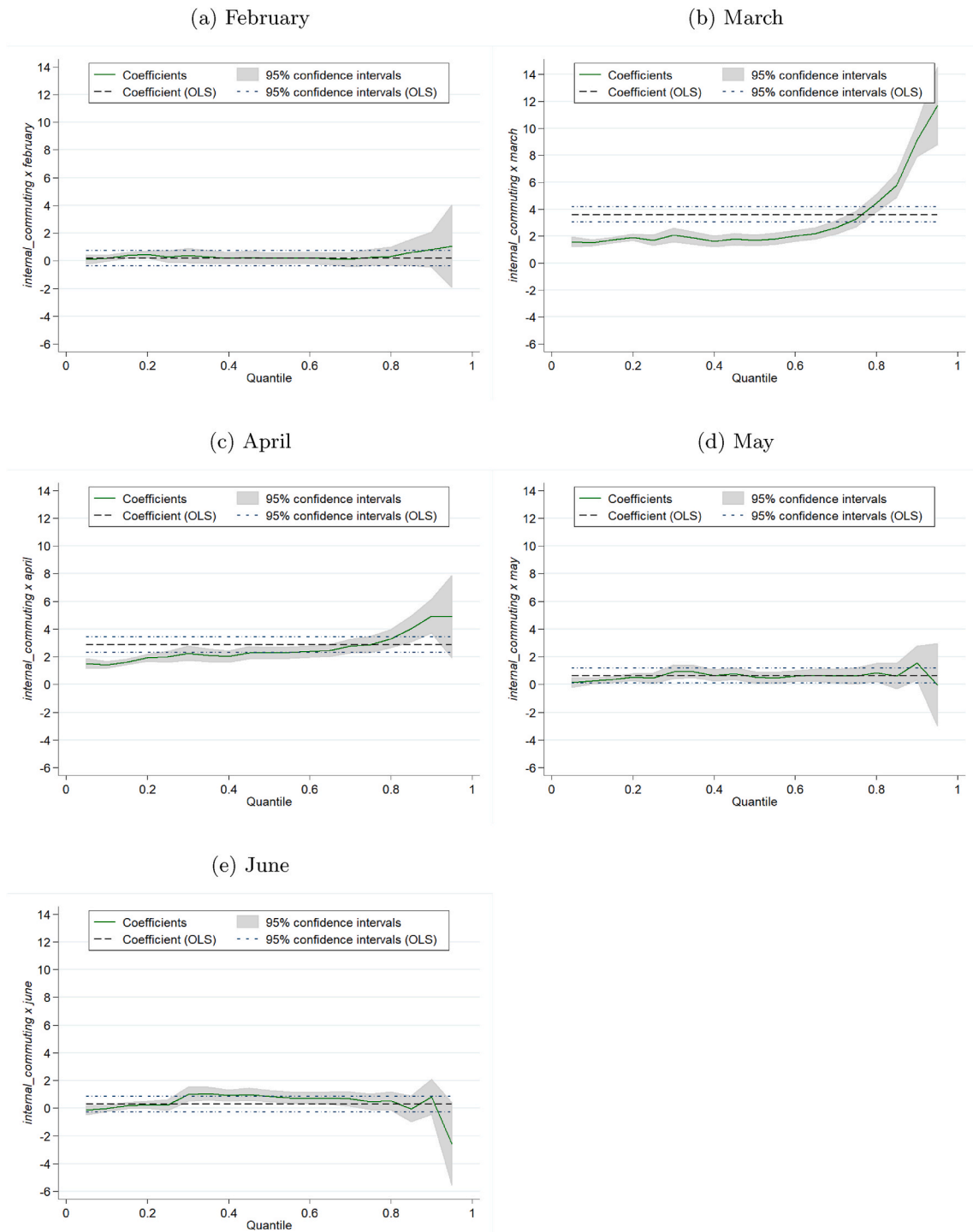


Fig. 5. Plots of quantile regression coefficients related to *internal_commuting*, by month
 Notes: Panel data quantile regressions for the specification in column 2 of Table 3.

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 first 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 Fig. 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

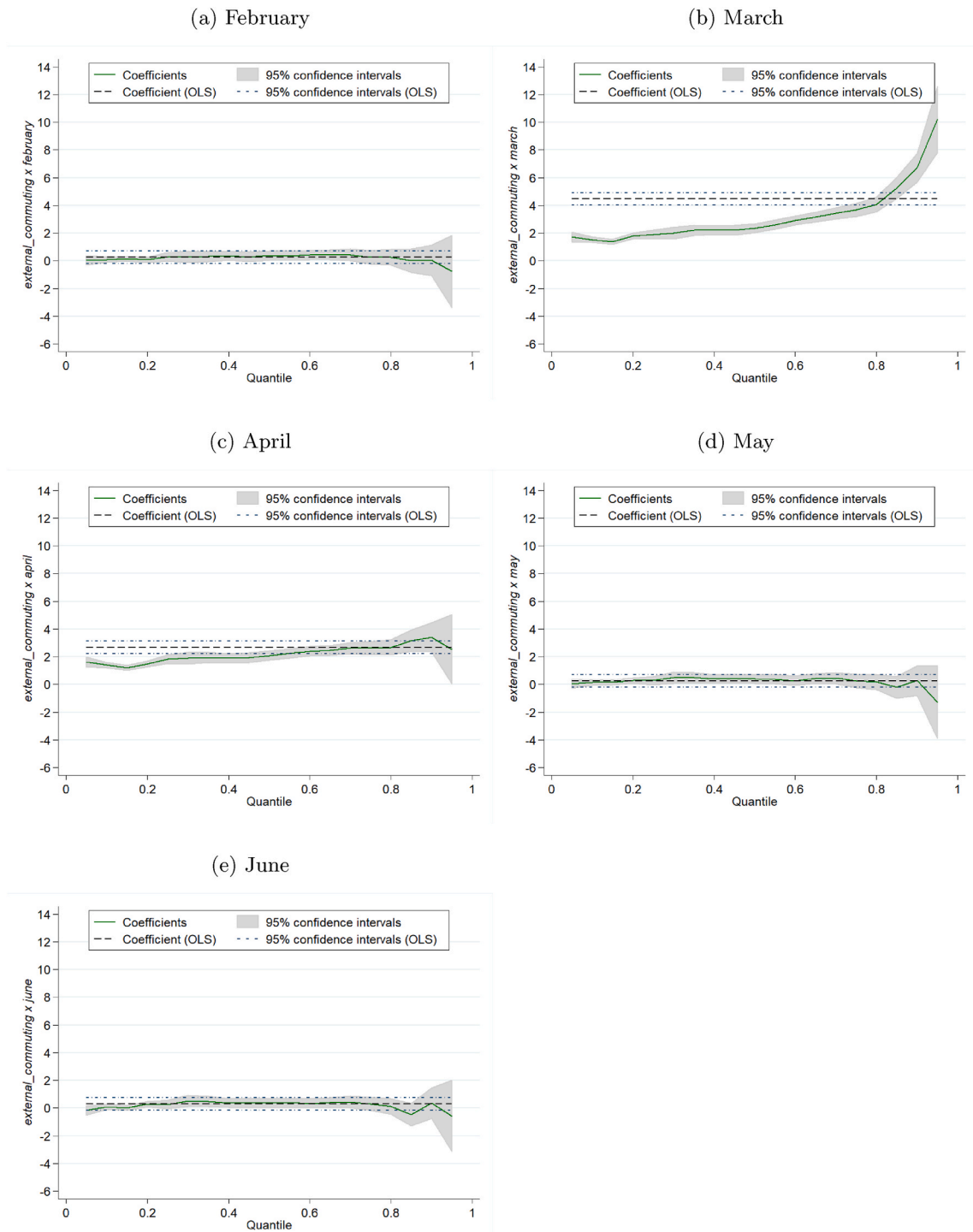


Fig. 6. Plots of quantile regression coefficients related to *external_commuting*, by month
 Notes: Panel data quantile regressions for the specification in column 2 of Table 3.

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.

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.

Among the heterogeneous set of policies aimed at containing COVID-19 virus transmissions, restrictions on public transport have been widely imposed by many countries. However, empirical evidence shedding light on the role of transit usage in the initial spread of the coronavirus disease is limited. We have contributed to this ongoing debate by investigating whether places in which the population was more prone to use public transport were more severely affected by the first wave of the pandemic. Italy, the first Western country to be deeply hit by the virus, was chosen as a case study.

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

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

The spread of the pandemic was measured as the daily excess mortality recorded in each Italian local labour market over the period 1 January and 30 June 2020, compared to the corresponding 2015–2019 average, as released by the National Institute of Statistics (ISTAT). Excess mortality was used as measure of COVID-19 diffusion in order to account for non-random differences in screening capacity among areas. Pre-existing levels of public transport usage, as well as the intensity of internal and external commuting flows, were obtained through the last census data. In addition, we controlled for those geographic, demographic, and economic characteristics that made some places more vulnerable to the pandemic than others. The estimated econometric model exploited the longitudinal dimension of our excess mortality data by analysing the explanatory variables around monthly time-breaks and through quantile regressions. Since no large-scale restrictions on individual mobility were enforced until the beginning March, and since COVID-19 fatalities are reported around 18–21 days after infection, our findings show that the intensity of commuting flows played a significant role in spreading the disease during the most critical months of March and April, while the association between transit usage and our outcome was statistically weak throughout all the period of analysis.

In other words, our findings suggest that it was the undertaking of a journey, not the transit mode used, that was a significant vehicle for the initial virus diffusion. This conclusion could have consequences for current transport policy. Social distancing rules have had repercussions not only on the overall capacity of the different transport systems, but also on the quality of the transit service experienced by some vulnerable groups of people, such as the elderly (Ravensbergen & Newbold, 2020). Although many public transport companies have already suffered a steep decline in ridership following the spread of COVID-19, continuous adaptations to public health recommendations within unpredictable temporal horizons are expected in terms of, among others, transit demand and supply profitability. These will, in turn, affect users’ transit behaviours and choice of transit mode, as the re-organization of transit services compliant with safety protocols has been found to increase the likelihood of ridership (Kapatsila & Grise, 2021) while mitigating the risk of virus transmission (Hu et al., 2021).

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

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

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

threaten their economic sustainability. This could bring to the development of a whole range of possible modal and technological changes that could slightly transform the way in which public transport will be used in the next years. Besides the impending inevitability of driverless cars, it may embrace a more frequent use of demand-responsive forms of public transport in possible combination with individual and active systems (Bruzzone et al., 2021). This may also promote a new operation based on a more substantial use of big data, a better energy employment, more attention to reducing external costs, and the possible integration of freight and passenger demand shares within the same vehicle (Cavallaro & Nocera, 2021). These actions should prevent the empty core problem (Button, 2005), a phenomenon well-known to air transport companies that could be extended, *mutatis mutandis*, to all traditional transport modes within a partially privatised market. Steps typical of this process include the need to increase transport capacity, an increase in costs,

Table 6
Transit usage and mortality growth (δ_p).

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

service unsustainability, bankruptcies and, ultimately, a reduction in competitiveness of the whole system. It is important to guarantee support for the surviving public transport companies during this transition phase to ensure both the plurality of supply and the retention of acceptable levels of competition.

Declaration of competing interest

We have no conflicts of interest to disclose.

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(online), and the 4th Meeting on Transport Economics and Infrastructure 2022 (Barcelona).

Appendix A. Quantile regressions

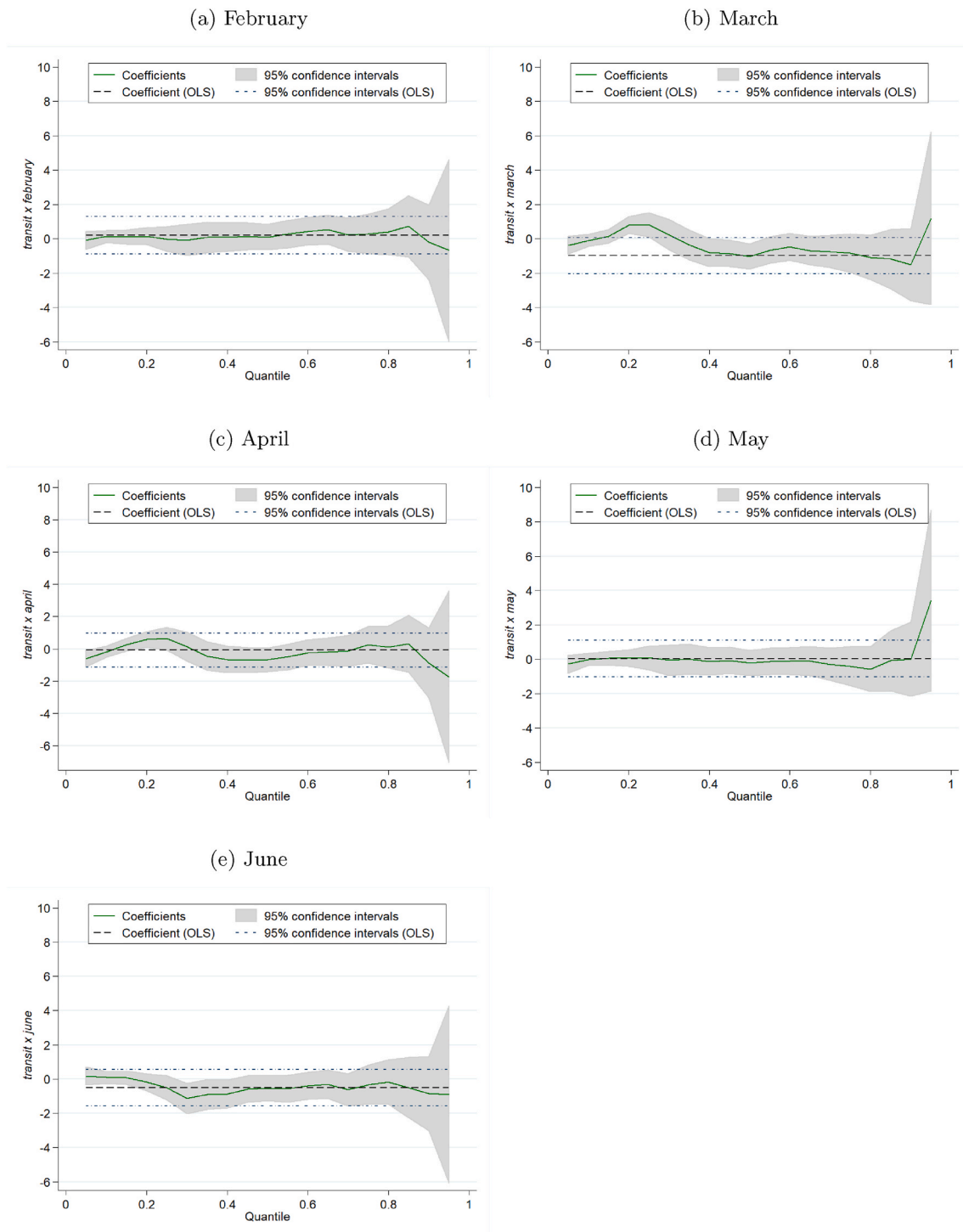


Fig. A.1. Plots of quantile regression coefficients related to *transit*, by month
 Notes: Panel data quantile regressions for the specification in column 4 of Table 3.

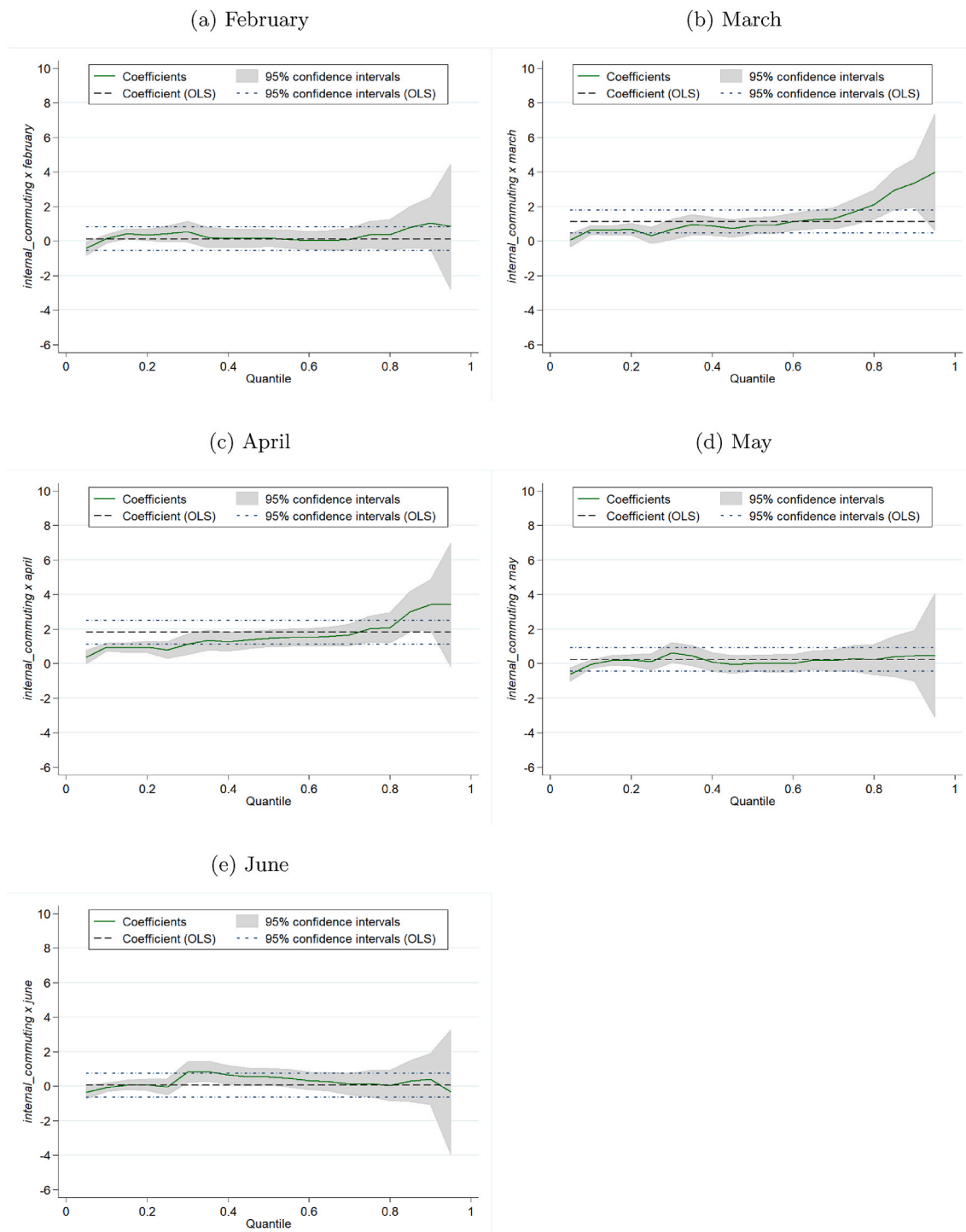


Fig. A.2. Plots of quantile regression coefficients related to *internal_commuting*, by month
 Notes: Panel data quantile regressions for the specification in column 4 of Table 3.

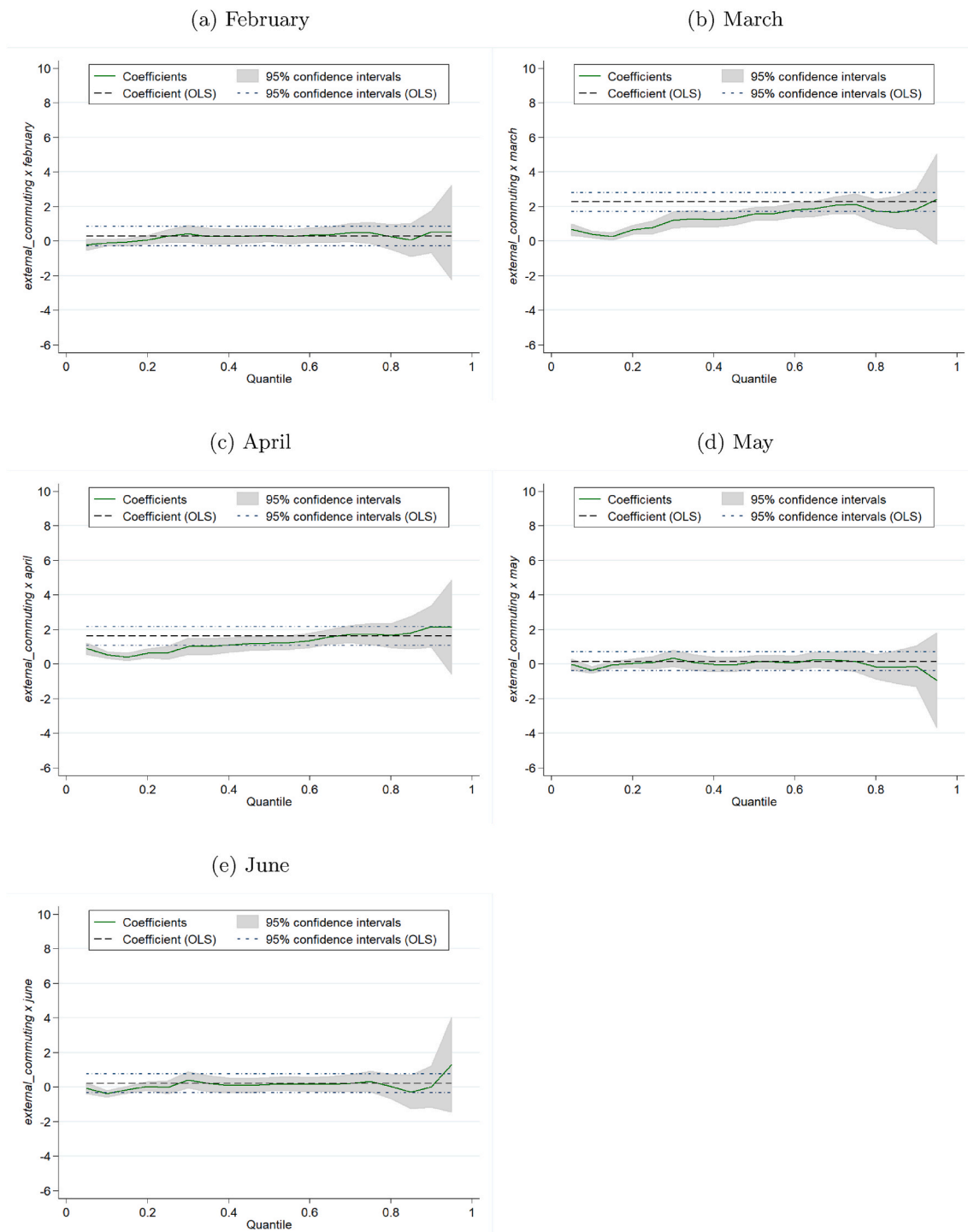


Fig. A.3. Plots of quantile regression coefficients related to *external_commuting*, by month
 Notes: Panel data quantile regressions for the specification in column 4 of Table 3.

Table A1
Transit usage and mortality growth (quantile regressions analysis – part 2).

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

	<i>mortality_growth</i>			
	(1)	(2)	(3)	(4)
<i>transit</i> × February	0.077 (0.381)	0.076 (0.386)	0.206 (0.400)	0.207 (0.428)
<i>transit</i> × March	-0.945 (0.907)	-1.070 (0.830)	-1.273 (0.970)	-0.976 (0.930)
<i>transit</i> × April	-0.336 (0.699)	-0.537 (0.637)	-0.158 (0.663)	-0.079 (0.681)
<i>transit</i> × May	0.576 (0.445)	0.489 (0.448)	0.116 (0.502)	0.036 (0.530)
<i>transit</i> × June	-0.181 (0.458)	-0.199 (0.461)	-0.425 (0.505)	-0.507 (0.527)
<i>internal_commuting</i> × February		0.188 (0.230)	0.229 (0.272)	0.134 (0.273)
<i>internal_commuting</i> × March		3.600*** (0.662)	2.183*** (0.618)	1.126* (0.611)
<i>internal_commuting</i> × April		2.871*** (0.433)	2.236*** (0.527)	1.815*** (0.496)
<i>internal_commuting</i> × May		0.657** (0.286)	0.304 (0.356)	0.246 (0.350)
<i>internal_commuting</i> × June		0.287 (0.269)	0.059 (0.342)	0.058 (0.342)
<i>external_commuting</i> × February		0.251 (0.190)	0.282 (0.210)	0.287 (0.218)
<i>external_commuting</i> × March		4.468*** (0.824)	3.821*** (0.845)	2.261*** (0.607)
<i>external_commuting</i> × April		2.652*** (0.433)	2.280*** (0.481)	1.627*** (0.443)
<i>external_commuting</i> × May		0.263 (0.220)	0.213 (0.267)	0.159 (0.278)
<i>external_commuting</i> × June		0.287 (0.201)	0.156 (0.222)	0.205 (0.230)
<i>altitude</i> × February			0.000 (0.000)	0.000 (0.000)
<i>altitude</i> × March			0.001* (0.000)	0.001** (0.000)
<i>altitude</i> × April			0.000** (0.000)	0.000** (0.000)
<i>altitude</i> × May			0.000** (0.000)	0.000** (0.000)
<i>altitude</i> × June			0.000 (0.000)	-0.000 (0.000)
<i>coastal</i> × February			0.047 (0.051)	0.032 (0.053)
<i>coastal</i> × March			-0.265** (0.116)	0.009 (0.113)
<i>coastal</i> × April			-0.098 (0.078)	0.017 (0.080)
<i>coastal</i> × May			0.080 (0.058)	0.087 (0.060)
<i>coastal</i> × June			-0.014 (0.062)	-0.024 (0.067)
<i>ln_density</i> × February			0.001 (0.020)	-0.002 (0.021)
<i>ln_density</i> × March			0.155** (0.061)	0.012 (0.058)
<i>ln_density</i> × April			0.062* (0.035)	-0.002 (0.037)
<i>ln_density</i> × May			0.078*** (0.026)	0.066** (0.026)
<i>ln_density</i> × June			0.037 (0.024)	0.037 (0.025)
<i>house_m²_pc</i> × February			0.007 (0.004)	0.011* (0.006)
<i>house_m²_pc</i> × March			0.018* (0.010)	-0.004 (0.011)
<i>house_m²_pc</i> × April			0.023*** (0.007)	0.013* (0.008)
<i>house_m²_pc</i> × May			0.010* (0.005)	0.008 (0.006)
<i>house_m²_pc</i> × June			0.000 (0.004)	0.001 (0.006)
<i>share_over75</i> × February				-1.013

(continued on next page)

Table B.1 (continued)

	<i>mortality_growth</i>			
	(1)	(2)	(3)	(4)
				(0.994)
<i>share_over75</i> × <i>March</i>				−1.427
				(1.940)
<i>share_over75</i> × <i>April</i>				−0.603
				(1.386)
<i>share_over75</i> × <i>May</i>				−0.058
				(1.137)
<i>share_over75</i> × <i>June</i>				0.088
				(1.036)
<i>hospital_beds</i> × <i>February</i>				0.011
				(0.008)
<i>hospital_beds</i> × <i>March</i>				0.019
				(0.012)
<i>hospital_beds</i> × <i>April</i>				0.006
				(0.009)
<i>hospital_beds</i> × <i>May</i>				0.007
				(0.006)
<i>hospital_beds</i> × <i>June</i>				0.007
				(0.007)
<i>pm10</i> × <i>February</i>				−0.000
				(0.002)
<i>pm10</i> × <i>March</i>				0.053***
				(0.008)
<i>pm10</i> × <i>April</i>				0.025***
				(0.004)
<i>pm10</i> × <i>May</i>				0.005*
				(0.003)
<i>pm10</i> × <i>June</i>				0.000
				(0.003)
<i>district</i> × <i>February</i>				−0.044
				(0.032)
<i>district</i> × <i>March</i>				0.224
				(0.136)
<i>district</i> × <i>April</i>				0.060
				(0.067)
<i>district</i> × <i>May</i>				−0.040
				(0.041)
<i>district</i> × <i>June</i>				−0.039
				(0.037)
<i>constant</i>	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
<i>R</i> 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

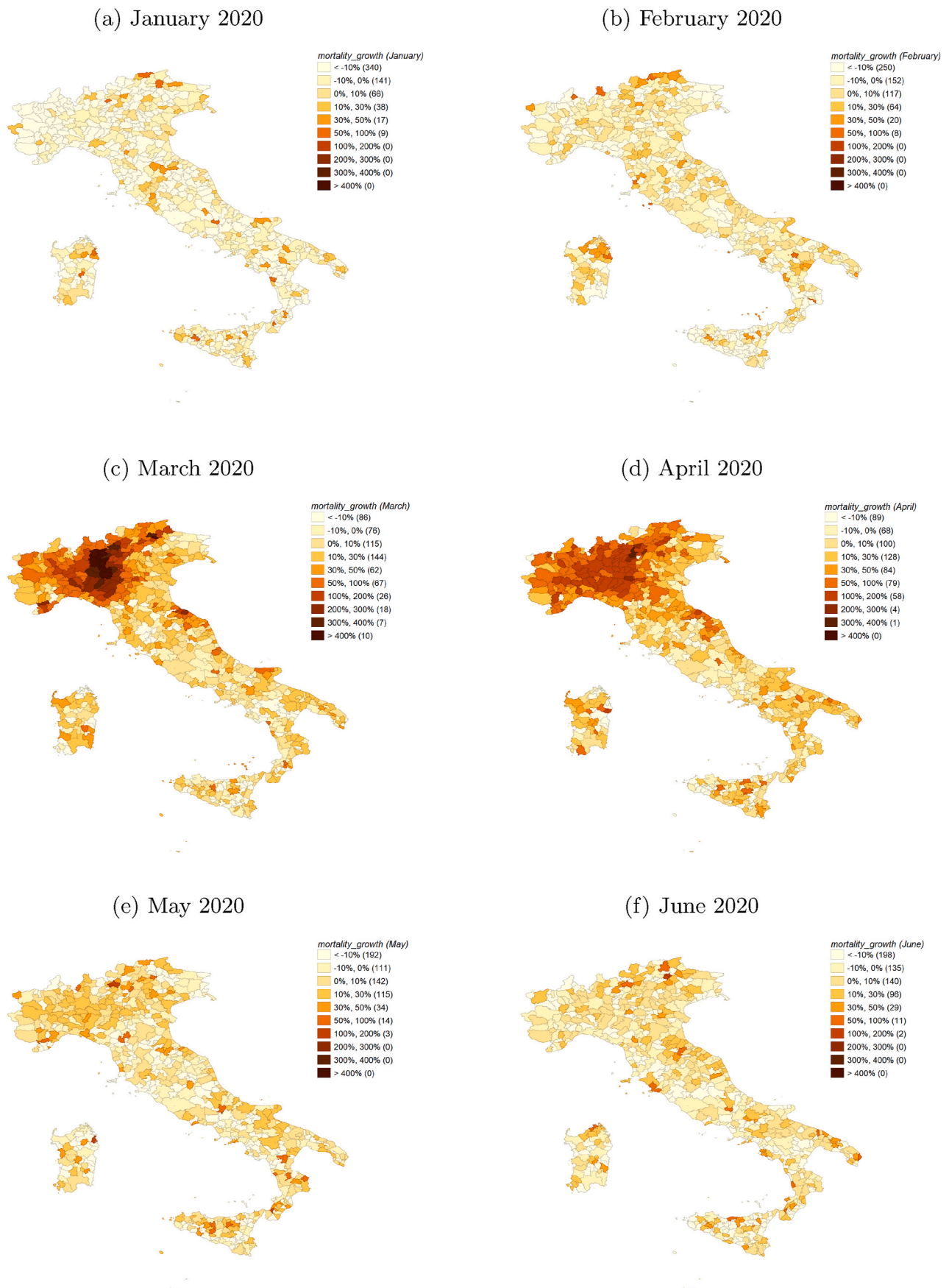


Fig. C.1. *mortality_growth*, by monthly averages and LLM
 Notes: the number of LLMs belonging to each percentage range are in parentheses. Source: Authors' own elaboration.

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