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SUPPLEMENT PAPER

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The life-saving effect of hospital proximity

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Summary

We provide a new assessment of the effect of hospital proximity in an emergency situation—road-traffic accidents—exploiting the exogenous variation in the proximity to cities that are legally allowed to have a hospital on the basis of their population size. Our instrumental variable results show that a one-standard-deviation increase in the distance to the nearest hospital (5 km) raises the fatality rate by 13.84% at the sample average. This figure is equal to 0.92 additional deaths per 100 accidents. We show that both ordinary least squares and difference-in-differences estimates, common approaches in the literature, provide a downward-biased measure of the true effect of hospital proximity because they do not fully solve spatial sorting problems. Proximity is more important when the level of road safety is low, when emergency services are less responsive, and when the nearest hospital has relatively low quality standards.

KEYWORDS

access to care, difference in differences, hospital proximity, instrumental variables, road-traffic accidents

1 | INTRODUCTION

In an emergency situation, being close to rather than far from a hospital can greatly affect the probability of survival. Although the importance of hospital proximity might be intuitive, assessing the overall costs of a change in the distance to a hospital has several empirical challenges. First, endogeneity problems arise when assessing the life-saving effect of hospital proximity using data on common life-threatening pathologies such as cardiac arrests or strokes.[1] Hospital locations and quality are rarely random: Compared to rural areas, urban areas are covered by more and better quality hospitals. People who are more likely to use healthcare services tend to live near hospitals rather than far from them, leading to spatial sorting problems. Second, a variation in proximity can generate both costs and benefits, and calculating these effects is not easy. For instance, when the increase in distance to the nearest hospital is due to hospital mergers, a benefit may arise because larger hospitals (i.e., high-volume hospitals) can provide higher quality services than small hospitals (i.e., low-volume hospitals).[2]

Although a proper cost–benefit analysis has not been implemented so far, the existing literature has addressed spatial sorting by exploiting hospital closures, as they result in changes in hospital proximity. Papers using this identification strategy, which we define as the "closure approach," have shown that hospital proximity does reduce acute myocardial infarction (AMI) mortality rates (Avdic, 2016; Buchmueller, Jacobson, & Wold, 2006). Although the closure approach relies on more reliable assumptions than a basic ordinary least squares (OLS), it does not fully solve the spatial sorting

[1]The first 90 min are crucial to surviving cardiac arrest, and the 60 min after the first stroke symptoms are called the *goldenhour* (Saver et al., 2010).
[2]Moreover, the calculation of net benefits from the reallocation of facilities is difficult, because new or remaining hospitals could register longer waiting lists depending on the new definition of the catchment area.

problem. It assumes that closures are random, which is rarely the case: Smaller and less efficient hospitals are more often the target of closures (Capps, Dranove, & Lindrooth, 2010; Lindrooth, Lo Sasso, & Bazzoli, 2003).

This paper provides a new assessment of the life-saving effect of hospital proximity that differs from the existing literature in both the outcome used and the econometric identification strategy. Our outcome of interest is the fatality rate of road-traffic accidents (i.e., the number of deaths on the number of accidents) at the municipal level for all Italian municipalities as recorded from 2000 to 2012. Road-traffic accidents represent an emergency situation (Pons et al., 2005) in which the patient cannot choose where to be hospitalized, as the emergency service will make the decision on her behalf.[3] Avoiding a specific cardiovascular pathology raises fewer concerns regarding spatial sorting (Bentham, 1986), but these concerns cannot be completely ruled out. For instance, if more severe accidents occur closer to hospitals, as shown in Section 4.2, then OLS estimates are biased. As a consequence, our contribution represents an improvement of the existing literature on the link between road-traffic accidents and proximity to an emergency department, which does not address the possible spatial sorting of accidents (Bentham, 1986; Brodsky & Hakkert, 1983).

Our primary focus is proximity defined as the absolute distance to the nearest hospital. Hence, our contribution also differs from the literature that exploits the differential distance between the nearest hospital and a hospital providing a specific treatment or characterized by a certain quality level to instrument for the probability of receiving a specific treatment or quality of care (e.g., Kessler & McClellan, 2000; McClellan, McNeil, & Newhouse, 1994) or the role of proximity in the decision to be hospitalized in the first place (e.g., Daysal, Trandafir, & van Ewijk, 2015).

Finally, we apply an instrumental variable (IV) approach to address the spatial sorting of accidents. Our identification exploits a population size requirement that has constrained the location of Italian hospitals since 1968. A 1968 law (n. 132/1968) set the minimum population size required to open a new hospital at 25,000 residents. Hence, we instrument the distance to the nearest hospital using the distance to the nearest municipality that, just after the 1968 law, counted slightly more than 25,000 inhabitants. We use the 1971 census population (i.e., the first available census after 1968) to identify those municipalities with more than 25,000 inhabitants as those most likely to have a hospital.

Overall, our strategy exploits "selected" randomness in the geographical distribution of municipalities in 1971 to explain the life-saving effect of hospital proximity. We justify this randomness with respect to road-traffic fatality rates by testing our model on different samples following a simple intuition. Suppose that three municipalities counted fewer than 25,000 inhabitants in 1971; hence, they are all less likely to have a hospital during the period 2000–2012. However, the nearest municipality of Municipality 1, counting more than 25,000 inhabitants in 1971, had 150,000 inhabitants, whereas Municipalities 2 and 3 were located near municipalities with 30,000 and 45,000 inhabitants, respectively. Because being near to a 150,000-inhabitant municipality in 1971 could directly affect road-traffic fatality rates in the present, for example, through levels of local development,[4] we define our reference sample as including all municipalities with fewer than 25,000 inhabitants in 1971, that do not currently have a hospital, and for which the nearest municipality with more than 25,000 inhabitants in 1971 counted a maximum of 50,000 inhabitants. However, our results are robust to alternative definitions of the reference sample as described in Section 3.1 and to different measures of proximity.

Using additional descriptive data on fatality rates by accident type from two Italian regions, we first provide evidence of spatial sorting in the severity of accidents. We then show that both the OLS and difference-in-differences (DD) estimates are downward biased when compared to the IV results. An OLS model underestimates the actual effect of being near a hospital because the most severe accidents tend to occur in proximity to a hospital.[5]

Specifically, our IV results show that a one-standard-deviation increase in the distance to the nearest hospital (i.e., 5 km) induces a 0.92-percentage-point increase in the road-traffic fatality rate (13.84% at the mean fatality rate). This is equivalent to an increase in the number of deaths by 0.92 per 100 accidents. Using a measure of the value of a statistical life (VSL) provided by the Organization for Economic Cooperation and Development (OECD, 2012), we assign a specific monetary value to the observed effect: Decreasing hospital proximity by a standard deviation costs society 3.82 million euros per 100 accidents.

We investigate three possible factors that might affect the importance of proximity by exploiting the characteristics of emergency services, the characteristics of the nearest hospital, and differences in road safety captured by different levels of road safety in the north and south. Proximity is more relevant when the level of road safety is low (i.e., more severe

[3]In public healthcare systems, patients are not allowed to direct the ambulance to a specific hospital, and the ambulance has no discretion to decide where to transport the patient. Differently, in the US, there is some discretion in emergency situations.
[4]Although we control for elements correlated with local development, such as population density and income levels, some concerns may remain.
[5]The OLS bias reconciles our findings with both the evidence from Yamashita and Kunkel (2010), who show that hospital proximity has no significant impact on heart disease mortality rates once the socioeconomic characteristics of patients are considered, and the evidence from Avdic (2016), who assesses the impact of proximity only for the first year after a hospital closure.

accidents); when emergency services are poorly equipped for rapid and effective interventions (i.e., radio coverage and use of helicopters and medical cars); and when the nearest hospitals are of low quality.

Finally, in Appendix B, we test our models using a different outcome—maternal screenings for pregnant women—and find that proximity does not robustly affect their incidence. Therefore, our results offer relevant insights into how to compensate for the costs imposed on emergencies by decreased proximity. However, the best response to such a change might differ depending on the type of procedure considered.

The remainder of the paper is organized as follows. Section 2 provides an overview of the institutional background and accounts for the data. In Section 3, we define our identification strategy, and Section 4 presents both descriptive statistics and results. The analysis of the mechanisms behind the importance of proximity is in Section 5, and Section 6 concludes.

2 | INSTITUTIONS AND DATA

The emergency care service in Italy consists of operative headquarters (Centrali Operative) organized on a provincial basis (Giorgetti, 2012). The service receives emergency calls through a toll-free, 24-hr public first aid number (i.e., 118). The calls are managed by headquarter dispatchers, who coordinate the activities of emergency personnel and are a mix of trained responders and physicians. In particular, operative headquarters are responsible for activating the closest available ambulance and for identifying the closest emergency department.[6] According to the legislation on emergency care, victims should receive proper hospital assistance within 20 min, at most, of being reached by the ambulance.

Between 2000 and 2012, 723 public hospitals offered emergency care services.[7] Through information from the Ministry of Health, we geocoded their positions and calculated the *Distance* for nearly 8,000 Italian municipalities. *Distance* is the Euclidean geographical distance from each municipality centroid to the address of the closest hospital. Therefore, we proxy the travel distance to the nearest hospital with straight-line or "as the crow flies" distances. Because we lack specific information on accident locations, the use of the centroid is a reasonable approximation, especially when the reach of the municipality is small, as in the case of our subsamples. However, the Euclidean distance may differ from the actual travel distance (Figure A1 in the Supporting Information), especially for mountain municipalities. Hence, we also use STATA and Google geocoding to calculate the driving distance from each municipality centroid to the address of the closest hospital. We merge the data on *Distance* with a set of data on road-traffic accidents and hospital performance and provincial-level data on emergency services.

2.1 | Road-traffic accident data

Given the lack of data at the accident level, we use the information collected by the police and processed by the National Institute of Statistics at the municipal level. Road-traffic accidents are recorded by place of occurrence. This dataset provides information on the number of accidents and the number of deaths. We construct our outcome of interest, *Fatality*, as the ratio between the number of deaths and the number of road-traffic accidents at the municipal level. Distinguishing between death before and death after hospitalization is not possible.

2.2 | Emergency network data

There are no yearly data on the characteristics of the emergency care service, but a survey administered by the Ministry of Health reports 103 operative headquarters managing calls through the 118 emergency number in 2005 (Ministero della Salute, 2007). Among the information in the survey, we focus on the four variables with a 100% response rate.

The first is the extent of *radio coverage*. Radio frequencies are used for communication between headquarters and ambulances. Consequently, wider radio coverage ensures more reliable and extended communications between headquarters and ambulance staff. Second, we have the number of *helicopter interventions* out of the total number of interventions per operative headquarters. Air medical services reach and transport patients faster and provide a more stable ride with

[6] Municipalities along regional borders benefit from the assistance of hospitals just across the border when these are nearer than in-region hospitals. In our sample, the nearest hospitals of 414 municipalities are in another region.

[7] Nearly all public hospitals offer emergency care, and thus, we refer to hospital and emergency departments interchangeably. The only exceptions are rehabilitation and/or geriatric facilities (i.e., 43 facilities). Private hospitals do not belong to the 24-hr public first aid service.

fewer accelerations or decelerations and less vibration. Moreover, they allow staff to move patients from smaller or less well-equipped hospitals to larger facilities once the patient is stabilized. In 2005, there were 44 helicopter rescue points. The third variable captures the prevalence of *physicians* among dispatchers at each headquarters. More highly trained dispatchers might be better skilled at obtaining crucial information from callers, evaluating the severity of injuries, and understanding the type of first intervention needed. Finally, we derive the incidence of *medical cars* per headquarters. This type of emergency vehicle transports trained medical staff and allows doctors to treat or stabilize victims at the scene while waiting for an ambulance. They may also reduce response time, as they move faster and more easily through bumpy and/or busy roads than full-sized ambulances.[8]

2.3 | Hospital data

Information on hospital characteristics such as the number of beds or wards is not available for the entire sample of hospitals, so we recovered data on hospital volumes from the National Outcome Evaluation Program (Programma Nazionale Esiti), a monitoring program operated by the Ministry of Health since 2007. In 2010, the plan held the most comprehensive set of information for 608 hospitals.[9] High volumes are correlated with lower mortality rates per procedure, such that high-volume hospitals are considered higher quality hospitals (Luft, Garnick, Mark, and McPhee, 1990). The intuition is that high-volume hospitals benefit from the learning-by-doing process whereas low-volume hospitals do not (Guccio & Lisi, 2016; Ho, 2000; Kristensen, Thillemann, & Johnsen 2014; Nuffield Institute for Health, 1996; Sound, 2010).

In particular, we collected volumes for the following procedures: AMI, strokes, nononcological surgeries, and congestive heart failures (CHF). The first two were selected because they are related to emergency services. Nononcological surgeries and CHF control for skills that could be useful to help the victim of a crash through an initial intervention. We do not use information on the volumes of each procedure individually because low volume for a single procedure may be not particularly informative in terms of expectations of overall quality (McClellan & Staiger, 1999). Therefore, we use the z-score average among all four z-score volume indexes as in Bloom, Propper, Seiler, and Van Reenen (2015).

3 | ECONOMETRIC STRATEGY

We begin by estimating a basic OLS model in which distance to the nearest hospital, *Distance*, is our variable of interest, explaining variations in the fatality rates of road-traffic accidents, *Fatality*, as described in Equation 1:

$$Fatality_{mt} = \delta \ Distance_m + Z_m'\sigma + X_{mt}'\tau + \gamma_h + \pi_p + \beta_t + \epsilon_{mt} \tag{1}$$

where γ_h are the nearest hospital fixed effects, π_p are provincial fixed effects, and β_t are year fixed effects.[10] The provincial fixed effects account for the organization of the emergency operative headquarters, which are managed at the provincial level. The nearest hospital fixed effects allow us to control for differences in hospital characteristics, such as their size, their managerial organization, and, to some extent, their performance. Standard errors are clustered at the municipal level to address serial correlation problems. Z_m' and X_{mt}' are vectors of municipal characteristics that can affect the probability of having an accident and the speed with which first aid arrives. Z_m' includes a categorical variable for municipal altitude and a dummy for coastal municipalities. First aid could encounter greater difficulties in reaching an accident in a mountain municipality. Moreover, coastal municipalities implement special emergency plans for tourists because they experience a substantial increase in population during the spring–summer season. Finally, X_{mt}' includes population density and the yearly average income.[11] The average income approximates the financial resources available to municipal administrations through local taxation, with wealthier municipalities expected to have better infrastructure systems (e.g., more street lighting and better road paving). Population density controls not only for the rapidity with which an injured person can receive assistance but also for the greater use of private transportation and a higher likelihood of road-related accidents being reported as we move from urban to rural areas (Clark & Cushing, 2004).

[8]Figure A2 in the Supporting Information shows the differences between an ambulance and a medical car.

[9]Beginning in 2011, risk-adjusted data are available for a few hospitals, and volumes are no longer reported. The program provides some indexes (e.g., AMI or CHF readmission rate) that could be used as quality indicators. However, these are not publicly available, and they cover fewer hospitals than the information on hospital volumes.

[10]Nearest hospital fixed effects and provincial fixed effects can be estimated because the nearest hospital is not necessarily located in the same province as municipality m. Our dataset contains 1,480 municipalities with the nearest hospital in another province.

[11]For a better explanation of the variables, see Table A1 in the Supporting Information.

We expect that δ in Equation 1 is not correctly identified when using OLS whenever the type or severity of accidents is not randomly distributed across nearby hospitals. The use of controls for the emergency service (i.e., provincial fixed effects) and the characteristics of municipalities might not be sufficient to overcome spatial sorting problems. In this respect, some previous works attempt to identify the effect of hospital proximity by exploiting the exogenous variations in the distance to the nearest hospital generated by hospital closures. Consistent with these studies, we identify δ by modifying the model in Equation 1 as reported in Equation 2, which defines a DD approach. From 2000 to 2012, 29 hospitals were converted to rehabilitation centers and thus were considered closed as far as emergency services are concerned.[12] $Treated_m$ is a dummy variable equal to 1 if, for municipality m, the distance to the nearest hospital changed during our period of interest. In this specification, *Distance* is time varying according to the closure year.

$$Fatality_{mt} = \delta Distance_{mt} + \lambda Treated_m + Z_m'\sigma + X_{mt}'\tau + \gamma_h + \pi_p + \beta_t + \epsilon_{mt} \quad (2)$$

However, even the DD approach does not completely eliminate concerns regarding the correct identification of δ. First, the decision to close hospitals is not random. Generally, the targets for closure are hospitals that are smaller and less efficient and have lower quality standards.[13] Second, defining the exact time of a hospital closure is not always straightforward. A progressive closure of wards often occurs; whereas some are shut down, others remain operative. Hence, a sharp definition of closure can be problematic. Finally, as hospital closures are not a frequent event, this approach relies on variations affecting only a very small proportion of observations. For instance, in our dataset, the DD exploits the changes in *Distance* for approximately 0.04–0.03% of all municipalities.

To overcome endogeneity problems affecting both the basic OLS and the DD estimator, we exploit a 1968 Italian law that constrained the minimum population size required to open a new hospital to 25,000. Before that year, hospital locations reflected the location of care centers that had been in place since the beginning of the previous century and long before that time in larger cities. The 1968 legislation was intended to reorganize the entire healthcare system. The reorganization had three primary mechanisms: mergers of existing facilities, a set of rules for new facilities, and the acquisition of existing private facilities by the public healthcare system.[14] The 1968 legislation is particularly important because it established the setting for the creation of a new national healthcare system, which was inaugurated in 1978. As a consequence, we use the distance from each municipality (centroid) to the nearest municipality (centroid) that counted more than 25,000 inhabitants in 1971 (i.e., the first census after 1968) as an instrument to measure the real effect of the distance to the nearest hospital on fatality rates.[15]

Not every municipality above the 25,000 population threshold in 1971 had a hospital in 2000–2012. However, some municipalities below that threshold do have a hospital. We estimate the effect of *Distance* on *Fatality* through two-stage least squares using *Distance* 71 as an instrument for *Distance*, and hence, the second- and first-stage equations are the following:

$$Fatality_{mt} = \delta Distance_{mt} + Z_m'\sigma + X_{mt}'\tau + \gamma_h + \pi_p + \beta_t + \epsilon_{mt} \quad (3)$$

$$Distance_{mt} = \lambda Distance\,71_m + Z_m'\vartheta + X_{mt}'\varphi + \gamma_h + \pi_p + \beta_t + \upsilon_{mt} \quad (4)$$

3.1 | Sample selection

To correctly identify the effect of *Distance* on *Fatality*, our instrument, *Distance*71, must satisfy two conditions. First, the instrument must be highly correlated with the instrumented variable, *Distance*, which is easily verifiable through the first-stage statistics. Second, the instrument must affect *Fatality* only through *Distance*; it must be orthogonal to other unobservable characteristics. Our identification relies on the randomness of the geographical distribution of municipalities in 1971. This randomness is more plausible when we compare municipalities that were close to centers *just* above

[12] Four hospitals were closed, and 25 hospitals were converted into rehabilitation or geriatric structures without an emergency department. During the same period, 20 hospitals with an emergency department were opened, and among of these, 17 are located in a municipality with more than 25,000 inhabitants.

[13] The majority of European countries have repeatedly lowered the number of acute beds per 1,000 inhabitants to limit the number of hospitals (Busse, Petrakova, & Prymula 2001; Koppel et al., 2008; McKee, 2004).

[14] Before War War II, a systematic attempt to reorganize the healthcare system was conducted based on the Royal Decree of 30 September 1938, n.1631, and the Prime Minister Decree of 20 July 1939. For example, the location of hospitals was constrained to a set of specific criteria according to which the designated area had to be easily accessible.

[15] Table A2 in the Supporting Information provides descriptive evidence that the distribution of the population across the 25,000 threshold in 1971 remains stable in the following decades. Using the 1971 census also has the advantage of considering the long process often required when a new hospital needs to be opened. For instance, the plan to open a hospital at Castelvetrano began in the 1970s, stopped during the 1980s, and then restarted, with the hospital opening in 1992. Figure A3 in the Supporting Information shows the distributions of *Distance* and *Distance* 71, which is also depicted by Figure A4 in the Supporting Information.

Samples

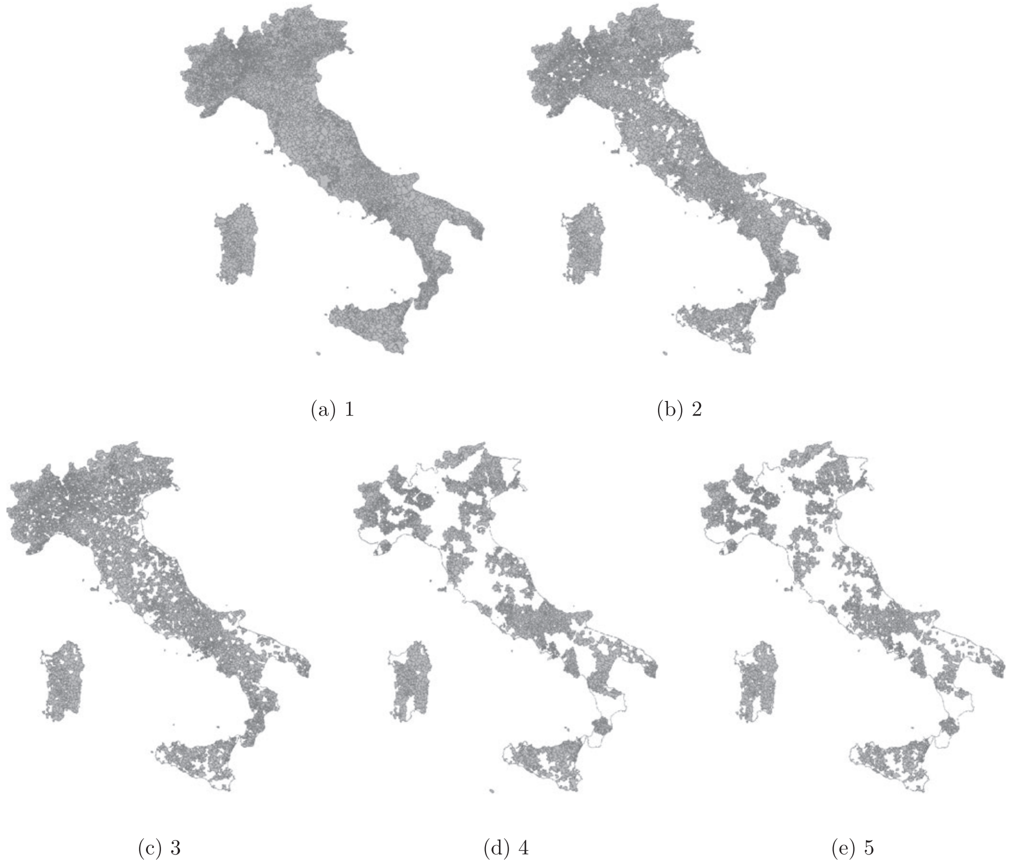

FIGURE 1 Samples. *Notes*: The figure shows our different subsamples. (1) All Italian municipalities. (2) Municipalities with fewer than 50,000 inhabitants and no hospital in 1971. (3) Municipalities with fewer than 25,000 inhabitants in 1971. (4) Municipalities close to a city with a population between 25,000 and 50,000 inhabitants and with fewer than 25,000 inhabitants in 1971. (5) Municipalities close to a city with a population between 25,000 and 50,000 inhabitants with fewer than 25,000 inhabitants and no hospital in 1971

25,000 inhabitants in 1971; thus, we defend this untestable assumption by testing our specifications with five differently specified samples.

The first sample includes all municipalities, as shown by the example in panel (a) of Figure 1, which also displays the other four samples. The second sample includes all municipalities with fewer than 50,000 inhabitants in the 1971 census that do not have a hospital. The aim is to exclude metropolitan areas and large cities that, besides having more and better hospital services, might also have better emergency response times. The third sample retains all municipalities with fewer than 25,000 inhabitants in the 1971 census. These municipalities are less likely to have a hospital on the basis of the 1968 reform. However, we might still be including municipalities located on the outskirts of large cities. All other things equal, being a municipality on the outskirts of Rome or Milan might have some effect on road-traffic fatality rates. Hence, we define the fourth sample as municipalities that had fewer than 25,000 inhabitants in 1971 and for which the nearest municipality had a population between 25,000 and 50,000 inhabitants. Finally, the fifth sample is the same as the fourth, except for the exclusion of those municipalities that have a hospital even if they had fewer than 25,000 inhabitants in 1971. The results from the fifth sample are our baseline specification.

As shown in Table 1, from 2000 to 2012, the overall average distance to the nearest hospital is 8.56 km, and fatality rate is approximately six deaths for every 100 accidents. In the fifth sample, these measures are slightly higher: 6.68 deaths for every 100 accidents, located 9.6 km from the nearest hospital on average.[16]

[16]Every subsample shows a positive correlation between *Distance* and *Fatality*; see Figure A5 in the Supporting Information.

TABLE 1 Descriptive statistics

Variable	**All (1)**	**No hosp + Pop1971 < 50,000 (2)**	**Pop1971 < 25,000 (3)**	**Pop1971 < 25,000 + nearest < 50,000 (4)**	**Pop1971 < 25,000 + nearest < 50,000 + no hosp (5)**
Fatality rate	6.046	6.357	6.236	6.519	6.687
	(17.408)	(18.153)	(17.794)	(18.521)	(19.094)
Distance	8.560	9.648	8.927	8.821	9.625
	(5.562)	(5.400)	(4.934)	(5.548)	(5.088)
Distance 1971	18.471	17.621	18.106	17.717	17.457
	(12.350)	(11.982)	(12.007)	(12.033)	(11.978)
Deaths	77.97	44.81	50.52	50.00	42.31
	(336.300)	(97.22)	(106.44)	(106.54)	(92.48)
Accidents	3,335.79	1,127.92	1,301.30	1,294.33	1,012.57
	(3,331.558)	(2,241.51)	(2,422.81)	(2,372.75)	(1,775.75)
Population density	348.741	308.453	301.387	326.133	320.37
	(693.712)	(559.866)	(623.087)	(641.207)	(655.733)
Income	16,399	16,252.88	16,303	16,069	16,011.34
	(3,859.57)	(3,820.376)	(3,830.16)	(3,859.97)	(3,874.01)
Plains	54.501	54.182	53.59	56.124	56.607
	(49.797)	(49.871)	(49.825)	(49.624)	(49.562)
Partially mountainous	8.866	7.571	8.304	8.128	7.389
	(28.425)	(27.594)	(26.455)	(27.327)	(26.159)
Totally mountainous	36.634	38.246	38.106	35.748	36.004
	(48.181)	(48.599)	(48.565)	(47.926)	(48.002)
Coastal	9.291	7.469	8.093	9.734	8.971
	(29.03)	(26.289)	(27.273)	(29.642)	(28.577)
Volumes of AMIs	117.585	117.805	113.727	95.906	98.74
	(128.847)	(128.322)	(126.212)	(99.378)	(100.49)
Volumes of strokes	83.25	83.595	81.144	66.848	68.24
	(85.355)	(85.381)	(83.947)	(60.806)	(61.32)
Volumes of CHFs	185.268	185.120	181.408	163.185	165.64
	(156.309)	(155.784)	(153.742)	(130.856)	(132.09)
Volumes of surgeries	812.175	815.039	788.274	587.343	601.78
	(1,033.145)	(1,023.871)	(999.995)	(594.999)	(597.49)
Observations	81,212	71,900	77,473	42,296	38,790
Municipalities	7,954	7,219	7,665	4,266	3,985

Notes: Mean values reported. Standard deviations in parentheses. *Distance* and *Distance* 1971 are in kilometers. For the overall sample, the average *Distance* in miles is 5.561 (*SD* 3.802), and the average for 1971 in miles is 11.840 (*SD* 7.118). Income is in per capita 2012 euros. AMI = Acute myocardial infarction; CHF = congestive heart failure. Surgeries: nononcology surgeries. Volume of procedure refers to the number of events per procedure in 2010.

4 | EMPIRICAL ANALYSIS

4.1 | Evidence on the spatial sorting of accidents

Focusing on road-traffic accidents rather than on a cardiovascular pathology raises fewer concerns regarding spatial sorting, but it does not eliminate them. If the most deadly accidents occur near a hospital, an OLS model would systematically underestimate the true effect of hospital proximity. This is, in a sense, a form of omitted variable bias. Assume that two potentially deadly accidents occur near a hospital, but only one results in a fatality because of hospital proximity. Far from the same hospital, two other accidents occur, one potentially deadly and the other not deadly. Because of the distance to the hospital, the outcome is one fatality. The final outcome is one death near the hospital and one far from it, with zero effect of proximity. However, the alternative of not having a hospital at all would have been two fatalities versus one fatality: The hospital actually halved the fatality rate. In other words, an OLS model would suffer from omitted variable bias because the severity of accidents is not observable and is negatively correlated with *Distance*.

To investigate whether road-traffic accidents are characterized by spatial sorting problems, we use municipal data from the Lombardy and Veneto regions. For these two regions, which account for 2,110 municipalities (26.10% of all Italian municipalities), we recover additional information on the number of deaths per type of accident at the municipal level.

Types of Accidents

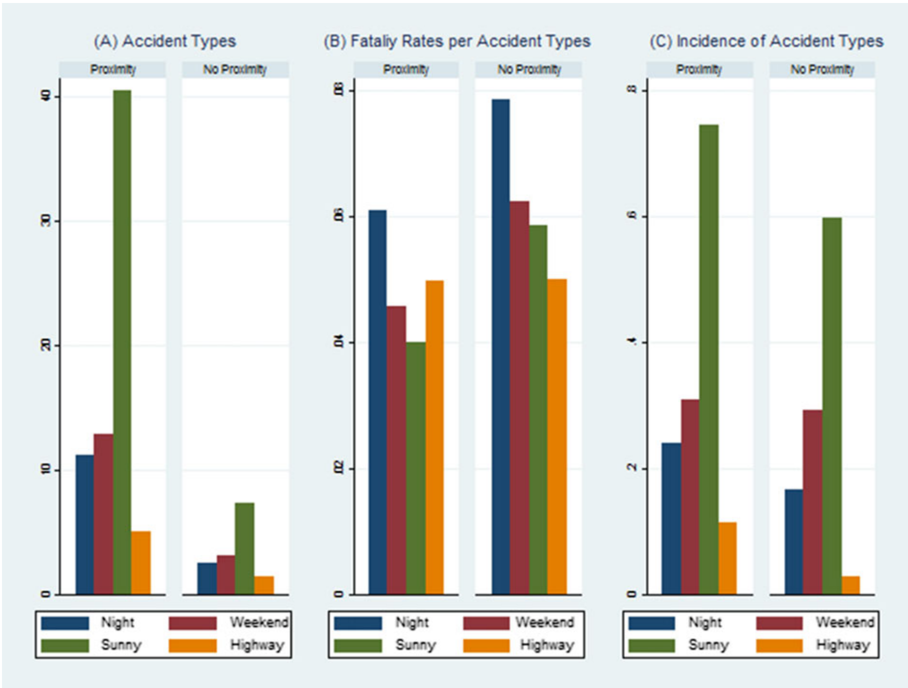

FIGURE 2 Types of accidents. *Notes*: Road-traffic accidents between 2000 and 2012 at the municipal level for Lombardy and Veneto. Proximity is defined as being nearer than 6.58 km to a hospital and not proximity as being farther than 6.58 km. The median value of *Distance* for municipalities in Lombardy and Veneto is 6.58 km. In figure (a), the vertical axis represents the average number of accidents per type at the municipality level; in figure (b), the vertical axis is the municipal average ratio between the number of deaths per type and the number of accidents per type, whereas in figure (c), the vertical axis represents the incidence of each accident type out of the total number of accidents. *T* tests for the significance of the differences between the two subsamples are statistically significant [Colour figure can be viewed at wileyonlinelibrary.com]

Hence, we derive the fatality rate for accidents that occurred over weekends, at night, in particular weather conditions, and on highways.[17]

Fatality rates might systematically vary across different types of accidents: Some accidents are more severe than others. For instance, according to the Italian National Institute of Statistics (ACI-ISTAT, 2013), the fatality rate is higher at night, largely because of greater infringement of speed limits. During weekend nights, fewer but more severe accidents occur: 43% of nighttime accidents occur on Friday and Saturday nights, when the fatality rate is approximately 42% (ACI-ISTAT, 2010).

The most severe accidents occur on highways. In 2013, highways showed a higher fatality rate (3.5%) than urban roads (1.7%; ACI-ISTAT, 2014). Highways are safer by design, but they are higher risk roads because of higher speed limits and the monotony of driving on them that is associated with reduced driver alertness and performance. Finally, the vast majority of deaths (79%) are registered under good weather conditions (ACI-ISTAT, 2014) as the level of driver attention decreases.

We calculate the median distance (i.e., 6.58 km) to the nearest hospital for municipalities in Lombardy and Veneto. We then seek to determine any systematic difference in the number of the most deadly types of accidents, their incidence in the total number of accidents, and their fatality rate between municipalities located near (Proximity = 1 below the median distance) and far from a hospital (Proximity = 0). The graphical analysis for Lombardy and Veneto presented in Figure 2 reveals the existence of spatial sorting by accident type (i.e., the most deadly accidents tend to occur near a hospital) and emphasizes the importance of addressing this problem when measuring the effect of hospital proximity, as the fatality rate of the most deadly accidents is lower the nearer they occur to a hospital.

[17]We cannot combine the information on the types of accidents. We can recover only the fatality rate over the weekend *or* at night, not *over weekend nights*. Such detailed information is not publicly available at the municipal level.

TABLE 2 Results on fatality rate

Variable	All (1)	No hosp + Pop1971 < 50,000 (2)	Pop1971 < 25,000 (3)	Pop1971 < 25,000 + nearest < 50,000 (4)	Pop1971 < 25,000 + nearest < 50,000 + no hosp (5)
Panel A: OLS					
Distance	0.078***	0.071***	0.081***	0.076***	0.057**
	(0.012)	(0.016)	(0.013)	(0.019)	(0.025)
Panel B: DD					
Distance	0.079***	0.073***	0.082***	0.077***	0.059**
	(0.014)	(0.019)	(0.015)	(0.020)	(0.027)
Panel C: IV					
Second-stage statistics: dependent variable: fatality rates					
Distance	0.133***	0.161***	0.171***	0.200***	0.185***
	(0.034)	(0.045)	(0.049)	(0.063)	(0.060)
Durbin–Wu–Hausman test					
p-values	0.089	0.051	0.033	0.035	0.024
Kleibergen–Paap LM test					
p-values	0.000	0.000	0.000	0.000	0.000
First-stage statistics: dependent variable: distance to the hospital					
Distance_1971	0.324***	0.281***	0.253***	0.283***	0.305***
	(0.016)	(0.015)	(0.016)	(0.022)	(0.020)
R^2	0.509	0.567	0.491	0.557	0.634
Adj R^2	0.504	0.562	0.486	0.55	0.628
Partial R^2	0.119	0.122	0.072	0.094	0.151
Robust F	426.553	349.678	235.301	163.768	226.064
Provincial FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Nearest hospital FE	Yes	Yes	Yes	Yes	Yes
Observations	81,212	71,900	77,473	42,296	38,790
Municipalities	7,954	7,219	7,665	4,266	3,985
Mean	6.046	6.357	6.236	6.519	6.687

Notes: All coefficients and standard errors are multiplied by 100. Robust standard errors are clustered at the municipal level in parentheses. OLS = ordinary least squares; DD = difference in differences; IV = instrumental variable.
* Significance at the 10% level.
** Significance at the 5% level.
*** Significance at the 1% level.

4.2 | Results

Table 2 shows the results obtained using different methods, as well as the evidence from the first stage, which highlights the strength of our instrument.[18] The significance of the effect of hospital proximity on fatality rates is assessed by every method and in every sample.

As stated, the results from the fifth sample are our baseline specification. Although the direction of the effect of *Distance* on *Fatality* is consistent across models, the OLS coefficients are almost one third of the IV coefficients. As expected, the OLS estimates are downward biased due to the presence of spatial sorting. This increases the robustness of our main identification, thereby rendering concerns of omitted variable bias less plausible. A hidden bias sensitivity analysis (Altonji, Elder, & Taber, 2005) moves from the assumption that OLS estimates are an upper bound of the true effect, which could eventually be equal to zero. Our findings reveal a different situation: OLS is a lower bound of a true effect that could ultimately be infinite.

[18]See Tables A3, A4, and A5 in the Supporting Information for the results on the other variables included in the models. Tables A6 and A7 in the Supporting Information show the results without controls and without fixed effects. Additionally, being our outcome a variable in a 0–1 interval, we checked the distribution of the predicted fatality rate, and we realized that 8% of the predicted values were outside the unity interval (i.e., below 0). We then implemented a generalized linear model fractional Logit model with IV (using the *qvf* Stata command with binomial function). The estimated odds ratios indicate that each extra kilometer between the accident place and the nearest hospital increases by 8% the (relative) fatality rate, a number which is fairly comparable to the point estimates we obtain with the linear probability model. The generalized linear model results indicate a clear robust and positive relationship between the distance to the nearest hospital and the fatality rate, in the direction assessed by our analysis.

TABLE 3 Simulated effects of the instrumental variable results

Distance hospital (km)	Time (min and s) 50 km/h	70 km/h	90 km/h	Fatality rate (%)	Extra deaths (100 accidents)	VSL (100 accidents million euro)
1	1.2	0.9	0.7	2.77	0.18	0.76
5	6.0	4.3	3.3	13.84	0.92	3.82
10	12.0	8.6	6.7	27.68	1.85	7.64
15	18.0	12.8	10.0	41.52	2.77	11.47
20	24.0	17.1	13.3	55.36	3.70	15.29
25	30.0	21.4	16.7	69.20	4.62	19.11
30	36.0	25.7	20.0	83.03	5.55	22.93

Notes: For these simulations, we use the coefficients from panel C in column (5) of Table 2. Fatality rate = number of deaths as a share of road-traffic accidents; VSL = value of a statistical life; the reference value used is the average EU-27 value of statistical life as measured by the Organization for Economic Cooperation and Development (2012), which amounts to 4,131,970 euros.

Specifically, a 1-km increase in *Distance* induces a 0.057-percentage-point increase in *Fatality*, which is equivalent to an average increase of 0.85% at the mean of *Fatality* in the fifth sample. The DD results are similar: a 0.059-percentage-point increase per kilometer (i.e., a 0.88% relative increase) and a 0.29-percentage-point increase (i.e., a 4% relative increase in *Fatality*) when *Distance* increases by one standard deviation (i.e., 5 km). The IV estimate yields different results. A 1-km increase in *Distance* is equal to a 0.18-percentage-point increase in *Fatality*, and a one-standard-deviation increase produces a relative increase of 13.8% in *Fatality*. After an increase of 6 km, an additional death is registered every 100 accidents.[19]

To better appreciate the practical implications of the estimated effects, Table 3 presents calculations for increases in distance to the nearest hospital of up to 30 km. We also provide a travel time proxy for the increased distance based on three possible traveling speeds (i.e., 50, 70, and 90 km/h).[20] A 5-km increase in *Distance* translates into 3 to 6 min of increased travel time, whereas an increase of 10 km corresponds to a travel time that is nearly 7 to 12 min longer. We also assign some monetary value to the additional loss of life using the VSL. The VSL represents the amount of money that society is willing to pay to avoid fatal risks or to assume such risks. Despite its limitations, the VSL provides *governments with a reference point for assessing the benefits of risk reduction efforts* (Viscusi & Aldy, (2003), p. 5) and is widely used in the evaluation of public policies (Ashenfelter, 2006). This reference point should be considered a lower bound of the true costs of the loss of a human life because it does not include the effects of the loss on the victim's relatives.

Several approaches can be used to quantify the VSL conditional on the policy evaluated (e.g., road safety vs. environmental issues), and estimates differ from country to country (Viscusi & Aldy, 2003). As a benchmark, we use the average EU-27 VSL as measured by the OECD (2012). Every additional kilometer costs 0.76 million euros per 100 accidents. A one-standard-deviation increase, 5 km, will cost society 3.82 million euros per 100 accidents.[21] In 2012, Italy alone counted 188,228 road-traffic accidents, whereas the EU and the US registered more than one and five million road-traffic accidents, respectively.

5 | WHEN PROXIMITY MATTERS: MORE OR LESS

Factors that influence both the probability of accidents and the promptness of emergency response may increase or decrease the importance of hospital proximity. Analyzing these factors has important policy implications and is useful to define where to invest to minimize the impact of decreased proximity once the decision to close a hospital is made. For this reason, we consider a generic approximation of the road safety level, the characteristics of the emergency care service, and the nearest hospital's quality.

[19]The results are robust to the use of travel distance; see Table A8 in the Supporting Information.

[20]Using data on Sweden, Petzäll, Petzäll, and Nordström (2011) estimate the average speed of emergency transportation at 85.8 km/h. However, the actual speed depends on many factors, including traffic density, speed, and weather conditions. Therefore, providing a sharper translation of travel time is complicated.

[21]The average EU-27 VSL as measured by the OECD (2012) amounts to 4,131,970 euros; thus, every additional kilometer costs society 0.185 * 4,131,970 euros (= 0.76 million euros) per 100 accidents. Similarly, a one-standard-deviation increase (5 km) cost 0.185 * 5 * 4,131,970 euros (= 3.82 million euros) per 100 accidents.

TABLE 4 Heterogeneous importance of proximity

		Emergency service characteristics				Quality as indicated by hospital characteristics	
	Road safety	**Radio coverage**	**Helicopter use**	**Physicians**	**Medical cars**	**Fixed effects**	**Volume levels**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	North	Less	Less	Less	Less	Low	Low
Distance	0.254	0.607***	0.552***	0.331*	0.673***	0.247	0.351**
	(0.164)	(0.213)	(0.201)	(0.194)	(0.224)	(0.161)	(.171)
	South	More	More	More	More	High	High
Distance	0.719***	0.263**	0.255*	0.488**	0.388**	0.476***	0.034
	(0.241)	(0.178)	(0.186)	(0.192)	(0.193)	(0.172)	(0.188)
Difference	0.465**	−0.344**	−0.297**	0.157	−0.360***	0.229**	−0.317**
	(0.210)	(0.136)	(0.136)	(0.128)	(0.130)	(0.109)	(0.128)
Observations	38,790	35,681	35,681	35,681	35,066	38,790	38,790
Municipalities	3,985	3,598	3,598	3,598	3,598	3,985	3,985

Notes: Dependent variable = *Fatality*. In Models (2), (4), and (5), *Less* = below the median value and *More* = above the median value. For Model (3), *Less* = below the mean value and *More* = above the mean value. In Models (6) and (7), *Low* = below the median value and *High* = above the median value. In Models (6) and (7), we also control for the interaction between *Distance* and *South*, and we include the dummy *South* in the regressions. All models are run on the fifth subsample. Each model includes provincial, year, and nearest-hospital fixed effects. In Model (6), nearest-hospital fixed effects are not included. The explanation for each variable is in Table A1 in the Supporting Information. Clustered standard errors at the municipal level are in parentheses. The discrepancies in the number of observations result from missing information in the data on the emergency care service produced by the Ministry of Health (Ministero della Salute, 2007).

*Significance at the 10% level.

**Significance at the 5% level.

***Significance at the 1% level.

We generate dummies, *D*, for each characteristic and interact them with *Distance* using our IV approach to estimate the model. For each factor, we report the results for *Distance* in each subsample defined on *D* and the significance of the difference between the two samples. This difference is robust to a full set of interactions of *Distance* with covariates at the municipality level (i.e., population density, average income, the categorical variable for the municipality's altitude, and the dummy for coastal municipalities). The aim is to exclude the possibility that the differential impact of *Distance* across samples is determined by other observable confounding characteristics of municipalities.[22]

Where *D* is the dummy for each factor. For instance, for the heterogeneity of north versus south, $D = 1$ if a municipality is located in the south. Because both *Distance* and *Distance***D* are endogenous, we use two instruments to identify the effect of distance: *Distance*71 and *Distance*71**D*. Similarly, all the interactions of *Distance* with covariates at the municipal level are also endogenous; thus, we instrument them by including their interaction with *Distance*71. The results of this analysis are reported in Table 4.

5.1 Road safety

Road safety implies both good road conditions and cautious behavior by drivers. The general state of infrastructure is expected to affect the provision of first aid and the severity of an accident. Yet most severe accidents can also be associated with less-than-optimal enforcement mechanisms of road safety rules, as drivers will adopt a suboptimal level of precaution. We expect that more severe accident outcomes will be more affected by hospital proximity. To investigate this, we exploit the differences between the north and south of Italy. Southern municipalities are known for their poor infrastructure level compared with their northern counterparts. Moreover, between 2009 and 2012, only 76% of southern drivers regularly wore the front seat belt as opposed to 93% of northern drivers. Similarly, the use of the rear seat belt is a regular habit for 34% of passengers in northern regions but only 12.5% in southern regions (Istituto Superiore di Sanitá, 2013).

[22]The significance of the difference between the coefficients of *Distance* in the two subsamples is the parameter λ of the following second-stage model for Sample 5, as defined in Section 3:

$$Fatality_{mt} = \delta Distance_m + \lambda D * Distance_m + \alpha D + Z_m^{'}\sigma + X_{mt}^{'} + Distance_m * Z_m^{'}\chi + Distance_m * X_{mt}^{'}\rho + \gamma_h + \pi_p + \beta_t + \epsilon_{mt}$$

Column (1) of Table 4 reports the value for the impact of *Distance* in the north and in the south as well as the differences between the two areas. Hospital proximity appears to be more relevant in the south than in the north, and the difference is significantly different from zero. Hence, adding an additional kilometer to the nearest hospital in the south increases the fatality rate by 0.71 percentage points. By contrast, in the north, this increase is equal to 0.25 percentage points, and the effect is not statistically significant.

5.2 | Emergency service characteristics

We first exploit the geographical coverage of the radio system of each operative headquarters by dividing the sample at the median value of radio coverage (i.e.,80%). The results in column (2) of Table 4 show that higher levels of radio coverage correspond to smaller effects of proximity. The difference is equal to 0.34 percentage points for each additional kilometer and is statistically significant. For the use of helicopter rescue, we refer to the mean value (0.7%) since up to the 25th percentile of the distribution, this variable is equal to zero. In the case of operative headquarters relying more on helicopter use, column (3) suggests that proximity is less relevant.[23]

More intense use of medical personnel, physicians (18%), as dispatchers does not appear to provide any benefit in terms of reducing the importance of hospital proximity, as shown in column (4). However, more intensive use of medical cars does provide a benefit, as reported in column (5). Headquarters employing more medical cars out of the total number of available vehicles (i.e., 12%) experience a significant decrease in the importance of proximity by 0.36 percentage points per kilometer.

5.3 | Nearest hospital characteristics

The evidence indicates that every additional kilometer decreases the probability of survival because it causes an injured individual to become a more serious case. She or he will arrive at the hospital in worse condition as the time to reach the emergency room increases. Assessing whether proximity is more or less relevant conditional on the quality or performance of the nearest hospital is an empirical question. Both high- and low-quality hospitals can save both easy and serious cases, but we could expect that, on average, high-quality hospitals tend to save more of both. In this case, fatality rates should increase the farther the accident victim is from a high-quality hospital. However, it is possible that serious cases are likely to be saved only at high-quality hospitals but have fewer or no chances at low-quality hospitals.[24] In this case, every additional kilometer is more deadly if the nearest hospital is of low rather than high quality.

Case-mix-adjusted quality indexes are not available to the public and for all Italian hospitals. Hence, we use two proxies. First, we use the estimated fixed effects of the nearest hospitals from the second-stage results of our baseline specification. The fixed effects are a good proxy for a general combination of management, size, and performance, which rarely undergo dramatic changes (McClellan & Staiger, 1999). Because they are derived from an equation explaining variations in fatality rates, greater fixed effects capture hospital characteristics correlated with higher fatality rates. Second, we use the z-score of annually treated AMI, stroke, nononcology surgeries, and CHF cases to approximate the hospital volume levels (Ministero della Salute, 2013).

Low (high) quality is expressed by above (below) the median fixed effects and below (above) the median volumes. Columns (6) and (7) show that proximity is more important when the nearest hospital reports larger fixed effects and lower activity levels. The two proxies go in the same direction: The distance to the worse hospitals has the greatest (negative) effects on survival probability. Hence, low-quality hospitals tend to save more easy cases than difficult cases.

6 | CONCLUSIONS

We provide a new assessment of the impact of hospital proximity on the probability of survival using data on road-traffic accidents. To overcome spatial sorting problems resulting from nonrandom distributions of accident types around hospitals, we exploit a 1968 Italian law that mandated a population size of 25,000 inhabitants as a requirement to open a new

[23]Because we control for the interactions between *Distance* and the mountain characteristics of municipalities and for the interaction with population density and income, the effect of helicopter use cannot be linked to these alternative explanations.

[24]This point is similar to a discussion by McClellan and Staiger (1999) on the lower numbers of complications in low-quality hospitals. Because serious cases will die in low-quality hospitals, the survivors are better cases with a lower incidence of complications.

hospital. We use an IV approach in which we instrument the hospital distance between 2000 and 2012 (i.e., our observation period) with distance to the nearest municipality satisfying the population requirement just after 1968. As such, our approach relies on the intention to treat, as we consider an institutional setting in which hospitals were also operating before 1968. Our analysis shows that a one-standard-deviation increase in the distance to the nearest hospital increases fatality rates by 0.92 percentage points (13.84% at the mean fatality rate). Translating this effect into a monetary value based on the VSL provided by the OECD (2012) represents a cost to society of 3.82 million euros per 100 accidents.

Although our focus is on the cost side, and we do not account for potential benefits stemming from decreased proximity associated with hospital closures and mergers (e.g., higher quality in postmerger, high-volume facilities relative to premerger, low-volume facilities), we offer some interesting insights into how to compensate for the costs imposed by emergencies when proximity varies. In fact, the analysis of the mechanisms through which proximity affects road-traffic fatality rates shows that low levels of road safety, poor emergency care services, and low-quality hospitals increase the importance of hospital proximity. This means that a first response to an increase in the distance to the hospital should target the healthcare system itself. Specifically, possible policies should invest in hospital quality, and in a more effective organization of the emergency network, including the use of the most advanced technologies (i.e., drones).[25] With respect to the latter, our analysis stresses the role played by the communication system used by the emergency network and the relevance of more flexible and faster means of transport such as medical cars and helicopters. In addition, in the specific case of road-traffic accidents, the negative impact of a decrease in hospital proximity could also be partially counterbalanced by investing in road maintenance and increased enforcement of traffic safety measures.

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[25]The use of drones, for instance, decreases response times and can be helpful in precisely detecting the severity of emergencies and guiding first aid. See, for instance, the project *Drones for Good* at https://www.youtube.com/watch?v=y-rEI4bezWc.

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SUPPORTING INFORMATION

Additional Supporting Information may be found online in the supporting information tab for this article.

Correction added on 2 October 2017, after first Online publication. Supporting information was replaced with correct data file.

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