DEMS WORKING PAPER SERIES

Where are you?

The problem of location during emergencies

Elena Lucchese

No. 439 – April 2020

Department of Economics, Management and Statistics
University of Milano – Bicocca
Piazza Ateneo Nuovo 1 – 2016 Milan, Italy
http://dems.unimib.it/

Where are you? The problem of locating the patient in an emergency

Elena Lucchese*

Abstract

Rapid response to an emergency call is crucial to its outcome, but little is known about the determinants of response time. Using a difference-in-differences strategy, it is shown that the time it takes to find the patient's location accounts for 30% of response time. The analysis compares the time required to cover each segment of the ambulance trip – from the hospital to the patient's location and then back to the hospital – according to whether the patient is at home or at some other location that responders can more easily locate. The magnitude of the effect does not appear to be affected by the distance travelled. It is suggested that introducing a technology that gives care providers precise information about a patient's location would substantially improve performance at a minimal cost.

JEL classification: D29, D90, I12, I18, R41

Keywords: Ambulance, Emergency, Organizational Performance, Response Time.

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*Department of Economics, Management and Statistics, University of Milan Bicocca, E-mail: elena.lucchese@unimib.it

1 Introduction

The emergency medical setting is the front line of the health care system and one of its crucial nodes (Berchet, 2015). Emergency departments manage patients with an immediate need for care and handle, on average, 33.5 visits per 100 population each year (OECD, 2011).[1] To foster the efficient use of resources, it is important to understand the determinants of performance in this setting (Baicker et al., 2012).[2] This may also help to explain the different returns on health expenditure observed across jurisdictions and over time.[3] However, the paucity of data has limited the possibility of carrying out a rigorous analysis.

In an emergency, a rapid response is of crucial importance in reducing the likelihood of negative outcomes. For instance, Jena et al. (2017) show that marathons increase mortality by lengthening ambulance response time. Wilde (2013) and Avdic (2016) show that patients located farther away from the hospital are more likely to die in an emergency. Rapid response is also important in other types of emergencies. For example, Blanes i Vidal and Kirchmaier (2017) have shown that a quick response by police is a crucial determinant of clearance rate. It is usually assumed that emergency responders are already maximizing their performance and therefore, in order to reduce response time, it is necessary to increase the number of available vehicles.[4] This is a reasonable assumption given the focus on response time measures, which are also used as the main indicators in evaluating the overall

[1]It has been estimated that the emergency departments in the US are responsible for about 1/3 of all acute medical visits and 1/2 of all hospital admissions: https://news.brown.edu/articles/2013/04/emergency (last access: March 2020).

[2]This approach is also recommended by the standard economic model of healthcare due to Auster et al. (1972).

[3]See, for instance, the discussion by Chandra et al. (2016), Finkelstein et al. (2016), Skinner and Staiger (2015) and Chandra and Staiger (2007), among others.

[4]See, for instance, Wilde (2013) and Blanes i Vidal and Kirchmaier (2017).

quality of a healthcare system.[5]

The results of the current research show that improving the ability of responders to navigate to the scene could reduce response time by about 30%. The emergency mission is usually initiated by an emergency call during which important information is communicated. Of crucial importance is accurately conveying the address of the patient. However, in many instances, this information may be unknown to the caller or – due to the shock of the moment – may not be communicated correctly. The magnitude of the problem is quantified using a difference-in-differences identification strategy that takes into consideration three main factors. First, each run is composed of two segments: from the dispatch to the scene (the way there), and from the scene to the hospital (the way back). Second, the likelihood of the responder experiencing a problem in locating his destination differs between the two segments. On the way to the scene, the driver locates the patient according to the information provided during the emergency call. On the way back, the driver knows the address of the hospital precisely. Finally, it is easier to locate some destination types than others. In particular, and as pointed out in David and Harrington (2010), public places (such as a mall or a downtown street) are usually more familiar to responders than the location of a private residence.

The current analysis makes use of uniquely precise information about the driving time of ambulances. The information was gathered using a software program that automates data collection in real time, thus minimizing the likelihood of mistakes and misreporting that can occur when information is self-reported by care

[5]Given the importance attributed to response time, precise measures of performance have been established. The ambulance service in Europe must meet specific response-time targets which are usually defined by regulation or national law (ec.europa.eu/health). In the US, local health care agencies contractually set response time levels together with ambulance providers (Ludwig, 2004).

providers following the event, as in the case of non-automated data collection. The sample includes data on 196,740 ambulance runs that took place in the Italian region of Liguria over a two-year period (2013-2014).[6] The analysis focuses on runs classified as urgent, i.e., when a quick response matters the most, and in particular those that originate from the hospital where the patient is taken to, such that the characteristics of the journey are similar in both segments. This is important in order to avoid results driven by systematic differences between the segments, such as, for instance, a longer distance covered on the way there than on the way back.[7] The final sample therefore includes 18,863 observations. The estimates for the full sample are also reported and the results are found to be similar.

The identification of the effect of interest relies on the difference between driving times at the mission level (the way there vs the way back) and how that difference varies with destination type (private residence vs other locations). In this way, the results are free of the compounding effect of factors that are constant over time – within a given mission – and factors that change over time, regardless of the destination type.[8] Examples of the former are the characteristics of the ambulance crew (such as their experience) and of the vehicle (such as the level of technology onboard). An example of the latter is the fact that there is a patient onboard on the way back but not on the way there.

Locating the patient can be viewed as a *last mile* problem. Indeed, the problem usually arises when the ambulance is close to the patient's location. It therefore

[6] The regional setting is particularly relevant in this context given that healthcare services are organized and managed at the regional level in most European countries.

[7] This may be the case if the patient is reached by an ambulance located farther away than the hospital he is transported to. In many instances, the ambulance does not depart from the hospital but rather from some other waiting area.

[8] A mission lasts for about one hour.

follows that the magnitude of the problem should not be particularly sensitive to the total distance driven. To verify this, the sample is split into groups according to distance driven. The difference-in-differences estimates show that the effect is indeed similar across these groups. The effect is also estimated for different levels of urgency and it is found that the delay increases with the urgency of the mission. This supports the idea that the stress of an urgent situation may affect the quality of communication and the severity of the problem in locating the patient.

The analysis quantifies the delay in ambulance arrival due to the problem and proposes the adoption of a technology that identifies the address of the destination directly from the emergency call, thus improving the ability of the responder to navigate to the scene. The proposed solution makes use of smartphone technology to convey GPS or WiFi-based location data to emergency service providers. This information is sent directly to the call center without any active involvement of the caller and does not require any previous download of applications.[9] It is conservatively estimated that adopting this technology can potentially reduce the average response time by over one quarter at a cost of only about 2,500 euros.

The rest of the paper is organized as follows: Section 2 describes the data. Section 3 presents a descriptive analysis. Section 4 introduces the empirical methodology. Section 5 presents the results and discusses their robustness and sensitivity to alternative specifications. Section 7 discusses policy recommendations and concludes.

[9]For further details, see the technical report DTR/EMTEL-00035 by the European Telecommunications Standards Institute (ETSI).

2 Data and Setup

The analysis makes use of administrative data collected for the Italian district of Liguria during 2013 and 2014. In 2012, Liguria introduced an innovative information system that records data in real time rather than it being self-reported by the ambulance crew after the incident, thus generating a uniquely precise dataset. Driving times – the core variable of interest – is computed using data that are automatically recorded by the system, including when the rescue vehicle departs, when it arrives at the scene, when it departs the scene and when it arrives at the hospital. The full dataset includes 196,740 observations. After excluding non-urgent missions and the cases in which the ambulance was dispatched from a location other than the hospital to which the patient was transported, the sample is reduced to 18,863 observations.[10] Observations with missing information for the variable of interest were also excluded. The sample construction is described in Table 1.

The analysis also takes into consideration the destination type by including a dummy that takes a value of one for a private residence and zero otherwise.

Robustness tests are carried out for patient characteristics, including age, gender, pathology, and urgency. Patients are classified according to three age categories: <35, $35 \geq$ age ≤ 65 years and > 65 years. Pathology is classified according to three groups: injury, cardiovascular distress, and others. The first two groups together account for about 40% of all urgent conditions. An analysis that also takes into consideration a detailed classification of pathologies is presented as part

[10] Cases in which patients died before reaching the hospital are excluded from the final sample because they were no longer urgent for some part of the way back. The number of observations reported in the regression results is double since each mission is observed twice, once for each segment.

of the analysis.

2.1 Institutional Setting

Emergency medical calls are received at a centralized call center where trained nurses collect information from the caller and assess the pathology and degree of urgency. During the call, the nurse asks a predetermined set of questions, specifically designed to maximize the quality of information collected.[11] The nurse fills in a form with the information collected and conveys it to the ambulance crew that is dispatched to the scene. Emergency service guidelines prescribe the ambulances to respond to urgent calls as quickly as possible but to drive more slowly on the way back in order to avoid abrupt braking and accelerations that may worsen the health condition of the patient onboard.[12]

The ambulance crew, which consists of trained paramedics, is in continual contact with the call center which can provide it with further support if needed. The call center monitors all the ambulances and their locations and dispatches the closest one to the scene. The crew notifies the call center the moment they arrive on the scene. They then diagnose the pathology and provide first aid. Finally, the patient is transported to the nearest hospital that can provide appropriate treatment. The choice of the hospital is made by the call center, based on the situation of each hospital at that moment. The ambulance service is provided free of charge, although a fee of 25 euros is charged if the situation was not an

[11] The procedure, adopted by all developed healthcare systems, is described in a manual called *Dispatch*. In Liguria, nurses attend specific courses that train them in the procedure described in the manual. The procedure involves a hierarchy of questions that enables a diagnosis of symptoms as one of 17 classes of pathology and according to 4 levels of urgency.

[12] For additional information on the guidelines, see Bermano et al. (2013).

emergency.[13]

3 Descriptive Statistics

As shown in Table 1, the size of the full sample is about ten times larger than the final sample. The largest cut is due to the restriction that the ambulance departs from the hospital to which the patient is transported. Indeed, most ambulances depart from stations distributed around the region to ensure better coverage of the region. Hospitals are usually located within or close to urban areas and as a result, 81% of the observations in the final sample are missions performed in densely populated municipalities, in contrast to 53% of the full sample (see Table 2). Nonetheless, the distribution of the other characteristics is similar in both samples. On average, the way there takes 15 minutes and the way back about 3 minutes less. About 60% of destinations are private residences. Injury and cardiovascular problems each account for about 20% of urgent ambulance runs. About 14% of patients are less than 35 years old and 28% are between 35 and 65 years old. Finally, there is an equal probability of a run taking place on any given day of the week.[14]

Figure 1 shows the driving times for the full sample in the left panel and for the final sample in the right panel. The difference in driving times between the segments is similar in the two samples.

[13]Pregnant women, children under the age of 14, the disabled, and low-income individuals are exempt from paying the fee.

[14]The equal probability of calls on any day of the week is used to test for sample selection.

4 Identification Strategy

An ambulance mission is composed of two driving segments: the way there (from the dispatch location to the scene) and the way back (from the scene to the hospital). The problem of locating the patient arises during the first segment, i.e. on the way there. The way back, in contrast, is usually familiar to responders. This is particularly true for ambulance missions dispatched from the hospital to which the patient is transported. Therefore, a simple way to quantify the problem of locating the patient is to examine the difference in driving time between the two segments. Given that this difference is calculated at the mission level, it is not affected by factors that are fixed for each mission, such as the characteristics of the vehicle or of the ambulance crew.

In general, each episode lasts for about one hour. The driving time is expected to be longer on the way there than on the way back, as mentioned. There may be factors other than location that systematically differ between the two segments and therefore they may also drive the results. An example is the presence of the patient inside the ambulance only during the second segment. In order to isolate the effect of interest from the compounding effect of factors of this kind, it is calculated as a second difference across destination types. This is possible since the severity of the problem in locating the patient varies with destination type. Indeed, as discussed by David and Harrington (2010), it is usually more difficult to locate a private residence than some other destination type, such as workplaces, schools or main streets, which are more likely to be familiar to responders. Therefore, the difference in driving time between segments is compared across destination types (residences vs others) in order to eliminate the compounding effect of factors that change over time, regardless of the destination type.

The regression model is specified as follows:

$$DT_{es} = \alpha_0 + \alpha_1 Go_m + \alpha_2 Residence_e + \alpha_3 Go_e \times Residence_e + u_{es},$$

where DT is driving time during segment s of episode e. Go is a dummy variable that takes a value of one for the way there and zero for the way back. $Residence$ is a dummy variable that takes a value of one if the destination is a residence and zero otherwise. The error term u captures the residual components that affect driving time.

The constant term, α_0, captures the amount of time required, on average, to drive back to the hospital from destinations other than a residence. The parameter α_1 is the extra time required to reach other destinations. The parameter α_2 is the extra time required to drive back to the hospital from other destinations. The parameter of interest, α_3, captures the problem of locating the patient by measuring the extra time required on the way there – relative to the way back – to reach a private residence versus other destination types. Alternatively, the parameter α_3 can be interpreted as the extra time required to reach a private residence versus other destinations, relative to the time required on the way back from a private residence versus other locations.

The identifying assumption requires a common trend between the treatment and control groups. In our context, this means that the difference in driving time between the two destination types would have been the same in the absence of a problem in locating the patient.[15] This condition cannot be directly tested because it requires counterfactual outcomes. However, it can be hypothesized that the problem arises primarily at the end of the first segment, once the ambulance is already close to the destination. If that is the case, the severity of the location problem should not be proportional to the distance driven by the ambulance. Therefore, Equation 4 is estimated for different groups of patients according to distance from the hospital, and the parameter α_3 should be similar across the groups while the other parameters might differ.

5 Results

The final sample is split into five groups according to distance from the hospital: < 5 km, ≥ 5 and <10, ≥ 10 and <15, ≥ 15 and <20, and ≥ 20. Equation 4 is estimated for each group.[16] The estimation results are reported in Table 3. For ease of interpretation, the plot of the parameters is presented in Figure 3. Each panel presents one of the parameters in Equation 4, and each point represents a different distance group.

The estimates of α_3 are positive, indicating that the difference in driving time between the two segments is greater when the destination is a private residence than some other destination type. The magnitude of the effect is stable across distance groups and is about 50% of the time required to drive back to the hospital, which is captured by α_0.

[15] Alternatively, the difference in driving time between the two segments would have been the same across destination types in the absence of a location problem.

[16] The distribution of distances is shown in Figure 2. The average distance travelled by an ambulance is 9 km, while the median distance in 6 km. About 90% of observations involve destinations within 20 kilometers of the hospital.

The magnitude of α_1 is small and not statistically different from zero. In other words, the driving time for other destinations is about the same for each segment. The estimates of α_2 are negative and significantly different from zero for two of the groups, implying that the time required to drive back to the hospital from a private residence might be less than that required to drive back from other destinations. The magnitude of α_0 increases with distance implying that the time required to drive back to the hospital from both other locations and private residences (given by the sum of parameters α_0 and α_2) increases with distance from the hospital.

5.1 Heterogeneity and Robustness of the Results

Table 4 reports the results across different age groups (< 35, ≥ 35 and < 65, and ≥ 65 year) and according to gender. The location problem, as represented by α_3, leads to 25% longer driving time for the younger group (column 1) and 40% in the other age groups (columns 2 and 3). The delay is 40% of the potential driving time for females and 50% for males (columns 4 and 5, respectively). As reported in Table 8 in the Appendix and as shown in Figure 6, the relationship between age and driving time is not statistically different across distance groups.

Table 5 reports the results according to a more detailed specification of the pathology. Cardiovascular, respiratory, neurological, psychiatric, and gastrointestinal disorders together with poisoning and injuries account for over 70% of emergency calls. The ambulance delay varies from 30-45% across pathologies, apart from a psychiatric disorder or poisoning, in which case the effect is about double that. These two outliers are probably associated with greater confusion on the part of the caller and therefore result in less clarity during the emergency call.

The plot of the results is presented in Figure 4.

Table 6 reports the estimates across distance groups for non-urgent calls.[17] The magnitude of the effect in this case is smaller than that in the case of urgent calls and is equal to about 35% of the time required to drive back to the hospital. A smaller effect is consistent with the idea that the location problem is exacerbated by unclear communication in the case of urgent calls due to the shock and fear of the moment, relative to non-urgent calls.

Table 7 reports additional results related to heterogeneity. Columns (1) and (2) report the results for missions carried out during the day and missions carried out at night, respectively.[18] It is reasonable to expect that the problem of locating the patient is exacerbated at night. Indeed, the delay is about 17% larger for missions that take place at night. In this case, the results are driven by the longer time taken to reach a residence, but also by the shorter time required on the way back, probably due to lighter traffic, as captured by α_0. Columns (3) and (4) report the results for the missions carried out during rush hour.[19] Given that the parameter of interest is calculated as the difference between driving times, it is expected that the effect will be smaller since rush hour traffic will delay the ambulance in both segments. Indeed, the estimates show that the effect is 8% smaller during rush hour.

Column (5) reports the results for the triple difference which is obtained by including non-urgent missions as well. The third difference is calculated between urgent and non-urgent missions. This allows us to compare ambulance perfor-

[17]The dispatch of an ambulance to respond to non-urgent calls can be deferred in favor of urgent calls. However, this does not affect the results discussed here since driving time is calculated from the ambulance's departure.

[18]Night time is defined as 10 pm to 6 am, as in David and Harrington (2010).

[19]Rush hour is defined as 7 am to 10 am and 5 pm to 7 pm.

mance across patients at the same type of location but with conditions of differing severity. The results for the third difference eliminate the compounding effect of factors that are fixed during the episode or that change during the episode but are unaffected by destination type or the severity of the patient's condition. The results indicate that reaching a patient in his home takes 0.78 minutes longer in the case of urgent calls. This represents about 6% of the time required to drive back to the hospital, as captured by α_0. This result supports the hypothesis that urgent calls are characterized by less clarity.

Finally, column (6) reports the result of a placebo test, in which other destinations are excluded from the sample. The sample is then randomly split into two groups and each is attributed a different destination type. The estimate of interest is not statistically different from zero, supporting the hypothesis that the problem of location is most relevant in the case of ambulance missions whose destination is the patient's residence.

6 How to mitigate the problem of location

The aim of responders to an emergency call is to reach the scene as quickly as possible. For this reason, the precision of the directions provided by the caller is of crucial importance in determining response time. New technologies are constantly being adopted by service providers in order to improve response time, such as computer-aided dispatch systems and mobile location systems installed in ambulances so that the call center can know their locations and dispatch the closest one to the event.[20]

[20] For further details about these technologies, see Athey and Stern (2002), among others.

In 2016, a new tool was developed to identify the location of a caller based on the data sent from his smartphone. The system does not require any previous download of applications and it automatically activates when an emergency number is dialed. In order, to receive the information conveyed by the caller's phone, the call center only has to install a plug-in into its management system.[21] The call center personnel need to be trained in order to correctly manage this additional source of information, which is the only cost of adopting the system. In order to reasonably estimate the efficiency gain, consider the following example: Assume that half of the calls take advantage of the system and that this halves the problem of locating the patient for the treated group. The result would then be a reduction in average driving time by 1.25 minutes, which is 8% of the average and 11% of a standard deviation. Thus, adopting a system of this kind would significantly improve performance and deliver more efficient use of available resources.

Lucchese (2020) and Wilde (2013) show that a one-minute change in ambulance response time affects the mortality of patients by about one percentage point. In Liguria, which is the source of our sample, there are about 100,000 urgent ambulance missions each year. This means that reducing the ambulance response time by one minute could potentially save 1,000 lives.

By assigning an economic value to a life, we can estimate the value of interventions aimed at reducing response time. The standard approach is to employ the Value of a Statistical Life (VSL) measure.[22] The version adopted here is that

[21]This technology has been built into Android phones since 2016 and into Apple phones since 2018. For further information, see the technical report DTR/EMTEL-00035 by the European Telecommunications Standards Institute (ETSI).

[22]VSL measures are intended to provide policymakers with a reference point to quantify the benefit of risk-reduction efforts. Viscusi and Aldy (2003) present a comprehensive review of the literature that developed VSL measures and discuss the main differences between the various approaches and their application in public policy decisions.

developed by Murphy and Topel (2006), according to which the value of a year of life is four times the individual's annual income. Given the gross annual income in Liguria, the value of reducing average response time by one minute would therefore be about 117 million euros per year, a sizable increase in welfare by any standard.

7 Conclusion

In emergency situations, a rapid response is of crucial importance to the outcome. A better understanding of the determinants of response time is important in order to formulate policies that improve the effectiveness of emergency services. The findings of the analysis indicate that the problem of locating the patient lengthens response time by about 5 minutes, which is about 30% of the time required to arrive at the scene.

It is often the case that an emergency call does not clearly communicate the caller's location to responders. Collecting location information directly from the caller's phone would improve the ability of responders to locate patients and would also reduce the cost of organizational forgetting due to personnel turnover, as discussed by David and Brachet (2011).

Recent technological developments allow the adoption of such a system at minimal cost. In Liguria, where ambulances perform about 100,000 urgent runs per year, the value of reducing response time by one minute is estimated at 117 million euros per year, such that the benefits clearly outweigh the cost.

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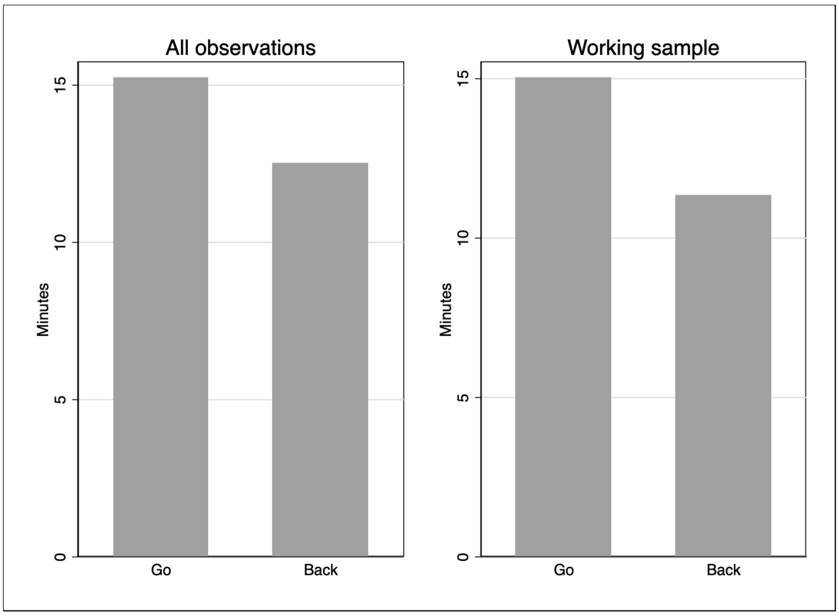
Appendix

Figure 1: Driving time by segment: from the dispatch to the scene of the accident (go) and from the scene to the hospital (back). All observations (left panel) and working sample (right panel)



NOTES: Driving times are expressed in minutes. The working sample includes only urgent missions in which the ambulance departed from the hospital to which the patient was transported.

Figure 2: Distribution of the distances covered by the ambulances (working sample)

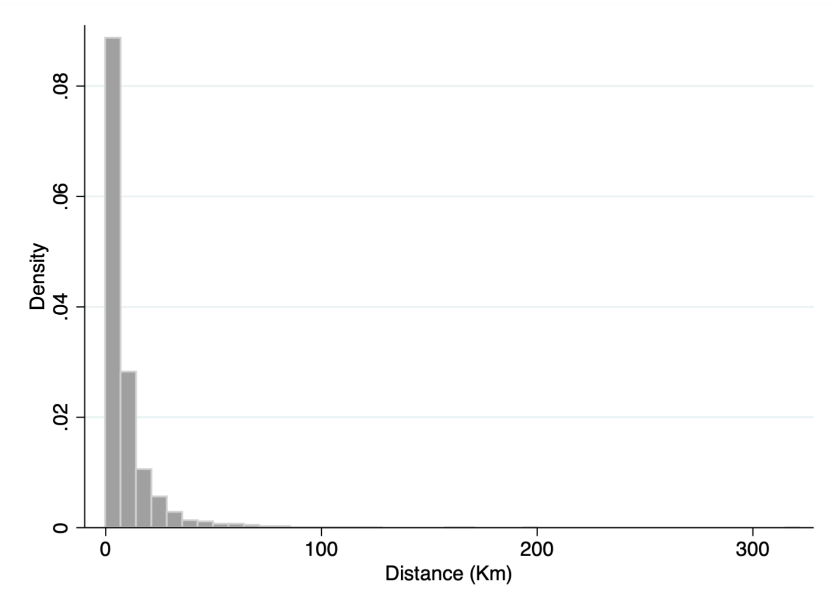
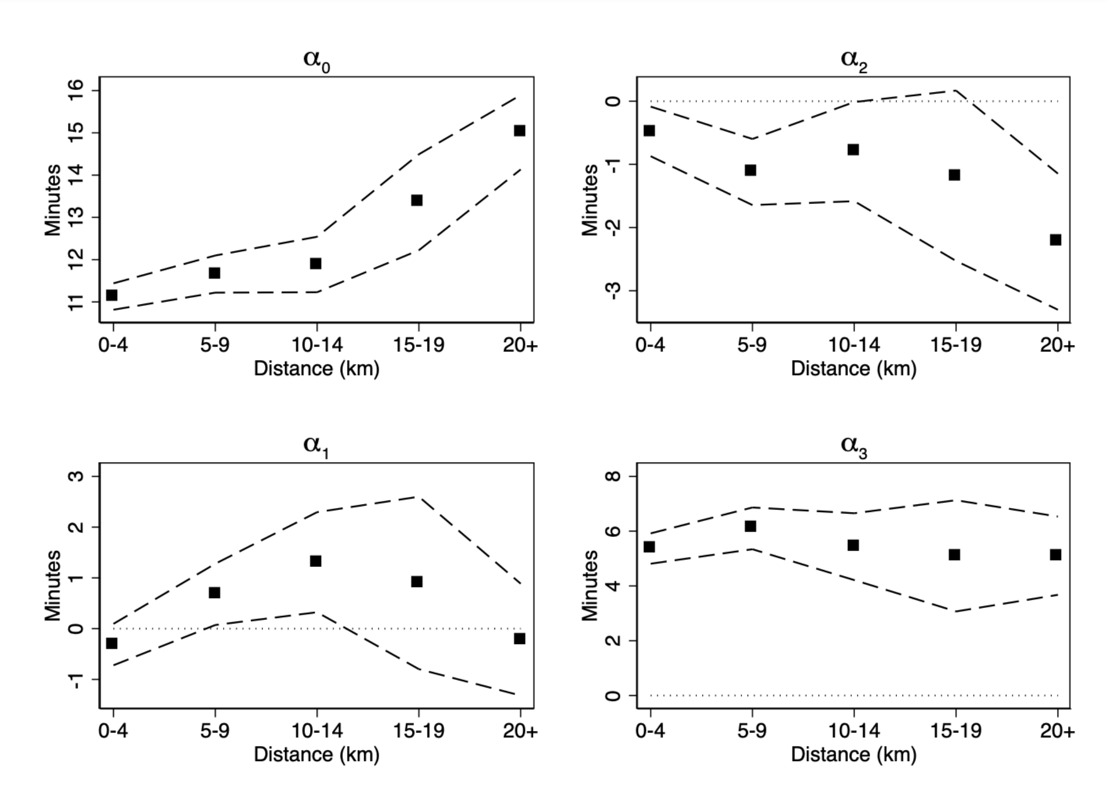
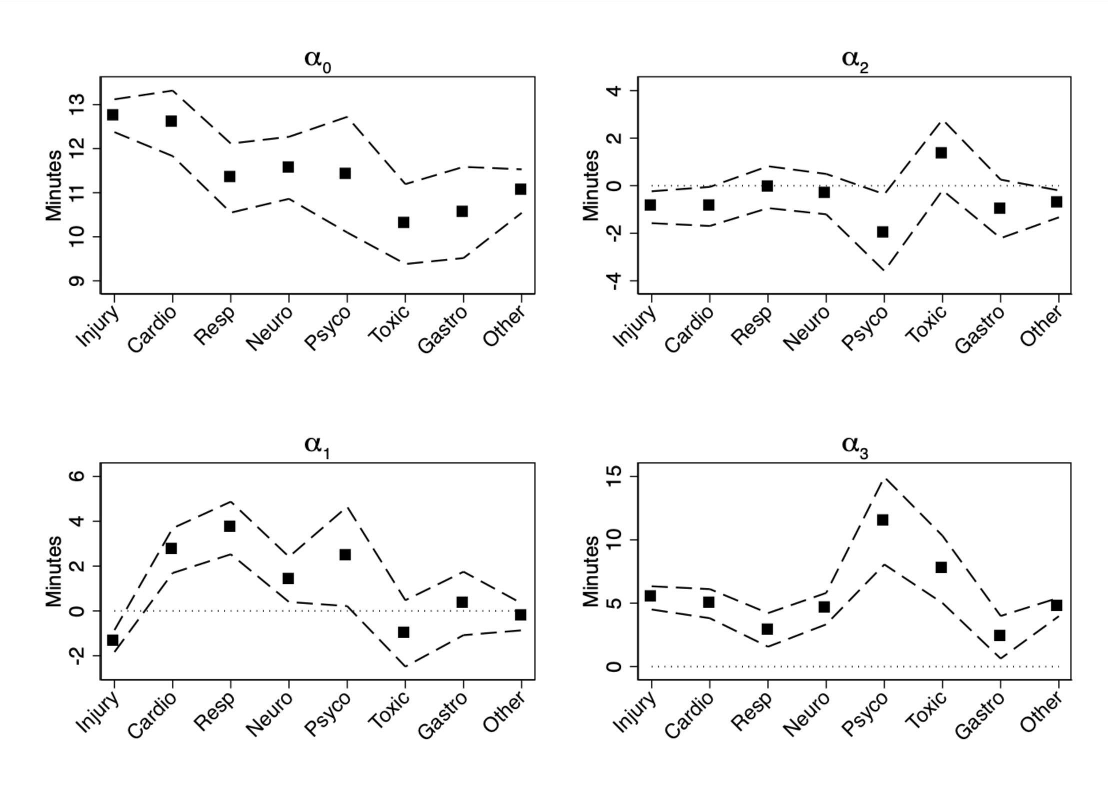


Figure 3: Plot of the estimated parameters by distance covered by the ambulance



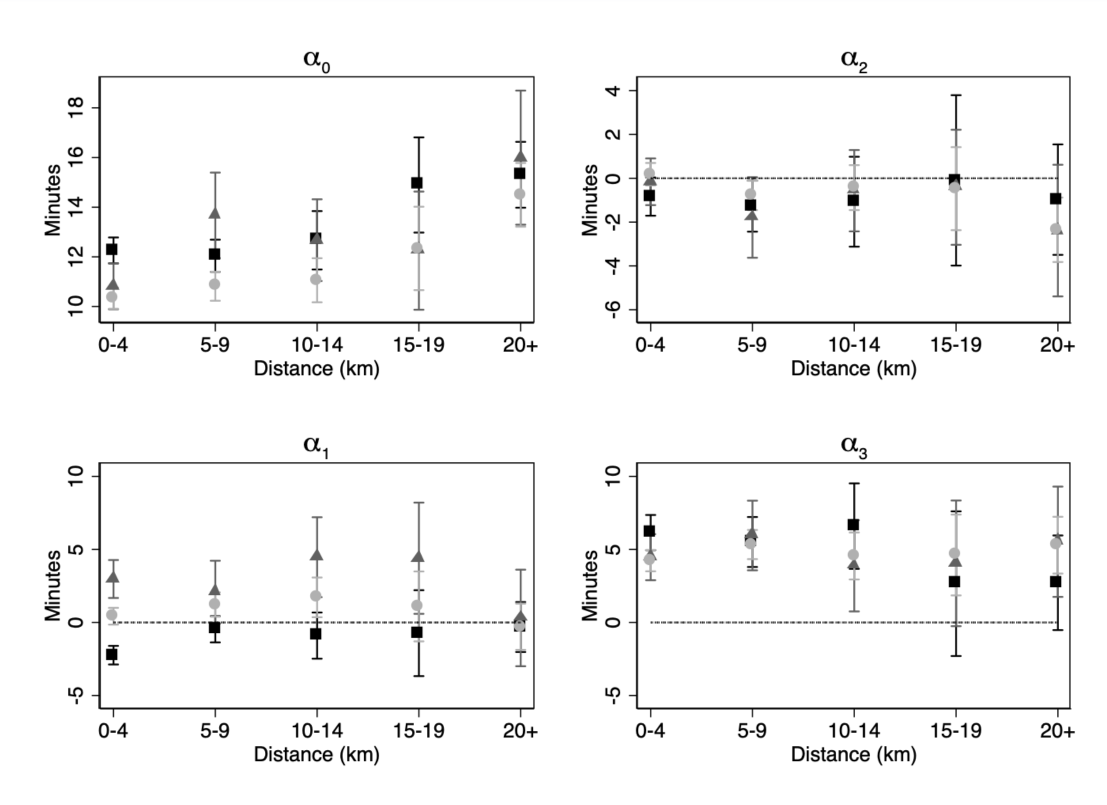
NOTES: Distances are grouped according to 0-4, 5-9, 10-14, 15-19 and ≥20 kilometers. The dashed lines represent the 95% confidence intervals.

Figure 4: Plot of the estimated parameters by type of pathology



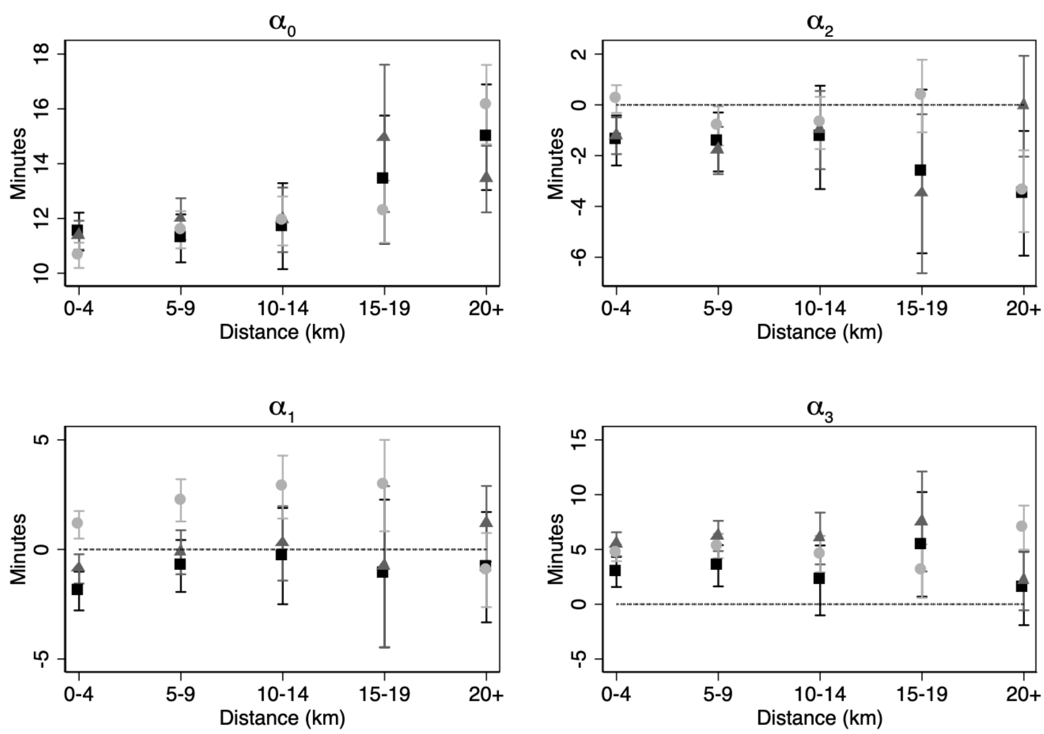
NOTES: The dashed lines represent the 95% confidence intervals.

Figure 5: Plot of the estimated parameter by distance and pathology



NOTES: Distances are grouped according to 0-4, 5-9, 10-14, 15-19 and ≥20 kilometers. The pathologies are grouped into injury (square), cardiovascular (triangle), and others (circle). The results are reported with 95% confidence intervals.

Figure 6: Plot of the estimated parameter by distance and patient's age



NOTES: Distances are grouped according to 0-4, 5-9, 10-14, 15-19 and ≥20 kilometers. Ages are grouped according to <35 year old (square), 35≥age<65 year old (triangle), and ≥65 year old (circle). The results are reported with 95% confidence intervals.

Figure 7: Distribution of the distances covered by the ambulances (non-urgent calls)

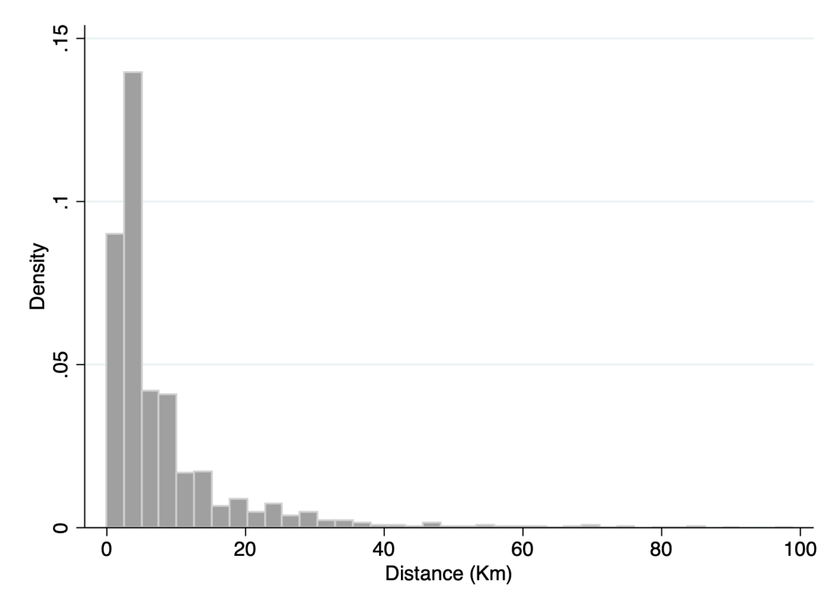
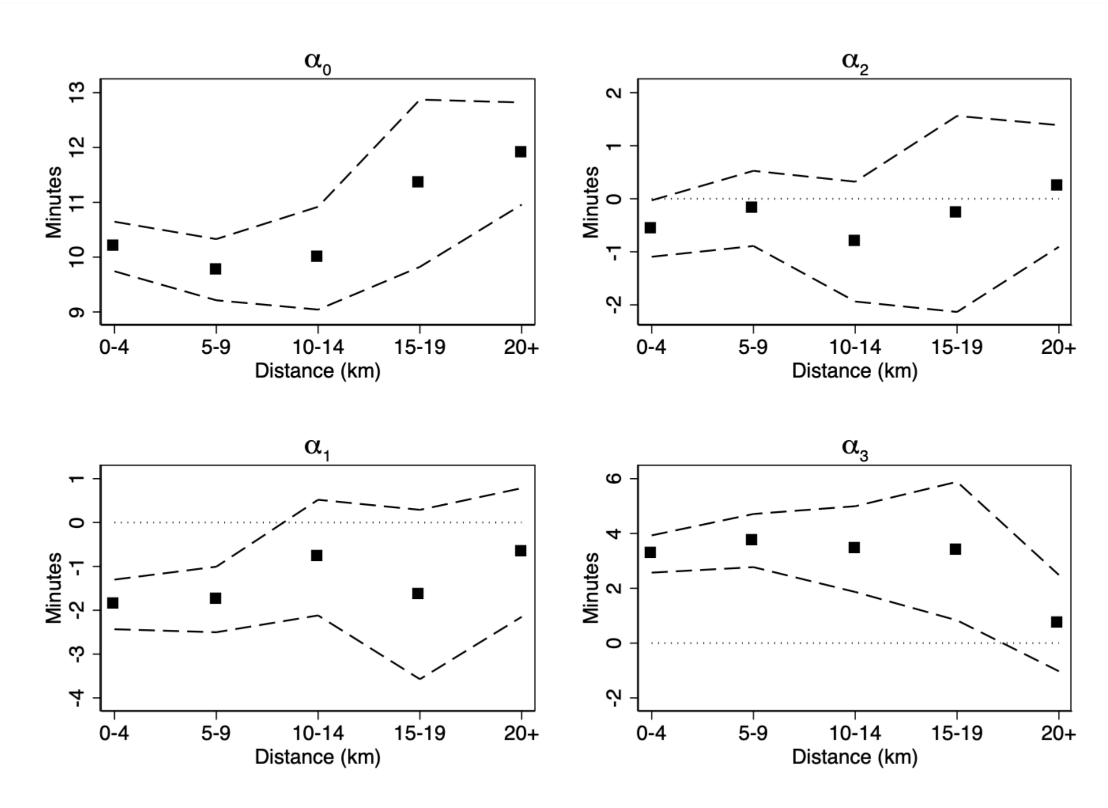


Figure 8: Plot of the estimated parameters by distance covered by the ambulance (non-urgent calls)



NOTES: Distances are grouped according to 0-4, 5-9, 10-14, 15-19 and ≥20 kilometers. The dashed lines represent the 95% confidence intervals.

Table 1: Sample Construction

Sample description or step	Observations
Raw mission data	646,574
Missions for which origin and final destination are the same	44,704
Drop missing origin and final destination	43,436
Drop low-priority ambulance missions and out-of-hospital deaths	30,916
Drop missing driving time and extreme values (1- or 120+)[1]	23,161
Drop missing distance	20,335
Drop missing patient's age or pathology	18,863

NOTES: [1] Driving times shorter than 1 minute or longer than 120 minutes are excluded.

Table 2: Descriptive Statistics

	Full sample		Working sample	
Variables	Mean	Std. Dev.	Mean	Std. Dev.
Driving time on the way there	15.2	(10.9)	15.0	(10.5)
Driving time on the way back	12.5	(11.9)	11.3	(9.3)
% Residence	61.9	(48.6)	62.2	(48.5)
Distance (Km)	17.5	(22.6)	8.9	(11.3)
% Injury	23.0	(42.1)	20.9	(40.7)
% Cardio	14.5	(35.2)	18.2	(38.6)
% Other	62.5	(48.4)	60.9	(48.8)
% Age (< 35)	16.7	(37.3)	14.1	(34.9)
% Age (35-64)	26.2	(44.0)	27.8	(44.8)
% Age (65+)	57.1	(49.5)	58.0	(49.4)
% High pop. density	52.8	(49.9)	81.1	(39.1)
% Medium pop. density	39.8	(49.0)	18.8	(39.1)
% Monday	14.5	(35.3)	15.5	(36.2)
% Tuesday	14.4	(35.1)	14.6	(35.4)
% Wednesday	14.3	(35.1)	14.2	(34.9)
% Thursday	14.1	(34.9)	14.3	(35.0)
% Friday	14.4	(35.1)	14.2	(34.9)
% Saturday	14.1	(34.8)	13.5	(34.1)
% Sunday	14.0	(34.7)	13.7	(34.4)
Observations	196,740		18,863	

Notes: The full sample includes all urgent calls. The final sample includes the urgent calls when the ambulance departed from the hospital to which the patient was brought.

Table 3: Estimated parameters by distance covered by the ambulance

	(1)	(2)	(3)	(4)	(5)
Go	-0.31	0.68**	1.31***	0.90	-0.22
	(0.21)	(0.31)	(0.50)	(0.87)	(0.56)
Residence	-0.48**	-1.12***	-0.80**	-1.18*	-2.22***
	(0.20)	(0.27)	(0.40)	(0.69)	(0.55)
Go × Residence	5.37***	6.10***	5.43***	5.10***	5.10***
	(0.28)	(0.39)	(0.62)	(1.04)	(0.73)
Constant	11.13***	11.66***	11.89***	13.36***	15.01***
	(0.16)	(0.22)	(0.33)	(0.58)	(0.45)
Distance (Km)	<5	5-9	10-14	15-19	≥20
Observations	16,566	10,472	4,486	2,172	4,030

NOTES: The distances are grouped according to <5, 5-9, 10-14, 15-19 and ≥20 kilometers. Robust standard errors appear in parenthesis.

Table 4: Estimated parameters by age group and gender

	(1)	(2)	(3)	(4)	(5)
Go	-1.29***	-0.35	1.41***	0.36	-0.00
	(0.34)	(0.26)	(0.25)	(0.23)	(0.23)
Residence	-1.71***	-1.29***	-0.67***	-0.81***	-1.02***
	(0.34)	(0.27)	(0.21)	(0.21)	(0.21)
Go $\times$ Residence	3.03***	5.61***	5.15***	5.01***	6.40***
	(0.50)	(0.39)	(0.29)	(0.29)	(0.30)
Constant	11.94***	11.98***	11.85***	11.68***	12.12***
	(0.25)	(0.20)	(0.18)	(0.18)	(0.17)
Group	<35	35-64	≥65	Female	Male
Observations	5,338	10,504	21,884	18,866	17,800

NOTES: The results by age group (<35, 35≥age<65, and ≥65 years) are reported in columns 1-3. The results by gender appear in columns 4-5. Robust standard errors appear in parenthesis.

Table 5: Estimated parameters by type of pathology

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Go	-1.34***	2.69***	3.70***	1.41***	2.43**	-1.00	0.33	-0.27
	(0.25)	(0.51)	(0.60)	(0.51)	(1.13)	(0.75)	(0.72)	(0.31)
Residence	-0.90***	-0.87**	-0.06	-0.35	-1.97**	1.30*	-0.97	-0.76***
	(0.34)	(0.42)	(0.45)	(0.43)	(0.82)	(0.76)	(0.63)	(0.29)
Go × Residence	5.42***	4.96***	2.89***	4.57***	11.50***	7.66***	2.31***	4.70***
	(0.47)	(0.59)	(0.68)	(0.63)	(1.76)	(1.35)	(0.86)	(0.37)
Constant	12.75***	12.57***	11.33***	11.57***	11.41***	10.29***	10.55***	11.04***
	(0.19)	(0.38)	(0.40)	(0.36)	(0.67)	(0.46)	(0.53)	(0.25)
Pathology	Injury	Cardio	Respiratory	Neuro	Psyco	Poison	Gastro	Other
Observations	7,900	6,862	4,502	3,974	1,128	1,028	1,492	10,840

NOTES: The pathology is reported at the bottom of the table. Robust standard errors appear in parenthesis.

Table 6: Estimated parameters by distance covered by the ambulance (non-urgent calls)

	(1)	(2)	(3)	(4)	(5)
Go	-1.87***	-1.75***	-0.80	-1.64*	-0.68
	(0.29)	(0.38)	(0.67)	(0.99)	(0.75)
Residence	-0.56**	-0.18	-0.81	-0.29	0.24
	(0.27)	(0.36)	(0.58)	(0.94)	(0.59)
Go $\times$ Residence	3.25***	3.74***	3.43***	3.36***	0.73
	(0.35)	(0.49)	(0.80)	(1.29)	(0.90)
Constant	10.19***	9.77***	9.98***	11.35***	11.89***
	(0.23)	(0.28)	(0.48)	(0.78)	(0.48)
Distance (Km)	<5	5-9	10-14	15-19	≥20
Observations	10,124	4,936	2,000	852	1,772

NOTES: The distances are grouped according to <5, 5-9, 10-14, 15-19 and ≥20 kilometers. Robust standard errors appear in parenthesis.

Table 7: Other estimate results: by time of day, traffic conditions, triple difference with severity of patient's condition, and placebo test.

	(1)	(2)	(3)	(4)	(5)	(6)
Go	0.07	0.66*	-0.15	0.64***	-2.83***	0.10
	(0.18)	(0.38)	(0.21)	(0.24)	(0.17)	(0.19)
Residence	-0.61***	-1.36***	-1.16***	-0.59***	-1.61***	
	(0.17)	(0.29)	(0.19)	(0.23)	(0.14)	
Go × Residence	4.99***	6.70***	6.09***	4.97***	4.36***	
	(0.24)	(0.44)	(0.27)	(0.33)	(0.22)	
Go × Urgent					3.45***	
					(0.17)	
Res. × Urg.					1.20***	
					(0.13)	
Go ×Res× Urg.					0.75***	
					(0.26)	
Placebo						-0.27
						(0.27)
Go × Placebo						0.32
						(0.37)
Constant	12.01***	11.47***	12.06***	11.71***	11.39***	11.99***
	(0.13)	(0.26)	(0.16)	(0.18)	(0.10)	(0.14)
	Day	Night	No traffictime	Traffictime	DDD	Placebo
Observations	27,510	10,216	23,446	14,280	57,686	14,262

NOTES: Robust standard errors in parenthesis.

Annexes

Table 8: Estimated parameters by distance covered by the ambulance and patient's age

Panel A: Age $<$ 35					
Distance (Km)	<5	5-9	10-14	15-19	≥20
	(1)	(2)	(3)	(4)	(5)
Go	-1.90***	-0.75	-0.31	-1.10	-0.81
	(0.45)	(0.60)	(1.12)	(1.72)	(1.28)
Residence	-1.40***	-1.46**	-1.28	-2.62	-3.48***
	(0.50)	(0.59)	(1.04)	(1.64)	(1.25)
Go × Residence	2.94***	3.51***	2.17	5.46**	1.44
	(0.70)	(0.96)	(1.63)	(2.43)	(1.71)
Constant	11.52***	11.27***	11.72***	13.42***	14.96***
	(0.35)	(0.45)	(0.80)	(1.19)	(0.98)
Observations	2,530	1,458	524	264	562
Panel B: Age 35 - 64					
Go	-0.89***	-0.13	0.28	-0.78	1.17
	(0.34)	(0.51)	(0.87)	(1.87)	(0.88)
Residence	-1.22***	-1.80***	-0.99	-3.50**	-0.05
	(0.37)	(0.48)	(0.79)	(1.60)	(1.01)
Go × Residence	5.48***	6.23***	6.00***	7.55***	2.14
	(0.56)	(0.70)	(1.21)	(2.33)	(1.37)
Constant	11.39***	11.98***	11.95***	14.93***	13.44***
	(0.27)	(0.39)	(0.60)	(1.37)	(0.62)
Observations	4,704	2,960	1,142	572	1126
Panel C: Age $\geq$ 65					
Go	1.12***	2.24***	2.85***	2.91***	-0.94
	(0.32)	(0.49)	(0.73)	(1.06)	(0.86)
Residence	0.23	-0.83**	-0.71	0.35	-3.40***
	(0.28)	(0.39)	(0.52)	(0.73)	(0.82)
Go × Residence	4.69***	5.31***	4.57***	3.02**	6.99***
	(0.39)	(0.57)	(0.85)	(1.25)	(1.03)
Constant	10.65***	11.59***	11.91***	12.24***	16.16***
	(0.24)	(0.35)	(0.46)	(0.58)	(0.74)
Observations	9,332	6,054	2,820	1,336	2,342

NOTES: Distances are grouped according to 0-4, 5-9, 10-14, 15-19 and ≥20 kilometers. Panel A reports the results for patients <35 years old, panel B for patients 35≥age<65 years old, and panel C for patients ≥65 years old. Robust standard errors appear in parenthesis.

Table 9: Estimated parameters by distance covered by the ambulance and patient's pathology

Panel A: Injury					
Distance (Km)	<5	5-9	10-14	15-19	≥20
	(1)	(2)	(3)	(4)	(5)
Go	-2.24***	-0.47	-0.90	-0.73	-0.31
	(0.33)	(0.46)	(0.81)	(1.50)	(0.87)
Residence	-0.84*	-1.27**	-1.07	-0.10	-0.98
	(0.45)	(0.59)	(1.05)	(1.98)	(1.29)
Go × Residence	6.15***	5.51***	6.60***	2.66	2.72
	(0.61)	(0.87)	(1.49)	(2.53)	(1.65)
Constant	12.26***	12.04***	12.67***	14.89***	15.30***
	(0.27)	(0.33)	(0.60)	(0.98)	(0.68)
Observations	3,740	2,018	748	452	942
Panel B: Cardiovascular					
Go	2.98***	2.07*	4.47***	4.40**	0.31
	(0.66)	(1.10)	(1.40)	(1.94)	(1.69)
Residence	-0.16	-1.79*	-0.57	-0.41	-2.39
	(0.54)	(0.94)	(0.95)	(1.34)	(1.53)
Go × Residence	4.47***	5.95***	3.88**	4.05*	5.53***
	(0.80)	(1.22)	(1.59)	(2.19)	(1.93)
Constant	10.81***	13.67***	12.67***	12.25***	15.99***
	(0.47)	(0.88)	(0.84)	(1.21)	(1.38)
Observations	2,432	2,094	1,020	486	830
Panel C: Other					
Go	0.43	1.23***	1.72**	1.10	-0.29
	(0.29)	(0.42)	(0.69)	(1.22)	(0.81)
Residence	0.19	-0.78**	-0.43	-0.47	-2.35***
	(0.26)	(0.34)	(0.52)	(0.97)	(0.75)
Go × Residence	4.23***	5.33***	4.55***	4.62***	5.29***
	(0.37)	(0.51)	(0.82)	(1.41)	(0.99)
Constant	10.33***	10.82***	11.06***	12.34***	14.50***
	(0.22)	(0.30)	(0.45)	(0.86)	(0.65)
Observations	10,394	6,360	2,718	1,234	2,258

NOTES: Distances are grouped according to 0-4, 5-9, 10-14, 15-19 and ≥20 kilometers. Panel A reports the results for injured patients, panel B for patients experiencing a cardiovascular event, and panel C for other pathologies. Robust standard errors appear in parenthesis.