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**Manuscript title: Does Every Minute Really Count? Road Time as an
Indicator for the Economic Value of Emergency Medical Services**

Running title: Road Time for Economic Value of EMS

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ABSTRACT

Objectives: This article builds on the literature regarding the association between emergency medical service (EMS) response times and patient outcomes (death and severe injury). Three issues are addressed in this paper with respect to the empirical estimation of this relationship: the endogeneity of response time (systematically quicker response for higher degrees of urgency), the non-linearity of this relationship, and the variation between such estimations for different patient outcomes.

Methods: Binomial and multinomial logistic regression models are used to estimate the impact of response time on the probabilities of death and severe injury using data from French Fire and Rescue Services (FRS). These models are developed with (total) response time as an explanatory variable, and then with *road time* hypothesized as representing the exogenous variation within (total) response time. Both models are also applied to data subsets based on response time intervals.

Results: The results show that *road time* yields a higher estimate for the impact of response time on patient outcomes than (total) response time. The impact of *road time* on patient outcomes is also shown to be non-linear. These results are of both statistical significance (model coefficients are significant at the 95% confidence level) and economical significance (when taking into account the number of annual interventions performed).

Conclusions: When using heterogeneous data on EMS interventions where endogeneity is a clear issue, *road time* is a more reliable indicator to estimate the impact of EMS response time on patient outcomes than (total) response time.

HIGHLIGHTS I

- Empirical work on the impact of EMS response time on patient outcomes has provided mixed results.

HIGHLIGHTS II

- This paper displays the endogenous characteristics of response time when estimating its impact on patient outcomes, and provides a novel solution to the estimation of this relationship by using *road time*.

HIGHLIGHTS III

- This paper will help health-care decision makers better understand the relationship between response time and patient outcomes. The results can contribute to more reliable evaluation of policies aimed at optimising EMS response time.

Introduction

Background

Emergency medical services (EMS) are confronted like many public sectors by a requirement to develop their operations within a conjuncture of dwindling budgets and resources. In order to guarantee optimal societal decision making, it is therefore essential that these services reliably measure the societal impact of their actions to facilitate economic evaluation within a cost-benefit framework.

Such economic evaluation is useful for public decision-making because it can bring clarity to the benefits that can be expected from a public investment and thus help to rationalise the decision-making process. With regards to EMS, these benefits correspond primarily to avoided deaths, for which there have been significant efforts to develop a monetary value, most notably through the Value of a Statistical Life (VSL)¹.

Response time is a key element of EMS because the very nature of medical emergencies implies that they must be treated urgently. (Total) response time measures the time frame from the moment an emergency call is made, to the moment an equipped vehicle arrives on the scene, and can be divided into three sub-sections: *call time* (from the moment the call is taken by a handler, to the moment the alert is raised), *gathering time* (from the moment the alert is sent out, to the moment a medical team is dispatched) and *road time* (from dispatch to arrival on the scene).

In France, around 15,000,000 calls are received each year by the ambulance service² and close to 19,000,000 calls by the Fire and Rescue Service (FRS)³. By comparison, around 11,000,000 calls are received on an annual basis by the UK ambulance service⁴, whilst the US fire department receives over 20,000,000 calls per year for medical aid⁵.

There is a significant societal burden associated to calls for emergency medical aid. Between 2015 and 2018, FRS in France took charge of close to 10,000,000 patients for some form of medical assistance, of which around 1,000,000 suffered severe injury and close to 215,000 died⁶.

The mean response time for FRS in France is currently around 14 minutes⁷. This is much greater than the top-tier EMS response times observed in the UK and USA of between 7 and 8 minutes for the greatest degree of medical emergency^{8,9}. It is, however, inferior to second-tier ambulance response in the UK which stands at around 20 minutes. According to Cabral et al¹⁰, average EMS response time is under 10 minutes in a number of European countries.

The impact of response time on patient outcomes has received relatively little attention from economists despite significant work in operations research and the use of System Status Management (SSM) to optimise response time by adapting EMS supply to demand^{11,12}. Response time can also represent a form of quality control for EMS services: the lower the response time, the higher the quality of the service for citizens. This can be perceived through the wide use of response time as a performance indicator¹³ and as a benchmark by public decision makers¹⁴. Nevertheless, increasing the cover of EMS services by reducing response time will always have a cost. It is therefore in the societal interest to determine the optimum level of EMS and adjust public spending in these services accordingly.

To facilitate such societal decision making with regards to the cover provided by EMS services, one must be able to estimate the benefits that will result from increasing cover, or the costs from reducing it, in order to then compare them with the financial cost or savings associated to such changes. These societal impacts can be quantified as the risk to human life and provide the basis for the approach presented in this article, relating response time to different patient outcomes.

Literature

Lerner et al¹⁵ concluded that there have not been many studies that attempt to determine the economic value of out-of-hospital emergency care. The existing literature relating response time to patient outcomes is largely limited to medical research based on out-of-hospital cardiac arrest¹⁶⁻²⁴ or trauma victims²⁵⁻²⁹. However, there is definitely not a clear consensus on the impact of EMS response time on patient outcomes³⁰⁻³⁵. Furthermore, the scope of this research does not address the overall impact of EMS response times on patient outcomes when considering heterogeneous interventions.

One notable study from Wilde³⁶ that does address this issue raised the question of the endogeneity of response time. To quote her: *“EMS personnel may respond more quickly to the most serious and life-threatening situations. Such triage makes it difficult to obtain unbiased estimates of the benefits of lower response times, even when data are available”*. Such downward bias could lead to incorrect conclusions being made regarding the efficiency of public policy with regards to optimising EMS response time. She addressed this issue using the distance between the nearest EMS agency headquarters and the scene of the incident as an instrumental variable. Our work will aim to provide further evidence with regards to the endogeneity of response time using a different estimation procedure.

In the Thai context, marginal effects of response time on patient outcomes for different EMS interventions were calculated from logistic regression models and translated to a cost-benefit framework using a Thai-specific VSL³⁷. The same form of model has also been used to assess the impact of response time on life-saving from residential fires³⁸. This form of model provides the empirical framework for our paper.

The existing literature also raises the question of the non-linearity of the impact of response time on patient outcomes. Two approaches have been suggested and/or applied in the literature: Jaldell et al³⁷ suggest using a moving average estimation by subsetting the dataset to provide a better fit, whilst Ma et al³⁹ use an additive model to estimate smooth associations between response time and patient outcomes. Assuming a linear relationship is a very strong assumption, and with a view to using marginal effects within a cost-benefit analysis (CBA) framework, such an assumption could lead to the use of incorrect estimates if the impact of response time were to vary greatly at different response time intervals. This would be of particular nuisance to the economic evaluation of public policies aimed at optimising response time. For example, if the impact of response time on patient outcomes is non-linear, then the evaluation of a policy capable of reducing response time from 10 to 9 minutes could prove unreliable if an average marginal effect - calculated on data spreading a wide range of response times - was used to estimate the reduction in the probability of observing some given patient outcomes associated to the policy.

There have been few studies which associate probabilities of severe injury to response time. Jaldell et al³⁷ found that response time had a greater effect on the probability of severe injury than on death. Wilde³⁶ found that the probability of hospitalisation increased with response time. This research suggests that the societal benefits associated to reductions in response time are not limited to reducing patient fatalities. Should this be the case, the impact of response time on non-fatal patient outcomes should also be monetised in CBA of policies optimising response time. Nevertheless, the study of such outcomes seems to have been largely neglected in the literature on response time. This is surprising given that there can be significant costs associated to severe injury, both from a medical point of view in terms of hospitalisation costs, but also from a societal perspective in terms of utility. There are of course limits to such approaches given that,

for example in France, monetary values that exist for severe injury are simply based on an arbitrary percentage of VSL⁴⁰: $3,000,000\text{€} \times 0.15 = 450,000\text{€}$.

The aforementioned papers that calculate the marginal effect of response time on patient outcomes use logistic regression techniques because this is the most common statistical approach to estimating probabilities associated to discrete variables. By associating a change in response time to a change in the probability of observing a given patient outcome, one can determine the societal benefits of a reduction in response time by multiplying the appropriate VSL by this estimate, as has been shown in previous research³⁷. This is pertinent to the theoretical foundations of VSL because changes in risk exposure can be directly related through the utility function: $E(U) = (1-R) U(y)$.

Research Objectives

Three hypotheses are formulated from the key points raised above: 1. the impact of response time on patient outcomes is underestimated in data with heterogeneous EMS interventions; 2. the impact of response time on patient outcomes is non-linear; 3. response time has a significant impact on the probability of severe injury, one that diverges from its impact on the probability of death.

The first hypothesis deals with the endogeneity problem raised by Wilde³⁶. In this paper, *road time* is used in the estimation equation for the impact of response time on patient outcomes and is compared to (total) response time.

The second hypothesis addresses the question of the non-linearity of the impact of response time on patient outcomes. Following the suggestion of Jaldell et al³⁷, this paper subsets data into 5-minute, overlapping intervals in order to provide a more flexible estimation procedure in the

interest of determining whether the impact of a delay in EMS response time on observed patient outcomes is linear across different time intervals, or whether it is increasing or decreasing.

The third hypothesis assesses the impact of response time on the probability of severe injury. Jaldell et al³⁷ found that the marginal effect of response time is greater for severe injury than for death. Our work will aim to replicate or reject this finding using a different dataset.

Methods

Data

Data was collected over a four-year period (2015-2018) from three French *départements* (an administrative unit of a similar size to an English county). This dataset covers all interventions carried out by FRS under the category *emergency assistance to individuals* - excluding fire rescue. The French context is a very distinctive case where FRS respond to a wide range of incidents: from critical medical emergencies to road traffic accidents. Each *département* is graded A, B or C - an index based primarily on population size.

A data request was made across all *départements* making up mainland France (of which there are 20 graded A, 37 graded B and 40 graded C). FRS were contacted through the national network of financial controllers, 29 *départements* acknowledged the request, but only 4 provided appropriate data. A sample containing one *département* from each category was thus established and used for the estimations within this article. The representativeness of the sample is discussed in the discussion section.

This dataset most notably includes response time divided into the sub-sections of *call time*, *gathering time* and *road time*. These time intervals are transmitted by the intervention team to the call handler and entered into a centralised database. Patient outcomes are measured on an ordinal

scale with values of *uninjured*, *slight injury*, *severe injury* and *death*. This scale is systematically used across FRS in France. These outcomes are determined by the head of the intervention team at the moment of patient discharge or upon arrival at a hospital. Deaths could be observed at any time during the intervention (on arrival at the scene, when administering emergency medical aid or during transport).

Model

This paper deploys both a binomial and multinomial logistic model to estimate the marginal effects of response time and *road time* on patient outcomes. The binomial model considers the binary case of *death* and *survival*, whilst the multinomial model uses *unharmed* (as the sum of *uninjured* and *slight injury*) as the reference level of the dependent variable, with an estimation for both *severe injury* and *death*. Marginal effects are calculated for each model to reflect the change in a delay of one minute on the probability of observing a given patient outcome. A full description of these models can be found in the appendix.

Estimation

Equation 1 displays the estimation procedure for the binomial model:

$$\log\left(\frac{P(Y = \text{Death})}{P(Y = \text{Survival})}\right) = \beta_0 + \beta_1 x_1 + \beta_2 \text{Victim_Age} + \beta_3 \text{Victim_Gender} + B_K \cdot X_i \quad (1)$$

x_1 represents response time in model 1 and *road time* in model 2. X_i corresponds to K vectors of dummy variables associated to different *département* categories, different years and different intervention categories (*critical medical emergency*, *physical trauma*, *road traffic accident* and

other). Models 3 and 4 follow the exact same procedure for the multinomial case. These four models use all data points for response times inferior to 60 minutes.

Data sub-samples are then created across different response time intervals and a different model estimated across each interval for both the binomial and multinomial cases. The first interval is composed of response times from 4-8 minutes (yielding the marginal effect at 6 minutes), the second from 5-9 minutes and so on, up to the interval 38-42 minutes, beyond which data becomes too sparse.

Results

Descriptive data in Table 1 provides an overview of the profile of victims' age and sex, as well as the different sub-sections of response time in relation to the observed patient outcomes in each *département* making up the sample. Figure 1 displays the distribution of interventions by response time for each category of *département*. Figure 2 displays the proportion of observed deaths at each minute of *call time*, *gathering time*, *road time* and (total) response time.

Table 2 displays the results of the four regression models using all data points. (Total) response time displays a negative coefficient in Model 1 and this result is statistically significant, thus suggesting that probability of death is decreasing in response time. By comparison, model 2 provides a positive coefficient for *road time* which is also statistically significant and indicates that probability of death is increasing in response time. Model 3 displays a positive and statistically significant coefficient for the impact of (total) response time on probability of severe injury. This same coefficient remains statistically significant and grows in magnitude when using *road time* as the explanatory variable.

The marginal effects can be calculated using the regression coefficients from Table 2. Using the results of model 4, we obtain average marginal effects of 0.02 and 0.1 percentage points for the increases in probability of death and severe injury with respect to a one-minute delay in *road time*.

The results of the moving average models are represented graphically in Figures 3 and 4. These graphics present the marginal effects which have been calculated after estimating the logistic regression models for each sub-sample, using *road time* as the primary explanatory variable. Figure 3 shows that probability of death is increasing in response time at all time intervals. However, this effect is not linear (all data points would form a horizontal line in the presence of perfect linearity). Figure 3 shows that a one-minute delay has the greatest impact on probability of death when response time is between 15 and 20 minutes. The marginal effect of a one-minute delay in response time in this interval is approximately 0.2 percentage points.

Figure 4 provides additional insight regarding the impact of *road time* on probability of severe injury. The data points show that the probability of severe injury is increasing across all levels of response time, but unlike in the case of death, the marginal effect is greatest for response times superior to 30 minutes, at which point the marginal effect is approximately 0.25 percentage points.

Discussion

Interpretation of Results

One can observe from Figure 1 that the number of interventions varies greatly according to the category of *département*. Furthermore, response times are lower in A category *départements* where more interventions are performed compared to B and C categories. Longer *road time* for B

and especially C graded *départements* suggests that these are more rural areas. Longer *gathering time* for C graded *départements* is most likely due to the fact that rural areas are manned by volunteer rather than full-time staff.

Our results show that the impact of a delay in response time on patient outcomes is significantly different when using *road time* as the unit of measure in place of (total) response time. The motivations for using *road time* are based on the possible endogeneity problem related to (total) response time. We hypothesize that any endogeneity in response time is most likely due to *call time*, where human perception of an urgency can influence the rapidity of response. Such a relationship can be observed in Figure 2. The negative coefficients obtained in models 1 and 3 are counterintuitive and we suggest that this is because (total) response time displays strong endogenous characteristics leading to model misspecification. This could explain the reason that previous research has not always identified a statistically significant relationship between response time and patient outcomes. We believe that *road time* should therefore be preferred in any future research.

Our results have also demonstrated that estimating the average marginal effect of response time on patient outcomes provides very different results depending on the response time interval used in the estimation procedure. This is a result of the non-linearity of the relationship between response time and patient outcomes visible in Figures 3 and 4. The average marginal effect of a one-minute delay in response time on probability of death is ten times greater when estimated across the response time interval 17-21 minutes than the average marginal effect estimated across the full dataset.

With regards to the impact of delays in EMS response time on the probability of severe injury, our initial results replicate those of Jaldell et al³⁷, showing that the magnitude of the impact of

such a delay (measured in our case by *road time*) is greater on probability of severe injury than death. However, the estimations displayed in Figures 3 and 4 suggest that the magnitude of this impact depends very much on the response time interval being studied. Similar estimates could not be found for neighbouring European countries in peer-reviewed work.

Finally, given the desire to use such estimations in CBA, it is important to consider the monetary values that would be associated to these marginal effects. Were one to use the values currently employed in France⁴⁰, the marginal effect of response time on the probability of death would be multiplied by 3,000,000€ and the marginal effect for severe injury by 450,000€. Given the magnitude of the estimated marginal effects and how greatly they have been shown to vary in this paper over different response time intervals, it is easy to see that the use of an inappropriate estimate would lead to incorrect monetary benefits being associated to a policy aimed at optimising response time.

Limits

By using *road time* in our estimation procedure instead of (total) response time, we implicitly assume that the impact of any change in *road time* on patient outcomes is equivalent to any identical change in (total) response time. That is to say that there is perfect substitution between *call time*, *gathering time* and *road time*. We believe this to be a reasonable assumption to make in order to circumvent the endogeneity problem.

Whilst our results provide evidence that *road time* can reduce bias due to endogeneity when estimating the impact of response time on patient outcomes, there are still reasons that could lead to some downward bias when using this variable in the estimation procedure. For example, the behaviour of emergency response vehicle drivers could lead to higher driving speeds for more

urgent interventions, thus leading to a lower *road time*. Perhaps a greater problem relates to the possibility of vehicles being strategically dispatched from different zones closer or further from the scene - based on the degree of urgency - to reduce the probability of simultaneous interventions within the same sector. This would lead to greater endogeneity in *road time*. One could also imagine that the topography and meteorological conditions could lead to statistical noise in the estimation procedure using *road time*.

Our work does not consider the role of *on-scene-time* and *time-to-hospital*. This particular topic is treated in the literature covering the *golden hour* principle^{41,42} and did not form part of the research goals of this paper. We do, however, realise that these time intervals could have an impact on the observed patient outcomes in our dataset.

Furthermore, the notion of patient outcomes used in our dataset is what one could categorise as *intermediate* outcomes because they translate the health state when the patient is discharged from the EMS vehicle crew to the hospital staff. There is clearly a need to quantify *final* patient outcomes with regards to EMS interventions. This, however, remains tricky due to the logistical and administrative difficulties involved in tracking patients from the moment they are taken charge of by EMS until their dispatch from hospital.

Our sample appears to lack some representativity with respect to mainland France as a whole. Over the period studied, the average response times for A, B and C graded *départements* in mainland France were respectively 11min2sec, 11min41sec and 12min52sec. By comparison, our samples provide averages of 7min56sec, 8min57sec and 11min12sec. In terms of activity volume, average annual intervention numbers were respectively 72,156, 29,588 and 12,479. This compares to averages from our sample of 129,056, 51,263 and 15,358. The proportion of

observed deaths across all interventions was 0.017, 0.021 and 0.026 respectively. Our sample presents values of 0.012, 0.019 and 0.026.

Average response times of the A, B and C graded *départements* used in this study are thus significantly lower than national averages, and EMS intervention numbers significantly higher. We would therefore suggest that these three *départements* represent a level of performance above the national average. It is nonetheless difficult to say what might be the impact of this on the representativity of our results. We would expect that if response time is already optimised in these *départements*, then our model estimates may be lower than would otherwise be so.

Future Research

We would hope to address some of the potential issues related to the exogeneity of *road time* in future research with data covering a larger array of French *départements*. Further empirical studies into the use of *road time* as an estimator for the impact of EMS response time on patient outcomes in other contexts would be welcomed. It would also be interesting to see work on this topic dealing simultaneously with *call time*, *gathering time*, *road time*, *on-scene time* and *time-to-hospital*, as we are not aware of any such existing research. Finally, given that the findings of our paper further develop the growing literature on the relationship between EMS response times and non-fatal patient outcomes^{36,37}, we believe further research should be conducted on this relationship.

Conclusions

This paper presents a novel solution to the endogeneity problem of response time by estimating the impact on patient outcomes using *road time*. Working with heterogeneous EMS intervention data from French FRS, we find that the probabilities of both death and severe injury are

increasing in *road time*. We obtained lower estimates when using (total) response time within the same model framework, and thus suggest that endogeneity is a significant problem when performing such estimations on heterogenous EMS data. Our data suggest that this endogeneity is primarily driven by *call time*. Furthermore, we find that the marginal effect of *road time* on patient outcomes is non-linear, and that this non-linear relationship varies for different outcomes. These findings can help to produce more reliable CBA of public policies aimed at optimising EMS response time to improve patient outcomes.

References

1. OECD. *Mortality Risk Valuation in Environment, Health and Transport Policies*. OECD Publishing; 2012.
2. Haute Autorité de Santé. *Évaluation de la prise en charge des urgences – SAMU SMUR et soins critiques*. https://www.has-sante.fr/upload/docs/application/pdf/2020-11/fiche_pedagogique_urgences_samu_smur.pdf
3. Direction Générale de la Sécurité Civile et de la Gestion des Crises (DGSCGC). *Les Statistiques Des Services d'Incendie et de Secours (Édition 2018) ; 2018*. Available from : <https://mobile.interieur.gouv.fr/Publications/Statistiques/Securite-civile/2017>. [Accessed August 20, 2021]
4. National Audit Office. *NHS Ambulance Services ; 2017*. Available from : <https://www.nao.org.uk/wp-content/uploads/2017/01/NHS-Ambulance-Services.pdf>. [Accessed August 20, 2021]
5. National Fire Protection Agency. *NFPA Fire Experience Survey*. Available from: <https://www.nfpa.org/News-and-Research/Data-research-and-tools/Emergency-Responders/Fire-department-calls>. [Accessed August 20, 2021]
6. Direction Générale de la Sécurité Civile et de la Gestion des Crises (DGSCGC). *Les Statistiques Des Services d'Incendie et de Secours ; 2015-2018*. Available from : <https://mobile.interieur.gouv.fr/Publications/Statistiques/Securite-civile>. [Accessed August 20, 2021]
7. Direction Générale de la Sécurité Civile et de la Gestion des Crises (DGSCGC). *Les Statistiques Des Services d'Incendie et de Secours (Édition 2020) ; 2020*. Available from : <https://www.interieur.gouv.fr/fr/Publications/Statistiques/Securite-civile/2019>. [Accessed August 20, 2021]
8. Kay I. *Ambulance Quality Indicators (AQI) Statistical Note, 13 May 2021; 2021*. Available from: <https://www.england.nhs.uk/statistics/statistical-work-areas/ambulance-quality-indicators/ambulance-quality-indicators-data-2021-22/>. [Accessed August 20, 2021]
9. Mell HK, Mumma SN, Hiestand B, et al. *Emergency medical services response times in Rural, Suburban, and Urban areas*. *JAMA Surg*. 2017;152(10):983-984.
10. Cabral EL dos S, Castro WRS, Florentino DR de M, et al. *Response time in the emergency services*. *Acta Cir Bras*. 2018;33(12):1110-1121.
11. Goldberg JB. *Operations Research Models for the Deployment of Emergency Services Vehicles*. *EMS Manag J*. 2004;1(1):20-39.
12. Lam SSW, Zhang J, Zhang ZC, et al. *Dynamic ambulance reallocation for the reduction of ambulance response times using system status management*. *Am J Emerg Med*. 2015;33(2):159-166.

13. Al-Shaqsi SZK. *Response time as a sole performance indicator in EMS: Pitfalls and solutions*. Open Access Emerg Med. 2010;(2):1-6.
14. NHS Providers. *The ambulance service: understanding the new standards*. Available from: <https://nhsproviders.org/the-ambulance-service-understanding-the-new-standards>. [Accessed August 13, 2021].
15. Lerner EB, Maio RF, Garrison HG, Spaite DW, Nichol G. *Economic Value of Out-of-Hospital Emergency Care: A Structured Literature Review*. Ann Emerg Med. 2006;47(6):515-524.
16. Lee DW, Moon HJ, Heo NH. *Association between ambulance response time and neurologic outcome in patients with cardiac arrest*. Am J Emerg Med. 2019;37(11):1999-2003.
17. Bürger A, Wnent J, Bohn A, et al. *The effect of ambulance response time on survival following out-of-hospital cardiac arrest-an analysis from the German resuscitation registry*. Dtsch Arztebl Int. 2018;115(33-34):541-548.
18. Chang I, Lee SC, Shin S Do, et al. *Effects of dispatcher-assisted bystander cardiopulmonary resuscitation on neurological recovery in paediatric patients with out-of-hospital cardiac arrest based on the pre-hospital emergency medical service response time interval*. Resuscitation. 2018;130:49-56.
19. Kłosiewicz T, Skitek-Adamczak I, Zielinski M. *Emergency medical system response time does not affect incidence of return of spontaneous circulation after prehospital resuscitation in one million central European agglomeration residents*. Kardiol Pol. 2017;75(3):240-246.
20. Rajan S, Wissenberg M, Folke F, et al. *Association of Bystander Cardiopulmonary Resuscitation and Survival According to Ambulance Response Times after Out-of-Hospital Cardiac Arrest*. Circulation. 2016;134(25):2095-2104.
21. O’Keeffe C, Nicholl J, Turner J, Goodacre S. *Role of ambulance response times in the survival of patients with out-of-hospital cardiac arrest*. Emerg Med J. 2011;28(8):703-706.
22. Vukmir RB. *Survival from prehospital cardiac arrest is critically dependent upon response time*. Resuscitation. 2006;69(2):229-234.
23. Chase D, Roderick P, Cooper K, et al. *Using simulation to estimate the cost effectiveness of improving ambulance and thrombolysis response times after myocardial infarction*. Emerg Med J. 2006;23(1):67-72.
24. Gold LS, Fahrenbruch CE, Rea TD, Eisenberg MS. *The relationship between time to arrival of emergency medical services (EMS) and survival from out-of-hospital ventricular fibrillation cardiac arrest*. Resuscitation. 2010;81(5):622-625.
25. Nasser AAH, Nederpelt C, El Hechi M, et al. *Every minute counts: The impact of pre-hospital response time and scene time on mortality of penetrating trauma patients*. Am J Surg. 2019;220:240-244.

26. Harmsen AMK, Giannakopoulos GF, Moerbeek PR, et al. *The influence of prehospital time on trauma patients outcome: A systematic review*. *Injury*. 2015;46(4):602-609.
27. Byrne JP, Mann NC, Dai M, et al. *Association between Emergency Medical Service Response Time and Motor Vehicle Crash Mortality in the United States*. *JAMA Surg*. 2019;154(4):286-293.
28. Mahama MN, Kenu E, Bandoh DA, Zakariah AN. *Emergency response time and pre-hospital trauma survival rate of the national ambulance service, Greater Accra (January - December 2014)*. *BMC Emerg Med*. 2018;18(1):3-9.
29. Ali Ali B, Fortún Moral M, Belzunegui Otano T, et al. *Influence of prehospital response times in the survival of trauma patients in Navarre*. *An Sist Sanit Navar*. 2015;38(2):269-278.
30. Blackwell TH, Jay S, Kaufman. *Response time effectiveness: comparison of response time and survival in an urban emergency medical services system*. *Acad Emerg Med*. 2002;9(4):288-295.
31. Blackwell TH, Kline JA, Willis JJ, Hicks GM. *Lack of association between prehospital response times and patient outcomes*. *Prehospital Emerg Care*. 2009;13(4):444-450.
32. Blanchard IE, Doig CJ, Hagel BE, et al. *Emergency medical services response time and mortality in an urban setting*. *Prehospital Emerg Care*. 2012;16(1):142-151.
33. Weiss S, Fullerton L, Oglesbee S, Duerden B, Froman P. *Does ambulance response time influence patient condition among patients with specific medical and trauma emergencies?* *South Med J*. 2013;106(3):230-235.
34. Pons PT, Markovchick VJ. *Eight minutes or less: does the ambulance response time guideline impact trauma patient outcome?* *J Emerg Med*. 2002;23(1):43-48.
35. Pons PT, Haukoos JS, Bludworth W, et al. *Paramedic response time: Does it affect patient survival?* *Acad Emerg Med*. 2005;12(7):594-600.
36. Wilde E. *Do emergency medical system response times matter for health outcomes?* *Health Econ*. 2008;1131(2007):1127-1131.
37. Jaldell H, Lebnak P, Amornpetchsathaporn A. *Time Is Money , But How Much ? The Monetary Value of Response Time for Thai Ambulance Emergency Services*. *Value Heal*. 2014;17(5):555-560.
38. Runefors M. *Measuring the Capabilities of the Swedish Fire Service to Save Lives in Residential Fires*. *Fire Technol*. 2019;56:583-603.
39. Ma L, Zhang H, Yan X, Wang J, Song Z, Xiong H. *Smooth associations between the emergency medical services response time and the risk of death in road traffic crashes*. *J Transp Heal*. 2019;12:379-391.
40. Commissariat Général à la stratégie et à la prospective. *L'évaluation Socio-Économique Des Investissements Publics* ; 2013. Available from :

https://www.strategie.gouv.fr/sites/strategie.gouv.fr/files/atoms/files/cgsp_evaluation_socioeconomie_29072014.pdf. [Accessed 20 August, 2021]

41. Newgard CD, Schmicker RH, Hedges JR, et al. *Emergency Medical Services Intervals and Survival in Trauma: Assessment of the “Golden Hour” in a North American Prospective Cohort*. *Ann Emerg Med*. 2010;55(3):235-246.
42. Dinh MM, Bein K, Roncal S, Byrne CM, Petchell J, Brennan J. *Redefining the golden hour for severe head injury in an urban setting: The effect of prehospital arrival times on patient outcomes*. *Injury*. 2013;44(5):606-610.

Fig. 1 - Distribution of response time for each category of *département*

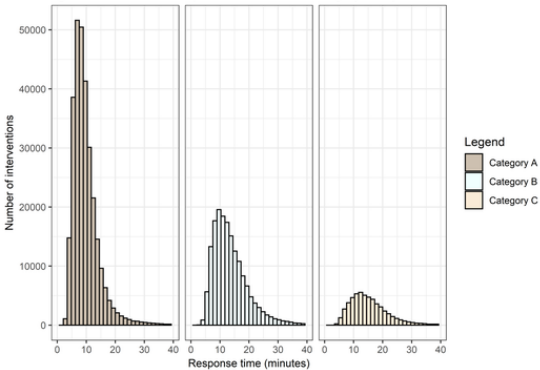


Fig. 2 - Possible sources of endogeneity in response time

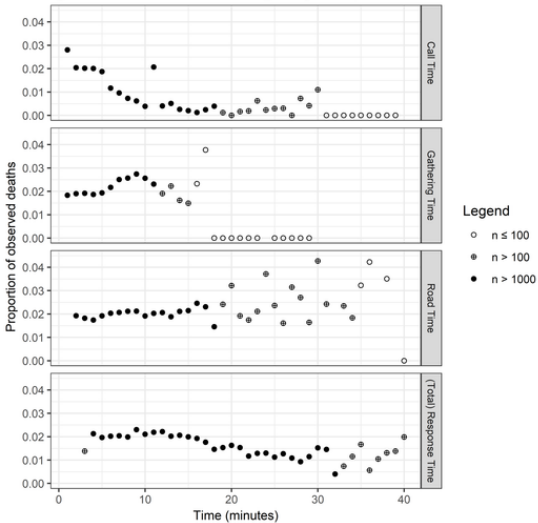


Fig. 3 - Non-linearities in the marginal effect of *road time* on probability of death

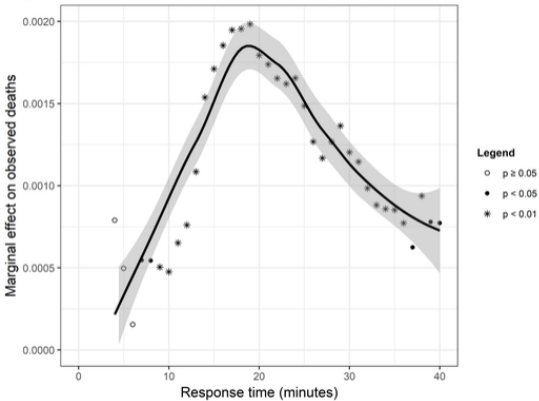


Fig. 4 - Non-linearities in the marginal effect of road time on different patient outcomes

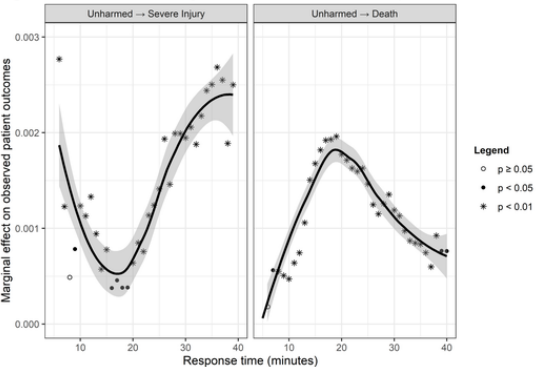


Table 1: Observed patient outcomes by sex, age and response time sub-sections

CATEGORY	DEATH			SEVERE INJURY			UNHARMED			OVERALL		
	A (n=5,816)	B (n=2,985)	C (n=1,511)	A (n=27,862)	B (n=4,038)	C (n=7,556)	A (n=264,026)	B (n=161,805)	C (n=46,648)	A (N=297,704)	B (N=168,828)	C (N=55,715)
MALE	3,732 (64.2%)	1,899 (63.6%)	1,034 (68.4%)	16,083 (57.7%)	2,352 (58.2%)	4,629 (61.3%)	136,950 (51.9%)	83,090 (51.4%)	24,647 (52.8%)	156,765 (52.7%)	87,341 (51.7%)	30,310 (54.4%)
FEMALE	2,084 (35.8%)	1,086 (36.4%)	477 (31.6%)	11,779 (42.3%)	1,686 (41.8%)	2,927 (38.7%)	127,076 (48.1%)	78,715 (48.6%)	22,001 (47.2%)	140,939 (47.3%)	81,487 (48.3%)	25,405 (45.6%)
VICTIM AGE												
Mean	66.1	68.2	67.9	58.1	55.5	57.8	46.9	48.7	53.0	48.3	49.2	54.1
(SD)	(18.4)	(18.1)	(18.7)	(24.1)	(25.3)	(25.2)	(26.2)	(26.9)	(27.3)	(26.2)	(26.9)	(26.9)
Median	67.0	70.0	70.0	62.0	58.0	61.0	45.0	48.0	54.0	48.0	49.0	56.0
[Min, Max]	[0, 103]	[0, 99.0]	[1.00, 99.0]	[0, 108]	[0, 99.0]	[0, 99.0]	[0, 115]	[0, 99.0]	[0, 99.0]	[0, 115]	[0, 99.0]	[0, 99.0]
Missing	0 (0%)	0 (0%)	30 (2.0%)	0 (0%)	0 (0%)	121 (1.6%)	0 (0%)	0 (0%)	817 (1.8%)	0 (0%)	0 (0%)	968 (1.7%)
CALL TIME												
Mean	1.35	2.84	2.78	1.54	4.25	4.35	1.98	4.85	4.07	1.93	4.80	4.07
(SD)	(1.81)	(2.34)	(2.03)	(2.42)	(3.50)	(3.48)	(3.44)	(4.04)	(3.86)	(3.34)	(4.01)	(3.78)
Median	0.983	2.17	2.28	1.03	2.98	3.33	1.18	3.37	2.67	1.17	3.32	2.72
[Min, Max]	[0.517, 46.4]	[0.517, 29.1]	[0.517, 23.0]	[0.517, 50.1]	[0.567, 29.0]	[0.517, 29.8]	[0.517, 56.2]	[0.517, 30.0]	[0.517, 30.0]	[0.517, 56.2]	[0.517, 30.0]	[0.517, 30.0]
GATHERING TIME												
Mean	2.87	2.97	4.83	2.80	3.04	5.18	2.67	3.09	4.64	2.69	3.09	4.71
(SD)	(1.93)	(1.38)	(2.96)	(1.86)	(1.51)	(3.01)	(1.79)	(1.52)	(2.96)	(1.80)	(1.52)	(2.97)
Median	2.15	2.72	4.22	2.10	2.75	4.65	2.07	2.82	3.70	2.07	2.82	3.80
[Min, Max]	[0.517, 15.7]	[0.517, 13.2]	[0.517, 23.6]	[0.517, 19.4]	[0.517, 26.2]	[0.517, 22.3]	[0.517, 21.6]	[0.517, 28.5]	[0.517, 22.8]	[0.517, 21.6]	[0.517, 28.5]	[0.517, 23.6]
ROAD TIME												
Mean	5.45	6.11	7.39	5.46	6.21	7.22	5.18	5.85	6.70	5.21	5.86	6.79
(SD)	(3.76)	(5.17)	(5.89)	(3.53)	(5.15)	(5.66)	(3.18)	(4.40)	(4.76)	(3.23)	(4.43)	(4.93)
Median	4.72	4.98	6.08	4.73	5.00	6.00	4.50	4.77	5.73	4.52	4.78	5.80
[Min, Max]	[1.02, 55.7]	[1.02, 53.3]	[1.02, 50.7]	[1.02, 54.5]	[1.02, 52.9]	[1.02, 52.6]	[1.02, 57.5]	[1.02, 55.2]	[1.02, 55.8]	[1.02, 57.5]	[1.02, 55.2]	[1.02, 55.8]

Note: Patient outcomes *slight injury* and *uninjured* are combined under the outcome heading *unharmmed*. SD corresponds to standard deviation, Max to maximum value and Min to minimum value. Response times are displayed in minutes so that 5.5 is equal to 5 minutes and 30 seconds.

Table 2: Logistic regression models of patient outcomes on response time and road time

BINOMIAL REGRESSION MODELS			MULTINOMIAL REGRESSION MODELS		
	MODEL 1	MODEL 2	(REF=UNHARMED)	MODEL 3	MODEL 4
RESPONSE TIME	-0.030*** (0.002)		SEVERE INJURY	0.004*** (0.001)	
			DEATH	-0.029*** (0.002)	
ROAD TIME		0.009*** (0.002)	SEVERE INJURY		0.017*** (0.001)
			DEATH		0.012*** (0.002)
VICTIME AGE	0.026*** (0.0005)	0.026*** (0.0005)	SEVERE INJURY	0.013*** (0.0002)	0.014*** (0.0002)
			DEATH	0.028*** (0.0005)	0.030*** (0.0005)
VICTIM GENDER (MALE=1)	0.668*** (0.022)	0.664*** (0.021)	SEVERE INJURY	0.368*** (0.011)	0.365*** (0.011)
			DEATH	0.727*** (0.022)	0.723*** (0.022)
CATEGORY B (REF=CATEGORY A)	0.492*** (0.025)	0.390*** (0.025)	SEVERE INJURY	-0.008 (0.015)	-0.007 (0.015)
			DEATH	-0.023 (0.029)	-0.036 (0.029)
CATEGORY C (REF=CATEGORY A)	0.827*** (0.033)	0.637*** (0.032)	SEVERE INJURY	-0.039** (0.015)	-0.038** (0.015)
			DEATH	0.032 (0.029)	0.013 (0.029)
2016 (REF=2015)	-0.022 (0.029)	-0.036 (0.029)	SEVERE INJURY	-0.099*** (0.015)	-0.097*** (0.015)
			DEATH	-0.223*** (0.029)	-0.238*** (0.029)
2017 (REF=2015)	0.035 (0.029)	0.016 (0.029)	SEVERE INJURY	-1.182*** (0.018)	-1.180*** (0.018)
			DEATH	0.363*** (0.025)	0.264*** (0.025)
2018 (REF=2015)	-0.202*** (0.029)	-0.216*** (0.029)	SEVERE INJURY	0.633*** (0.016)	0.630*** (0.016)
			DEATH	0.951*** (0.034)	0.767*** (0.032)
TRAUMA (REF=CRITICAL MEDICAL EMERGENCY)	-3.018*** (0.063)	-2.998*** (0.063)	SEVERE INJURY	-1.295*** (0.017)	-1.294*** (0.017)
			DEATH	-3.184*** (0.063)	-3.164*** (0.063)
ROAD TRAFFIC ACCIDENT (REF=CRITICAL MEDICAL EMERGENCY)	-1.868*** (0.058)	-1.872*** (0.058)	SEVERE INJURY	-0.997*** (0.023)	-1.007*** (0.023)
			DEATH	-2.000*** (0.058)	-2.007*** (0.058)
OTHER (REF=CRITICAL MEDICAL EMERGENCY)	-2.154** (0.025)	-2.165*** (0.025)	SEVERE INJURY	-1.346*** (0.013)	-1.342*** (0.013)
			DEATH	-2.329*** (0.025)	-2.340*** (0.025)
CONSTANT	-4.399*** (0.046)	-4.708*** (0.044)	SEVERE INJURY	-2.334*** (0.022)	-2.382*** (0.021)
			DEATH	-4.312*** (0.046)	-4.623*** (0.044)

Note: Regression coefficients and their statistical significance: * p<0.1; ** p<0.05; *** p<0.01. Standard errors in brackets.