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Emergency Department Departures: Untangling the Complexities of Early Exits in a Large Italian region

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SUMMARY

Leaving Emergency Departments (ED) early is an important failure of these structures, constituting a risk for the health of the people who renounce the benefits of such healthcare, and a cost to the countries that finance healthcare service for their citizens. In order to implement actions to reduce the extent of this failure, an understanding of the characteristics of patients who leave EDs early is needed. This research scrutinizes the determinants of early ED departure in the hospitals of the region of Campania, Italy, where around a tenth of the Italian population lives. We adopt a quantitative framework, utilizing a novel robust dataset of about 1,000,000 observations, employing both Probit and Logit estimators. Our analysis reveals that factors including being a woman, having Italian citizenship, arriving by ambulance, severity of condition, and reporting a trauma, are associated with decreased probability of premature ED departure, while residing in high-income municipalities and being under 65 correlates with an increased likelihood of early leaving. The value of this information for policymakers and healthcare providers is discussed.

Keywords: Emergency Department; Early Emergency Department Departure; Healthcare Access; Patient Decision-making; Emergency Department Efficiency

BACKGROUND

Premature departure (i.e. before the conclusion of visit procedures) from the Emergency Department (ED) of a hospital is an important problem that poses health risks for individuals who forego the benefits of available healthcare. Moreover, it is a waste of the limited resources of EDs [1], and a public cost for countries that provide healthcare to their citizens. Indeed, as is well known, various governments around the world offer health services to their citizens without requiring the final user to (directly) pay for these. An extensive scientific debate discusses the economic efficiency of these situations, which is largely unrelated to the medical nature of the specific service, and which can more generally be referred to the nature of common goods, an approach that goes back to Hardin's seminal article [2]. Indeed, given the well-known and widely studied incentives for consumers to consume more than needed when they do not pay for a good, an ample scientific debate deals with the issue. Usually, when it comes to health, economists try to find the optimal balance in a difficult trade-off between economic efficiency and giving equal opportunities to citizens from different backgrounds.

Countries with largely publicly funded healthcare, although the extent to which it is free at the point of use varies, such as the United Kingdom (where the National Health Service provides healthcare that is free at the point of use for residents, funded through taxation), Sweden (where patients usually pay small fees for visits, while some services, like child healthcare, are free), Norway (where patients pay co-payments until they reach an annual limit, after which further care is free), Spain (where the public healthcare system offers universal coverage, and most services are free for residents, with some groups, like unemployed citizens, receiving completely free care), and Italy (where the National Health Service provides free healthcare for residents, covering services like doctor visits, emergency care, and hospitalization, while some specialist services may require co-payments), differ

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significantly in their political institutions and social structures. These differences have been analysed in detail in the comparative healthcare literature [3,4].

Among these countries, of particular interest is the case of Italy, a nation where the vast majority of health services are provided to citizens by the public healthcare system, which is paid for mostly with taxpayers' money, with no, or with very limited, direct charges to users [5].

The literature suggests that when a government provides health services without asking for a payment from the final user, there is an increase in their utilization, particularly among the unemployed and less educated [6], and that this leads to a reduction of household health expenditure [7,8]. On the other hand, while the implementation of user fees has been suggested to have economic benefits as well [9] – although issues of equal access need to be addressed – the point has also been raised that individual fees inevitably elevate the financial burden borne by individuals and alleviate the redistribution of wealth from affluent and healthy individuals to those who are economically disadvantaged and unwell [10]. It has also been suggested that there is a risk that free government health services may primarily benefit the better-off, suggesting the need for targeting measures and alternative financing mechanisms [11].

While of general importance, optimizing the delivery of health services to users is even more important when these services are offered for free, since some market-created incentives that would improve efficiency in a scenario where the final user directly pays are not in place in the case of healthcare funded by the taxpayer. Among these services, we believe the case of EDs to be of special interest, for at least three reasons. First, reducing the number of unnecessary visitors to EDs is a crucial means of preventing their congestion and keeping these departments operating smoothly, which is important given the fundamental role they play in safeguarding people's health, and the fact that by their very nature these departments work with emergencies. Second, a patient who leaves an ED prematurely signifies the inadequacy of an emergency care delivery system in achieving its objectives of delivering assistance to individuals requiring urgent medical attention [12]. Notably, it has already been suggested that patients who leave EDs before the doctor's visit are a useful indicator of the quality of emergency care [13]. Hence, it seems important to understand who leaves early and why, in order to suggest policies that may improve the efficacy of these departments. Third, financing EDs involves considerable cost to public expenditure, and hence optimizing the process is an important way to avoid unnecessary public spending and a waste of public resources.

Among all the challenges involved in running an ED, avoiding having patients who abandon the ED before their visit procedures have concluded is crucial, if this investment of public money is to be optimized. Abandoning an ED before the conclusion of visit procedures incurs a considerable public cost for countries that offer this service to their citizens, such as Italy. It happens frequently; in 2019 and in the first two months of 2020 (i.e. before the COVID-19 emergency erupted in Italy, imposing lockdowns and creating incentives to avoid hospitals), there were 214,757 of these events in hospitals in Campania (a region of Italy) alone. Of these over a quarter, 54,722 patients, left before even seeing a physician. The cost for a white code, i.e. a visit to the ED that is not considered an emergency by the doctors, and hence is not supported by public spending (a provision created to prevent citizens from visiting the ED as a way of avoiding the lengthier non-emergency route to access to healthcare), was established in Italy by law 296/2006 as being €25, for patients who did not benefit from any supplementary exam or visit by a specialist. Using this very conservative estimate as the baseline cost imputed to those early leavers (and please note that this is the bare minimum to be considered), to compute the waste of resources one should also add the cost of an ambulance bringing the patient there (9,914 of the aforementioned cases who left hospital before their treatment had concluded were brought to the hospital by an ambulance).

Hence, if we estimate an ambulance call at having an average cost of €150 (a cost which depends, obviously, on the distance, though for relative short rides €150 is usually the minimum price requested by private ambulances), the total cost of these events was €5,368,925 for curtailed visits, plus €1,487,100 for ambulance rides, giving a total of €6,856,025 for the fourteen months considered. Assuming that this waste that occurred in Campania is representative of the rest of Italy, given that the region hosts around a tenth of the Italian population (5.802 million out of a population of 59.11 million), the national cost of this early leaving would be about €4,897,160 per month. Considering the very conservative attitude adopted in this estimation the real expenditure would appear to be considerable, and this could be avoided, or at the very least reduced, by knowing more about the characteristics of patients that abandon EDs before the conclusion of their treatment. This would allow hospitals and policymakers to implement policies designed specifically to address these subjects and reduce this inefficiency.

Previous scientific literature suggests that patients leave the ED for a variety of reasons, including long waiting times, spontaneous resolution of symptoms, and dissatisfaction with staff or facilities. These findings emerge across different national contexts: Carmel et al. analyzed patients in Israel, which operates a universal health insurance model with public and non-profit health plans [14]; Fernandes et al. examined the Canadian system, which offers universal, publicly funded healthcare at the provincial level [15]; Fry et al. investigated this behavior in Australia, which also has a universal healthcare system supported by Medicare [16]; Hsia et al. studied the phenomenon in the United

States, where access to care is often contingent on private insurance coverage[12]; Lee et al. reported on Hong Kong, which provides a predominantly public healthcare system funded through taxation [17]; and Lerner addressed the issue within the U.S. system [18], like Weiss et al., which focuses on dissatisfaction with staff communication [19]. More recent work by Rowe et al., which focuses on symptom improvement [20], and Mohsin et al., both in Australia, a system with universal healthcare [21], and Mahmoudian-Dehkordi et al. in Iran, a mixed public-private system, confirms similar motives in different contexts [22].

Low acuity ratings are particularly associated with early departure, as shown in studies from Canada [15,23], and again in the U.S. [24]. The study by Hsia et al. underscores that patients with limited insurance coverage, a uniquely U.S. concern, are more likely to leave without being seen [12]. Demographically, those who leave early are often younger, single men with less severe conditions, as observed by Carmel et al. in Israel [14].

Nonetheless, it is important to highlight that most of these previous findings are obtained in countries with very different healthcare systems and cultures (the previous cited articles use data from countries including Australia, Canada, Hong Kong, Israel, Taiwan, and the US). This heterogeneity may easily create distinct sets of incentives for the patients to decide to stay or leave, leading to limited external validity for these results. For instance, consider the relevance of having health insurance to such a decision for patients in the US, where ED visits must often be paid for, as compared to Italy.

To the best of our knowledge, there are a few retrospective studies focusing on the consequences of leaving ED early, but there is no contribution that specifically examines the characteristics of patients that do so in Italy. In Italy, ED departments are usually open 24/7, and patients may arrive via ambulance services or independently. Following the initial diagnosis, the triage process commences, determining whether patients should be admitted, and with what level of priority, or discharged. A colour code is assigned to the patient, according to the severity of his/her condition, and hence according to the urgency of receiving treatment. EDs contend with heightened service demand, leading to elevated costs. Additionally, EDs typically function within the constraints of limited human resources and budgetary allocations [1]. One study has highlighted that this lack of available literature makes it critical to identify the determinants that could be associated with visits to the ED [25], and that this acquiring knowledge is essential for directing interventions at the hospital level to enhance the accessibility of emergency medical services [12]. This seems especially important, since as of now efficiency measurements assessing performance in the emergency department lack uniformity and standardization [26]. Moreover, a retrospective cohort study of Lazio's EDs suggests that patients that leave before being visited by a doctor have a greater risk of ED re-admission compared to discharged patients, even though the effects on hospitalization and mortality are more controversial [13].

In the present study, we aim to fill this gap in the literature by identifying the characteristics of both the patients that left the ED before being visited by a physician, and those that left before the closure of their medical record (i.e. the conclusion of the procedure). We do so by means of a quantitative analysis that exploits data about all the patients that visited EDs in Campania, Italy, between 1 January 2019 and 28 February 2020 (a cut-off point chosen in order to prevent the COVID-19 emergency from affecting our findings).

Our results, obtained through regression analysis with both Probit and Logit estimators, suggest that distance from the ED does not affect the decision to leave early, while being a woman, being an Italian citizen, living in a municipality with higher education levels, arriving at the ED by ambulance, having a more serious condition, and being in the ED because of trauma, are all characteristics correlated with a lower probability of leaving the ED early. Moreover, being under 65 years old (for all the sub-categories of age considered), and residing in a municipality with higher income per capita are characteristics correlated with a higher probability of leaving early.

METHODS

To identify the characteristics correlated with leaving the ED early within a quantitative framework, we require data about ED patients, their socio-demographic characteristics, and information about the specific context of their experience. For our main source of data we relied on the STAR-EMUR Regione Campania's dataset on ED admissions in each hospital of the region. This source offers micro-level data about every patient in every ED of all of Campania's hospitals, and it is the only official one for Italy. It is compiled for the Italian Superior Institute of Health (Istituto Superiore di Sanità) by each hospital and offers micro-level data about each and any patient in all the hospital EDs in the Campania region. Data contains anonymised individual-level data for each ED admission, including the patient's age, gender, municipality of residence, and nationality (Italian or not). It also reports how the patient arrived at the ED (e.g., ambulance or other means), the exact time of check-in and of the medical consultation (if any), and the primary reason for seeking emergency care, as recorded in the triage assessment. No personal identifiers or clinical history are included, in full compliance with privacy regulations.

We gathered these data from 2019 to the end of February 2020, to avoid the inclusion of data from the COVID-19 emergency and the related restrictions on movement, which are likely to affect both the dynamic of going to the ED and of leaving it early.

Unfortunately, no information is provided in this dataset about education or income level of the patient, which may affect the decision to leave early.

To enrich the set of data on which we perform our analysis, we attached to the aforementioned dataset the following data:

- Data about the geographical location of the hospitals in Campania, in order to be able to calculate the distance between the residence of the patient, as gathered in the previous dataset, and the ER.
- The distance, expressed in time (minutes), that is required to travel between the patient's municipality of residence and the hospital (data taken from the Italian National Statistic Agency – ISTAT);
- The per capita taxable income from work in the patient's municipality of residence (data taken from the Italian Revenue Agency);
- The share of population over 9 years old in the municipality that in 2021 (last available census data) had a secondary education (high school) diploma (both data about the education level and the population are taken from ISTAT) to obtain a measure of education.

In this way, we managed to impute to each observation information that are unfortunately not available at the individual level. Given both the size of the sample (we included 980,579 observations for the regression that has as dependent variable the patients that left before the closure of the medical record, and 806,194 for those that left before being seen by a doctor, i.e. all those who survived the listwise deletion process), and the small size of many municipalities (the average population of the municipalities present in the sample is just 15,429.51 inhabitants), we believe that this strategy is empirically reliable, since the municipality average is representative enough of the observations to which it is imputed.

With these operations, we built a dataset with information about patients that left the ED early, both before being seen by a physician (labelled "Leaves before Being Visited") and before the closure of the medical record (labelled "Leaves before MR closure") which are our dependent variables, augmented with four matrixes of independent variables.

The first, labelled *Demographic*, controls for the characteristics of the patient, and is composed of six dichotomous dummy variables to distinguish between the ages of the patients (following Agovino et al., [27]), we included dummies to control for patients under 15 years old, those between 15 and 24, 25–34, 35–44, 45–54, and 55–64, with the omitted, and hence reference, modality being patients over 65 years old), and two dichotomous dummy variables: a first signalling whether the patient is female, and a second signalling whether she or he is Italian citizen. The second matrix, labelled *Municipality*, controls for the characteristics of the municipality of residence of the patient, and is composed of the logarithm of the per capita income of the municipality, to control for an income effect; the distance in time from the municipality to the hospital, to control for the investment made to reach the hospital, and the share of municipal population that in 2021 had a high-school diploma, as a measure of education. The third matrix, labelled *Incident*, controls for the characteristic of the emergency that led to the ED, and is composed of four dichotomous dummies: the first two are equal to one if the patient was coded as yellow or red upon admittance; the third control for whether she or he arrived in an ambulance; and, finally, one controls for whether the patient reports a trauma as her or his main problem. Finally, the last matrix includes hospital-level fixed effects, to prevent any local specificity from affecting our results. Descriptive statistics about the variables are presented in Table 1, while Table 2 reports the distribution of

Table 1. Descriptive Statistics

Label	Variable	Obs	Mean	Std. dev.	Min	Max
Leaves before Being Visited	Dichotomous dummy variable, equal to 1 if the patient abandoned the ED before being visited by a physician	980,579	0.0399081	0.1957433	0	1
Leaves before MR closure	Dichotomous dummy variable, equal to 1 if the patient abandoned the ED before the closure of the Medical Record	980,579	0.0734066	0.2608029	0	1
Under 15 y.o.	Dichotomous dummy variable, equal to 1 if the patient is between 0 and 15 years old	980,579	0.1355515	0.3423119	0	1
15–24 y.o.	Dichotomous dummy variable, equal to 1 if the patient is between 16 and 24 years old	980,579	0.1096046	0.3123965	0	1

(*Continued*)

Table 1. Descriptive Statistics (Continued)

Label	Variable	Obs	Mean	Std. dev.	Min	Max
25–34 y.o.	Dichotomous dummy variable, equal to 1 if the patient is between 25 and 34 years old	980,579	0.1314723	0.3379164	0	1
35–44 y.o.	Dichotomous dummy variable, equal to 1 if the patient is between 35 and 44 years old	980,579	0.1272993	0.3333081	0	1
45–54 y.o.	Dichotomous dummy variable, equal to 1 if the patient is between 45 and 54 years old	980,579	0.1353333	0.3420794	0	1
55–64 y.o.	Dichotomous dummy variable, equal to 1 if the patient is between 55 and 64 years old	980,579	0.1240012	0.3295831	0	1
Women	Dichotomous dummy variable, equal to 1 if the patient is a woman	980,579	0.4882738	0.4998627	0	1
Ita.Citizen	Dichotomous dummy variable, equal to 1 if the patient is an Italian citizen	980,579	0.988931	0.1046253	0	1
Log Income pc	Logarithm of the taxable income from work per capita of the municipality of residence of the patient	980,579	9.775822	0.1677096	9.129075	10.21894
Eff.Dist.in time	Distance in minutes between the municipality of residence of the patient and the hospital	980,579	16.95452	28.37142	0	762
Secondary Education pc	Share of the municipality population aged 9+ in 2021 that has at least a secondary education diploma	980,579	0.3393009	0.0267932	0.1693936	0.4693042
Yellow code	Dichotomous dummy variable, equal to 1 if the patient has been coded as yellow in the triage	980,579	0.226611	0.418639	0	1
Red code	Dichotomous dummy variable, equal to 1 if the patient has been coded as red in the triage	980,579	0.013799	0.1166559	0	1
Arr.Ambulance	Dichotomous dummy variable, equal to 1 if the patient has arrived at the ED in an ambulance	980,579	0.1035031	0.3046151	0	1
Trauma main probl.	Dichotomous dummy variable, equal to 1 if the patient has reported trauma as the main problem	980,579	0.2194887	0.4139004	0	1

key patient characteristics across those who left the ED before being seen by a physician and those who completed the process.

Statistically significant differences are observed for all variables considered. Women were slightly less likely to leave early compared to men (3.85% vs. 4.13%, $p < 0.001$), while Italian citizens exhibited a higher early departure rate (4.02%) than non-citizens (1.62%, $p < 0.001$). Patients arriving by ambulance were markedly less likely to leave (1.15%) than those who arrived independently (4.32%, $p < 0.001$), consistent with the assumption of more severe conditions. Similarly, those presenting with trauma were less likely to leave early (2.84%) than non-trauma patients (4.31%, $p < 0.001$).

After these preliminary operations to build the dataset, we ran a regression to estimate the correlations between certain characteristics of the patient and their decision to leave the ED early. We opt to use both Probit and

Table 2. Distribution of observed characteristics in patients that leave before the visit and patients who do not

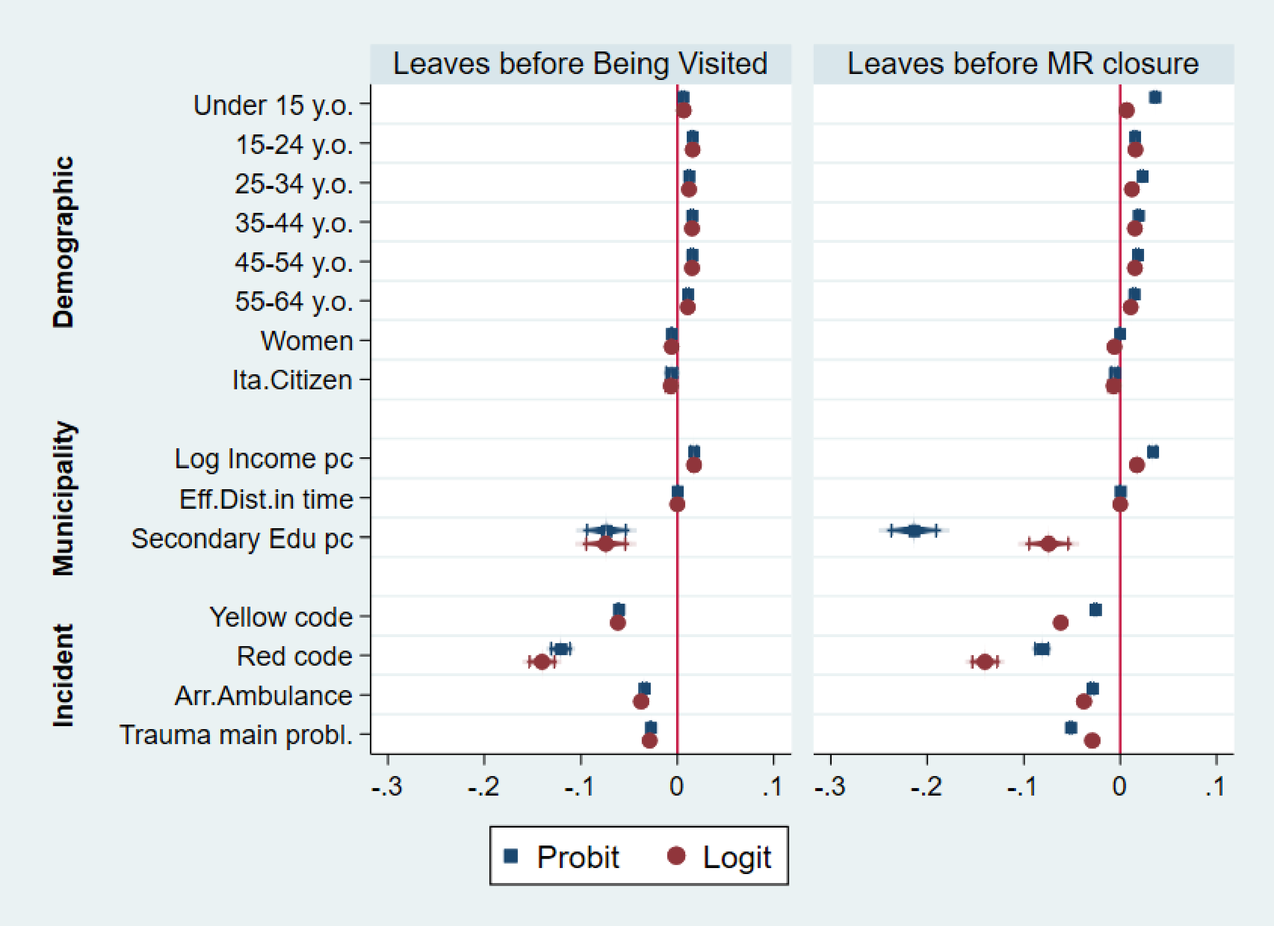
	Leaves before being visited		
Gender	**No**	**Yes**	**Total**
M	481,068	20,705	501,773
	95.87%	4.13%	100.00%
F	460,365	18,426	478,791
	96.15%	3.85%	100.00%
NR	13	2	15
	86.67%	13.33%	100.00%
Total	941,446	39,133	980,579
	96.01%	3.99%	100.00%
Pearson chi^2 (2)	52.8092	Pr=0.000	
Italian Citizen			
No	10,678	176	10,854
	98.38%	1.62%	100.00%
Yes	930,768	38,957	969,725
	95.98%	4.02%	100.00%
Total	941,446	39,133	980,579
	96.01%	3.99%	100.00%
Pearson chi^2 (1)	160.7994	Pr=0.000	
Arrived in Ambulance			
No	841,120	37,966	879,086
	95.68%	4.32%	100.00%
Yes	100,326	1,167	101,493
	98.85%	1.15%	100.00%
Total	941,446	39,133	980,579
	96.01%	3.99%	100.00%
Pearson chi^2 (1)	2.4e+03	Pr=0.000	
Trauma main problem			
No	732,332	33,021	765,353
	95.69%	4.31%	100.00%
Yes	209,114	6,112	215,226
	97.16%	2.84%	100.00%
Total	941,446	39,133	980,579
	96.01%	3.99%	100.00%
Pearson chi^2(2)	953.4385	Pr=0.000	

Logit estimators, which are the natural choice given the dichotomous nature of our dependent variable [28–31]. More details about the estimations, and some robustness checks, are provided in Appendix 1.

RESULTS

Results of the marginal effects of the estimation are presented in Figure 1, for both Probit (whose values

Figure 1. Regression results (Marginal Effects)



are represented by blue squares) and Logit (whose values are represented by red circles) regressions, run with robust standard errors.

On the left-hand side of the figure are the marginal effects computed in a regression where the dependent variable discriminates for patients that leave the ED before being seen by a physician. On the right-hand side, meanwhile, are the results when the dependent variable discriminates for patients who left before closure of their medical record, i.e. the conclusion of the procedure. The solid and blurred lines after the square and the circle represent confidence intervals of 95% and 90%, respectively, which are quite small, possibly because of the size of the sample.

An initial result is that the marginal effects for both the estimators are very similar, suggesting some robustness in our findings and indicating that these are not dependent on the chosen estimator. Moreover, we can also see that for the two different dependent variables the results also follow very similar patterns. This suggests that the determinants of leaving the ED early are similar in both cases.

Not all the variables report a statistically significant marginal effect: the distance (expressed in minutes) between the municipality of residence of the patient and the ED is not, suggesting that this variable does not affect the decision to leave the ED. On the other hand, notably, women, Italian citizens, those residing in more educated municipalities, patients that arrived by ambulance, individuals with severe health conditions (i.e. red or yellow codes), and those that reported a trauma, exhibit a reduced likelihood of premature ED departure. On the other hand, residing in municipalities with higher income per capita, and being younger than 65, are factors associated with an increased probability of early departure. These multivariate patterns align with the univariate findings suggested by Table 2, reinforcing the profile of early leavers as generally less acute and more autonomous patients.

DISCUSSION

This research, conducted on observational data from Campania, Italy, from January 2019 to February 2020, discerned several factors influencing early departure from ED. Our findings, and our observation of increase premature departure among patients from higher-income municipalities, does not align with prior research indicating low-income, uninsured patients' increased likelihood of early ED departure [23,24]. This suggests that in Italy the people leaving early are possibly those that have alternative, better options, possibly because of the fact that the health system is mostly public funded. Additionally, akin to research on lower acuity ratings predicting early departure [17,18], our study also suggests a negative correlation between severity (red or yellow codes) and early departure, with a lower probability of leaving correlated to the most severe code (red). Moreover, all the variables controlling for the age of the patients have positive coefficients, suggesting that patients younger than 65 are more likely to leave early than patients older than 65 (the omitted, and hence reference, modality).

Intriguingly, though it confirms previous results, our study also diverges from some findings in the literature, as our sample reveals that women are less likely to leave the ED prematurely compared to men, contrary to suggestions of single men being more inclined to early departure, a result derived over twenty years ago from an analysis in Israel [14]. This warrants further exploration of underlying factors, especially in light of the well-known differences in risk-aversion between genders, which suggests that women should leave early less frequently [32].

Furthermore, the lack of significance regarding the distance (in minutes) between the municipality where the patient resides and the ED can be seen as indicating the unimportance of this factor in determining early departure from ED. This is quite interesting, since the finding can be seen as meaning that the investment (in terms of time) made to reach the ED in Campania apparently does not play a role in deciding whether or not to leave the ED. This may be interpreted as suggesting that this cost is not too high, and hence that there is a good distribution of EDs across Campania. On the other hand, it is also important to highlight that our analysis, as with any analysis of a big, heterogeneous sample, reports mean values as the result. Hence, we cannot exclude that the distribution of access to each ED creates disparities in the opportunity to access some of the EDs, which, though statistically not significant, are of course an important policy issue for people who live in municipalities that are not served by a hospital, or one with an ED.

It is also interesting to highlight the role played by education in our setting. Our results suggest that people who live in more educated municipalities are less likely to leave the ED early: this is a finding that implies interesting consequences. First, it highlights the importance of education in this setting too, and indicates a further return on investments in education. Second, assuming that education is correlated to health literacy, as a part of the literature does, this underlines the importance to public health of raising the levels of health literacy (and in Italy its levels are unfortunately very low [33–35]. By implying further benefits to public spending from having a more educated population, this result has important consequences in terms of budget allocation. For all these reasons, more research into the relationship is needed.

The findings of this study have several implications for healthcare providers and policymakers. By understanding the factors that contribute to earfigure 1ly ED departure, healthcare providers can develop targeted interventions to reduce the occurrence of this phenomenon. Policymakers can also consider implementing policies that address the underlying factors that drive early ED departure, such as socioeconomic and education disparities in the population.

Providers, armed with insights into the determinants of early ED departure, can strategically design multifaceted interventions. Improving communication strategies within the ED setting, tailoring patient education initiatives to highlight the potential consequences of premature departure, and actively addressing healthcare access barriers are pivotal steps for mitigating this phenomenon. Furthermore, healthcare providers may explore collaborative efforts with local emergency services to optimize ambulance protocols, ensuring timely and appropriate patient care upon arrival at the ED.

Simultaneously, policymakers bear the responsibility for formulating comprehensive strategies to address the societal underpinnings of premature ED departure. Recognizing the role of education and income disparities, policymakers should prioritize the expansion of affordable healthcare initiatives, thereby bolstering equitable access to medical services. Crafting policies that specifically target hospital serving areas with lower income per capita and lower education levels, as well as fostering community-based healthcare initiatives, are critical measures for promoting patient retention within emergency healthcare systems.

In tandem, fostering cross-sectoral collaborations between healthcare providers and policymakers becomes imperative. By integrating efforts, stakeholders can collectively develop and implement interventions that not only address immediate concerns within the ED but also contribute to broader systemic improvements in healthcare accessibility and equity.

CONCLUSIONS

In summary, this study has investigated the determinants of early ED departure in Campania, Italy, leveraging a dataset of around 1,000,000 observations and employing Probit and Logit estimators with robust standard errors. Within this quantitative framework, significant association emerged, revealing that factors such as being a woman, having Italian citizenship, having a higher level of education, arriving at the ED by ambulance, having a more severe condition, and whether or not the health issue is traumatic, are all characteristics associated with a decreased likelihood of premature ED departure. Conversely, residing in municipalities with lower income per capita and being younger than 65 are factors linked to an increased probability of early leaving.

While providing interesting new results on the characteristics of early ED leavers in Campania, Italy, which to the best of our knowledge have not been discussed by previous literature, this research is not exempt from limitations, which must be acknowledged. The observational nature of the data poses constraints on establishing causal relationships, and the focus on a specific geographic region may limit external validity and hence generalizability to broader contexts. Additionally, despite the extensive dataset with micro-level data, there may be unaccounted confounding variables that could influence the observed associations. These limitations underscore the need for caution in extrapolating findings beyond the study's specific context.

Looking ahead, future research could explore the nuanced dynamics of patient-physician communication within the ED setting, investigating how effective communication strategies may influence the likelihood of ED early departure. While the focus of this study is on demographic and clinical characteristics associated with patients who leave the ED early, it is important to highlight that is crucial to delve into the underlying reasons behind their decisions. Future research could incorporate qualitative methods, such as patient interviews or surveys, to directly capture these motivations. By understanding the "why" behind premature departures, healthcare providers can develop more targeted and effective interventions to address these specific concerns. Moreover, our study as an underlying assumption that all premature departures from the ED are undesirable. This may not hold universally. Authors suggested that some patients who leave ED without being seen or against medical advice tend to have positive outcomes, particularly if their initial assessment suggests low acuity. Hence, it is essential to differentiate between cases where early departure poses a significant health risk and those where patients may reasonably manage their conditions through alternative healthcare settings, even although it is unfortunately very hard to have data that allow for such a distinction. Nonetheless, recognizing it can help refine our interpretation of the data and avoid biases that might skew the study's conclusions.

Furthermore, examining the impact of socio-cultural factors on patient decision-making processes during ED visits could provide valuable insights into the intricate interplay between individual characteristics and healthcare outcomes. Exploring the temporal trends in early ED departure rates and their correlation with evolving healthcare policies would also contribute to a more comprehensive understanding of this phenomenon. These potential avenues of research aim to enrich our understanding of early ED departure dynamics, offering valuable insights for refining interventions and policies in emergency healthcare.

These findings not only contribute to the academic understanding of early ED departure but also hold practical implications. The insights gleaned from this research serve as a foundation for targeted interventions aimed at mitigating premature departures, thereby bolstering the overall efficiency of ED systems. By incorporating these findings into healthcare practices, providers can refine patient care strategies, optimize resource allocation, and potentially enhance patient outcomes. As the healthcare landscape evolves, these research outcomes provide a timely and valuable resource for informing evidence-based interventions and policies to address the complex dynamics surrounding early ED departure in the Italian context.

In conclusion, our investigation provides valuable insights into the characteristics of patients who leave the ED early in Italy. These findings can inform interventions aimed at reducing the occurrence of early ED departure, enhancing the overall efficiency of ED systems, and improving patient outcomes.

JEL codes I11; I12; I18

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DECLARATIONS OF INTEREST

No author perceives any conflict of interest

DATA AVAILABILITY

The data that support the findings of this study are not openly available due to reasons of sensitivity and are available from the corresponding author upon reasonable request.

REFERENCES

1. Scaletti, A. (2014). Evaluating investments in health care systems: health technology assessment. Springer.
2. Hardin, G. (1968). The Tragedy of the Commons. Science, 162(3859): 1243–1248. http://www.jstor.org/stable/1724745
3. Wendt, C., Frisina, L., Rothgang, H. (2009). Health-care system types: A conceptual framework for comparison. Social Policy & Administration, 43(1): 70–90.
4. Böhm, K., Schmid, A., Götze, R., Landwehr, C., Rothgang, H. (2013). Five types of OECD health-care systems: Empirical results of a deductive classification. Health Policy, 113(3): 258–269.
5. France, G., Taroni, F., Donatini, A. (2005). The Italian Healthcare System. Health Economics, 14 (S1): S187-S202.
6. Hangoma, P., Robberstad, B., Aakvik, A. (2018). Does Free Public Health Care Increase Utilization

and Reduce Spending? Heterogeneity and Long Term Effects. World development, 101: 334–350.
7. Xu, K., Evans, D. B., Kawabata, K., Zeramdini, R., Klavus, J., Murray, C. J. (2003). Household catastrophic health expenditure: a multicountry analysis. The lancet, 362(9378): 111–117.
8. Azzani, M., Roslani, A.C., Su, T.T. (2019). Determinants of Household Catastrophic Health Expenditure: A Systematic Review. Malaysian Journal of Medical Science, 26(1): 15–43.
9. Griffin, C.C. (1988). User Charges for Health Care in Principle and Practice, An EDI discussion paper, 37, World Bank, Washington DC.
10. Hurley, J. (2013). User charges for health care services: some further thoughts. Health Economics, Policy and Law, 8: 537–541.
11. Gwatkin, D.R. (2004). Are free government health services the best way to reach to poor? Health, Nutrition and Population (HNP) discussion paper, World Bank, Washington, DC.
12. Hsia, R. Y., Asch, S. M., Weiss, R. E., Zingmond, D., Liang, L. J., Han, W., McCreath, H., Sun, B. C. (2011). Hospital determinants of emergency department left without being seen rates. Annals of emergency medicine, 58(1): 24–32.
13. Mataloni, F., Colais, P., Galassi, C., Davoli, M., Fusco, D. (2018) Patients who leave Emergency Department without being seen or during treatment in the Lazio Region (Central Italy): Determinants and short term outcomes. PLoS ONE 13(12): e0208914.
14. Carmel, A., Amital, H., Shemer, Y., Sahar, A. (1998). Why do they leave? Clinical characteristics of patients who leave the emergency room against medical advice. Harefuah, 134(6): 445–449, 503.
15. Fernandes, C.M., Daya, M.R., Barry, S., Palmer, N. (1994). Emergency department patients who leave without seeing a physician: the Toronto Hospital experience. Annals of emergency medicine, 24(6): 1092–6.
16. Fry, M., Thompson, J., Chan, A.C. (2004). Patients regularly leave emergency departments before medical assessment: A study of did not wait patients, medical profile and outcome characteristics. Australian Emergency Nursing Journal, 6: 21–26.
17. Lee, K.M., Wong, T.W., Chan, R.P., Lau, C.C. (1998). A study of patients who leave without notice in an A & E department. Accident and emergency nursing, 6(2): 118–121.
18. Lerner, B.H. (1992). Patients leaving emergency departments without being seen by a physician. JAMA, 267 2, 231–2.
19. Weiss, S. J., Derlet, R., Arndahl, J., Ernst, A. A., Richards, J., Fernández-Frackelton, M., ... Levy, D. (2010). Estimating the degree of emergency department overcrowding in academic medical centers: Results of the National ED Overcrowding Study (NEDOCS). Academic Emergency Medicine, 11(1): 38–50.
20. Rowe, B. H., Channan, P., Bullard, M., Blitz, S., Saunders, L. D., Rosychuk, R. J., ... Holroyd, B. R. (2006). Characteristics of patients who leave emergency departments without being seen. Academic Emergency Medicine, 13(8): 848–852.
21. Mohsin, M., Forero, R., Ieraci, S., Bauman, A. E., Young, L., Santiano, N., ... Jorm, L. (2007). A population follow-up study of patients who left an emergency department without being seen by a medical officer. Emergency Medicine Journal, 24(3): 175–179.
22. Mahmoudian-Dehkordi, A., Sadoughi, F., Sheikhtaheri, A. (2020). Reasons for patients leaving emergency departments against medical advice: A cross-sectional study in Iran. BMJ Open, 10(1): e031240.
23. Liao, H.C., Liaw, S.J., Hu, P., Lee, K., Chen, C., Wang, F. (2002). Emergency department patients who leave without being seen by a doctor: the experience of a medical center in northern Taiwan. Chang Gung medical journal, 25(6): 367–373.
24. Khanna, R., Chaudhry, M., Prescott, M.V. (1999). Emergency department patients who leave the department without being seen by a doctor. European journal of emergency medicine: official journal of the European Society for Emergency Medicine, 6(3): 233–235.
25. Campagna, S., Borraccino, A., Politano, G., Benso, A., Dalmasso, M., Dimonte, V., Gianino, M.M. (2021). Determinants Associated With the Risk of Emergency Department Visits Among Patients Receiving Integrated Home Care Services: A 6-Year Retrospective Observational Study in a Large Italian Region. International Journal of Health Policy Management, 10 (10): 605–612.
26. Di Laura, D., D'Angiolella, L., Mantovani, L., Squassabia, G., Clemente, F., Santalucia, I., Improta, G., Triassi, M. (2021). Efficiency measures of emergency departments: an Italian systematic literature review. BMJ Open Qual., 10(3): e001058.
27. Agovino, M., Musella, G., Pisano, S., Scaletti, A. (2021). Assessing the impact of tourist flows on emergency department treatment speed for residents and tourists. The case of Sorrento. Socio-Economic Planning Science, 77: 101004.
28. Cameron, A. C., Trivedi, P. K. (2010). Microeconometrics Using Stata. Rev. ed. College Station, TX: Stata Press.
29. Long, J. S. (1997). Regression Models for Categorical and Limited Dependent Variables. Thousand Oaks, CA: SAGE.
30. Pampel, F. C. (2000). Logistic Regression: A Primer. Thousand Oaks, CA: SAGE.
31. Powers, D. A., Xie, Y. (2008). Statistical Methods for Categorical Data Analysis. 2nd ed. Bingley, UK: Emerald.
32. Eckel, C. C., Grossman, P. J. (2008). Men, women and risk aversion: Experimental evidence. Handbook of experimental economics results, 1: 1061–1073.
33. Palumbo, R., Annarumma, C., Adinolfi, P., Musella, M., Piscopo, G. (2016a). The Italian Health Literacy Project: Insights from the assessment of health literacy skills in Italy, Health Policy, 120 (9): 1087–1094.
34. Cognetti, G., Poltronieri, E., De Castro, P., Scarinci, V., Perilli, R. (2019). Searching health information on the Internet: results of a survey in a cohort of 414 elderly people in Italy, Journal Medical Internet Research Preprints. 04/08/2019:15760
35. Velasco, V., Gragnano, A., Gruppo Regionale HBSC Lombardia 2018, Vecchio, L.P. (2021). Health Literacy Levels among Italian Students: Monitoring and Promotion at School. International Journal Environmental Research and Public Health, 18: 9943.

APPENDIX 1 – DETAILS OF THE EMPIRICAL ANALYSIS

To study the determinants of early departure from ED and answer our research question, we model the early leaving from ED, both before being seen by a physician and before the closure of the medical record, as a function of four matrixes: demographic, municipality, incident, and hospital. In more formal terms, we estimate equation (1):

$$EL=\alpha+\beta_1\ Demo+\beta_2 Muni+\beta_3 Incident+\ \beta_4 Hospital+\varepsilon \quad (1)$$

where EL (early leaving) is a dichotomous dummy variable operationalized in two different ways: in different regressions it may either assume the value of 1 if the patient left before being seen by a physician, or if she or he left before the closure of the medical record, which is when the procedure is concluded and the patient is discharged. This variable is expressed as the function of four matrixes:

- *Demo*, a matrix composed of eight variables, describing the demographic characteristics of the patient: *Under 15 years old*, *15–24 y.o.*, *25–34 y.o.*, *35–44 y.o.*, *45–54 y.o.*, and *55–64 y.o.*, *Women*, and *Italian citizenship*. All these variables are dichotomous dummy variables built from data gathered from Regione Campania's dataset on ED admissions;
- *Municipality*, a matrix composed of three variables, describing the characteristics of the municipality where the patient lives. Given the lack of better information, these allow us to attach more data to each patient. These three variables are *Log Income pc*, the logarithm of the per capita income of the municipality; *Eff.Dist.in time*, the effective distance (in minutes) between the municipality and the hospital; and *Secondary Edu. Pc.*, the share of population aged 9+ living in the municipality that has a secondary education diploma in 2021. This latter variable is our operationalization of education and, by extension, of health literacy;
- *Incident*, a matrix composed of four dichotomous dummy variables, describing the characteristics of the reasons for which the patient went to the ED. These are *Yellow* and *Red code*, variables equal to 1 if the patient was coded at admittance by this level of urgency; *Arr.Ambulance*, a variable discriminating for patients that arrived by ambulance, and *Trauma main probl.*, a variable equal to 1 if the main problem of the patient has been reported as a trauma;
- *Hospital*, a matrix of hospital-level fixed effects, to prevent any specificity of the ED or the area in which it is located from affecting the results.

Equation (1) has been estimated through Probit and Logit estimators, with robust standard errors, always including the hospital-level fixed effects, and adding the matrixes with the most relevant determinants one at a time, to see what happens to the coefficients when the covariates are added. The results of the computation of both the coefficients and the marginal effects, for both the operationalizations of the dependent variable, are reported respectively in tables A1, A2, A3 and A4, for the Probit estimator, and A5, A6, A7 and A8 for the Logit estimator.

Table A1. Coefficients – Probit - Det.of abandoning ER before visit

	(A1.1)	(A1.2)	(A1.3)
	Leaves before Being Visited	Leaves before Being Visited	Leaves before Being Visited
Under 15 y.o.	0.283^{***}	0.285^{***}	0.0653^{***}
	(29.08)	(29.19)	(6.37)
15–24 y.o.	0.339^{***}	0.339^{***}	0.174^{***}
	(36.04)	(36.01)	(17.55)
25–34 y.o.	0.319^{***}	0.320^{***}	0.134^{***}
	(34.89)	(34.94)	(13.93)
35–44 y.o.	0.340^{***}	0.341^{***}	0.170^{***}
	(37.27)	(37.35)	(17.70)
45–54 y.o.	0.312^{***}	0.313^{***}	0.170^{***}
	(34.49)	(34.54)	(18.00)
55–64 y.o.	0.224^{***}	0.224^{***}	0.120^{***}
	(23.41)	(23.46)	(12.08)

(*Continued*)

Table A1. Coefficients – Probit - Det.of abandoning ER before visit (Continued)

	(A1.1)	(A1.2)	(A1.3)
	Leaves before Being Visited	**Leaves before Being Visited**	**Leaves before Being Visited**
Women	–0.0371***	–0.0370***	–0.0667***
	(–7.30)	(–7.27)	(–12.70)
Ita.Citizen	–0.0887**	–0.0901**	–0.0659*
	(–2.34)	(–2.38)	(–1.70)
Log Income pc		0.152***	0.192***
		(7.12)	(8.73)
Eff.Dist.in time		0.0000190	0.0000990
		(0.19)	(1.01)
Secondary Education pc		–0.953***	–0.821***
		(–7.18)	(–5.99)
Yellow code			–0.676***
			(–74.34)
Red code			–1.352***
			(–20.79)
Arr.Ambulance			–0.382***
			(–28.35)
Trauma main probl.			–0.310***
			(–44.66)
Hospital Fixed Effects	YES	YES	YES
Constant	–1.845***	–2.992***	–3.181***
	(–39.89)	(–14.68)	(–15.22)
Observations	806194	806194	806194
Pseudo R^2	0.086	0.087	0.125
Log lik.	–143017.0	–142976.6	–136978.2
Chi-squared	21520.9	21561.7	28727.1

t statistics in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A2. Coefficients – Probit - Det.of abandoning ER before medical record closure

	(A2.1)	(A2.2)	(A2.3)
	Leaves before MR closure	**Leaves before MR closure**	**Leaves before MR closure**
Under 15 y.o.	0.379***	0.381***	0.293***
	(50.22)	(50.46)	(36.85)
15–24 y.o.	0.160***	0.161***	0.123***
	(20.98)	(21.09)	(15.44)
25–34 y.o.	0.249***	0.251***	0.187***
	(35.43)	(35.62)	(25.36)
35–44 y.o.	0.214***	0.216***	0.153***
	(29.67)	(29.90)	(20.37)
45–54 y.o.	0.197***	0.198***	0.147***
	(27.49)	(27.72)	(19.82)

(*Continued*)

Table A2. Coefficients – Probit - Det.of abandoning ER before medical record closure (Continued)

	(A2.1)	(A2.2)	(A2.3)
	Leaves before MR closure	**Leaves before MR closure**	**Leaves before MR closure**
55–64 y.o.	0.160*** (21.51)	0.162*** (21.69)	0.117*** (15.41)
Women	0.0207*** (5.10)	0.0200*** (4.94)	–0.00415 (–1.01)
Ita.Citizen	–0.0502*** (–3.02)	–0.0428** (–2.57)	–0.0479*** (–2.84)
Log Income pc		0.228*** (13.30)	0.275*** (15.80)
Eff.Dist.in time		0.000360*** (4.95)	0.000452*** (6.22)
Secondary Education pc		–1.867*** (–16.45)	–1.733*** (–15.04)
Yellow code			–0.210*** (–35.44)
Red code			–0.659*** (–19.25)
Arr.Ambulance			–0.235*** (–25.60)
Trauma main probl.			–0.415*** (–69.12)
Hospital fixed effects	YES	YES	YES
Constant	–1.471*** (–54.66)	–3.045*** (–18.72)	–3.361*** (–20.38)
Observations	980579	980579	980579
Pseudo R^2	0.108	0.109	0.125
Log lik.	–229522.4	–229347.4	–225071.1
Chi-squared	48940.4	48985.3	50337.5

t statistics in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A3. Marginal Effects– Probit - Det.of abandoning ER before visit

	(A3.1)	(A3.2)	(A3.3)
	Leaves before Being Visited	**Leaves before Being Visited**	**Leaves before Being Visited**
Under 15 y.o.	0.0264*** (29.05)	0.0265*** (29.17)	0.00585*** (6.37)
15–24 y.o.	0.0316*** (35.91)	0.0316*** (35.88)	0.0156*** (17.53)
25–34 y.o.	0.0297*** (34.78)	0.0298*** (34.82)	0.0120*** (13.92)

(*Continued*)

Table A3. Marginal Effects– Probit - Det.of abandoning ER before visit (Continued)

	(A3.1)	(A3.2)	(A3.3)
	Leaves before Being Visited	**Leaves before Being Visited**	**Leaves before Being Visited**
35–44 y.o.	0.0317*** (37.12)	0.0318*** (37.20)	0.0152*** (17.67)
45–54 y.o.	0.0291*** (34.36)	0.0291*** (34.41)	0.0152*** (17.97)
55–64 y.o.	0.0208*** (23.37)	0.0209*** (23.42)	0.0108*** (12.07)
Women	–0.00345*** (–7.29)	–0.00344*** (–7.27)	–0.00598*** (–12.69)
Ita.Citizen	–0.00826** (–2.34)	–0.00838** (–2.38)	–0.00591* (–1.70)
Log Income pc		0.0142*** (7.11)	0.0172*** (8.73)
Eff.Dist.in time		0.00000177 (0.19)	0.00000887 (1.01)
Stud.in pop.18–26		–0.0886*** (–7.18)	–0.0736*** (–5.99)
Yellow code			–0.0606*** (–72.95)
Red code			–0.121*** (–20.77)
Arr.Ambulance			–0.0342*** (–28.28)
Trauma main probl.			–0.0278*** (–44.47)
Hospital Fixed Effects	YES	YES	YES
Observations	806194	806194	806194

*Marginal effects; t statistics in parentheses (d) for discrete change of dummy variable from 0 to 1 * p < 0.1, ** p < 0.05, *** p < 0.01*

Table A4. Marginal Effects– Probit - Det.of abandoning ER before medical record closure

	(A4.1)	(A4.2)	(A4.3)
	Leaves before MR closure	**Leaves before MR closure**	**Leaves before MR closure**
Under 15 y.o.	0.0476*** (50.45)	0.0478*** (50.69)	0.0362*** (36.94)
15–24 y.o.	0.0201*** (20.99)	0.0202*** (21.11)	0.0152*** (15.45)
25–34 y.o.	0.0312*** (35.50)	0.0314*** (35.70)	0.0231*** (25.38)
35–44 y.o.	0.0268*** (29.68)	0.0271*** (29.92)	0.0189*** (20.37)

(Continued)

Table A4. Marginal Effects– Probit - Det.of abandoning ER before medical record closure (Continued)

	(A4.1)	(A4.2)	(A4.3)
	Leaves before MR closure	**Leaves before MR closure**	**Leaves before MR closure**
45–54 y.o.	0.0246*** (27.49)	0.0249*** (27.72)	0.0181*** (19.81)
55–64 y.o.	0.0201*** (21.51)	0.0203*** (21.69)	0.0145*** (15.41)
Women	0.00259*** (5.10)	0.00251*** (4.94)	–0.000512 (–1.01)
Ita.Citizen	–0.00629*** (–3.02)	–0.00536** (–2.57)	–0.00591*** (–2.84)
Log Income pc		0.0286*** (13.30)	0.0339*** (15.80)
Eff.Dist.in time		0.0000451*** (4.95)	0.0000558*** (6.22)
Stud.in pop.18–26		–0.234*** (–16.46)	–0.214*** (–15.05)
Yellow code			–0.0259*** (–35.50)
Red code			–0.0814*** (–19.25)
Arr.Ambulance			–0.0290*** (–25.61)
Trauma main probl.			–0.0513*** (–69.27)
Hospital Fixed Effects	YES	YES	YES
Observations	980579	980579	980579

*Marginal effects; t statistics in parentheses (d) for discrete change of dummy variable from 0 to 1 * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$*

Table A5. Coefficients – Logit - Det.of abandoning ER before visit

	(A5.1)	(A5.2)	(A5.3)
	Leaves before Being Visited	**Leaves before Being Visited**	**Leaves before Being Visited**
Under 15 y.o.	0.647*** (30.26)	0.650*** (30.39)	0.154*** (6.96)
15–24 y.o.	0.738*** (36.99)	0.738*** (36.95)	0.366*** (17.65)
25–34 y.o.	0.698*** (35.70)	0.699*** (35.74)	0.280*** (13.76)
35–44 y.o.	0.738*** (38.04)	0.740*** (38.13)	0.352*** (17.53)
45–54 y.o.	0.676*** (35.04)	0.677*** (35.08)	0.353*** (17.80)
55–64 y.o.	0.489*** (23.82)	0.490*** (23.86)	0.250*** (11.92)

(Continued)

Table A5. Coefficients – Logit - Det.of abandoning ER before visit (Continued)

	(A5.1)	(A5.2)	(A5.3)
	Leaves before Being Visited	**Leaves before Being Visited**	**Leaves before Being Visited**
Women	–0.0727*** (–6.78)	–0.0724*** (–6.76)	–0.140*** (–12.74)
Ita.Citizen	–0.192** (–2.37)	–0.195** (–2.41)	–0.156* (–1.92)
Log Income pc		0.328*** (7.16)	0.401*** (8.64)
Eff.Dist.in time		0.00000902 (0.04)	0.000155 (0.76)
Stud.in pop.18–26		–1.992*** (–7.13)	–1.708*** (–5.99)
Yellow code			–1.418*** (–70.92)
Red code			–3.230*** (–17.76)
Arr.Ambulance			–0.864*** (–27.49)
Trauma main probl.			–0.665*** (–44.60)
Hospital Fixed Effects	YES	YES	YES
Constant	–3.393*** (–34.00)	–5.887*** (–13.45)	–6.149*** (–13.88)
Observations	806194	806194	806194
Pseudo R^2	0.087	0.087	0.125
Log lik.	–142970.7	–142929.2	–136946.7
Chi-squared	20745.7	20811.6	30423.0

t statistics in parentheses ** p < 0.1, ** p < 0.05, *** p < 0.01*

Table A6. Logit-Det.of abandoning ER before medical record closure

	(A6.1)	(A6.2)	(A6.3)
	Leaves before Being Visited	**Leaves before Being Visited**	**Leaves before Being Visited**
Under 15 y.o.	0.647*** (30.26)	0.650*** (30.39)	0.154*** (6.96)
15–24 y.o.	0.738*** (36.99)	0.738*** (36.95)	0.366*** (17.65)
25–34 y.o.	0.698*** (35.70)	0.699*** (35.74)	0.280*** (13.76)
35–44 y.o.	0.738*** (38.04)	0.740*** (38.13)	0.352*** (17.53)
45–54 y.o.	0.676*** (35.04)	0.677*** (35.08)	0.353*** (17.80)
55–64 y.o.	0.489*** (23.82)	0.490*** (23.86)	0.250*** (11.92)
Women	–0.0727*** (–6.78)	–0.0724*** (–6.76)	–0.140*** (–12.74)

(*Continued*)

Table A5. Coefficients – Logit - Det.of abandoning ER before visit (Continued)

	(A6.1)	(A6.2)	(A6.3)
	Leaves before Being Visited	**Leaves before Being Visited**	**Leaves before Being Visited**
Ita.Citizen	–0.192** (–2.37)	–0.195** (–2.41)	–0.156* (–1.92)
Log Income pc		0.328*** (7.16)	0.401*** (8.64)
Eff.Dist.in time		0.00000902 (0.04)	0.000155 (0.76)
Secondary Edu pc		–1.992*** (–7.13)	–1.708*** (–5.99)
Yellow code			–1.418*** (–70.92)
Red code			–3.230*** (–17.76)
Arr.Ambulance			–0.864*** (–27.49)
Trauma main probl.			–0.665*** (–44.60)
Constant	–3.393*** (–34.00)	–5.887*** (–13.45)	–6.149*** (–13.88)
Observations	806194	806194	806194
Pseudo R^2	0.087	0.087	0.125
Log lik.	–142970.7	–142929.2	–136946.7
Chi-squared	20745.7	20811.6	30423.0

t statistics in parentheses * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A7. Marginal Effects-Logit-Det.of abandoning ER before visit

	(A6.1)	(A6.2)	(A6.3)
	Leaves before Being Visited	**Leaves before Being Visited**	**Leaves before Being Visited**
Under 15 y.o.	0.0288*** (30.12)	0.0289*** (30.25)	0.00667*** (6.95)
15–24 y.o.	0.0328*** (36.71)	0.0328*** (36.67)	0.0159*** (17.62)
25–34 y.o.	0.0310*** (35.45)	0.0311*** (35.49)	0.0121*** (13.74)
35–44 y.o.	0.0328*** (37.73)	0.0329*** (37.82)	0.0153*** (17.50)
45–54 y.o.	0.0301*** (34.79)	0.0301*** (34.82)	0.0153*** (17.77)
55–64 y.o.	0.0217*** (23.73)	0.0218*** (23.78)	0.0109*** (11.91)
Women	–0.00323*** (–6.78)	–0.00322*** (–6.76)	–0.00607*** (–12.73)
Ita.Citizen	–0.00854** (–2.37)	–0.00866** (–2.41)	–0.00679* (–1.92)

(*Continued*)

Table A7. Marginal Effects-Logit-Det.of abandoning ER before visit (Continued)

	(A6.1)	(A6.2)	(A6.3)
	Leaves before Being Visited	**Leaves before Being Visited**	**Leaves before Being Visited**
Log Income pc		0.0146*** (7.15)	0.0174*** (8.63)
Eff.Dist.in time		0.000000401 (0.04)	0.00000675 (0.76)
Stud.in pop.18–26		–0.0886*** (–7.13)	–0.0742*** (–5.99)
Yellow code			–0.0616*** (–68.84)
Red code			–0.140*** (–17.72)
Arr.Ambulance			–0.0375*** (–27.36)
Trauma main probl.			–0.0289*** (–44.22)
Hospital Fixed Effects	YES	YES	YES
Observations	806194	806194	806194

t statistics in parentheses* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A8. Marginal Effects – Logit - Det.of abandoning ER before MR closure

	(A7.1)	(A7.2)	(A7.3)
	Leaves before Being Visited	**Leaves before Being Visited**	**Leaves before Being Visited**
Under 15 y.o.	0.0288*** (30.12)	0.0289*** (30.25)	0.00667*** (6.95)
15–24 y.o.	0.0328*** (36.71)	0.0328*** (36.67)	0.0159*** (17.62)
25–34 y.o.	0.0310*** (35.45)	0.0311*** (35.49)	0.0121*** (13.74)
35–44 y.o.	0.0328*** (37.73)	0.0329*** (37.82)	0.0153*** (17.50)
45–54 y.o.	0.0301*** (34.79)	0.0301*** (34.82)	0.0153*** (17.77)
55–64 y.o.	0.0217*** (23.73)	0.0218*** (23.78)	0.0109*** (11.91)
Women	–0.00323*** (–6.78)	–0.00322*** (–6.76)	–0.00607*** (–12.73)
Ita.Citizen	–0.00854** (–2.37)	–0.00866** (–2.41)	–0.00679* (–1.92)
Log Income pc		0.0146*** (7.15)	0.0174*** (8.63)
Eff.Dist.in time		0.000000401 (0.04)	0.00000675 (0.76)
Stud.in pop.18–26		–0.0886*** (–7.13)	–0.0742*** (–5.99)

(*Continued*)

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Table A8. Marginal Effects – Logit - Det.of abandoning ER before MR closure (Continued)

	(A7.1)	(A7.2)	(A7.3)
	Leaves before Being Visited	**Leaves before Being Visited**	**Leaves before Being Visited**
Yellow code			–0.0616*** (–68.84)
Red code			–0.140*** (–17.72)
Arr.Ambulance			–0.0375*** (–27.36)
Trauma main probl.			–0.0289*** (–44.22)
Hospital Fixed Effects	YES	YES	YES
Observations	806194	806194	806194

*Marginal effects; t statistics in parentheses (d) for discrete change of dummy variable from 0 to 1 * p < 0.1, ** p < 0.05, *** p < 0.01*