THE IMPACT OF AN INCREASE IN FOREIGNERS ON THE WAITING TIMES IN HEALTHCARE IN MALTA

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Dissertation submitted in partial fulfilment of the award of the

Degree of Master of Science in Economics, M.Sc. (Melit.)

September 2024

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ABSTRACT

The increasing presence of foreign residents in Malta has raised questions about its impact on essential public services, including healthcare. As Malta's only major public hospital, Mater Dei Hospital's Emergency Department (ED) is critical to meeting the healthcare needs of both locals and foreigners. With the continuous growth of the foreign population, concerns have emerged regarding potential strains on the system, particularly in terms of increased waiting times in emergency care.

This study investigates the impact of foreign residents on waiting times in Malta's healthcare system, specifically at Mater Dei Hospital's Emergency Department (ED). The objective is to assess whether foreign residents experience longer waiting times than Maltese residents and to identify the main factors contributing to these delays. Using data spanning from 2017 to 2023, the research employs an Ordinary Least Squares (OLS) regression model to examine various determinants of ED waiting times, including nationality, age, gender, arrival type, triage level, and the need for admission.

The methodology involved comprehensive data cleaning and preparation of over 600,000 anonymous observations from Mater Dei's records to fully adhere to ethical considerations. Separate regressions were run for the years 2017, 2020, and 2023 to account for temporal variations, particularly the effects of the COVID-19 pandemic. The results showed that although nationality has a statistically significant impact on waiting times, its influence is relatively low compared to other variables. These findings underscore the need for policy measures to manage ED demand, particularly for non-native populations, and improve the overall efficiency of Malta's healthcare system.

ACKNOWLEDGEMENTS

First and foremost, I would like to express my deepest gratitude to my supervisor, Dr. Carl Camilleri, for his invaluable guidance, support, and encouragement throughout this dissertation. His insights, feedback, and expertise were crucial in shaping my research direction and for that, I am truly grateful.

I would also like to thank my girlfriend whose unwavering support, patience, and understanding have been a constant source of strength throughout this journey. I would also like to extend my heartfelt thanks to my family and friends, whose love, encouragement, and support have been instrumental not only during this dissertation but throughout my entire academic journey. Without these people's constant motivation and belief in me, this journey would not have been possible.

Lastly, I would like to thank Dr. Amanda Bugeja and Dr. Sandra Distefano whose insightful suggestions helped me shape the foundation of my research, and I am deeply appreciative of the data they generously provided, which was crucial for the successful completion of this work.

To all of you, I owe a debt of gratitude for helping me reach this milestone.

TABLE OF CONTENTS

TABLE OF FIGURES AND TABLES

Figures:

Tables:

LIST OF ACRONYMS

BLUE	Best Linear Unbiased Estimator
ED	Emergency Department
ESI	Emergency Severity Index
LOS	Length of Stay
NSO	National Statistics Office
OLS	Ordinary Least Squares
VIF	Variance Inflation Factor

1. INTRODUCTION

1.1. CONTEXT

Despite the ever-changing world of Economics, the main issue has always been scarce resources (Adesina, 2017). Indeed, policymakers have to ensure that the available resources are allocated in the most efficient way possible. However, making these decisions is not an easy task, even more so considering that we live in a globalised world, where factors are continuously changing.

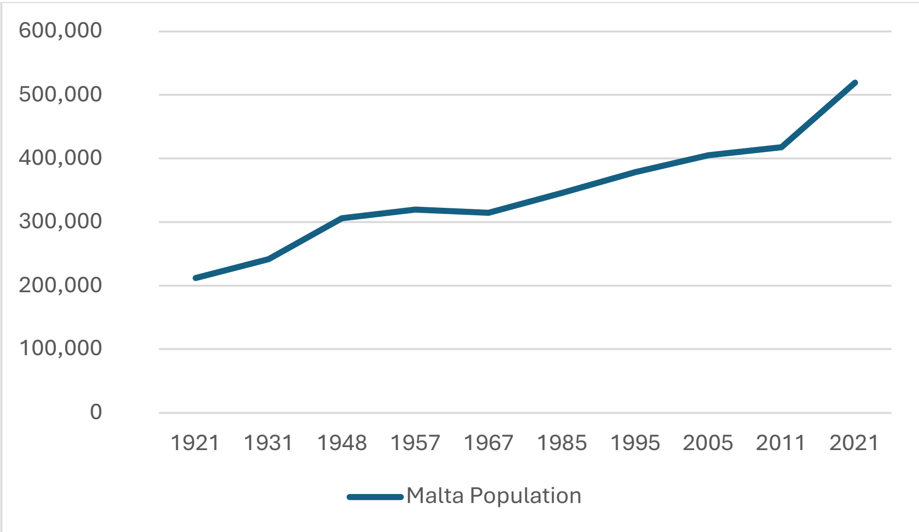
One of these phenomena across the globe is the movement of people to other countries. Malta is no exception to being exposed to this phenomenon and some factors heighten the exposure to it. When Malta joined the European Union in 2004, people living in other member states started being able to freely visit and live in Malta due to the freedom of movement between member states (European Commission, 2024). Additionally, in previous years Malta had eased the ability of Third Country Nationals to be able to work and live in Malta, albeit some measures are now being taken to regulate this.

Both of these have contributed to an exponential increase in the number of foreigners visiting and residing in Malta. While the presence of foreigners has several benefits to the economy such as contributing to economic growth (Peri, 2013), policymakers have to be aware that several sectors may be affected by this increase in foreigners. These challenges to the host countries' economies relate to waste management, healthcare services, the education system, and many more. One of the major current concerns in Malta is the Public Healthcare system's sustainability (Times of Malta, 2024). This is a serious issue not only because the public system is funded through taxpayer money, but also because health is one of the basic needs that needs to be given top priority in any country.

In Malta, Mater Dei Hospital, having opened its doors in 2007, is the main medical care provider in the country. It serves as a central pillar of the Maltese healthcare system, providing a wide range of medical services, including emergency care, specialised treatments, and educational opportunities for medical professionals. Upon its opening, Mater Dei Hospital served as a significant milestone in the Maltese healthcare system aimed at modernising healthcare and expanding its capacity from the previous main public hospital St. Luke's Hospital (Busuttil, 2007). It has now been seventeen years since Mater Dei Hospital was inaugurated and at that time the population was estimated to stand at 410,290 (National Statistics Office, 2007). This is significantly less than what the current population is estimated to be today and merits questioning whether the current capacity of Mater Dei is still satisfactory.

Figure 1.1 shows the midyear estimates of the Maltese population from the NSO census. As can be seen, the population of Malta has been steadily increasing since the 1970s. Moreover, in recent years, the rate of increase has accelerated. The latest census indicates that the population is approximately 519,562, representing an increase of around 110,000 since the construction of Mater Dei Hospital.

Figure 1.1.1: Malta's Population over the years



Having said this, it is important to keep in mind the current situation of the Maltese Islands when considering why immigration might affect the Maltese Public Healthcare system. Malta's healthcare system is characterised by one general government hospital, Mater Dei Hospital, which provides free medical services to the Maltese people under the National Health Service. In addition to Mater Dei, there are several Health Centres located across Malta and Gozo that also offer free healthcare services. However, these centres are limited in scope and cannot provide the critical care that is available exclusively at Mater Dei. Upon arrival at the reception desk, patients are registered in the ED system and asked to wait for assessment. Once called for triage, patients proceed to the triage room for an initial evaluation. Based on this assessment, patients are categorised by urgency. Urgent cases are prioritised and directed to Area 1, while less urgent cases may be asked to return to the waiting area until they are called and directed to Area 2 or Area 3. Doctors may then request examinations for specific patients, after which they are taken to the appropriate section and then returned to their cubicles. Following the initial diagnosis and treatment, the doctor in charge will determine whether the patient needs to be admitted to the hospital, kept under observation for 24 hours, or discharged to return home (Government of Malta, 2024).

Additionally, over the past years, Malta has experienced economic growth, ranging from 4.1% to 13.5% annually over the last ten years with 2020 being an anomaly of -3.5% growth as a result of the COVID-19 pandemic (Eurostat, 2024). As a result, through the Maltese government's strategy, the nation has also experienced a significant increase in the number of foreign residents. In fact, according to the National Statistics Office (NSO), the population in Malta stood at 519,562 in 2021 which grew more than 100,000 over the previous ten years. Moreover, at that date, the NSO reported that for every 5 people living in Malta, more than 1 of them was foreign, which results from the fact that 115,449 of the total population were non-Maltese. This was a more than fivefold rise in the percentage of foreigners living in Malta since 2011 (NSO, 2023). Therefore, it is possible to attribute the rise in the resident population to migration, even more so when one considers the fact that Malta has the lowest fertility rate in the European Union at 1.08 live births per woman in 2022 (Eurostat, 2024).

The expansion of the resident population in Malta has resulted in a lot of strain on the Public Healthcare system, which might have been one of the causes of a surge in excessive waiting times. This may lead to the Maltese residents believing that the increase in the population in Malta drives this congestion. Furthermore, given that foreign residents may, for more than one reason, experience higher waiting times than the native population, it may significantly impact their health.

Waiting times are critical policy concerns for the majority of countries around the world. The issue of waiting times in Malta's emergency department (ED) is a complex phenomenon that warrants investigation. The amalgamation of cost-free healthcare and capacity constraints leads to these waiting times which acts as a method of care rationing in the absence of pricing (Brindley et al. 2023). Having substantial waiting times will hinder efficiency in EDs (Forster, et al., 2003) and more importantly will have repercussions on customer satisfaction and health. The longer an individual waits, the more dissatisfied the person becomes and in turn could feel that the taxes that they are paying are not being used in the best way possible. More importantly, the more an individual waits in EDs, the worse the condition of the person could get and in turn become more costly both for the hospital and the person. Many factors may exacerbate ED crowding including hospital occupancy, patient demographics, and triage levels (Yoon et al., 2003) (Forster, et al., 2003) and with a changing population, all of these factors may be affected which would continue to challenge the ED occupancy. Ultimately, the findings and recommendations derived from this research have the potential to inform policy formulation and healthcare planning, with the ultimate goal of enhancing the quality and accessibility of emergency care for all individuals in Malta.

1.2. STUDY OBJECTIVES AND RESEARCH QUESTIONS

Although there has been research conducted to examine the waiting times of foreign residents at EDs, there is still limited research on this analysis in the local context. Therefore, this study aims to address this gap in the literature with the primary objective of identifying whether there are differences in waiting times between native and non-native residents. Specifically, this research aims to address relevant research questions that are currently of major interest in the country: (1) What are the effects foreign residents have on waiting times? (2) What are the differences in the utilisation of public healthcare between Maltese and Foreign residents?, and (3) What are the main factors that influence waiting times in Malta’s ED?

The purpose of this research is to delve deeper into how much being a foreign resident influences the individual waiting times of a patient visiting Malta's ED. EDs serve as a crucial mechanism in any healthcare system, where they provide immediate medical attention to individuals with injuries or illnesses (International Federation for Emergency Care, 2024). However, EDs often face challenges related to overcrowding and resource constraints (Afilalo, et al., 1995). The presence of foreigners, who would be demanding this service adds another layer of complexity to the scenario. Apart from the fact that EDs would need to increase their supply to meet this increase in demand which in turn increases the amount of spending the government has to put into healthcare, it is also possible that these foreigners would have different needs for which the system would be accustomed to (Steventon & Bardsley, 2011). Moreover, language barriers, cultural differences, and unfamiliarity with the healthcare system may mean that the efficiency and effectiveness of the emergency department’s services are affected and ultimately influence waiting times for both foreigners and native residents (Mahmoud, et al., 2013).

1.3. DISSERTATION STRUCTURE

The thesis consists of six chapters, each serving a specific purpose. In Chapter 2, an extensive review of the existing literature and empirical evidence related to the specific relationship under examination is presented. This section not only explores the theoretical foundations in this domain but also conducts a comprehensive analysis of the factors influencing waiting times. Moving on to Chapter 3, a detailed explanation of the methodological approach employed to analyse the relationship between waiting times and nationality is provided, along with a description of the data utilised for the study. Following this, Chapter 4 delves into a discussion of the results obtained and their implications. Chapter 5 then provides a summary of the overall findings and evaluates how they align with or diverge from the existing body of literature. Finally, Chapter 6 offers conclusive insights into the results and highlights the study's limitations.

2. LITERATURE REVIEW

2.1. INTRODUCTION

Immigration remains a highly debated and complex topic, particularly when examining its impact on healthcare systems. One significant aspect that has garnered attention is the utilisation of EDs by migrant populations. The literature on this topic reveals varied patterns of ED use among migrants compared to native populations, with studies showing both lower and higher rates of ED visits for migrants, depending on the context and region. Throughout this study, LOS and waiting times are used interchangeably. Both of them refer to the time between the point of registering at the ED and the time at which patients are discharged from the ED.

The question of whether migrants use EDs more or less frequently than native populations remains unresolved, as studies show mixed results. Additionally, the Length of Stay (LOS) in EDs for migrants compared to natives varies, with some studies reporting longer LOS for migrants due to factors like language barriers and the need for more comprehensive assessments. These inconsistencies highlight the need for further research to better understand the patterns of ED usage and LOS among migrant populations. This study aims to contribute to this ongoing discourse by providing insights from the Maltese context, exploring how migrants in Malta use EDs and if they affect LOS. By doing so, it seeks to identify the underlying factors influencing these patterns and to inform policies aimed at improving healthcare efficiency for all residents.

Apart from immigration, which is the main variable being analysed, several factors need to be considered to function as control variables. The literature speaks on various factors that affect LOS namely, supply-side factors, time-related factors, mode of arrival, age, gender, triage, testing, need for admission, income, and COVID-19. All of these factors are important considerations when analysing the effect a variable has on LOS which in this case is immigration. Table A-1, which is attached in the Appendix, summarises the papers by categorising which themes they relate to. This literature review offers a wide overview of how these factors affect LOS which will help in building a model to analyse the size and significance of foreigners on ED waiting times so that there is little to no omitted variable bias.

2.2. IMMIGRATION

The use of EDs by migrants is a prevalent issue that the literature talks about. Various studies see the importance of understanding the patterns of ED use among migrant populations and comparing their usage to native populations in different settings. A study in Switzerland found that asylum-seeking patients had a lower rate of ED visits compared to non-asylum-seeking patients (Brandenberger, et al., 2021). Similarly, international immigrants in England had around half the rate of hospital admissions compared to the general population, indicating lower utilisation of secondary care services (Steventon & Bardsley, 2011). This study goes on to explain that these findings are in line with the 'healthy migrant effect', which implies that migrants tend to be healthier upon arrival (Wild & Mckeigue, 1997) (Steventon & Bardsley, 2011).

Conversely, in Italy, immigrants were found to have higher standardised rates of ED visits for non-urgent matters compared to their Italian counterparts, as confirmed by the age-standardised being higher for immigrants regardless of gender (Di Napoli, et al., 2022). Similarly, Rodríguez-Álvarez, Lanborena, & Borrell (2019) found that immigrants use general practitioner and emergency services more frequently than native residents. In fact, immigrant women were found to have a 1.97 times higher probability of using emergency services compared to native women, while immigrant men had a 1.5 times higher probability compared to native men (Rodríguez-Álvarez, Lanborena, & Borrell, 2019). The higher usage of EDs in these studies was attributed to higher fertility, work-related conditions, and linguistic and cultural differences (Acquadro-Pacera, et al., 2024) (Di Napoli, et al., 2022) (Rodríguez-Álvarez, Lanborena, & Borrell, 2019).

These differences in results show that there is no consensus if there are real differences in waiting times between natives and immigrants. In fact, Acquadro-Pacera et al. (2024) indicate that no definitive trends have been identified regarding ED usage, and there is no agreement on whether migrants use EDs more or less than non-migrants. What was found from this review was that migrants tended to access EDs for less urgent matters and by walk-ins rather than by ambulance (Acquadro-Pacera, et al., 2024). Moreover, Wadsworth (2013) showed that there were no differences in hospital usage between immigrants and the native population in both Germany and England.

Another point of interest in the literature is whether there are differences in LOS between immigrants and natives, as well as, whether immigration brings about lengthened LOS. A study on Syrian refugees visiting the ED in Turkey found that their median LOS was significantly longer than that of other individuals where the median LOS for Syrian refugees was 512.5 minutes compared to 357 minutes for non-refugees (Gulacti, Lok, & Polat, 2017). Correspondingly, Zunino et al. (2021) noted that the average LOS for migrants was 3.9 hours, which was somewhat longer than that of other patients. On the contrary, Klingberg et al. (2020) found that the average LOS in the ED did not significantly differ between asylum seekers and Swiss nationals, where the average LOS for asylum seekers was 3 hours and 9 minutes, while for Swiss nationals, it was 3 hours and 22 minutes on. Furthermore, Giuntella, Nicodemo, & Vargas-Silva (2018) find no effect of immigration on waiting times in EDs within England's NHS, however, they advise that the limitations within the data resulted in excluding the years 2003-2006, where immigration from Eastern European countries increased substantially. The duration was notably impacted by language and communication barriers, as well as the limited use of interpreters (Klingberg, et al., 2020) (Zunino, et al., 2021).

The use of EDs by migrants varies across studies, with some indicating lower rates of visits while others report higher rates. There is no consensus on whether migrants use EDs more or less than non-migrants. LOS in EDs also shows mixed results, with some studies noting longer LOS for migrants, while others find no significant difference. Further research is needed to better understand these patterns and their implications. This study attempts to fill in this gap by providing insights from the Maltese situation.

2.3. SUPPLY

The supply side of a market is represented by the industry. Analysing supply relies on theories concerning firm behaviour, known as the theory of the firm (Morris, et al., 2012). The supply of healthcare encompasses the availability and provision of healthcare services by various entities, including hospitals, clinics, and healthcare professionals. In Malta, primarily, this industry is publicly funded, however, private hospitals and healthcare centres are also available to the public. It is shaped by numerous factors, including the labour market for healthcare workers, regulatory frameworks, and the financial resources available for healthcare provision. Furthermore, it will fluctuate over time and across different regions due to variations in budget size, production technology, and the availability of scarce resources such as healthcare professionals (Santana, et al., 2023).

The LOS of patients in EDs is influenced by various supply-side factors that directly impact the efficiency and effectiveness of patient care. Key factors that will be reviewed are staffing levels, bed occupancy, and bed availability. These factors play crucial roles in determining how fast patients wait and get taken care of in EDs.

2.3.1. Staffing

Research consistently shows a direct correlation between lower staffing levels and increased LOS in EDs. Lambe et al. (2003) investigated EDs in California and found that lower ratios of physicians and triage nurses to waiting room patients were associated with significantly longer waiting times. Their study revealed that patients waited an average of 56 minutes, and 42% of patients waited more than 60 minutes, with lower staffing levels exacerbating these delays (Lambe, et al., 2003). Moreover, Bucheli and Martina (2004) found that adding a physician to the busy evening shifts will help to decrease the LOS. Their results showed that the average LOS decreased from 176 minutes to 141 minutes for outpatients (Bucheli & Martina, 2004). Similarly, Hoot and Aronsky (2008) show that inadequate staffing is a common throughput factor leading to ED crowding and prolonged LOS. They noted that insufficient nurse and physician staffing levels could significantly delay patient treatment and movement through the ED (Hoot & Aronsky, 2008). In particular, the ratio of patients per medical doctor and nurse significantly impacts LOS. Specifically, an increase in these ratios is associated with a longer LOS, while a higher number of residents per patient is linked to a shorter LOS (Ba-Aoum, et al., 2023). Additionally, aligning staffing levels closely to patient demand leads to notable improvements in reductions in LOS (Sir, et al., 2017).

Increasing waiting times due to lower staffing levels can lead to various negative outcomes. According to Schneider et al. (2003), crowded and understaffed EDs may experience increased medical errors due to the high workload and frequent interruptions faced by the limited staff. Moreover, studies have shown that EDs with higher patient-to-nurse ratios see more patients leaving without being seen (Lambe, et al., 2003). Lower staffing can lead to a cycle of crowding, where prolonged patient stays further strain already limited resources, exacerbating the crowding problem.

Overall, lower staffing levels in EDs, contribute to increased waiting times for patients. This issue has broad implications other than increasing the LOS which include affecting patient outcomes, satisfaction, and overall healthcare system efficiency (Hoot & Aronsky, 2008)

(Lambe, et al., 2003). Understanding the importance of staff adequacy will go a long way in improving the LOS and hence improving ED crowding and most importantly patient care.

2.3.2. Bed Occupancy and Availability

Bed Occupancy and Availability are also important factors that contribute to prolonged ED waiting times. Bed Occupancy is a measure used to determine the proportion of hospital beds that are occupied at a given time. This is calculated by looking at the beds occupied compared to the hospital's total bed stock (Bosque-Mercader & Siciliani, 2023). Multiple Studies have assessed the impact of these variables as being critical to LOS in EDs (Forster, et al., 2003) (Alemu, et al., 2019).

Simulation modelling has shown that higher bed occupancy rates in hospitals correlate with longer waits for admission from EDs (Cooke, et al., 2004). When hospital beds are fully or close to being fully occupied, patients who need to be admitted from the ED will have to wait longer for an available bed, thus increasing their total LOS in the ED. When inpatients occupy ED beds while waiting for an inpatient bed to become available, this reduces the ED's capacity to manage new incoming patients, and, therefore, crowding will occur due to this backlog (Cooke, et al., 2004). Similarly, Kusumawati, Magarey, & Rasmussen (2019) offer an analysis of factors influencing LOS in an Indonesian hospital and reveal that bed availability is crucial. This reported that over half of the admitted patients experienced higher ED LOS due to a lack of beds, highlighting the competition between emergency and elective admission for bed space (Kusumawati, Magarey, & Rasmussen, 2019). Even worse, in Türkiye it was found that some patients who stayed for more than 24 hours were due to a lack of space in intensive care units (Mahsanlar, et al., 2014).

Lambe et al. (2002) show that in the 1990s, the number of EDs in California decreased significantly, however, the number of ED beds increased. Hospitals with higher bed occupancy often see an increase in the severity and complexity of cases handled in the ED, which can also contribute to longer LOS (Lambe, et al., 2002). Moreover, the study notes an increase in visits per ED which may be the reason why ED capacity would be insufficient to meet the ever-increasing demand for EDs. Increasing the number of beds available in hospitals can alleviate some of the pressures on EDs. This association comes with several adverse outcomes, as noted by Hoot and Aronsky (2008). These include delayed pain assessment and treatment, increased pain mortality, and a higher likelihood of patients leaving without being seen due to the increase in waiting times (Hoot & Aronsky, 2008) (Lambe, et al., 2002).

The relationship between bed occupancy and ED LOS is important, with high occupancy rates leading to longer stays in the ED, increased crowding, and adverse patient outcomes. Addressing this issue requires different approaches, including increasing ED bed capacity, and optimising patient flow (Cooke, et al., 2004) (Lambe, et al., 2002). By adopting these strategies, hospitals can improve the efficiency of their EDs and, therefore, reduce patient waiting times.

2.4. DEMAND

Traditionally economists classify the demand for a good as the quantity that consumers are willing and able to buy. Healthcare is no different in this sense. More specifically, Culyer (2012) gives a working definition where he argues that the demand for healthcare is the amount of utilisation where the perceived marginal health benefits of the care match the marginal cost of accessing it. This demand is influenced by both patients' and healthcare professionals' views on the perceived benefits and costs (Culyer, 2012). Consumer choice theory can be used to explain why consumers react to changes in various factors in specific ways (Morris, et al., 2012). Health is valued because it enhances individuals' quality of life and allows them to enjoy more leisure time and income. Being healthy provides direct utility, enabling people to feel better and engage in activities without physical limitations.

Additionally, the demand for health can be analysed through the human capital theory, which views health not only as a consumption good but also as an investment good. This perspective was greatly influenced by Michael Grossman's seminal work, which is foundational in health economics. Healthy individuals can work more days and be more productive, thus increasing their earnings. Therefore, investing in health through medical care, diet, and exercise becomes a means to improve future income and overall well-being (Grossman, 1972). Unlike other goods, price generally is not as important when it comes to affecting the demand for healthcare. This is because of either insurance coverage or because of publicly funded national health services, where the latter is more applicable to Malta’s case (Santana, et al., 2023).

Following this, it is understood that for one to gain better health, an individual would want to consume medical care. Therefore, it is easy to understand that the demand for medical care is a derived demand (Folland, Goodman, & Stano, 2013). People do not demand medical care for its own sake but because it helps produce better health. This distinction is crucial as it shapes the way individuals allocate their resources towards health-improving activities

2.5. TIME-RELATED FACTORS

Some studies observe how time-related factors such as the day of the week and time of day affect LOS in EDs. However, triage Level 1 patients were found to not be affected by these time-related effects (Ding, et al., 2010). Additionally, month of the year was not found to be significant in affecting LOS in EDs (Sarıyer, Ataman, & Kızıloğlu, 2020)[b]. However, another study found that Autumn had longer waiting times, although this study could not interpret this causally due to data being only from one year (Goodacre & Webster, 2005). An early study found significant changes in LOS according to the day of the week (Lew, 1966). Other studies find the same for EDs. Castner et al. (2016) conducted a retrospective analysis of ED visits among Medicaid patients, showing a clear pattern in ED utilisation. Mondays and Tuesdays saw a 17.09% increase in daily visit volume compared to the baseline, while the volume decreased by 5.76% on Fridays and even more over the weekend (Castner, et al., 2016) (Ding, et al., 2010). Goodacre and Webster (2005) found that in their study longer waiting times were on Mondays and Sundays where patients are predicted to wait roughly 23 minutes longer. This leads to differentials in LOS and similarly, Ding et al. (2010) reported that time-related factors, including the day of the week, were significant predictors of waiting room times and boarding times. Intriguingly, Sarıyer et al. (2020)[b], using a multivariate linear regression model, found that although weekends had higher ED volumes, there was a decrease in mean LOS, finding a coefficient of -3.12, indicating that the LOS is expected to decrease on weekends. However, Rathlev et al. (2007) found that the day of the week did not influence LOS, suggesting that this variable may have been overshadowed by the number of elective admissions, which shows an evident weekly pattern.

Studies observe some differences between day and night shifts when it comes to LOS in EDs. According to Hosseininejad et al. (2017), admissions during the evening shifts were significantly associated with prolonged LOS compared to those during morning shifts. Similarly, Downing, Wilson & Cooke (2004) found that patients arriving during the night were more likely to experience extended stays in the ED, as this group had the highest percentage of patients spending over 8 hours in the ED. Sarıyer et al. (2020)[b] also found that patients admitted during peak times, particularly in the evening, experienced longer LOS, suggesting that prioritising these periods will help in tackling this problem. On the other hand, Chaou, et al. (2016) find different effects of the period of day for different cohorts. For the discharged group, higher LOS was associated with day shift arrival, however, for the admission group night shift arrivals experienced longer ED LOS.

Time-related factors, such as the day of the week and time of day, significantly influence LOS in EDs. Weekdays see higher visit volumes and longer LOS, while weekends generally have shorter stays. Moreover, evening times and night shift arrivals contribute to extended LOS, highlighting the need for aimed strategies to manage LOS effectively across different times and patient groups.

2.6. ARRIVAL TYPE

Another factor influencing waiting times observed in the literature is the mode of arrival. These are usually split between walk-ins and ambulance arrivals. Generally, ambulance arrival was subject to higher LOS in EDs resulting in a 0.6-hour increase (Yoon, Steiner, & Reinhardt, 2003). Literature finds that patients arriving by ambulance generally experience longer stays (Casalino, et al., 2014) (Sarıyer, Ataman, & Kızıloğlu, 2020)[a] (Sarıyer, Ataman, & Kızıloğlu, 2020)[b] (Lowthian, et al., 2012). Lowthian et al. (2012) and Downing, Wilson, & Cooke (2004) report that these patients tend to be older and in a more serious condition. Consequently, these patients would necessitate more complex assessments and increase the likelihood of admission. Moreover, Casalino et al. (2014), while conducting a study in France found patients arriving by ambulance had an odds ratio of 1.96 for extended ED-LOS compared to those arriving by other means.

However, other studies show that ambulance arrivals had shorter waiting times since most of the time they would have been admitted straight to the treatment room, and therefore waiting time was zero (Ding, et al., 2010) (Goodacre & Webster, 2005). Even though these patients were found to have shorter waiting times, they would experience longer treatment times (Ding, et al., 2010). However, Goodacre & Webster (2005) suggest that this had minimal clinical significance.

The mode of arrival significantly impacts ED LOS. Patients arriving by ambulance generally experience longer stays due to more serious conditions. These patients are often older and in poorer health, necessitating longer ED visits. While some studies show that ambulance arrivals may have shorter initial waiting times due to direct admission to treatment rooms, their overall treatment time is longer.

2.7. AGE

Several studies consistently also underscore the importance age has on the LOS of patients. Older patients tend to generally have a longer ED LOS compared to younger patients (Ba-Aoum, et al., 2023) (Kreindler, et al., 2016) (Vegting, et al., 2015). Patients aged 65 years and older represent a significant portion of ED visits and tend to have higher clinical acuity and complexity, which prolongs their LOS (Casalino, et al., 2014) (Downing, Wilson, & Cooke, 2004). Moreover, patients over 75 years old had notably longer LOS compared to younger patients, highlighting the relationship between advancing age and increased healthcare needs (Casalino, et al., 2014). Furthermore, Downing, Wilson & Cooke (2004) show that 39% of patients aged over 85 years spent longer than 4 hours in the ED.

Biber et al. (2013) showed that older trauma patients have substantially longer LOS than their non-trauma counterparts. However, they found that there was no significant difference between trauma and non-trauma patients who are aged less than 70 years old. (Biber, et al., 2013). A 10-year increase in age was associated with a 7 to 22-minute increase in treatment time at the 90th percentile (Ding, et al., 2010). Furthermore, Chaou, et al. (2016) found that in the discharged patient group higher age was significantly associated with lengthened ED LOS, where for every additional year of age, the ED LOS increased by 1.2%. This difference is primarily due to the increased complexity and severity of conditions in older patients, necessitating longer stays (Chaou, et al., 2016) (Downing, Wilson, & Cooke, 2004). However, the effect of age on ED LOS is not uniform across all patient groups as the specific conditions and the need for consultations also significantly impact the duration of their stay (Vegting, et al., 2015).

In conclusion, older patients experience longer ED stays due to higher clinical complexity. These findings highlight the need for tailored ED strategies to address the complex needs of older patients.

2.8. GENDER

From the literature, gender has emerged as another prevalent factor that was investigated. Some studies show that females tend to have longer LOS in EDs compared to males (Geurts, et al., 2012) (Hosseininejad, et al., 2017) (Lowthian, et al., 2012) (Serinken, et al., 2008). A study in Türkiye found that women stayed significantly longer in the ED than men, which was partly due to more frequent abdominal complaints requiring extensive diagnostic testing (Serinken, et al., 2008). Moreover, Hosseininejad et al. (2017), found the same in an Iranian ED, by basing the results on univariate analysis, attributing an odds ratio of 1.42. This indicates that females were 42% more likely to experience prolonged stays in the ED. Geurts, et al. (2012) note that females were admitted twice as often resulting in longer LOS. Additionally, Lowthian et al. (2012) show that patients experiencing LOS longer than 4 hours were associated with being female among other factors.

On the other hand, a study by Alnahari and A'aqoulah (2024) found that males were more likely to have prolonged LOS compared to females, with an odds ratio of 1.20, suggesting that males had a 20% higher likelihood of prolonged LOS. This could be due to males tending to be drivers and have a higher likelihood of being involved in road accidents (Alnahari & A'aqoulah, 2024). Conversely, many studies find that gender is insignificant to prolonged LOS (Biber, et al., 2013) (Casalino, et al., 2014) (Nippak et al., 2014) (Weiss, et al., 2012). Nippak et al. (2014) found no variation in LOS in ED in their study, implying that differences observed in other studies might be due to the theory that men delay seeking medical help, which results in them being more sick and subsequently needing a longer inpatient stay than women.

In conclusion, the literature presents mixed results on the impact of gender on LOS in EDs. Several studies indicate that females generally have longer LOS compared to males while some research suggests that males may experience prolonged LOS. Other studies, however, find no significant difference in LOS based on gender. Overall, while gender appears to influence LOS in some contexts, it is not a universally significant factor.

2.9. TRIAGE

Triage levels, which categorise patients based on the severity of their condition, likewise play a significant role in determining LOS. All patients seeking emergency care must be assessed by an ED nurse and classified to prioritise those with the most urgent medical needs requiring immediate attention (Qureshi, 2010). Many studies have observed whether the triage level of the patient matters for LOS in EDs, however, there are mixed results.

Some of the literature finds that the intermediate triage levels are the ones that experience the highest LOS in EDs. Yoon, Steiner, & Reinhardt (2003) examine key causes of ED overcrowding and find that patients in Levels III and IV generally had the longest waiting times with 366.4 minutes and 251.2 minutes respectively. On the other hand, the shortest LOS was triage Level I where the LO was of 151.3 minutes (Yoon, Steiner, & Reinhardt, 2003). Castalino et al. (2014) used multivariate analysis to confirm that acuity levels were a significant predictor for ED LOS. Similarly, Ba-Aoum, et al. (2023) that triage level was among the strongest determinants of LOS. Again, they found that patients in the intermediate triage levels had the longest LOS, whereas triage Level 1 patients had the shortest LOS because they required immediate attention (Ba-Aoum, et al., 2023).

Conversely, other studies show the opposite, or that Triage Levels do not matter for LOS (Chaou, Chiu, Yen, & Ng, 2016). Sarıyer, Ataman, & Kızıloğlu (2020)[b] analysed 25 different types of diagnosis and found those that are generally considered urgent cases in the triage system have longer LOS, while non-urgent complaints, like nausea, show the opposite. Additionally, abnormal vital signs are related to longer LOS while substance use was found to result in shorter LOS (Geurts, et al., 2012). Hosseininejad et al. (2017) also show that higher triage levels, indicating more severe conditions were associated with longer LOS. Specifically, patients triaged at Level I had significantly longer stays compared to those at lower triage levels (Hosseininejad, et al., 2017). Kusumawati, Magarey, & Rasmussen (2019) confirmed this finding as well as they found that patients classified as triage Level 1 experienced the longest ED LOS with a median of 364 minutes, while those in triage Level 5 had the shortest median LOS of 15 minutes. However, Nippak, et al. (2014) found that the triage level did not show a significant main effect on LOS. However, patients classified under higher urgency triage levels had shorter ED LOS, while longer ED LOS was reported for each subsequent triage level (Nippak, et al., 2014).

Ultimately, triage levels significantly impact the LOS in EDs. Some studies find that intermediate triage levels had the longest LOS while others suggest that higher urgency patients are associated with higher LOS. Other studies suggest that triage levels are not a significant factor for LOS, however, this does not seem to be universal. Overall, triage levels influence LOS, but their specific impact varies.

2.10. NEED FOR SPECIFIC TESTING WHILST AT THE ED

Studies have also shown the importance of including testing as a variable for prolonged LOS in EDs. Diagnostic tests, including blood tests, imaging, radiology tests, and other laboratory tests, are primary contributors to prolonged LOS in EDs (Casalino, et al., 2014) (Dadeh & Phunyanantakorn, 2020) (Davis, et al., 1995) (Gardner, et al., 2007) (Vegting, et al., 2015) (Kocher, et al., 2012) (Yoon, Steiner, & Reinhardt, 2003). Li et al. (2015) indicate that the number of tests and the LOS are directly related, where for every 5 additional tests ordered LOS increased by 10 minutes. Furthermore, Kocher et al. (2012) found that blood tests and advanced imaging significantly prolonged the ED LOS, with blood tests adding approximately 72 minutes and MRI scans adding around 64 minutes to the LOS for discharged patients. Dadeh and Phunyanantakorn (2020) add that the need for interdepartmental consultations, involving more than two specialists, was associated with substantially longer ED stays.

Furthermore, studies show that imaging is related to lengthened stays in EDs. Alemu et al. (2019) found that delays in laboratory test profiles, and delays in radiological services significantly prolonged LOS among other variables. Specifically, Yoon, Steiner, & Reinhardt (2003) found that Ultrasound imaging added an average of 4.7 hours, X-rays were associated with an extra 1.0 hours and CT scans added approximately 0.7 hours to the LOS in EDs. This was also found by Casalino et al. (2014) where patients who received CT scans or MRIs had a higher likelihood of extended stays. Kanzaria et al. (2014) also show that patients having advanced diagnostic imaging had higher LOS with the median being 252 minutes compared to 138 minutes for the rest.

In conclusion, the consistent findings across multiple studies point out the significance of diagnostic testing on the LOS in EDs. Diagnostic tests, including blood tests, imaging, and other laboratory procedures, are primary contributors to prolonged LOS. The relationship between the number of tests ordered and LOS is evident, with each additional test incrementally increasing the time patients spend in the ED. Advanced imaging, such as MRI and CT scans, notably extends LOS, as does the need for interdepartmental consultations. Clearly, the impact of testing is established and should be taken note of when analysing waiting times in EDs.

2.11. NEED FOR ADMISSION TO A HOSPITAL WARD

As mentioned earlier, hospital admission is another factor that impacts patient waiting times in EDs (Kreindler, et al., 2016) (Kusumawati, Magarey, & Rasmussen, 2019). Lowthlan et al. (2012) show that the likelihood of admission rises with age, contributing to prolonged stays, especially among the elderly. Downing, Wilson and Cooke (2004) find that admission significantly increases the time patients spend in the ED. Patients requiring admission were 2.64 times more likely to spend 4–8 hours and 4.84 times more likely to spend over 8 hours in the department compared to those not admitted (Downing, Wilson, & Cooke, 2004). Gardner, et al. (2007), also found increased LOS for admitted patients where the median waiting time was 255 minutes compared to 120 minutes for discharged patients, while they also noted that intensive care unit admissions had a shorter LOS. Interestingly certain ethnicities and the location of the hospital also affected the LOS of admitted patients (Gardner, et al., 2007). Moreover, longer ED LOS is strongly associated with admission to a medical or surgical ward or transfer to another facility (Casalino, et al., 2014).

Similarly, Forster et al. (2003) demonstrated that increased hospital occupancy leads to longer ED stays for admitted patients. Their observational study at a 500-bed hospital showed that a 10% increase in hospital occupancy resulted in an 18-minute increase in the median ED LOS for admitted patients (Forster, et al., 2003). Weiss et al. (2012) identified that the need for inpatient admission was the factor most strongly associated with extended ED stays. The added wait time was approximately 3 hours for patients admitted in-house, 5 hours for those transferred to another unit within the system, and over 6 hours for those transferred to an external unit (Weiss, et al., 2012).

Moreover, Stephens et al. (2014) found that mental health EDs also suffer from this association of the need to be admitted and increased LOS. All of this further shows that admission contributes to delays in patient care since EDs are not prepared to treat them as necessary (Happell, Palmer, & Tennent, 2010) (Clarke, et al., 2005). Chang et al. (2012) found that psychiatric patients remaining in the ED for 24 or more hours often required admission to specialised mental health facilities. This delay in securing placement exacerbates their LOS (Chang, et al., 2012).

The need for admission is a significant driver of extended LOS in EDs. There is a need for systematic improvements in bed management and resource allocation to address these delays effectively (Lowthian, et al., 2012). Implementing a triage system and grouping patients with similar severity or types of complaints will greatly enhance the effectiveness of the ED by reducing patient waiting times (Jarvis, 2016). Moreover, having established specialised observation units can alleviate the bottleneck effect observed in many EDs (Chang, et al., 2012).

2.12. INCOME

Another factor that may influence LOS in EDs is income and the lack of insurance support. Lambe, et al. (2003) found, using Ordinary Least Squares regression analysis, that per capita income was a significant determinant in waiting times. Specifically, EDs with lower per capita income experienced an increase of 10.1 minutes in LOS for every $10,000 decline in per capita income. Similarly, Downing, Wilson, & Cooke (2004) show that higher levels of deprivation are a characteristic that significantly increases the likelihood of spending more than 4 hours in the ED. Moreover, Hosseininejad, et al. (2017) state that the lack of insurance support is a significant factor contributing to extended LOS in EDs.

To sum up, the COVID-19 pandemic introduced factors that significantly extended LOS in EDs. Additionally, lower income and lack of insurance support also significantly increased LOS, highlighting various influences on ED wait times. These variables could be of importance when studying the factors of prolonged LOS.

2.13. COVID-19

One of the extraordinary developments in recent years has been the COVID-19 pandemic.. Lee, et al. (2023) studied the factors affecting LOS in the ED in the context of the COVID-19 pandemic. Given the unique circumstances, several factors may have influenced LOS which would not have normally influenced LOS under normal circumstances (Guo, et al., 2021). If patients had a fever or suffered respiratory symptoms they were required to be treated in isolation rooms after which patients required a real-time polymerase chain reaction during this time resulting in longer ED LOS (Lee, et al., 2023). Moreover, differences between factors affecting LOS in EDs were found. Before the COVID-19 pandemic, diabetes mellitus and medical consultations influenced ED LOS greater than 4 hours, whereas, during the pandemic, daytime visits, X-ray imaging, and COVID-19 diagnosis were the key factors (Rojsaengroeng, et al., 2023).

2.14. CONCLUSION

In conclusion, the utilisation of EDs by migrant populations and the factors influencing LOS present various challenges within healthcare systems. The literature reveals a lack of consensus on whether migrants use EDs more or less often than the local populations, with studies showing both higher and lower rates of visits. Additionally, the LOS in EDs for migrants varies, with some studies finding longer stays due to language barriers and comprehensive assessments, while others find no significant differences. The mixed results in the literature highlight the necessity for further research to understand the patterns of ED usage and LOS among migrant populations. This study contributes to this ongoing challenge by providing insights from the Maltese context, exploring how migrants use EDs and their impact on LOS.

Moreover, the review highlights the importance of considering various control variables such as staffing levels, bed occupancy, arrival type, age, gender, triage levels, testing, need for admission, income, and extraordinary factors like the COVID-19 pandemic. Although, the literature does not have full consensus on how these affect LOS, nevertheless, each of these factors plays a crucial role in influencing LOS in EDs and should be accounted for.

By addressing these factors, healthcare systems can develop more effective strategies to improve ED efficiency and patient care for both migrant and native populations. Ensuring adequate staffing, optimising bed management, and enhancing triage systems are essential steps toward achieving this goal. Moreover, understanding how the ongoing trend of the increasing population in Malta is important to investigate whether the current facilities are sufficient or whether further expansion is necessary to decrease the LOS in EDs, as this is considered to be a critical performance metric for healthcare systems efficiency. Overall, a deeper understanding of these dynamics will help create a more equitable and responsive healthcare environment for all residents.

3. DATA AND METHODOLOGY

3.1. INTRODUCTION

This study employed various analytic techniques during the initial stages to ensure the data was clean and well-prepared for analysis. These techniques were essential for uncovering patterns and transforming the data into a format suitable for regression modelling. The exploratory nature of this research made regression modelling an appropriate tool for addressing the research questions, allowing for a straightforward examination of relationships between variables. The regression model was run using STATA, a statistical tool used for Data Science.

This chapter begins with a discussion of the specific model used to analyse waiting times in the healthcare context. It also describes the various data sources utilised, highlighting their relevance and how the data was adapted for the needs of the study. Ethical considerations are also addressed to ensure the integrity of the research process. The chapter further explores the estimation methods applied and the limitations inherent in the chosen methodology.

3.2. WAITING TIMES MODEL

The methodological approach to this research entails the creation of an Econometric model using OLS regression. Many researchers have conducted studies to evaluate the effect of immigrants on healthcare (Giuntella, Nicodemo, & Vargas-Silva, 2018) (Paling, et al., 2020). This study will now be applied to the Maltese scenario, particularly Mater Dei's ED.

First, it is important to establish a theoretical framework. To show how immigration and waiting times are related, a simple demand and supply model for healthcare services can be used (Giuntella, Nicodemo, & Vargas-Silva, 2018) (Siciliani & Iversen, 2012). Before delving into this, however, it is important to understand how waiting times arise. The entire triage and caretaking process can encounter bottlenecks when there is excess demand. In these situations, waiting times will automatically adjust to bring supply and demand for healthcare back into equilibrium (Siciliani & Iversen, 2012).

Both demand and supply for healthcare are affected by waiting times (Giuntella, Nicodemo, & Vargas-Silva, 2018) (Martin & Smith, 1999) (Siciliani & Iversen, 2012). As mentioned, demand is not primarily affected by price, especially when individuals seek public healthcare. Instead, the cost patients experience is the waiting times. Naturally, the higher the waiting times, the less satisfied the patient becomes and as a result, they might decide to not get the treatment required. This trade-off is important to note as some patients experience this and has negative consequences if the majority of patients decide to leave the ED. Some may leave the ED to seek private healthcare if they can afford it. However, those who cannot afford to pay for private healthcare will remain without any treatment which results in a lessened health stock. Similarly, for the supply side, waiting times affect the utility function of hospital managers as their wages may be affected by these waiting times (Martin & Smith, 1999). The less the waiting times are, the more efficient the hospital will be and therefore, managers will be rewarded for their decisions. Following Siciliani & Iversen (2012), it is possible to describe the demand and supply functions in the following way:

$$Y^d = \alpha_0 + \alpha_1 w_i + \alpha_2 x_i^d + \alpha_3 z_i + e_i^d \qquad \text{(Eq. 3.2-1)}$$

$$Y^s = \beta_0 + \beta_1 w_i + \beta_2 x_i^s + \beta_3 z_i + e_i^s \qquad \text{(Eq. 3.2-1)}$$

Where Y^d and Y^s represent the demand and supply of healthcare, w_i represents the waiting time, and z_i are demand or supply shifters.

Under the assumption that there will be an equilibrium, it is possible to equate the two functions and make waiting times subject to the formula. Moreover, when this is done, the variable of immigration will be inserted to analyse how this affects waiting times (Giuntella, Nicodemo, & Vargas-Silva, 2018). The function will look as follows:

$$w_i = \lambda_0 + \lambda_1 x_i^d + \lambda_2 x_i^s + \lambda_3 z_i + e_i \qquad \text{(Eq. 3.2-3)}$$

Where:

$$\lambda_0 = \frac{\alpha_0 - \beta_0}{\beta_1 - \alpha_1}, \lambda_1 = \frac{\alpha_2}{\beta_1 - \alpha_1}, \lambda_2 = \frac{-\beta_2}{\beta_1 - \alpha_1}, \lambda_3 = \frac{\alpha_3 - \beta_3}{\beta_1 - \alpha_1}$$

$$w_i = \lambda_0 + \lambda_1 IMM_i + \lambda_2 x_{d,i} + \lambda_3 x_{s,i} + \lambda_4 z_i + e \qquad \text{(Eq. 3.2-4)}$$

Where:

- w_i is the waiting time for individual i
- IMM is a dummy where it takes the value of 1 if the individual is foreign and 0 otherwise.
- x_d describes other factors, such as the population, the percentage of elderly patients, and the population's health demands, that influence the demand for healthcare.

- x_s describes the other variables that affect the supply of healthcare for example number of beds and expenditure in the public health sector.
- z contains variables that affect both the demand and supply of healthcare.

Giuntella, Nicodemo, & Vargas-Silva (2018) explain that the impact of immigration on waiting times is uncertain. Immigration affects both demand and supply in healthcare by influencing demand factors, patients' and managers' expected wait times, and the availability of healthcare staff. They argue that, if the increase in immigrant population is not matched by a supply increase, waiting times may rise, especially in the short term due to budget constraints and unexpected population changes. However, if supply grows more than demand, waiting times could decrease. This might happen if natives move, seek private care, or if immigrants have lower healthcare needs. Areas with less elastic demand or less healthy immigrants may experience larger increases in waiting times (Giuntella, Nicodemo, & Vargas-Silva, 2018).

Specific to the data available the model looks as follows:

$$w_i = \lambda_0 + \lambda_1 nationality_i + \lambda_2 age_i + \lambda_3 gender_i + \lambda_4 arrival_i + \lambda_5 triage_i + \lambda_5 time_i + \lambda_6 day_i + \lambda_7 admission_i + +\lambda_8 admissions - to - discharge_i + e \qquad \text{(Eq. 3.2-5)}$$

Table 3.2-1 gives a summarised definition of what each variable means. Further explanation will be provided in the Data and Data Sources section. Eq. 1.2-5 will be utilised for the analysis. This equation will be executed for different years, and a comparison of the results will demonstrate how the effects have changed with the changes occurring during these years.

Table 3.2-1: Summarised description of variables

Variable Name	Variable Type	Definition
w_i	Numeric	Waiting time of individual *i*
$nationality_i$	Dummy	1 = Individual *i* is a Resident non-Maltese 0 = Individual *i* is either Maltese or a Tourist
age_i	Numeric	The midpoint of the age range individual *i* falls under
$gender_i$	Dummy	1 = Individual *i* is a Male 0 = Individual *i* is a Female
$arrival_i$	Dummy	1 = Individual *i* entered to the ED via walk-in 0 = Individual *i* entered the ED via other means
$triage_i$	Dummy	1 = Individual *i* falls under ESI-1 or ESI-2 0 = Individual *i* falls under other ESI levels
day_i	Dummy	1 = Individual *i* visited the ED during the day 0 = Individual *i* visited the ED during other times
$weekend_i$	Dummy	1 = Individual *i* visited the ED during the weekend 0 = Individual *i* visited the ED during weekdays
$admission_i$	Dummy	1 = Individual *i* required admission to hospital 0 = Individual *i* did not require admission to hospital
$admissions-to-discharge_i$	Numeric	The ratio of admissions to discharges during the day individual *i* visited the ED

Importantly, regression analyses operate under the assumption that the regressors are non-stochastic, meaning the explanatory variables are not random. Additionally, it is assumed that the error term (ε) adheres to the classical assumptions (Gujarati & Porter, 2010). These assumptions include:

1. The model assumes a linear relationship between the dependent and independent variables.
2. The independent variables are assumed to be independent of the error term, implying that the expected value of the errors has a zero mean and does not depend on the independent variables.
3. The error term is assumed to have a constant variance.
4. The error terms are assumed to be normally distributed.

3.3. DATA AND DATA SOURCES

From the data supplied by Mater Dei, the data can be best described as cross-sectional. This is because there is data on variables which are collected in a period for different individuals. The data available goes from 2017-2023, however, since the same individuals are not observed over the years, the dataset cannot be compiled to become a panel dataset. Therefore, a cross-sectional dataset was deemed to be suitable for this analysis.

The variables identified were collected from several sources. One of the fundamental obstacles in data analysis is the quality of the data collected. This underscores the importance of using reliable sources when compiling the dataset. The patient-level characteristics were gathered from Mater Dei Hospital and cover the years from 2017-2023 which implies a total of 612,753 observations. This includes the variables identified from the literature like age group, gender, whether a foreigner or not, triage level, patient's waiting time, arrival type and need for admission. Unfortunately, the tests carried out on the patient were not available. Additionally, the literature reveals that factors relating to supply-side factors also significantly impact the LOS. However, no data was available that would have positively affected the dataset. The only available data on supply-side factors were number of beds the hospital had and the number of full-time equivalents the hospital employed. These were only available on a yearly basis and therefore, would not have had any effect on the regressions.

From the original data collected from Mater Dei, the data had to go through a cleaning process. Firstly, the data contained an age group called 999. This does not indicate any age group and serves as a group for patients who do not have any records in the Mater Dei system and do not have any identification on them at the time of registering at the Mater Dei ED.

Then, from the Nationality variable, any patient under the Unknown category was also removed. These patients offer no usefulness to the estimations given that the person's nationality is important. Furthermore, when a patient who is a child and has not been registered with Identity Malta goes to the hospital, they will be given a temporary hospital number, hence the Child category under nationality was created. Sometimes, even when the child is older and comes to the hospital, the parents might not know the child's ID card number, so the temporary 'C' number will still identify the child. Given that there were not a lot of these cases, this category was removed to simplify the regression.

Similarly, any patient under the category ‘U’ for gender was also removed. This is because ‘U’ signifies that the gender is unspecified and for simplicity, these were removed to solely have Male and Female as control variables. Moreover, some entry methods did not have valid entries, for example, some had “Martina”, “Z” and “Prabhakar Reddy”. Moreover, some entry methods referred to the same entry method but were written down differently for example “Ambulance” and “Ambulance***”. These were grouped to apply to entering the ED via the Ambulance.

Subsequently, LOS was calculated after some adjustments were made to the original data. Firstly, the time made available was in the form of “2.15”. This was replaced with “2:15” as MS Excel identifies this as a time rather than a number. Moreover, when the time was, either o’clock, past 10, past 20, half past, 20 to or 10 to, the value written in the file would be “5” or “5:1”. In the former case, MS Excel would not recognise this as a time, therefore, using the replace all function, cells having an exact match of “5” were replaced by “5:00”. In the latter case, MS Excel would read “5:1” as “5:01” therefore these were replaced by “5:10” so that Excel recognises the correct time. This was also the case for the discharge time and the same process was done. After this, the date and time of both the registration and discharge were added together into one cell. This was done so that when subtracting the discharge time from the registration time, excel would take into consideration the date as well as the time. If the subtractions were only done using time, in instances where patients stayed at the ED overnight, problems would occur.

After this cleaning, all variables were separated according to the categories. For example, for Gender, a dummy was created for Male. This was done for each variable including Gender, Nationality, Entry Method, Triage Level, Need for Admission, and Time-related Factors. Also, LOS was calculated in minutes as this could prove to be useful when estimating the regression. Furthermore, from the literature time of day and day of the week was another variable that was found to significantly affect LOS in EDs. Subsequently, dummy variables for the Weekend and Day were created similarly to other dummy variables.

A total of eight separate variables were included in the analysis to assess the relationship in question. A summarised version of the dataset is included in the Appendix under Table A-2. These 20 observations relate to 20 different cases on 1st January 2017. The dependent variable 'w_i' included in the above equation refers to the number of minutes patient 'i' has waited in Mater Dei's ED. As explained, this is the difference between when the person was registered and when the person was discharged from the ED. The main independent variable '$nationality_i$' refers to the nationality of the patient 'i' at the ED. This variable is segregated into dummy variables. These dummy variables signify whether the patient is Maltese, Resident Non-Maltese, or Non-Resident. The latter implies that the patient is a tourist visiting the country for a short time and therefore would not be registered in Malta. The dummy variable for Maltese was not created, therefore, if the other nationality dummies are 0, the patient would be Maltese.

The independent variable 'age_i' refers to the age of patient 'i' when visiting the ED. This variable was given as ranges starting from 0-4 up to 90-94. Instead of creating dummy variables for every age, a middle point of the range was taken as the age of the patient. For example, a patient that is in the age range 40-44, 42 was taken as the patient's age. This was done so that a quantitative variable would be directly used in the regression. The independent variable '$gender$' refers to the gender of patient 'i' when visiting the ED. This comprises two different types of genders which are Male and Female. For this variable, a 1 would signify that the person is a male and female otherwise.

The independent variable '$arrival_i$' resembles the type of arrival patient 'i' has arrived with to the Mater Dei ED. The types of arrivals include walking, ambulance, helicopter, helicopter-ambulance, and other. The dummy for Walking was created, where a 1 would mean that the patient came in via walk-in. On the other hand, if the patient arrived by ambulance, for example, the Walking dummy variable would have a 0. This would be the same for all other types of arrivals.

The explanatory variable '$triage_i$' refers to the Emergency Severity Index (ESI) of patient 'I' at the point of the initial assessment at the Mater Dei ED. This consists of ESI-1 to ESI-5, ESI-SKIP and ESI-Blank. ESI-Blank is for people who were supposed to register at the reception desk but missed their triage appointment. Some registrations were mistakenly discharged from the A&E system and had to be re-registered without needing to be re-triaged. As for ESI-SKIP, these are for people who were re-registered or were seen by subspecialties like Ophthalmology or ENT and were sent directly to the appropriate department without needing to be triaged. For this variable, a dummy was created called triage where a 1 would signify that the patient was an ESI-1 or ESI-2 patient. Otherwise, the patient would have a 0 showing that they were part of the other categories.

Time-related factors are represented by the explanatory variables 'day_i' and '$weekend_i$'. 'day_i' shows the time of day the individual visited the ED. If this variable is 1 it means that the individual visited the ED between 6 a.m. and 6 p.m. Otherwise, the patient would have visited the ED during the remaining hours. On the other hand, '$weekend_i$'represents the day patient 'i' entered the ED. A dummy was created, where a 1 would mean that the patient visited the ED during the weekend, that is either Saturday or Sunday, while a 0 would mean otherwise.

Lastly, for patient-level factors, '$admission_i$' refers to whether or not the patient 'i' required a bed and, therefore, needed to be admitted. Here 1 would mean that the patient needed to be admitted into Mater Dei while 0 means that the patient did not need to be admitted to a bed. Moreover, $admissions - to - discharge_i$ shows the ratio of admissions to discharges on the day the patient visited the ED. This ratio could serve as a good instrument variable for bed occupancy given that no data was available for this.

3.4. ETHICAL CONSIDERATIONS

All ethical considerations were addressed regarding the data used in this research. In compliance with the University's Research Code of Ethics, the required 'self-assessment ethical clearance' form was completed and submitted only for records. Since the study relied solely on secondary data without collecting any primary data, the Faculty of Economics, Management, and Accountancy Research Ethics Committee confirmed the submitted form. Consequently, no additional ethical approval was needed from the University Research Ethics Committee. Furthermore, since this data was not available online, authorisations had to be gained from the

Mater Dei Chief Executive Officer, the Data Protection Officer at Mater Dei, the Chair of the A&E, and the Medical Director. All of these approvals were acquired before gaining the data.

Additionally, given the sensitivity of the data, which includes personal information about patients in Mater Dei's A&E, several measures have been implemented to protect privacy. First, Mater Dei anonymised the patient's data by encrypting patient ID cards, ensuring that individual patients could not be identified during the analysis. Furthermore, patients' ages were not recorded as specific numbers. Instead, they were grouped into 5-year intervals, for example, 0-4, 5-9, up until 94 and older patients fall under the 95+ category. These steps ensure that the sensitive data is as anonymised as possible, safeguarding patient privacy effectively. Moreover, the results of this study will have an embargo of at least one year to ensure that the study abides by ethical standards given the sensitivity of the data.

3.5. METHODOLOGY LIMITATIONS

The chosen methodology for the study was found to be suitable, but it has some limitations. Firstly, there were some inconsistencies in the registered times and discharge times, with some discharge times recorded as earlier than the corresponding registration times. This resulted in negative waiting times, which is illogical. Although these observations were removed, they raise concerns about potential input errors in the data provided by the Clinical Performance Unit from Mater Dei, which cannot be controlled. This is known as measurement error. If there are errors in the measurement of the dependent variable, like in this case, the estimated variances of the estimators will be larger compared to when there are no measurement errors (Gujarati & Porter, 2010). This is because the errors get added to the overall error term. Given the uncertainty surrounding this limitation, there may also be errors of measurement in the explanatory variable. As a result, the OLS estimators will be biased and inconsistent (Gujarati & Porter, 2010).

Secondly, information about the tests patients underwent was not available. According to the literature, this is an important factor influencing waiting times. The number of tests a patient undergoes affects the waiting time as they wait for the tests, wait for the results, and then professionals take action based on those results. The absence of this information may introduce errors in the regression and lead to biased coefficients, known as omitted variable bias. Not only are coefficients biased but also they would be inconsistent as well (Gujarati & Porter, 2010).

Lastly, supply-side variables like available beds and the number of doctors in the ED were not available for individual cases. Literature indicates that these variables play a significant role in waiting times. More available beds in the ED mean shorter wait times, and a higher number of doctors and nurses leads to shorter LOS in the ED as they can handle more patients simultaneously, reducing queues. Due to the unavailability of this data, alternative variables such as the number of full-time equivalents employed by Mater Dei and the number of beds available in Mater Dei were used. These may not be the exact variables found to be significant in the literature, making the OLS estimators unbiased and consistent, but resulting in inefficient coefficients. This means that the variances of the coefficients will be larger than if the correct variables were used, and, therefore, the OLS estimators will not be the Best Linear Unbiased Estimators (BLUE).

4. RESULTS

4.1. INTRODUCTION

In accordance with the methodological approach outlined in the previous chapter, tests and estimations were conducted using the statistical software Stata. This chapter includes various tests for model robustness and remedial measures applied to the models where necessary. In addition, the empirical findings of the study concerning the differences in waiting times between non-Maltese residents and other nationalities are presented. Furthermore, other variables are examined to ensure that the results align with the a priori expectations.

4.2. DIAGNOSTIC TESTING

When using OLS, several assumptions are important to consider, as mentioned previously. If any of these assumptions are not met, issues may arise in the regression analysis. This model may be susceptible to two problems: Multicollinearity and Heteroscedasticity. Both of these concepts are addressed in this section, and appropriate measures are taken as necessary.

Table 4.2-1 gives the regression results for all of the years available in the dataset, therefore from 2017 to 2023. This model gives the aggregate results of the dataset and is used to test for Multicollinearity and Heteroscedasticity. This regression includes all of the variables discussed previously and also includes a variable for COVID-19 is also added where a 1 signifies that the patient visited the ED when restrictions were in place because of COVID-19. Otherwise, this variable would be 0, hence the patient would have visited the ED during times when no restrictions were in place.

Table 4.2-1: Estimation Results for Aggregate Dataset

	(1)
VARIABLES	Model 1
age	-0.104
	(0.097)
gender	-17.964***
	(3.845)
nationality	69.422***
	(5.917)
walking	-5.020
	(4.159)
triage	-60.244***
	(4.227)
day	-17.425***
	(4.020)
admission	87.955***
	(4.493)
admissionstodischarges1	81.386***
	(13.566)
weekend	-13.089***
	(4.303)
covid19	-18.731***
	(4.690)
Constant	315.460***
	(11.633)
Observations	612,753
R-squared	0.001

Standard errors in parentheses

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

Overall, the coefficients illustrate how much the dependent variable is expected to change with a one-unit increase in the independent variable, holding all other variables constant. The main variable of interest is nationality, where being a resident non-Maltese increases the length of stay by around 69 minutes. The coefficient is also statistically significant, suggesting a strong relationship between nationality and length of stay, with the positive coefficient indicating that being non-Maltese is associated with longer stays in Mater Dei's ED.

For each additional year in age, the length of stay in minutes decreases by 0.1 minutes. This, however, is not statistically significant, so we cannot conclude a meaningful relationship between age and the dependent variable. Moreover, being male reduces the length of stay by approximately 18 minutes. The result suggests that gender significantly impacts the length of stay, and the negative coefficient indicates that men have a shorter stay. The walking variable reduces the length of stay by 5 minutes. However, it is not statistically significant, so the variable is not a reliable predictor of length of stay in this model. Additionally, if the patient was registered as ESI-1 or ESI-2, the waiting time is reduced by 60.244 minutes. This is also statistically significant, which means that higher triage levels are associated with shorter stays.

Patients who visited the ED during the day or the weekend experienced a reduction in waiting time by about 17 and 13 minutes respectively when compared to nighttime and weekdays. Both of these variables are also statistically significant. Moreover, the need for admission and the admission-to-discharge ratio show that they increase the waiting times of patients by around 88 and 81 minutes respectively. Additionally, both are also statistically significant which shows that they matter for waiting times. Lastly, the presence of COVID-19 is statistically significant and reduces the length of stay by 18.731 minutes.

The constant does not generally offer much value, however, given that most variables, apart from age and the admission-to-discharge ratio, are dummy variables the constant describes a type of patient. If all the dummy variables are equal to zero, the constant represents a patient that is female, is not a resident non-Maltese, visited the ED via means other than walking, was not registered as ESI-1 or ESI-2, that is was not diagnosed as high severity, came during the night, did not need to be admitted, came during a weekday and did not visit the ED during COVID-19 times. When all these are true the patient would have a baseline waiting time of approximately 315 minutes. However, this will change depending on the age of the patient and the admissions-to-discharges ratio of the day the patient visited the ED. These characteristics will be the same for the constants of the estimations run apart from the COVID-19 variable.

4.2.1. Multicollinearity

Multicollinearity occurs when there are exact or near-exact linear relationships among explanatory variables in a regression model (Gujarati & Porter, 2010). While perfect multicollinearity is rare, near or very high multicollinearity is common in practical applications. This occurs due to the nature of the data collection process, often when experiments are poorly designed or when the data is purely observational. For example, when two predictors measure similar phenomena, they tend to be highly correlated (Garg & Tai, 2013). Moreover, multicollinearity occurs when new independent variables are generated from existing ones, such as when interaction terms or polynomial terms are included in the model. This type of multicollinearity is more of a mathematical artefact rather than a problem with the data itself (Daoud, 2017).

When multicollinearity is present several consequences will be present. Gujarati & Porter (2010) and Paul (2006) list these consequences as follows:

1. When the explanatory variables have an exact linear relationship, known as perfect multicollinearity, the least-squares estimator cannot be computed.
2. When variables are highly correlated but not perfectly, the OLS estimators have large variances and covariances, making it challenging to obtain precise estimates.
3. The wide variances result in wider confidence intervals, which increases the likelihood of accepting the null hypothesis due to the larger standard errors. The correlation among the variables in the model affects the size of the standard error.
4. Despite multicollinearity, the t-ratio for one or more coefficients may appear insignificant. Yet, the overall R^2 value of the model can still be high.
5. OLS estimators and their standard errors are highly sensitive to even small changes in the data, which means that the results may lack robustness.

Considering these consequences, it is easy to see that multicollinearity can be very serious. One of the ways to detect multicollinearity in a regression is to use a correlation matrix. By examining the correlation between variables, it would be possible to detect whether there is multicollinearity between variables. Generally, the rule of thumb used is that any value in excess of 0.8 may be susceptible to multicollinearity (Gujarati & Porter, 2010). Given that most of the independent variables are dummy variables, only the non-dummy variables will be tested for multicollinearity.

From Table 4.2.1-1 we can deduce that none of the variables suffer from multicollinearity. This is because the is way less than the 0.8 mark. Therefore, it can be said that the variables used for the regressions do not suffer from multicollinearity and no remedial measures need to be done.

Table 4.2-2: Correlation Matrix between non-dummy variable

Variable	age	admissions-to-discharges
age	1.00	
admissions-to-discharges	0.0386	1.00

4.2.2. Heteroscedasticity

Heteroscedasticity is a condition in regression models where the variance of the error terms is not constant across observations (Carapeto & Holt, 2003). In a typical linear regression, the assumption is that the error terms have constant variance, which is called homoscedastic (Gujarati & Porter, 2010). When this assumption is violated, the errors are said to be heteroscedastic. This can occur due to various reasons such as omitted variables, outliers, incorrect model specification, or the presence of interactions or nonlinear relationships that are not properly accounted for (Long & Ervin, 2000).

Gujarati & Porter (2010) list a number of consequences when regressions under OLS experience heteroscedasticity. These include:

1. The Ordinary Least Squares (OLS) estimates stay unbiased even when there is heteroscedasticity. However, the presence of heteroscedasticity compromises the efficiency of these estimates. The OLS estimates will no longer have the minimum variance among linear unbiased estimators, which leads to inefficient estimates and therefore will not remain Best Linear Unbiased Estimators (BLUE).
2. The standard errors of the OLS estimates can become biased, which leads to unreliable hypothesis tests and confidence intervals. This means that statistical significance tests, such as t-tests and F-tests, may provide incorrect inferences. This is particularly troublesome because these tests rely on the assumption of constant error variance.

To detect whether the regression experiences heteroscedasticity, the White test for Heteroscedasticity was run on Stata. In this test, the null hypothesis states that the regression has constant variance, while the alternative hypothesis suggests that the regression does not have constant variance, indicating the presence of heteroscedasticity. To determine whether the null hypothesis can be rejected, we examine the p-value of the computed chi-square value. If the p-value is reasonably large, it indicates that we fail to reject the null hypothesis. (Gujarati & Porter, 2010). Usually, the p-value needs to be above 5% for the null hypothesis to be accepted.

Table 4.2-3: White's test for Heteroscedasticity

White's test
H_0: Homoskedasticity
H_a: Unrestricted heteroskedasticity
$chi^2(57) = 133.01$
$Prob > chi^2 = 0.0000$

Table 4.2.2-1 gives out the result from the White Test for the regression. Since the p-value is less than 5%, it is possible to reject the null hypothesis and, therefore, it can be said the model suffers from heteroscedasticity.

On Stata, one of the ways to correct for any heteroscedasticity is to use robust standard errors. A standard error measures uncertainty around a sample estimate, such as the mean of observations or a regression coefficient. Standard errors are typically calculated based on assumptions underlying the statistical model used in the estimation. However, heteroscedasticity can lead to incorrect standard errors (Gujarati & Porter, 2010). Alternatively, robust standard errors adjust the model-based standard errors using the empirical variability of the model residuals. By doing so, robust standard errors can provide a better assessment of the sample-to-sample variability of the estimates when the statistical model assumptions are violated (Mansournia, et al., 2021).

Table 4.2.2-2 shows the result when Equation 1.2-5 was run with and without robust standard errors. As can be seen, the coefficients remain unchanged from the regression without robust standard errors, however, the standard errors have changed. By using robust standard errors, the problem of heteroscedasticity has been eliminated and now t-values can be reliably used.

Table 4.2-4: Estimation results for Aggregate Dataset with Robust Standard Errors

	(1)	(2)
VARIABLES	Agg Model	Agg Model - Robust
age	-0.104	-0.104
	(0.097)	(0.106)
gender	-17.964***	-17.964***
	(3.845)	(3.827)
nationality	69.422***	69.422***
	(5.917)	(11.163)
walking	-5.020	-5.020
	(4.159)	(4.354)
triage	-60.244***	-60.244***
	(4.227)	(5.221)
day	-17.425***	-17.425***
	(4.020)	(4.015)
admission	87.955***	87.955***
	(4.493)	(4.670)
admissionstodischarges1	81.386***	81.386***
	(13.566)	(9.635)
weekend	-13.089***	-13.089***
	(4.303)	(4.622)
covid19	-18.731***	-18.731***
	(4.690)	(3.448)
Constant	315.460***	315.460***
	(11.633)	(11.539)
Observations	612,753	612,753
R-squared	0.001	0.001

Standard errors in parentheses

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

4.3. ESTIMATION RESULTS

This section provides a summary of the empirical results obtained from separate estimations conducted for three different years: 2017, 2020, and 2023. These specific years were chosen to analyse the impact of immigration on the waiting times at Mater Dei's Emergency Department. Additionally, 2020 was selected because it corresponds to the peak of the COVID-19 pandemic, during which various restrictions were enforced. It is essential to consider this factor when interpreting the results for that year. Moreover, a separate model was run for every year but instead of having the variable for resident non-Maltese the variable was changed to Maltese. If this variable is 0, it would mean that the waiting time is referring to someone who is non-Maltese irrespective of whether or not they are a resident.

4.3.1. Estimation Results of 2017 Waiting Times

Table 4.3-1: Estimation results for 2017 with Robust Standard Errors

VARIABLES	Model 1 - 2017	Model 2 - 2017
age	0.273***	0.259***
	(0.034)	(0.035)
gender	-15.753***	-15.718***
	(1.333)	(1.334)
nationality/Maltese	1.410	1.920
	(2.397)	(1.910)
walking	4.533***	4.394***
	(1.382)	(1.391)
triage	-37.735***	-37.823***
	(1.300)	(1.304)
day	-0.626	-0.567
	(1.335)	(1.336)
admission	105.494***	105.423***
	(1.286)	(1.288)
admissionstodischarges1	24.031***	24.031***
	(7.826)	(7.825)
weekend	-16.027***	-16.040***
	(1.418)	(1.418)
Constant	235.731***	235.183***
	(4.960)	(4.996)
Observations	85,906	85,906
R-squared	0.062	0.062

Standard errors in parentheses

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

In Table 4.3.1-1, the summarised results of the estimated data for 2017 are shown. This analysis uses linear regression and involves 85,906 observations. It aims to assess the connection between the dependent variable 'w' and various independent variables such as age, gender, nationality, walking, triage, and others.

As a baseline, the constant shows that patients that would have all of the dummies equal to 0. Those patients experienced waiting times of 236 minutes, which is altered depending on their age and the admissions-to-discharges ratio. The main variable of interest, 'nationality' suggests that being a resident non-Maltese increases the waiting time by 1.4. However, for this year this variable is not statistically significant, indicating that nationality does not have a meaningful effect on the dependent variable in this model. Furthermore, for Model 2, being Maltese is also found to be not significant and, therefore is not a good predictor for waiting times.

Moving on to the other independent variables, age and gender are both statistically significant patient-related factors. Age positively affects waiting time by 0.27 while being a male negatively affects waiting times at the ED by about 16 minutes while holding other variables constant. Moving on to arrival type, the 'walking' variable suggests that people who visit the ED via walk-ins experience an increase of approximately 4 minutes when compared to other arrival types. This variable is also statistically significant making it a reliable predictor of waiting times. On the other hand, the 'triage' variable suggests that people who were registered under ESI-1 or ESI-2 experienced less waiting times by around 38 minutes. This effect is statistically significant indicating that the triage level matters when it comes to waiting times.

When it comes to time-related factors, the variable 'day' is not statistically significant, and the regression suggests that people who visited the ED during the day experienced a small reduction in waiting times of around 0.6 minutes. However, given it is not statistically significant, it does not seem to matter for this year. On the other hand, the variable 'weekend' is statistically significant meaning that it matters for this year. The regression suggests the patients who visited the ED during the weekend experienced an approximate 16-minute decrease in their waiting time, holding other variables constant. Moving on to the variables 'admission' and 'admission-to-discharge' ratio, both increase the waiting time for individuals by around 105 and 24 minutes respectively. Moreover, both variables are statistically significant which means that both matter to affecting waiting times.

4.3.2. ESTIMATION RESULTS OF 2020 WAITING TIMES

Table 4.3.2-1: Estimation results for 2020 with Robust Standard Errors

	Model 1 - 2020	Model 2 - 2020
age	-0.555*	0.394
	(0.324)	(0.339)
gender	-31.164**	-38.275***
	(12.918)	(13.671)
nationality/maltese	120.497***	-200.819***
	(35.199)	(36.371)
walking	-29.791**	-27.861**
	(14.186)	(14.083)
triage	-12.873	-10.029
	(16.178)	(16.522)
day	-23.535	-24.153*
	(14.594)	(14.452)
admission	46.246***	48.209***
	(12.938)	(12.922)
admissionstodischarges1	1.802	0.582
	(45.735)	(45.952)
weekend	3.685	4.078
	(17.339)	(17.308)
Constant	395.229***	521.553***
	(51.174)	(53.092)
Observations	71,600	71,600
R-squared	0.001	0.002

Robust standard errors in parentheses

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

In Table 4.3.1-1, the summarised results of the estimated data for 2020 are displayed. This analysis used linear regression and involved 71,600 observations. Its purpose was to assess the relationship between the dependent variable 'w' and various independent variables such as age, gender, nationality, walking, triage, and others. It's important to note that this data relates to the peak of the COVID-19 pandemic. As a result, some of the results may have been impacted by this extraordinary time.

Based on the explanation given for Table 4.2-1's constant, patients with the characteristics described experienced an average waiting time of about roughly 395 minutes in 2020. This waiting time can vary based on factors such as age and the ratio of admissions to discharges. The primary factor of interest is the patient's nationality. Specifically, being a non-Maltese resident increases the length of stay by an average of 120 minutes. The statistical significance of this coefficient indicates a strong relationship between nationality and length of stay. The positive coefficient suggests that being non-Maltese is associated with longer stays in Mater Dei's ED. Moreover, being Maltese reduced the waiting times at the ED by around 201 minutes and is also statistically significant.

As an individual's age increases, the length of stay decreases by 0.56 minutes per year. This relationship is statistically significant at the 10% level, indicating that age has a meaningful impact on the length of stay. Additionally, being male is associated with a reduction in length of stay by roughly 31 minutes, which is statistically significant at the 5% level. The negative coefficient suggests that men generally have shorter stays. The walking variable is also significant, with a decrease in length of stay by about 30 minutes, making it a reliable predictor. Furthermore, patients registered as ESI-1 or ESI-2 experience a reduction in waiting time by approximately 13 minutes. However, this relationship is not statistically significant, meaning that higher triage levels do not reliably predict waiting times.

The data shows that patients visiting the emergency department during the day or the weekend experienced a reduction in waiting time by roughly 24 and 4 minutes, respectively. However, these changes are not statistically significant. Additionally, the need for admission and the admission-to-discharge ratio were found to increase patient waiting times by around 46 and 1.8 minutes, respectively. The need for admission is statistically significant, indicating its importance in determining waiting times. On the other hand, the admissions-to-discharges ratio is not statistically significant, suggesting that it is not a good predictor of waiting times.

4.3.3. Estimation Results of 2023 Waiting Times

Table 4.3.2-2 Estimation results for 2023 with Robust Standard Errors

	(1)	(2)
VARIABLES	Model 1 - 2023	Model 2 - 2023
age	0.148***	0.137***
	(0.034)	(0.035)
gender	-22.249***	-22.127***
	(1.429)	(1.429)
nationality/maltese	6.313***	-2.242
	(2.241)	(1.983)
walking	10.301***	10.498***
	(1.466)	(1.473)
triage	-79.037***	-79.194***
	(1.553)	(1.553)
day	-27.644***	-27.569***
	(1.406)	(1.406)
admission	97.212***	97.222***
	(1.445)	(1.446)
admissionstodischarges1	73.427***	73.399***
	(6.265)	(6.264)
weekend	-27.372***	-27.431***
	(1.526)	(1.525)
Constant	320.793***	324.031***
	(5.447)	(5.433)
Observations	94,200	94,200
R-squared	0.060	0.060

Robust standard errors in parentheses

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

In Table 4.3.3-1, the summarised results of the estimated data for 2023 are presented. This analysis utilises linear regression and comprises 94,200 observations. Its objective is to examine the relationship between the dependent variable 'w' and various independent variables such as age, gender, nationality, walking, triage, and others.

Patients described for all other constants experienced an average waiting time of 321 minutes. This waiting time is influenced by the patient's age and the ratio of admissions to discharges. The variable 'nationality' indicates that being a non-Maltese resident increases the waiting time by about 6 minutes. This variable is statistically significant, suggesting that nationality does have a meaningful impact on the waiting times in this model. Furthermore, when Model 2 was run, being was found to be insignificant in predicting the waiting times at the ED for 2023.

In terms of the other independent variables, both age and gender are statistically significant patient-related factors. Age has a positive effect on waiting time, increasing it by 0.148. On the other hand, being male decreases waiting times at the ED, by around 22 minutes when holding other variables constant. As for arrival type, the 'walking' variable indicates that individuals who visit the ED via walk-ins experience an increase of approximately 10 minutes compared to other arrival types. This variable is also statistically significant, making it a reliable predictor of waiting times. Conversely, the 'triage' variable suggests that individuals registered under ESI-1 or ESI-2 experience lower waiting times by about 73 minutes. This effect is statistically significant, indicating that triage level matters in determining waiting times.

In terms of time-related factors, the variable 'day' is statistically significant. The regression indicates that people who visited the ED during the daytime experienced a reduction in waiting times of approximately 27.6 minutes. Similarly, the variable 'weekend' is statistically significant, indicating that it has an impact. According to the regression, patients who visited the ED during the weekend experienced a decrease in waiting time of roughly 28 minutes, holding other variables constant. Furthermore, the variables 'admission' and 'admissions-to-discharges' ratio, both contribute to increased waiting times for individuals by around 97 and 73 minutes respectively. Additionally, both variables are statistically significant, suggesting that they have an impact on waiting times.

4.4. CONCLUSION

In analysing the regression models for the years 2017, 2020, and 2023, notable changes in the coefficients and statistical significance of the variables are observed. The most significant change is seen in the nationality variable, where being a non-Maltese resident has increasingly shown a strong positive relationship, with longer waiting times, especially in 2020, coinciding with the peak of the COVID-19 pandemic. Additionally, the converse was seen for being Maltese, where waiting times seemed to be less than other nationalities, especially in 2020. These coefficients changed sharply in 2020 and being a Non-Maltese resident remained statistically significant throughout, indicating that the impact of nationality on waiting times became more pronounced during these periods.

The data indicates that men typically experience shorter waiting times than women in all years. Age seemed to have a positive impact on waiting times in 2017 and 2023, but the trend reversed in 2020, suggesting a decrease in waiting time with increased age during the pandemic year. The shift might be due to changes in triage procedures or hospital policies related to COVID-19. The need for admission consistently had a strong impact on waiting times across all years. Higher triage levels significantly reduced waiting times, but this effect was not significant in 2020. Additionally, the need for admission and the admission-to-discharge ratio consistently increased waiting times, with the variables being highly significant except in 2020 for the admissions-to-discharges ratio.

The strength of these findings, especially after addressing heteroscedasticity in the data, confirms the reliability of the results. The changes in significance and the size of the coefficients, particularly for nationality and gender, highlight how demographic and procedural factors, as well as external factors such as COVID-19, impact the waiting times in the emergency department.

5. DISCUSSION

5.1. INTRODUCTION

In this section, a comparison of the results obtained from Mater Dei's ED data with existing literature is made. The goal is to address the original research questions and determine how these results align with or differ from existing research. Apart from discussing the main variable of the model, a brief discussion is also done on the other control variables used. A summary of the results is found from the 3 years the model was run in Table 5.1-1.

Table 5.1-1: Summarised results for all years

VARIABLES	(1) Model 1 - 2017	(2) Model 2 - 2020	(3) Model 3 - 2023
age	0.273***	-0.555*	0.148***
	(0.034)	(0.324)	(0.034)
gender	-15.753***	-31.164**	-22.249***
	(1.333)	(12.918)	(1.429)
nationality	1.410	120.497***	6.313***
	(2.397)	(35.199)	(2.241)
walking	4.533***	-29.791**	10.301***
	(1.382)	(14.186)	(1.466)
triage	-37.735***	-12.873	-79.037***
	(1.300)	(16.178)	(1.553)
day	-0.626	-23.535	-27.644***
	(1.335)	(14.594)	(1.406)
admission	105.494***	46.246***	97.212***
	(1.286)	(12.938)	(1.445)
admissionstodischarges1	24.031***	1.802	73.427***
	(7.826)	(45.735)	(6.265)
weekend	-16.027***	3.685	-27.372***
	(1.418)	(17.339)	(1.526)
Constant	235.731***	395.229***	320.793***
	(4.960)	(51.174)	(5.447)
Observations	85,906	71,600	94,200
R-squared	0.062	0.001	0.060

Robust standard errors in parentheses

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

5.2. EFFECTS OF IMMIGRATION ON WAITING TIMES

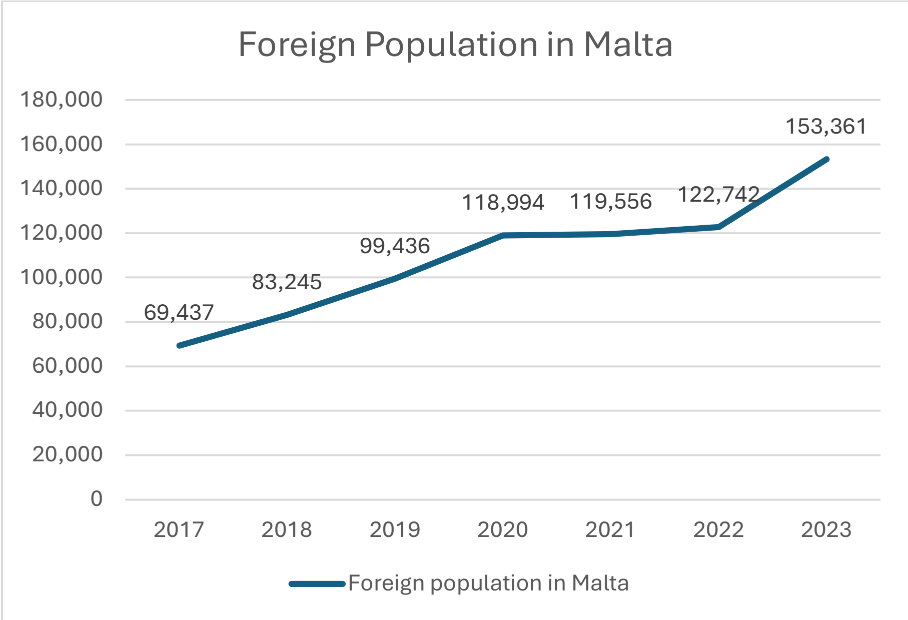
This sub-section aims to answer the first two research questions: (1) *"What are the effects foreign residents have on waiting times?"* (2) *"What are the differences in the utilisation of public healthcare between Maltese and Foreign residents?"*.

The impact of immigration on ED waiting times has been a central focus of this research, with notable differences emerging between Maltese and non-Maltese residents. In 2017, the influence of nationality on waiting times was minimal and statistically insignificant, with non-Maltese residents only experiencing a 1.41-minute increase in waiting times. However, in 2020, this effect became significant, with non-Maltese residents facing an increase of 120.497 minutes. In 2023, the effect reduced again, but non-Maltese residents still experienced an increase of 6.313 minutes in their length of stay (LOS).

The substantial spike in 2020 likely reflects the strain that the COVID-19 pandemic placed on healthcare systems, exacerbating pre-existing challenges faced by non-Maltese residents in accessing timely care. Rojsaengroeng et al. (2023) point out that the pandemic introduced further complications, particularly for migrant populations, who were disproportionately affected by the new protocols, such as COVID-19 testing requirements and isolation procedures. These challenges were likely more pronounced for non-Maltese residents in Malta, contributing to the significant increase in waiting times during the pandemic year. The fact that this effect diminished somewhat by 2023 suggests that as the pandemic subsided and healthcare systems adapted, the additional burden on non-Maltese residents was somewhat alleviated. Furthermore, as the literature highlights, migrants often encounter additional barriers when using healthcare services, such as language difficulties, unfamiliarity with healthcare systems, and cultural differences. Studies by Gulacti et al. (2017) and Zunino et al. (2021) support this, finding that migrants often experience longer waiting times compared to native populations due to these factors.

However, the literature also offers contrasting perspectives. For instance, Steventon & Bardsley (2011) and Brandenberger et al. (2021) found that in some contexts, migrants use emergency services less frequently than native populations and may not necessarily experience longer waiting times. These studies align with the results from 2017, where nationality had little to no effect on ED waiting times in Mater Dei, suggesting that in the absence of extraordinary pressures such as a global pandemic, the impact of immigration on waiting times might be less significant.

Figure 5.2.1: Foreign-born Population in Malta throughout the years



Despite these contrasting findings, the Maltese context, with its rapidly increasing foreign population since 2017, offers a unique environment for examining the relationship between nationality and healthcare demand. Figure 5.2.1 in this study illustrates the sharp rise in the number of foreign-born residents in Malta, coinciding with increased waiting times for non-Maltese residents. This aligns with Di Napoli et al. (2022), who found that in Italy, immigrants had higher ED visit rates for non-urgent matters compared to natives, further contributing to ED crowding. Similarly, Rodríguez-Álvarez, Lanborena & Borrell (2019) showed that immigrant populations tend to have higher utilisation rates of healthcare services.

However, it is important to note that some studies, such as those by Giuntella, Nicodemo & Vargas-Silva (2018), found no significant difference in ED waiting times due to immigration in the UK's NHS. This could be due to differences in healthcare systems, where countries with more integrated support systems for immigrants may mitigate the disparities seen in waiting times. In Malta, with its rapidly growing immigrant population and potentially overburdened healthcare system, the effects of immigration are more pronounced, as evidenced by the results from this study.

In conclusion, the findings of this study indicate that nationality plays a significant role in ED waiting times, particularly during periods of heightened pressure on the healthcare system, such as the COVID-19 pandemic. While the impact of nationality on waiting times was minimal in 2017, it became highly impactful in 2020, reflecting the increased strain on healthcare resources and the specific challenges faced by non-Maltese residents. These results are supported by much of the literature, which suggests that migrant populations tend to face longer waiting times due to a combination of systemic barriers and individual circumstances. However, the findings also highlight the complexity of this issue, as immigration does not always lead to longer waiting times, as evidenced by both the 2017 results and contrasting studies in other contexts. This underscores the need for further research into the specific factors influencing ED waiting times in different healthcare systems, with a particular focus on how immigration and healthcare policy intersect to affect access to care.

5.3. EFFECTS OF OTHER VARIABLES ON WAITING TIMES

In addition, this study generated results on the other variables gathered from the literature and it is important to highlight some key points from the results related to these variables. In this subsection, a concise analysis of these control variables will be presented. It will highlight their similarities or differences compared to the findings in the existing literature and answer the last research question of this study: (3) *"What are the main factors that influence waiting times in Malta's ED?"*

5.3.1. Age

The impact of age on ED waiting times has yielded mixed results across the years under study. In 2017, age showed a positive relationship with waiting times, increasing LOS by 0.273 minutes per year. Similarly, in 2023, age again had a positive impact, increasing LOS by 0.148 minutes. These results suggest that older patients generally experienced longer waiting times in the ED, which is consistent with the literature. Casalino et al. (2014) and Downing et al. (2004) highlight that older patients typically present more complex cases, requiring more in-depth assessments, thus leading to longer waiting times. However, a notable deviation occurred in 2020, where age decreased waiting times, reducing LOS by 0.555 minutes per year. This divergence could be attributed to the exceptional circumstances of the COVID-19 pandemic, during which triage procedures and prioritisation of certain patient groups may have shifted. This contrasts with the general literature, which consistently identifies older age as a factor contributing to longer ED stays, however, no study examining age was done during such extraordinary circumstances.

5.3.2. *Gender*

Gender also played a significant role in ED waiting times, with males consistently experiencing shorter waiting times across all three years. In 2017, males had a 15.753-minute reduction in LOS compared to females, with this difference growing substantially in 2020, where the reduction was 31.164 minutes. By 2023, the gap had narrowed slightly, but males still experienced a reduction of 22.249 minutes compared to females. The literature presents mixed findings on gender's influence on waiting times. Some studies, such as Hosseininejad et al. (2017) and Lowthian et al. (2012), suggest that females tend to have longer stays due to the complexity of conditions, which often require more diagnostic testing. This aligns with the observed longer stays for females in this study's analysis. However, studies like Alnahari & A'aqoulah (2024) also found that males may experience longer waits in specific cases, such as trauma, but overall, the study's results suggest that males benefit from shorter stays, which conforms with much of the literature on gender differences in healthcare utilisation.

5.3.3. *Arrival Type*

Mode of arrival played a crucial role in determining ED waiting times, with distinct differences between walk-in patients and those arriving by other means mainly ambulance. In 2017, walk-in patients experienced a 4.533-minute increase in LOS, and in 2023, this trend persisted, with walk-ins facing a 10.301-minute increase in waiting times. This is consistent with findings from Ding et al. (2010) and Goodacre & Webster (2005), which suggest that walk-ins typically face longer waits due to the non-urgent nature of their conditions. However, in 2020, walk-ins experienced a significant reduction of 29.791 minutes in waiting times, which may reflect changes in hospital protocols during the pandemic.

5.3.4. *Triage*

Triage level consistently influenced ED waiting times, with higher triage levels associated with significantly shorter waits. In 2017, being triaged under ESI-1 or ESI-2 reduced waiting times by 37.735 minutes, and in 2023, this reduction was even more pronounced, with a 79.037-minute decrease. These results are strongly supported by the literature, where studies like Ba-Aoum et al. (2023) and Yoon et al. (2017) demonstrate that patients with higher acuity are prioritised, resulting in shorter waiting times. Interestingly, in 2020, the triage level had no significant effect on waiting times. This is likely due to the increased demand for healthcare services during the pandemic, which may have disrupted normal triage processes.

5.3.5. *Need for Admission*

The need for admission was consistently one of the most significant factors influencing ED waiting times. In 2017, patients requiring admission experienced an increase of 105.494 minutes in waiting times, with similar increases observed in 2020 with 46.246 minutes and in 2023 with 97.212 minutes. These findings align with a substantial body of literature, which identifies the need for admission as a key driver of prolonged ED stays. Gardner et al. (2007) and Weiss et al. (2012) both indicate that admitted patients face longer waiting times due to the process of finding available beds, especially in overcrowded hospitals. Moreover, Forster et al. (2003) find that increased hospital occupancy leads to increased waiting times in EDs. In this study, the admissions-to-discharges ratio is used to indicate how many patients are being admitted rather than discharged. From the results, this was a significant variable, except for 2020, where the higher this ratio the higher waiting times patients experienced. The smaller increase in waiting times for admitted patients in 2020 might be linked to pandemic-related hospital management strategies, where admissions were streamlined to reduce pressure on the ED. Despite this anomaly, the overall trend of longer waiting times for admitted patients holds across all years, reinforcing the literature's findings that hospital admissions significantly prolong ED stays due to logistical and capacity constraints. The differences in 2020 might be linked to pandemic-related hospital management strategies. Despite this anomaly, the overall trend of longer waiting times for admitted patients holds across all years, reinforcing the literature's findings that hospital admissions significantly prolong ED stays due to logistical and capacity constraints.

5.3.6. *Time-related Factors*

In this study, time-related factors refer to what time of day and what day of the week the patient visited the ED. In 2017 and 2023, weekend visits resulted in 16.027-minute and 27.372-minute reductions, respectively, in waiting times. This aligns with the literature, where Sarıyer et al. (2020)[b] and Castner et al. (2016) found that weekends generally experience lower patient volumes. In contrast, 2020 showed no significant difference in weekend waiting times, which again can be attributed to the pandemic. This aligns with the findings of Rathlev et al. (2007), however, the reasons for the insignificance of the variable are different. In 2017 and 2020, the ‘day’ variable was insignificant, showing no difference between day and night visits. By 2023, daytime visits significantly reduced waiting times by 27.644 minutes. Studies like Hosseininejad et al. (2017) and Downing et al. (2004) align with the 2023 result, showing shorter waits during the day due to better staffing. The insignificance in 2017 and 2020 contrasts with literature that usually finds time of day relevant to wait times.

5.3.7. Conclusion

The findings relating to age, gender, arrival type, time-related factors, triage, and need for admission in Mater Dei's ED reveal several similarities and contrasts with the existing literature. While factors like age, triage, and need for admission align with broader patterns identified in the literature, pandemic-related anomalies, particularly in 2020, disrupted some of these established trends. However, overall, the results of this research confirm many of the findings seen in international studies while highlighting the specific context of Malta’s ED system.

6. CONCLUDING REMARKS AND LIMITATIONS

6.1. CONCLUSIONS

In conclusion, this study aimed to investigate the factors affecting waiting times in Malta's ED, with a focus on the role of nationality in predicting LOS. The results showed that although nationality has a statistically significant impact on waiting times, its influence is relatively low compared to other variables.

The analysis revealed that being a non-Maltese resident, especially during periods of high healthcare demand such as the COVID-19 pandemic, was linked to longer ED waiting times. This aligns with findings from other studies suggesting that language barriers, unfamiliarity with healthcare systems, and cultural differences may contribute to longer ED stays for foreign residents. However, despite its significance, the impact of nationality was overshadowed by other factors that more strongly influenced waiting times.

Key variables such as gender, triage level, need for admission, and operational factors (e.g., admission-to-discharge ratios) were found to play a more critical role in determining the duration of stays in the ED. Gender had a notable influence, with females tending to have longer waiting times than males, potentially due to differences in presenting conditions and the type of diagnostic tests they typically undergo. Triage levels were another significant factor, with higher urgency patients (ESI-1 and ESI-2) experiencing shorter waiting times compared to those with lower priority conditions. This is in line with the expected protocol of prioritising more urgent cases in emergency care. Additionally, the need for hospital admission was one of the most influential variables, as patients requiring admission often face longer delays due to bed availability and hospital capacity constraints. The admission-to-discharge ratio further highlighted operational bottlenecks, showing that as the number of admissions increases relative to discharges, waiting times are prolonged.

Time-related factors, such as visiting the ED during weekends or nighttime, also played a role in affecting waiting times, with patients visiting during these periods generally experiencing shorter stays compared to those arriving during peak daytime hours. Therefore, efforts need to be made to ensure that LOS during nighttime and weekdays is reduced to improve ED efficiency. The COVID-19 pandemic also had a notable, albeit complex, impact on waiting times. While the pandemic initially increased the strain on healthcare systems, the data suggested that waiting times were shorter in some cases during the pandemic, possibly due to changes in healthcare protocols, reduced non-emergency visits, or prioritisation of COVID-19-related cases. Moreover, when looking at the constant, which gives the waiting time of a person that is characterised with dummy variables which are 0, it is noticeable that it has significantly increased from 2017. Specifically, in 2023, this type of person would have experienced an increase in waiting times by around 85 minutes from 2017, indicating potential overcrowding or lack of efficiency in the ED.

In summary, while nationality is an important factor, it does not solely impact waiting times. Other variables such as gender, triage levels, and operational capacity were found to be more influential in determining waiting times. These findings highlight the importance of a comprehensive approach to understanding and managing waiting times in the ED. Policymakers and hospital administrators should focus on optimising resources, managing patient flow, and addressing capacity issues to improve efficiency. Additionally, attention should be given to reducing disparities in waiting times, particularly for foreign residents, by addressing potential language barriers and improving the overall inclusiveness of healthcare services.

6.2. LIMITATIONS

The study has a few limitations that may affect the conclusions and how its findings are applied. One major limitation is the absence of immigration and population data, which makes it challenging to understand how immigration changes impact ED waiting times over the years. Only yearly and population statistics were available and since the number of available data was for the years spanning from 2017 to 2023, using this data would not have been effective. Using nationality as a proxy for immigration status doesn't fully capture the complexities of immigration, such as the number of new arrivals each year, their socio-economic conditions, or their healthcare needs. This means that the study may not fully grasp or accurately estimate the influence of immigration on ED waiting times, potentially underestimating the pressures on the healthcare system from a growing population.

Another limitation is the potential omission of critical variables that could affect waiting times. While the study considered factors like age, gender, triage levels, and the need for admission, it may not have included all relevant variables, as reflected in the low R^2 obtained in the results. The study also faced challenges related to supply-related factors such as the number of beds available at the ED, the number of healthcare staff at the ED, and the overall capacity of the ED. These supply-side constraints significantly impact waiting times, and the absence of detailed data on these variables means that the model may not fully reflect the operational pressures faced by the ED. Additionally, the study's lack of data on the number and nature of diagnostic tests performed on patients may have led to an incomplete understanding of the factors influencing waiting times. This data is crucial as the complexity and duration of diagnostic testing, as well as delays in receiving test results can significantly contribute to prolonged ED stays.

6.3. POLICY IMPLICATIONS AND FURTHER CONSIDERATIONS

The results of this study demonstrate that while foreign residents do have statistically significant longer waiting times in Malta’s ED, the differences are relatively small when compared to other variables like triage level and need for admission. To address these findings, several policy recommendations can be proposed for the healthcare system, particularly for Mater Dei Hospital’s ED.

The ED should consider increasing staffing levels during times were waiting times are longer, for example, evenings and weekdays, to better manage both native and non-native populations. This would ensure quicker patient triage and shorter waiting times for urgent cases. With the continuous growth of Malta’s population, including an increase in foreign residents, expanding the ED could alleviate overcrowding and reduce waiting times for all patients. Furthermore, increasing the number of beds for admitted patients and improving the process of finding an available bed should be at the forefront of the agenda.

When it comes to facilitating non-native residents at the ED, one possible reason for increased waiting times for foreign residents could be language barriers. Implementing more robust translation services or offering cultural training for staff could improve communication and help speed up the treatment process. Moreover, educating both native and foreign residents on when and how to use the ED could help reduce non-urgent visits, thereby easing the burden on the department and shortening waiting times.

While this study offers significant insights into the impact of foreign residents on ED waiting times in Malta, there are several areas where further research could build upon these findings. The lack of available data on ED resources, such as bed occupancy rates and physician staffing levels, limited this study. Future research could incorporate more granular supply-side data to better understand how hospital capacity and resource allocation influence waiting times. Additionally, conducting a study using population statistics beyond just annual data could provide valuable insights into how population growth has impacted not only individual waiting times but also the average waiting times over the years. This type of study could also be extended to other areas in the hospital experiencing overcrowding. For instance, elective surgeries often have lengthy waiting lists and would benefit from further research in this area.

By addressing these areas, future research can further improve understanding of how healthcare systems can adapt to increasing demand, ensuring more equitable and efficient healthcare delivery for all residents.

APPENDIX

Table A-1 – Summary of Literature Review Papers and Themes

	Supply	Temporal factors	Arrival Type	Age	Gender	Triage	Testing	Need for Admission	Income	COVID-19	Immigration
Acquadro-Pacera, et al. (2024)											X
Alemu, et al. (2019)	X						X				
Alnahari & A'aqoulah (2024)					X						
Ba-Aoum, et al. (2023)	X			X		X					
Biber, et al. (2013)				X	X						
Bosque-Mercader & Siciliani (2023)	X										
Brandenberger, et al. (2021)											X
Bucheli & Martina (2004)	X										

Casalino, et al. (2014)			X	X	X		X	X			
Castner, et al. (2016)		X									
Chang, et al. (2012)								X			
Chaou, et al. (2016)		X		X		X					
Clarke, et al. (2005)								X			
Cooke, et al. (2004)	X										
Dadeh & Phunyanantakorn (2020)							X				
Davis, et al. (1995)							X				
Di Napoli, et al. (2022)											X
Ding, et al. (2010)		X	X	X							
Downing, Wilson, & Cooke (2004)		X	X	X				X	X		

Forster, et al. (2003)	X							X			
Gardner, et al. (2007)							X	X			
Geurts, et al. (2012)					X	X					
Giuntella, Nicodemo, & Vargas-Silva (2018)											X
Goodacre & Webster (2005)		X	X								
Gulacti, Lok, & Polat (2017)											X
Guo, et al. (2021)										X	
Happell, Palmer, & Tennent (2010)								X			
Hoot & Aronsky (2008)	X										
Hosseininejad, et al. (2017)		X			X	X			X		
Jarvis (2016)								X			

Kanzaria, et al. (2014)							X				
Kocher, et al. (2012)							X				
Klingberg, et al. (2020)											X
Kreindler, et al. (2016)				X				X			
Kusumawati, Magarey, & Rasmussen (2019)	X					X		X			
Lambe, et al. (2002)	X										
Lambe, et al. (2003)	X								X		
Lee, et al. (2023)										X	
Lew, (1966)		X									
Li, et al. (2015)							X				
Lowthian, et al. (2012)			X		X			X			
Mahsanlar, et al. (2014)	X										

Nippak, et al. (2014)					X	X					
Qureshi (2010)						X					
Rathlev, et al. (2007)		X									
Rodríguez-Álvarez, Lanborena, & Borrell (2019)											X
Rojsaengroeng, et al. (2023)										X	
Sarıyer, Ataman, & Kızıloğlu (2020)[a]			X								
Sarıyer, Ataman, & Kızıloğlu, 2020[b]		X	X			X					
Schneider, et al. (2003)	X										
Serinken, et al. (2008)					X						
Sir, et al. (2017)	X										

Stephens, et al. (2014)								X			
Steventon & Bardsley (2011)											X
Vegting, et al. (2015)				X			X				
Wadsworth (2013)											X
Weiss, et al. (2012)					X			X			
Wild & Mckeigue (1997)											X
Yoon, Steiner, & Reinhardt (2003)			X			X	X				
Zunino, et al. (2021)											X

Table A-2 – Sample of data

TICKET	Age	M	Maltese	Resident non-Maltese	Walking	Triage	LOS mins	Day	Admission	Admissions-to-discharges	Weekend
43324576	52	1	1	0	1	0	204	0	0	0.424418605	1
43324578	47	0	1	0	0	1	97	0	0	0.424418605	1
43324590	42	1	1	0	0	1	218	0	1	0.424418605	1
43324613	72	1	1	0	1	1	111	0	0	0.424418605	1
43324615	17	1	1	0	0	1	297	0	1	0.424418605	1
43324623	42	1	1	0	0	1	212	0	0	0.424418605	1
43324625	37	0	0	1	1	1	565	0	0	0.424418605	1
43324626	62	1	1	0	1	0	415	0	1	0.424418605	1
43324627	72	0	1	0	0	1	298	0	1	0.424418605	1
43324629	62	0	1	0	0	1	481	0	1	0.424418605	1
43324630	27	1	0	0	1	0	154	0	0	0.424418605	1
43324634	42	1	1	0	0	1	90	0	0	0.424418605	1
43324635	22	0	1	0	1	0	543	0	0	0.424418605	1
43324640	22	1	0	0	1	1	173	0	0	0.424418605	1
43324645	42	1	1	0	1	1	442	0	1	0.424418605	1
43324646	67	0	1	0	1	0	283	0	0	0.424418605	1
43324651	27	1	0	1	0	0	355	0	0	0.424418605	1
43324658	52	1	0	1	1	1	257	0	1	0.424418605	1
43324659	47	0	1	0	1	0	204	0	0	0.424418605	1
43324660	17	0	1	0	0	1	286	0	0	0.424418605	1

Figure A.1 Embargo Confirmation

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