STOCKHOLM SCHOOL OF ECONOMICS
Department of Economics
659 Degree Project in Economics
Spring 2015

THE DETERMINANTS OF DAILY EMERGENCY DEPARTMENT ATTENDANCE: A THEORETICAL APPROACH

Charlott Johansson (22797) and Caroline Yuan (22751)

ABSTRACT: The purpose of this study is to examine the determinants of daily ED attendance based on neoclassical theories. Using elements from the Grossman model and standard economic consumer theory, we build a theoretical framework for identifying and analyzing the determinants of emergency care. To evaluate our findings, we develop a prediction model. We use data from the emergency department at Uppsala University Hospital and the Health Care Guide to test if the health status of individuals and the relative price of an ED visit affect the number of ED admissions. Of the two hypotheses, we only find empirical support for the relative price hypothesis. Although our empirical findings do not support the hypothesis that health status is a determinant, we believe that further research is needed to reject its relevance in determining the demand for emergency care. Our findings imply that calendar variables should continue to be included in future prediction models and that variables capturing different types of health reduction, in terms of both size and how quickly the reduction happens and evolves, may be worthwhile to consider.

Keywords: Emergency care, Grossman, Consumer choice, Forecasting
JEL Classifications: I11, D11, C53

Supervisors:	Örjan Sjöberg and Martin Nordberg
Date submitted:	May 18, 2015
Date examined:	June 5, 2015
Discussants:	Julia Bruno and Tobias Settergren
Examiner:	Karl Wärneryd

ACKNOWLEDGEMENTS

First and foremost, we would like to express our gratitude towards our supervisors Örjan Sjöberg and Martin Nordberg, Medical Doctor at Stockholm South General Hospital and Karolinska Institutet, for their guidance and support throughout the writing of this thesis. A special thanks is owed to Charlotta Nordgren Thermaenius and Mervi Friberg at Uppsala University Hospital and Fredrik Tjäder at Uppsala Health Care Guide for sharing their time and expertise and providing us with high quality data. Finally, we wish to thank Per-Olov Edlund and Evelina Bonnier at Stockholm School of Economics for their valuable inputs regarding the econometrics used in this paper.

Contents

1. Introduction

The emergency department (ED) is at the frontline of acute health care delivery. In recent years, the demand for emergency care has increased and placed a growing strain on the emergency departments in Sweden (1). In an environment where health care resources are confined, these shifts in demand have increased the risk for ED overcrowding. The effects of overcrowding can be profound and result in a degradation of the entire care delivery process. Cost for health care rise as the efficiency of care diminishes (2) while the quality of prognosis, treatment and care suffers (3). Ultimately, patients' safety is endangered. Today, ED overcrowding is an ongoing problem on both a micro and macro level, affecting patients, hospital staff, health care administrators and policy makers (4).

One main aspect of addressing overcrowding is to forecast the magnitude and timing of patient inflow (5). A reliable prediction model could provide guidance on the allocation of resources (6) and function as a tool to redirect patients with less severe conditions (7). In an attempt to mitigate overcrowding at emergency departments, numerous prediction models have been developed using different sets of prediction variables. While calendar and weather information such as day of the week and temperature are most commonly used, more unique variables such as website visits to the Stockholm Health Care Guide have also been included. The objective has been to improve the accuracy of existing models rather than providing a theoretical justification to the choice of variables. Previously published papers are therefore pure correlational studies, resulting in an uncertainty surrounding the validity of their results. Without a theoretical foundation that underpins the design of the prediction model, one cannot reject the possibility that previous findings are purely coincidental. This renders them less reliable as a decision basis for emergency departments in their resource allocation and planning. The aim of this study is to address this issue and to identify and examine the determining factors behind the daily volume of ED patients. We hope to complement the existing field of research by contributing to their effort in providing a forecasting tool that can assist stakeholders in avoiding ED overcrowding. The study will be limited to daily fluctuations and we leave to future studies to examine variations within a given day. The research question is as follows: *What are the determinants of daily ED attendance?*

To answer this question we develop a theoretical framework using neoclassical theories and models. We intend to provide a systematic way of analyzing the daily demand for emergency care and a notion of generality. Michael Grossman's model on the demand for health and health care serves as the point of departure to derive the demand for medical care in general. Using the standard budget constraint model we apply Grossman's findings to ED visits specifically. Finally, through the use of the labor-leisure model, we arrive at our hypotheses:

1. *The number of ED admissions will be higher during periods when the overall health status is lower and lower during periods when the overall health status is higher.*
2. *The number of ED admissions will be lower during periods when the relative price of an ED visit is higher and higher during periods when the relative price of an ED visit is lower.*

The study is conducted based on the number of ED admissions to the largest hospital in Uppsala County, Uppsala University Hospital, between the years 2012 and 2014. To test the hypotheses we include variables denoting leisure and working time (day of the week, holiday and day after a holiday) and variables estimating the population's health status (phone calls to the Health Care Guide) in our model. Finally, we develop a prediction model based on data from the first two years to predict the number of ED visits for 2014 and then compare to the actual outcome to evaluate our findings.

The remainder of the paper is structured as follows: section two gives a brief background on medical care in Uppsala County today and is followed by a review of previous research on forecasting models for the number of ED visits in section three. Section four is devoted to economic theory. Here we build a theoretical framework for analyzing the determinants of ED attendance by deriving the demand for emergency care. The hypotheses that follow are presented in section five. The empirical method and data used to test and examine these hypotheses are described in section six and the results are summarized in section seven. Section eight is devoted to a discussion of our findings. We end the paper in section nine with some concluding remarks, the contributions of this study and suggestions for future research.

2. Background

The delivery of health care in Sweden is, with a few exceptions, publicly financed and organized on a county level (8). Uppsala is the fourth largest city in Sweden and Uppsala County has a population of almost 350 000 as of December 31, 2014 (9). The county hospital is Uppsala University Hospital (10) and it provides the majority of the population in the county with emergency care (9). There is only one additional provider of emergency care in the county (11).

2.1 Medical care in Uppsala County

On average, 150 patients are treated in the adult emergency department at Uppsala University Hospital every day (12). The department treats patients over the age of 15 with severe illnesses and injuries. Patients transported by ambulance with severe conditions are treated at the adult emergency department regardless of age. The emergency department for children treats patients under the age of 15 for surgical complaints and under the age of 18 for medical complaints (11). Patients with gynecological complaints, infectious diseases (daytime), diseases of the ear, nose and throat or psychiatric complaints are directed to their specific emergency departments (13). The second provider of emergency care in the county is Enköping Hospital, intended to serve the inhabitants of the southern part of the county and the type of medical care provided there is limited in comparison to Uppsala University Hospital (10). The daily volume of ED patients in Enköping is on average 51 (14). Although there are no other emergency departments in the county, the health care provided at other suppliers can in some cases substitute the care given at the emergency department.

In the cases when it is possible, care centers are the primary health care providers (15). There are 48 care centers in the county intended for all inhabitants, most of which are open between 8 a.m. and 5 p.m. on weekdays (16). Although two of these care centers (Tierp and Östhammar) operate at all hours of the day and treat more urgent matters, these are located outside of Uppsala and encourage patients to make an appointment before arrival (17, 18). Furthermore, there is one local emergency ward that treats basic urgent injuries and illnesses and is open between 7 a.m. and 11 p.m. every day (19).

The cost of a visit at the mentioned health care providers is listed in the table 2.1. Patients under the age of 20 years do not pay a fee for a visit.

TABLE 2.1 PATIENT FEES IN UPPSALA COUNTY

Health care provider	Fee
General practitioner	150 SEK
Emergency Department Uppsala University Hospital and Enköping Hospital	380 SEK
Emergency unit in Tierp and Östhammar	230 SEK
Local emergency ward (doctor)	230 SEK
Local emergency ward (nurse)	100 SEK

Table 2.1 Patient fees in Uppsala County. The table contains the patient fees for some health care providers in Uppsala County expressed in Swedish Crowns and sorted by health care provider (20).

3. Previous research

In this section, we give a brief review of previous empirical research. The summary will be limited to studies aiming to answer the same research question as the one presented in this paper: what are the determinants of daily ED attendance? We will look at papers that have developed prediction models using different empirical methods and variables. Noteworthy is that all but one of the papers reviewed in this section are published in medical journals. This seems to be the case for the majority of the prediction models for patients seeking urgent care we have found in our extensive search.

3.1 Previous forecasting studies on ED attendance

In 1981, Diehl et al (21) conducted one of the first studies aiming to tailor staffing levels to the inflow of patients by predicting the number of ED admissions using data from an ambulatory care center in Sudbury, Canada from 1975 to 1978. By matching the daily visits with concurrent calendar and metrological variables such as day of the week, month and daytime rainfall, the authors found that the attendance rates peaked on Mondays and gradually decreased for the rest of the week. More visits occurred during the summer months than during fall and winter and higher temperature correlated with more visits. Daytime rainfall was associated with fewer ED admissions. Based on data from an urgent center in Denver, Colorado from 1998 to 2000, H Batal et al (22) confirmed Diehl et al’s findings that the number of visits was highest on Mondays, with an almost linear decrease until Sunday. The stepwise linear regression model managed to predict patient volume in the validation set within +/-11%.

Although the use of calendar information to predict the daily demand for ED services is an approach that has been widely used in previous papers (22-27), the results on whether certain days of the week are associated with higher or fewer numbers of visits are mixed. Aiming to support operational, tactical and strategic planning in emergency departments, MJ Côté et al (23) found that the number of admissions was highest on Sundays, followed by Mondays and Saturdays using data on ED admissions from 2005 to 2006 from a hospital in Pennsylvania. The number of admissions was lowest on Fridays. HJ Kam et al (24) found similar results using data from 2007 to 2008 from a Korean hospital. The number of ED patients peaked on Sundays and began to decrease on Monday, staying low until Friday. The authors were able to forecast the daily admissions with a MAPE[1] of 7.4%. Even though the effect of certain days of the week on patient volume has been inconsistent, the majority of studies have concluded that calendar variables have explanatory value and should be included in future models (21-26, 28).

A more disputable question amongst previous authors however, has been whether to include weather variables in the forecasting models. A number of studies (5, 22, 25, 28) find that by controlling for calendar variables, weather has no explanatory value. A more recent study published in 2014 by SK Sahu et al (29) argues the opposite. The authors find that short-term forecasting on the number of non-elective hospital admissions was improved by including meteorological data. The study was based on data during 2008 to 2009 from two hospitals in the United Kingdom, one in southeast England and one in southern Wales. The MAE[2] using forecasted temperatures was 3.923 and 4.310 number of visits respectively. The authors found a negative correlation between the temperature and the number of admissions and argue that the daily temperature, rather than the month, is more appropriate when trying to predict the daily number of admissions rather than a monthly average. Results in the previously mentioned study by HJ Kam et al (24) also demonstrate that weather variables, in particular rain and temperature, should be considered when predicting the number of daily ED admissions.

Although calendar and weather information is most common, previous papers are not limited to these variables. Using a data set of all ED to Bromley Hospitals NHS in England from 1993 to 1999, SA Jones et al (30) found that the number of beds occupied due to emergency admissions is correlated to Public Health Laboratory Services (PHLS) data on influenza-like

[1] Mean absolute percentage error (MAPE) is calculated as the sum of all prediction errors divided by the number of fitted points.
[2] Mean absolute error (MAE) is calculated as the average of the absolute errors between the predicted and realized values.

illnesses. Although the RMS error[3] of the mean number of beds used for ED admissions was 3%, the authors point out that the forecasting error increases when data on influenza-like illnesses are added to the regression.

Being first to use Internet data to predict the number of ED visits, Ekström et al (31) found that visits to the Stockholm Health Care Guide website could be used to predict the number of ED admissions. The study was based on data from seven hospitals in Stockholm from 2011 to 2012 and the authors made one forecast for the entire Stockholm County as well as one of each hospital. The prediction model also included day of the week and resulted in a MAPE of 4.8% for the entire county. The MAPE for individual hospitals ranged between 5.2 and 13.1%. Although forecasts were most accurate on county level, the variable of website visits was statistically significant in the separate models for all the hospitals as well.

3.2 Limitations of previous studies

Numerous studies aiming to predict patient volumes in emergency departments have been conducted where different sets of prediction variables and classes of forecasting models have been applied. Understandably, the focus has been on improving the accuracy of existing models rather than providing a justification of the choice of variables. Nevertheless, this approach (that permeates all previous research) falls short on the premise that it produces pure correlational studies. Consequently, all research done within this field is of observational nature and can only be generalized to a limited extent to other emergency departments as previous authors have consistently pointed out (21-23, 26). Although previous forecasting models yield fairly accurate predictions, the lack of theoretical support results in an uncertainty surrounding their reliability and validity. One simply cannot determine whether they postulate an actual causality between the studied variables and the observed patient volume. Diverging trends can be difficult to capture and explanations to the contradicting results in previous papers hard to attain. This can arguably render previous studies as a less useful and even inappropriate decision basis for emergency departments in their resource allocation and planning. Without a theoretical framework that underpins the design of the prediction model, one cannot reject the possibility that the findings are purely coincidental.

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[3] Root-mean-square error (RMS error) is calculated as the square root of the mean of the squares of the errors between the predicted and realized values.

In the next section, we address this issue by developing a theoretical framework for analyzing the demand for emergency care. We will provide a systematic way of analyzing daily fluctuations in ED admissions and possible explanations to the contradicting results observed in previous studies. The aim is to provide a notion of generality that can fill the gaps in the current state of knowledge regarding the determinants of emergency care demand.

4. Theoretical framework

In order to explain the daily fluctuations in ED attendance, we need to first understand the underlying forces driving individuals' demand for emergency care. First, we will look at Michael Grossman's model on the demand for health and medical care. Secondly, we build on Grossman's findings and derive the demand for emergency care specifically using the standard budget constraint model. Finally, we use the labor-leisure model to better understand the individual's allocation of time. We believe that these theories combined will provide us with a theoretical framework for analyzing the determinants of ED attendance.

4.1 The Grossman model

For most consumers, a health care visit is considerably different from the regular trip to the supermarket. Many argue that health care is unlike any other type of good (32). This approach makes the derivation of the demand for medical care less straightforward. However, using Grossman's model of health production (33), the distinct features of health can be accounted for. Health is treated as both a consumption good (that yields utility directly as the individual feels good when healthy) and an investment good (that increase utility indirectly through fewer sick days, increased productivity and higher wages). Published in 1972, Grossman's model of the production of health has become one of the most influential works and starting points for subsequent studies within health economics (34). The central proposition put forward is that health can be viewed as a capital stock. This durable stock produces output in form of healthy days and depreciates over time in the absence of health investments. The health investments require both resources and time that individuals must trade off. This approach allows us to analyze how individuals choose to allocate resources to the production of health.

There are alternative theories that explain the demand for health. The Andersen model (35) for example provides a more conceptual view of motives behind the use of health services while

Zweifel (36) looks at the demand of health based on principal-agent theory. The advantage of Grossman's work is its foundation in traditional consumer theory and that the consumer is regarded as the sole actor influencing the demand for health and health care. It provides a consistent framework that can explain what drives the individual's decision to make health investments. Grossman's approach is what takes us the farthest in our analysis and will therefore be one of the main components of our theoretical framework. We will now give an overview of the Grossman model and how medical care is used to produce health.

4.1.1 Production of health

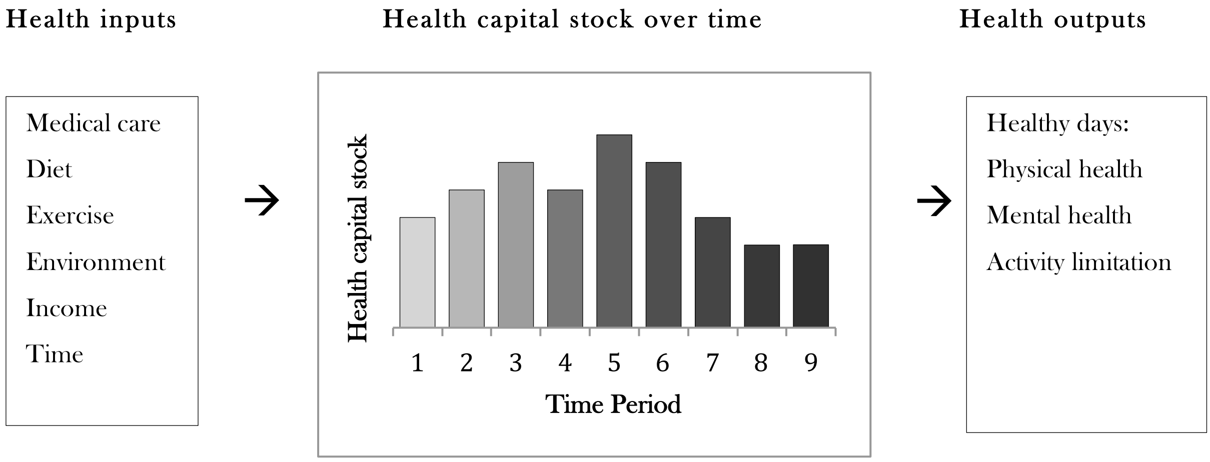

Figure 4.1 The concept of health capital stock. Reproduced from Folland et al (37).

As previously mentioned, Grossman views health stock as a capital good – the greater the individual's stock of health is; the more healthy days will the individual have. The health stock is depreciated gradually with age and more rapidly with illness or injury. At the health stock minimum, H_{min}, the numbers of healthy days are zero and death occurs. To increase the health stock the individual can make investments by applying various sets of health inputs. Grossman assumes that health investment is a time intensive good. The inputs used to produce health are not solely market purchased inputs such as medicine or physician visits, but also investments of the individual's own time in form of health-improving activities such as rest, diet and exercise. It is these two types of inputs combined that yield the desired health outputs in form of healthy days[4] as shown in figure 4.1. Following this reasoning, it is not health care services in itself that

[4] Grossman defines healthy days as physical and mental health and the absence of activity limitation

individuals demand, but rather health, when seeking medical care. Medical care is simply an input to produce health.

4.1.2 Optimal health capital stock

The optimal health capital stock will drive the individual's decision to invest in their health. As soon as the individual's health stock falls below the optimal level, the individual will make health investments and this will continue until equilibrium is reached. The reduction in health can occur when an individual is exposed to a health shock through illness or injury, making health status a factor influencing the demand for health.

As with other capital goods, the optimal health capital stock is determined by the intersection of the marginal efficiency of investment curve (MEI curve) and the cost of capital curve as shown in figure 4.2. MEI is the rate of return on the investment in health and is downward sloping. It captures the benefits mentioned earlier with improved health, such as increased productivity and fewer days lost to illness. The cost of capital curve reflects the interest rate, r, and the depreciation rate, δ, and represents the cost of holding a given amount of health capital such as spending time and money on exercising, dieting and medical care.

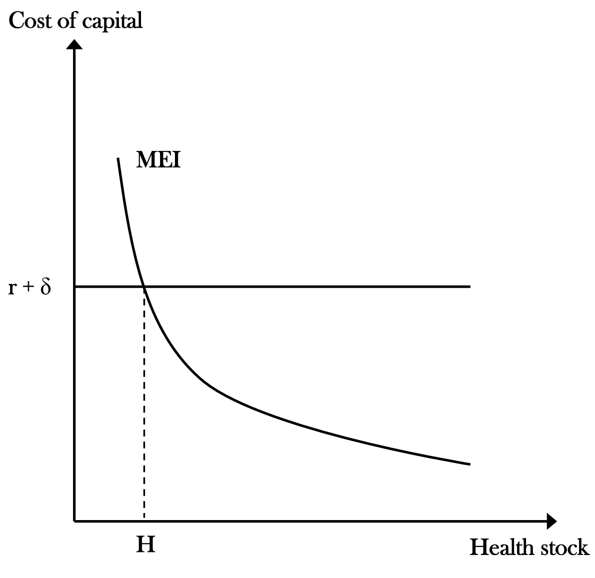

Figure 4.2 Optimal health capital stock. Reproduced from Folland et al (38).

Grossman argues that the MEI and cost of capital will depend on the individual's wage, age and education. For example, Grossman reasons that more educated people will choose a higher optimal health stock as they are assumed to be more efficient producers of health than their less educated counterparts, thus reducing the cost of holding a given health stock. Individuals with higher wage will have a higher level of optimal health stock, as the reward from being healthy is greater because they can earn more income for every healthy day. As the health deterioration often rises with age it requires more investments to keep it at the same level. Hence, the cost of capital is higher for older people, resulting in a lower optimal health stock (see Grossman [33] for a more elaborate explanation on the effect of wage, age and education). In summary, the demand of health is therefore mainly influenced by the individual's wage, age, education and health status.

4.1.3 Modifications to the Grossman model

As the aim of this paper is to identify the determinants of daily ED attendance, we will make some slight modifications to the Grossman model. Firstly, we let wage, age and education for any individual remain constant. We assume that these changes happen over a longer period of time and not on a daily basis. By assuming that age, wage and education do not change for the period the framework is applied, these factors do not impact the daily fluctuations in demand for medical care. A change in health status will therefore be the only remaining factor affecting the demand for health investment following Grossman's model. Secondly, as Grossman provides a more conceptual view of health, we make some slight adjustments to analyze the daily changes in the demand for medical care. Although Grossman recognizes that a higher wage will increase the opportunity cost of time of health investment, he does not take into account that this cost can vary for a given individual despite holding wage constant. More specifically, we believe that the opportunity of cost of time can change for a given individual depending on when the investment occurs. Thus, we account for the possibility that the opportunity cost of time can be a cause of daily fluctuations in the demand for medical care despite holding wage constant.

Having identified the main drivers of daily fluctuations in the demand for medical care, we will now apply our findings to the demand of emergency care specifically. We will apply the standard budget constraint model for this purpose. Combined with Grossman's theory on the demand for health and medical care, this model will form our framework for analyzing the demand for emergency care.

4.2 The standard budget constraint model

The standard budget constraint model is commonly used for describing an individual's allocation of resources. When investing in health, the individual faces both a monetary and time constraint. This can be incorporated in the model through the budget line while the individual's preferences for medical care can be included through indifference curves. The model therefore enables us to incorporate the characteristics of health investment, making it a suitable tool for analyzing the consumer's resource allocation to emergency care.

4.2.1. Assumptions

In order to derive the demand for emergency care specifically from the demand for medical care we need to make the central assumption that the determinants for emergency care and medical care are the same. More specifically, we assume that when the demand for medical care in general increases, the demand for emergency care will also increase. Although research by Backman et al argues that people view primary and emergency care similarly and that the majority of ED patients are non-urgent and more suited to seek care at primary centers (39), this is a fairly strong assumption. One might argue that the determinants for medical and emergency care differ depending on how sick the individuals perceive themselves to be. The monetary and time price may for example be irrelevant for people that are severely ill. Conversely, in the case for milder diseases or injuries, a reduction in health status will increase the demand for primary care but not necessarily the demand for emergency care. The effect of the assumptions on our empirical results will we come back to later on in the paper.

Furthermore, the use of standard indifference curve analysis under a budget constraint also imposes assumptions on the individual. The individual is assumed to be rational and perfectly informed, seek to maximize his utility and fully understand his own preferences (40). Although these are assumptions that underpin neoclassical economics, the extent to which these hold can be questioned when it comes to ED visits. In the case of emergency care, there is a possibility that the individual is not rational or in a position where he is able to make a choice. This is more likely to be the case for individuals who experience a severe health decrease. However, we refer back to Backman's findings (39) that the majority of ED patients are non-urgent and conclude that, with some exceptions, the standard budget constraint model can be applied.

4.2.2 Basic characteristics of the model

As in traditional consumer theory, the individual will maximize his utility by attaining the highest indifference curve given his or her budget constraint. In our case, the budget constraint will have to take into account both the monetary and time price. Therefore, we let the opportunity cost of time be denoted as P_T and the monetary cost P_M. The full price of an ED visit and other goods is the sum of both and can be denoted as:

$$P_{ED} = P_{MED} + P_{TED} \tag{4.1}$$

$$P_{OG} = P_{MOG} + P_{TOG} \tag{4.2}$$

We let *ED* denote the number of ED visits demanded per person on a day and *OG* a composite of all other goods, including other medical services apart from emergency care.
The budget line can therefore be described as:

$$Y = P_{OG} \text{ x } OG + P_{ED} \text{ x } ED \tag{4.3}$$

Note that the individual will demand zero ED visits when he is not ill. It is not until the demand for emergency care reaches a certain level that an actual ED visit takes place. Equilibrium is reached when the slope of the indifference curve, the marginal rate of substitution (MRS), is equal to the slope of the budget constraint line, the relative price, $-P_{ED}/P_{OG}$ of an ED visit. We will now examine what happens with the quantity of emergency care demanded when each curve shifts. All analyses are done *ceteris paribus.*

4.2.3 Shifts in indifference curves and the budget line

Figure 4.3 illustrates what happens when an individual is exposed to a health shock. Depending on the level of perceived health, the individual will have different sets of indifference curves, reflecting his preference for emergency care. The reduction in the level of perceived health can result from an actual decrease in health status and/or the belief that a decrease has occurred (the consumer's worry for his health). It is the reduction in the level of perceived health, not necessarily an actual reduction, which will affect the individual's preferences. As a result from the health decrease, the indifference curves will shift and result in the new equilibrium E_2 where the demand for emergency care is higher. This change in preferences continues until emergency care is a matter of life or death, implying that a person with a health stock near the minimum will want to spend nearly all his resources on emergency care.

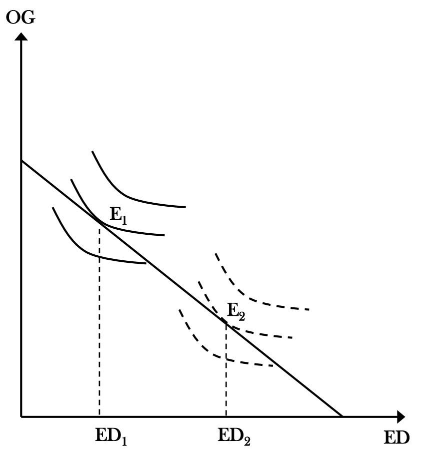

Figure 4.3 Change in the number of ED visits during a health shock. Reproduced from Folland et al (41).

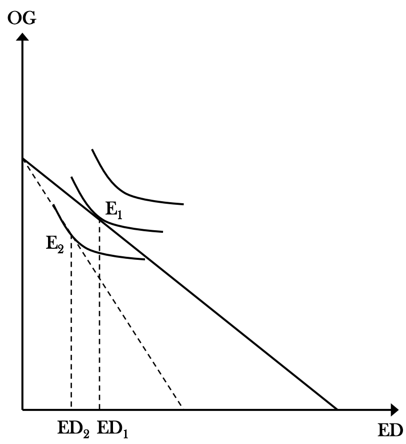

Figure 4.4 Change in the number of ED visits when the relative price changes. Reproduced from Folland et al (42).

Changes in the budget line can also yield changes in the demand for emergency care. An increase in the relative price of an ED visit results in a steeper slope of the budget line, yielding a new equilibrium E_2 where the individual demands less emergency care as illustrated in figure 4.4. As previously mentioned, the relative price consists of both a monetary cost and an opportunity cost of time. Based on Grossman's definition of health investment as a time intensive good, we assume that an ED visit is the time intensive good. An increase in the opportunity cost of time of an ED visit will therefore result in an increase in the relative price of an ED visit. To examine how the opportunity cost of time varies, we will use the labor-leisure model.

4.2.4 The labor-leisure model

In Morris Altman's model (43), labor and leisure time is determined by target real income, which is the income the individual ideally wants. The individual aims to maximize his utility by combining different sets of income and leisure for a given wage rate. For every wage, there is an equilibrium resulting from the choice of target income. The target income is affected by the individual's preferences for income and leisure at a given wage. According to Altman's model, the consumer will have to reach the target of the most important good (wage) before starting to consider the next important one (leisure). This results in the labor supply curve illustrated in figure 4.5.

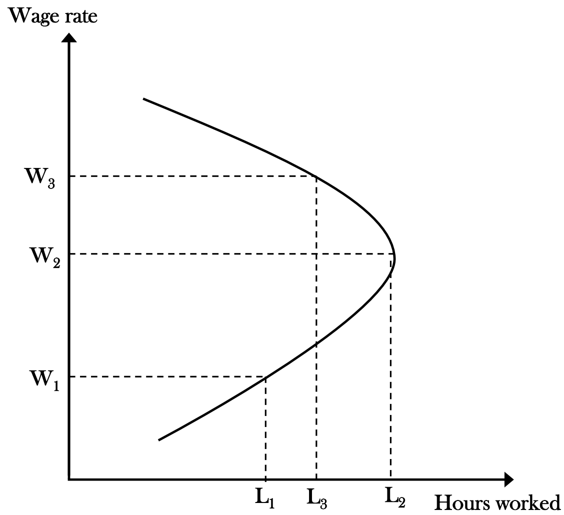

Figure 4.5 The labor-leisure model. Reproduced from Altman (43).

When the income is below the target, an increase in wage will increase the hours worked, as labor is preferred over leisure. Once the target income is reached, an increase in the wage rate will decrease the hours worked, causing the backward bending supply curve of labor. This is because increasing leisure has become relatively more important than increasing income as the target income has been reached, resulting from a change in preferences. This suggests that an individual who has reached his target income will value leisure higher than time spent working whereas working will be valued higher for an individual who has yet to reach his target income. More specifically, holding all other things equal including health status, an individual who has reached his target income will more likely to make an ED visit during working hours, as the opportunity cost is lower than during leisure hours.

4.2.5 Determinants of ED attendance

So far, our analysis has been at the level of the individual. As the aim of this study is to look at ED visits for an emergency department, we need to derive the total number of ED visits in the population. The total number is given by adding the number of ED visits demanded by each individual. Note that an individual only demands an ED visit when the demand for emergency care has reached a certain level, as mentioned earlier. Thus, the determinants of ED attendance on a population level will the same factors affecting the individual's demand for emergency care. Referring to the total number of ED visits on a day as V, the demand function for ED admissions can be summarized as follows:

$$V = f(P_{ED}, P_{OG}, HS) \tag{4.4}$$

where P_{ED} and P_{OG} is the price of ED visits and other goods respectively and HS represent the individuals' health status, that is the overall health status in the population. Hence, the relative price and the individuals' health status are the main determinants for ED attendance following the theoretical framework developed in this section.

5. Hypotheses development

The theoretical framework developed in the previous section is general in the sense that it can be applied to most settings. The hypotheses developed in section 5.1 will also share this feature. However, the generalizability makes them somewhat broad and thus difficult to test empirically. To address this issue, we operationalize our general hypotheses and apply them to our setting specifically.

5.1 General hypotheses

As earlier concluded, the daily volume of ED patients will vary depending on the relative price of an ED visit and the overall health status. When people are exposed to a health shock and perceive a reduction in health, the demand for emergency care will increase. We have now arrived at our first hypothesis:

> ***Health shock hypothesis:*** *The number of ED admissions will be higher during periods when the overall health status is lower and lower during periods when the overall health status is higher.*

Our theoretical findings also suggest that the relative price has an impact on the ED attendance. This leads to our second hypothesis:

Relative price hypothesis: *The number of ED admissions will be lower during periods when the relative price of an ED visit is higher and higher during periods when the relative price of an ED visit is lower.*

5.2 Operationalized hypotheses

As populations may vary in their health seeking behavior and the factors affecting the relative price of an ED visit might differ between health care delivery systems the operationalized hypotheses will be specific to the setting studied in this thesis. In ours setting, where the health care is publicly financed to a large extent, the opportunity cost of time will be relatively more important than in settings where the monetary cost of health care is higher (see equation 4.1).

5.2.1 Operationalized health shock hypothesis

In a study conducted in Stockholm, Sweden, Backman et al (44) describes non-urgent ED and primary care patients' use of information from Internet and telephone services before attendance. They find that non-urgent ED patients are more prone to seek health care information and advice than non-urgent primary care patients are. As Ekström et al (31) have already studied the effect of health care advice through the Internet we will investigate the effect of health care advice through telephone services. We have reason to believe that it is a more precise measure of health reductions as people use the service for seeking medical advice specifically and not for other purposes. To measure a change in the overall health status we will therefore use the number of phone calls to the Health Care Guide.

The Health Care Guide[5] is an online national source of information and services within health that offers telephone counseling for health related questions. Every county has its own Health Care Guide and the nursing hotline receives approximately 5.5 million calls in total every year. The service is open during all hours and nurses staff the telephone counseling service where the patients can receive medical advice (45). In an evaluation of the Health Care Guide, 34% of the respondents from Uppsala County said that they would have gone directly to the emergency department if they had not made a call to the Health Care Guide (46). Since only phone calls leading to a medical chart is recorded at the Health Care Guide, all calls in the data concerns a person's health status. The operationalized hypothesis that follows is:

[5] Also known as *Vårdguiden* in Swedish

Operationalized health shock hypothesis: *The number of ED visits will be higher when the number of phone calls to the Health Care Guide is higher and lower when the number of phone calls to the Health Care Guide is lower.*

5.2.2 Operationalized relative price hypothesis

As mentioned in section 2, the majority of the health care delivery in Sweden is publicly financed. This can be seen in the rather low patient fees presented in that same section. Therefore, the price of an ED visit in this setting will mainly be determined by the opportunity cost of time associated with it. As concluded in section 4.2.4 the opportunity cost of time will mainly vary depending on the presence of leisure and working hours and how much the consumer values each. The labor-leisure model implies that people who have reached their target income will value their leisure higher than one who has not. As limited research has been done which one of the two the individual values the most, we will turn to empirical studies done on the subject. These studies indicate that Swedes value their leisure and family life more and more. The number of people stating that work is more important than leisure decreased from eight out of ten during the 1980's to five out of ten during the 1990's. Today, the importance of work in terms of life quality is said to continue to decrease (47). Based on this we assume that the majority of people in Sweden have reached their target income and that they value leisure time more than working time. Consequently, a consumer who can delay the ED visit will have incentives to postpone it until the opportunity cost of time is lower. This increases the demand for ED visits on days following leisure time as visits might have been postponed.

Most people can be presumed to have more leisure time on weekends and holidays than on weekdays. Since only daily fluctuations in ED attendance are studied, days with relatively more working hours compared to other days will be considered as only working hours and the rest will be considered as all leisure hours. Thus, defining working time as Monday to Friday and leisure time as Saturday, Sunday and holidays (see appendix A for a list of days categorized as a holiday), the hypothesis is operationalized as follows:

Operationalized relative price hypothesis: *The number of ED visits is lower on holidays, Saturday and Sunday compared to the number of admissions to the ED on Monday-Friday and day after holidays. The number of ED admissions will be highest on Mondays and days after a holiday.*

6. Empirical method

We begin by discussing the data collection, and then proceed with describing the method used to test the hypotheses. We end by describing the method used when developing the prediction model.

6.1 Data collection

The data on ED visits are collected from the adult emergency department at Uppsala University Hospital. The data include all ED visits that have been recorded by the hospital of people that are over 18 years old. As seen in section 2.1, patients under the age of 18 will only be in the hospital records if they are classified as a certain type of medical case, these will therefore be excluded from the analysis. These circumstances imply systematic variation for patients under the 18 years that are recorded and could cause bias. Patients, for which the age has not been recorded, are also excluded from the analysis because we cannot say if they are under or over the age of 18. The data consists of observations from January 1, 2012 to December 31, 2014 and are reported on a daily basis where all visits during the 24 hours of a day are added.

The data on phone calls are collected from the Health Care Guide for the same period as the data on ED visits. All phone calls made to the Health Care Guide in Uppsala County that concern a person over the age of 18 years and have led to a medical chart are included in the data. The phone calls concerning a person under the age of 18 years have been excluded from the data to match the data of ED visits.

6.2 Hypothesis testing

All regressions are estimated with ordinary least square (OLS) and robust standard errors are used, as we cannot reject the null hypothesis when testing for heteroscedasticity. The hypotheses will be tested on the training set only (2012 and 2013) using linear regression. The statistical analysis is made in Stata 13. We will also test for multicollinearity. Even though multicollinearity does not violate OLS assumptions and the estimates are still unbiased, multicollinearity can make it more difficult to reject the null hypotheses as it increases standard errors. However, we do not detect a high degree of multicollinearity and therefore assume that it does not constitute a problem in our data (see appendix B).

One might argue that linear regression is an inappropriate modeling strategy for time series analysis due to the risk of autocorrelation. Autocorrelation violates a key inference assumption and would thus make our results less reliable. An alternative would be to use models in the ARMA[6] class (such as ARIMA[7] or SARIMA[8]). These models are based on the premise that the number of ED visits in the future is strongly correlated with the ED attendance today. However, based on the theoretical framework in section 4, we find no implication that previous levels of ED activity by themselves could affect attendance rates today if we control for the time period the health shock takes place through our independent variables. This is what we do in section 6.2.1 by including lag effects of the phone calls to the Health Care Guide. Hence, we believe that linear regression an appropriate modeling strategy to employ. Furthermore, in a systematic review of the different modeling strategies, Jones SS et al also concludes that linear regression based on calendar variables is a reasonable approach to predicting the daily volumes in ED attendance (25). A final reason for using linear regression is that it is commonly used in previous forecasting models for daily ED attendance (see for example [21] and [22]).

6.2.1 Regression models

We construct the following regression model:

$$Y_t = \beta_0 + \beta_1 * Calls0_t + \beta_2 * Calls1_t + \beta_3 * Calls2_t + \beta_4 * Calls3_t + \beta_5 * Calls4_t + \beta_6 * Calls5_t + \beta_7 * Holiday + \beta_8 * Dayafterholiday + \beta_9 * Tuesday + \beta_{10} * Wednesday + \beta_{11} * Thursday + \beta_{12} * Friday + \beta_{13} * Saturday + \beta_{14} * Sunday + \varepsilon_t$$

The dependent variable, Y_t, in the main regression will be the total number of ED visits in the data. To test whether there is a significant difference between each of the days of the week, seven versions of this regression are run. In each version, one day of the week is excluded. Regressions will also be run on a subset of the total number of ED visits to examine if our independent variables are able to capture the same amount of variation in the subgroups. We replace the total number of ED visits with the subgroups *Ambulance*[9], *Walking*[10], *Home*[11] and

[6] Autoregressive moving average (ARMA)
[7] Autoregressive integrated moving average (ARIMA)
[8] Seasonal autoregressive integrated moving average (SARIMA)
[9] Patients arriving by ambulance.
[10] Patients arriving on their own.
[11] Patients being sent home after the visit.

Admitted[12] *as* Y_t[13]. Arriving by ambulance and/or being admitted to the hospital as a result of the visit is used as a proxy for a more severe health reduction.

Our independent variable for measuring the health status will be calls to the Health Care Guide in Uppsala County up to five days in advance. We want to allow for the possibility that people do not seek care immediately when experiencing a decrease in their health status. These lag effects are chosen based on the recommendations from the Health Care Guide of how long to wait before seeking medical care. The service recommends patients to wait two to five days when experiencing fever or similar symptoms (48-51). Although ED patients experience other symptoms than fever, the recommendation for these are often based on how severe the symptoms have become rather than specifying how long to wait before seeking care (52-55). Finally, the variables measuring the opportunity cost of time are all dummy variables. Each dummy for day of the week takes on the value one for that specific day and zero for all other days of the week. Similarly, the dummy variable *Holiday* takes on the value one on holidays and zero on non-holidays following the list in appendix A. Finally, *Dayafterholiday* is one for days following a holiday[14] and zero otherwise.

6.2.2 Null and alternative hypotheses

For the health shock hypothesis will test the null hypothesis that there is no effect of phone calls to the Health Care Guide on the total number of ED visits against the (two-sided) alternative hypothesis that there is a significant effect of phone calls to the Health Care Guide on the total number of ED visits. We do the test for *Calls0* to *Calls5*. The null and alternative hypothesis is formulated as follows:

$$H_0\colon\ \beta_{Calls\,i} = 0, \qquad i = 0, \dots, 5$$
$$H_1\colon\ \beta_{Calls\,i} \neq 0 \qquad i = 0, \dots, 5$$

For the relative price hypotheses we will first test the null hypothesis that there is no significant difference between the number of ED visits on Day A and Day B against the (two-sided)

[12] Patients being admitted to the hospital after the visit.
[13] Note that Walking and Ambulance are mutually exclusive just as Home and Admitted are but that a patient can be categorized as both Walking and Home for example.
[14] Note that a day after a holiday that is also a holiday (ex. Christmas Day) is denoted as a holiday and not a day after a holiday.

alternative hypothesis that there is a significant difference between the number of ED visits on Day A and Day B:

$$H_0\colon\ \beta_{Day\,i} = \beta_{Day\,B}$$
$$H_1\colon\ \beta_{DayA} \neq \beta_{DayB}$$

$$A \neq B$$
$$A = Monday, \dots, Sunday$$
$$B = \ Monday, \dots, Sunday$$

We vary Day A and Day B so that the differences between all days of the week are tested against each other. Secondly, we test the following null hypothesis that there is no significant difference between the number of ED visits on a holiday and a non-holiday against the (two-sided) alternative hypothesis that there is a significant difference between the number of ED visits on a holiday and a non-holiday:

$$H_0\colon\ \beta_{Holiday} = 0$$
$$H_1\colon\ \beta_{Holiday} \neq 0$$

The last null hypothesis we will test is that there is no significant difference between the number of ED visits on a day following a holiday and a day not following a holiday against the (two-sided) alternative hypothesis that there is a significant difference between the number of ED patients on a day following a holiday and a day not following a holiday:

$$H_0\colon\ \beta_{Dayafterholiday} = 0$$
$$H_1\colon\ \beta_{Dayafterholiday} \neq 0$$

6.3 The prediction model

The prediction model will be estimated using a training set based on data from 2012 to 2013. The estimated model will then be used to predict the number of ED visits per day for the following year, 2014, referred to as the validation set. The predicted values will be compared to the actual number of visits during that year. We will use MAPE to see how close the predicted values are to the actual number of visits per day. This measure of prediction accuracy is used because it does not allow for negative and positive errors to cancel out and is easily interpreted. As data for *Calls0* cannot be obtained until the end of the day, it cannot be used in a forecasting model. For practical purposes, we therefore exclude this variable from our prediction model. As phone calls to the Health Care Guide from the previous day are used to predict the number of ED visits, we are not able to predict farther into the future than the following day.

Besides the independent variables used in the hypothesis testing, the prediction model will also include a variable measuring seasonal variation, mainly due to four reasons. Firstly, variables capturing seasonality are often used in previous research as mentioned earlier (see for example [21-23]). Secondly, the population may change over the year. Thirdly, the approximation of leisure and working hours may not hold during periods of vacation, as people have leisure all days of the week. Finally, the valuation of working relative to leisure hours might differ with the season, as different options for the leisure are available. The most common variables to account for seasonal variation are months and average daily temperature (see for example [21], [24] and [29]). In this study, we will include month as a dummy variable to account for seasonal variation. We do not include the daily average temperature because it requires another prediction. Also we believe that, controlling for month, day and health status, temperature will not contain sufficient explanatory value to justify its use.

We construct the following model for predicting the number of ED visits on a day:

$$Y_t = \beta_0 + \beta_1 * Calls1_t + \beta_2 * Calls2_t + \beta_3 * Calls3_t + \beta_4 * Calls4_t + \beta_5 * Calls5_t + \beta_6 * Holiday + \beta_7 * Dayafterholiday + \beta_8 * Tuesday + \beta_9 * Wednesday + \beta_{10} * Thursday + \beta_{11} * Friday + \beta_{12} * Saturday + \beta_{13} * Sunday + \beta_{14} * Feb + \beta_{15} * Mar + \beta_{16} * Apr + \beta_{17} * May + \beta_{18} * Jun + \beta_{19} * Jul + \beta_{20} * Aug + \beta_{21} * Sep + \beta_{22} * Oct + \beta_{23} * Nov + \beta_{24} * Dec + \varepsilon_t$$

To examine our prediction model, we will also have one prediction model with *Calls0* and one without calls altogether.

7. Results

We begin this section by presenting the results from the hypotheses testing. We then proceed with the results from the regressions on the subpopulations and the prediction model. The results are briefly commented upon in this section but will be further discussed in section eight. Throughout this paper, we will reject for p-values higher than 5%. See appendix C for descriptive statistics of the data.

7.1 Hypothesis testing

TABLE 7.1 MAIN REGRESSION WITH MONDAY EXCLUDED

Calls0	0.0511**
	(0.0260)
Calls1	0.00856
	(0.0252)
Calls2	0.00347
	(0.0246)
Calls3	0.0285
	(0.0227)
Calls4	-0.00963
	(0.0219)
Calls5	-0.00584
	(0.0226)
Holiday	-5.411
	(3.476)
Dayafterholiday	13.56***
	(3.016)
Tuesday	-7.034***
	(2.332)
Wednesday	-7.375***
	(2.545)
Thursday	-10.59***
	(2.787)
Friday	-10.95***
	(2.861)
Saturday	-28.74***
	(2.462)
Sunday	-26.29***
	(2.166)
Constant	137.1***
	(7.174)
Observations	726
R-squared	0.358

Table 7.1 Main regression with Monday excluded. The table contains the result of regressing the total number of patients arriving at the ED per day on all the variables but Monday and January. Robust standard errors in parentheses and *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

7.1.1 Health status

Calls0 is significant in the regression and has a positive coefficient, as predicted by the health shock hypothesis. The higher the number of calls to the Health Care Guide, the higher the number of visits to the ED on the same day. None of the variables *Calls1* to *Calls5* are significant and the variables *Calls4* and *Calls5* do not have the predicted sign. Due to the insignificant coefficients on Calls1 to Calls5, the effect of the number of calls to the Health Care

Guide on the number of visits to the ED one to five days later cannot be determined through this test.

7.1.2 Relative price

All variables measuring the opportunity cost of time, accept for *Holiday* is significant in the main regression. All variables also have the predicted sign of the coefficient. The negative coefficients on *Tuesday* to *Sunday* mean that the average number of patients is fewer on these days compared to the average number of patients on *Mondays*. The negative coefficient on *Holiday* means that the average number of patients is lower on a holiday than on a day that is not a holiday. The positive coefficient on *Dayafterholiday* means that the average number of patients is higher on a day following a holiday than a day not following a holiday. This is in line with the relative price hypothesis.

The result from the hypothesis testing on each day of the week is summarized in table 7.2 (see appendix D for the results from the regressions). For any two days of the week for which there is a significant difference in the number of patients arriving to the ED, there will be a "Yes" in the table below. Otherwise there will be a "No" in the table.

TABLE 7.2 RESULTS FROM THE HYPOTHESIS TESTING

	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Monday	-	Yes	Yes	Yes	Yes	Yes	Yes
Tuesday	Yes	-	No	No	No	Yes	Yes
Wednesday	Yes	No	-	No	No	Yes	Yes
Thursday	Yes	No	No	-	No	Yes	Yes
Friday	Yes	No	No	No	-	Yes	Yes
Saturday	Yes	Yes	Yes	Yes	Yes	-	No
Sunday	Yes	Yes	Yes	Yes	Yes	No	-

Table 7.2 Results from the hypothesis testing. The table contains the results from the hypothesis testing obtained by running the seven versions of the main regression with one day of the week excluded in each. If the p-value of an estimate is below 5% we can reject the null hypothesis that there is no difference between that day and the day excluded. This will result in a "Yes" in the table. If we cannot reject the null hypothesis, this will result in a "No" in the table.

There are significant differences between the number of ED admission on Mondays and all other days of the week. There are also significant differences between the number of ED admissions on Sundays or Saturdays and on weekdays. However, there are no significant differences between the number of patients arriving on a Tuesday, Wednesday and Thursday or between the number of patients arriving on a Saturday and Sunday. This is in line with the relative price hypothesis.

7.2 Regressions on subpopulations

TABLE 7.3 REGRESSION ON WALKING, AMBULANCE HOME AND ADMITTED

	Walking	Ambulance	Home	Admitted
Calls0	0.0639***	-0.00137	0.0229	0.0131
	(0.0209)	(0.0113)	(0.0191)	(0.0110)
Calls1	-0.00584	0.0154	0.00545	-0.00302
	(0.0191)	(0.0125)	(0.0175)	(0.0118)
Calls2	0.000574	0.00759	0.00104	0.000192
	(0.0193)	(0.0118)	(0.0168)	(0.0120)
Calls3	0.0121	-0.00771	0.00331	0.0182*
	(0.0208)	(0.0116)	(0.0180)	(0.0101)
Calls4	0.00157	0.00451	-0.00224	-0.00116
	(0.0189)	(0.0105)	(0.0171)	(0.0104)
Calls5	-0.00790	0.0110	-0.0216	0.00992
	(0.0192)	(0.0104)	(0.0167)	(0.0110)
Holiday	-11.04***	1.173	-3.180	-2.338**
	(2.802)	(1.244)	(2.467)	(1.182)
Dayafterholiday	10.35***	2.448*	10.29***	2.722**
	(2.746)	(1.434)	(2.537)	(1.355)
Tuesday	-5.829***	-0.252	-5.746***	-1.439
	(2.088)	(1.071)	(1.745)	(1.082)
Wednesday	-8.365***	0.921	-5.461***	-1.440
	(2.356)	(1.219)	(1.950)	(1.237)
Thursday	-8.800***	-2.362*	-5.938***	-4.826***
	(2.557)	(1.321)	(2.139)	(1.313)
Friday	-9.399***	-1.761	-6.591***	-3.832***
	(2.391)	(1.305)	(2.003)	(1.286)
Saturday	-26.74***	-1.945*	-16.87***	-11.22***
	(2.120)	(1.162)	(1.831)	(1.140)
Sunday	-25.24***	-1.595	-16.70***	-8.417***
	(1.771)	(1.040)	(1.568)	(1.040)
Constant	84.28***	37.67***	87.97***	43.34***
	(6.111)	(3.174)	(5.590)	(3.256)
Observations	726	726	726	726
R-squared	0.394	0.042	0.254	0.244

Table 7.3 Regression on Walking, Ambulance, Home and Admitted. The table contains the results of regressing the number of patients arriving at the ED per day in the patients groups Walking, Ambulance, Home and Admitted separately on all the variables but Monday and January. Robust standard errors in parentheses and *** p<0.01, ** p<0.05, * p<0.1

7.2.1 Walking versus Ambulance

The regression on the *Walking* subpopulation has a higher R-squared and a higher number of significant variables than the regression on the *Ambulance* subpopulation.

7.2.1.1 Health shock

Calls0 is significant in the regression on *Walking* only. It also has the predicted sign of the coefficient in this regression. The variables *Calls1* to *Calls5* are insignificant in both regressions just as in the regression on the total population. Their coefficients have other signs than in the regression on the total population but since they are highly insignificant we chose to overlook this result.

7.2.1.2 Relative price

All variables measuring the opportunity cost of time, including *Holiday,* which is not significant in the regression on the total population, are significant in the regression on only *Walking*. They also have the predicted sign and the coefficients are of approximately the same size in this regression as in the regression on the total population. In the regression on *Ambulance*, none of the coefficients are significant and several do not have the predicted sign.

7.2.2 Home versus Admitted

The regressions have rather similar R-squared, a bit lower than the regressions on the total population and *Walking* but higher than the regression on *Ambulance*. None of the variables on health shock are significant in any of the regressions but some of the variables on the opportunity cost of time are significant.

7.2.2.1 Health shock

The coefficients on *Calls0* to *Calls5* are insignificant in both regressions. Since they are highly insignificant we chose to overlook the results of the sign on their coefficients, of which not all are as predicted.

7.2.2.2 Relative price

All variables measuring the opportunity cost of time but *Holiday* are significant in the regression on *Home*. The coefficients have the predicted sign but are somewhat smaller than in the regression on the total population or *Walking*. In the regression on *Admitted*, all variables measuring the opportunity cost of time but *Tuesday* and *Wednesday* are significant. They do also have the predicted sign but the size of the coefficients is even smaller than in the regression on *Home*.

7.3 The prediction model

Since the R-squared are highest in the regression on *Walking,* the prediction model is developed for this category. Thus, *Walking* is the dependent variable in the prediction model. Also, since the empirical support for including phone calls is weak, a prediction model without the phone calls is constructed to see if they contribute to the prediction accuracy. Also, as *Calls0* is the only significant variable of the phone calls to the Health Care Guide, a model without *Calls0* is constructed to see if including it improves the prediction accuracy of the model.

TABLE 7.4: MEASURES OF PREDICTION ACCURACY FOR THE THREE PREDICTION MODELS

Measure	With Calls1-Calls5	Without Calls	With Calls0-Calls5
CFE[15]	-680	-838	-607
MAE	9.38	9.43	9.39
MAPE	11.10%	11.09%	11.12%

Table 7.4 Measures of prediction accuracy for the three prediction models. The table contains some measures of prediction accuracy obtained by comparing the predicted number of patients arriving in the patient group Walking with the actual number arriving in the same patient group.

The cumulative sum of forecast errors for the model with *Calls1* to *Calls5* is -680. This means that, over the whole year, the model underestimates the actual number of patients arriving at the ED with 680 patients. With a mean absolute deviation of 9.38, the prediction deviates with approximately 10 visits on average per day compared to the actual number for the predicted year. The MAPE of the prediction is 11.10%. This means that the model, on average, predicts 11.10% from the actual number of admissions. The results of the other two prediction models are very similar to the prediction model with *Calls1* to *Calls5*.

[15] Cumulative sum of forecast errors (CFE) is calculated as the sum of all prediction errors.

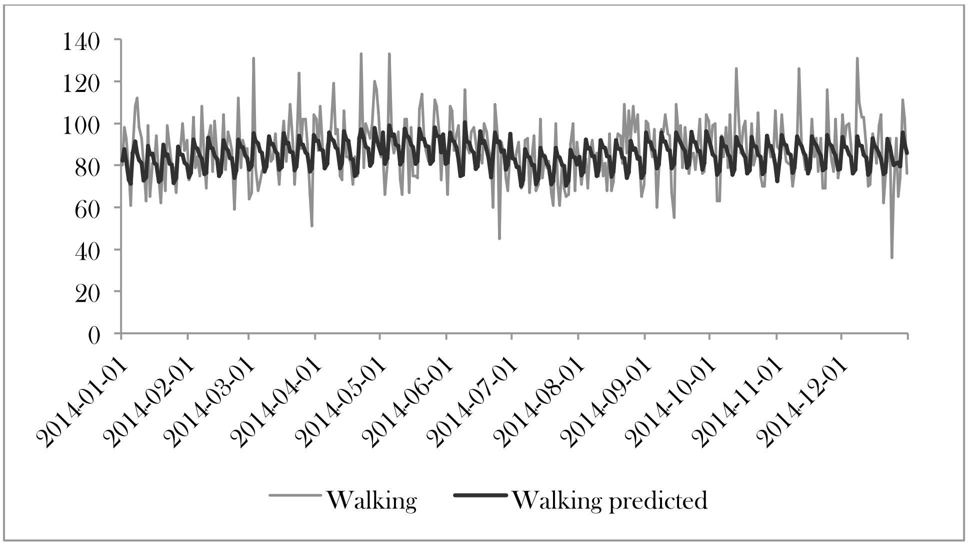

Figure 7.1 Number of patients in the category Walking arriving per day during 2014. The figure illustrated how the predicted (darker line) and the actual number (lighter line) of patients arriving per day in the category Walking varies during 2014.

The predicted number of patients has a smaller variation than the actual number of patients. This means that the model cannot make accurate predictions on days when there is a large deviation from the average number of *Walking* patients arriving to the ED.

8. Discussion

In this section we begin by discussing the results of the hypothesis testing where the theoretical framework developed in section four will be the point of departure to interpret our findings. We then examine the consequences following our choice of variables and data before proceeding with an evaluation of our prediction model. We end this section with the implications of our findings and address the external validity of this study.

8.1 Findings from the hypothesis testing

Out of the five null hypotheses concerning health shocks, we can only reject the null hypothesis that *Calls0* is equal to zero based on the results obtained in section 7.1.1. We fail to reject the null hypothesis for the remaining variables on phone calls to the Health Care Guide. Although the results obtained for *Calls0* support our hypothesis, we believe that it can be purely coincidental. This is because *Calls0* contains phone calls made the same day as the ED visits. Therefore, there is a risk that phone calls to the Health Care Guide that are used to explain the ED visits actually happened after the visit had taken place. This conflicts with our hypothesis that phone calls is a determinant with a causal effect on the number of ED admissions. A more reliable result could have been obtained by using shorter time intervals such as phone calls made before noon and ED visits made after noon. This idea is supported by previous studies, more specifically Ekström et al (31) who found that the best results for predicting the number of ED visits were obtained by using website visits from 6 p.m. to midnight from the preceding day. Furthermore, the coefficients for all variables on phone calls are close to zero. This implies that one phone call has a minor, if any, effect on the number of ED visits. *Calls1 to Calls5* are all insignificant and the range of the confidence interval implies that the effect of these variables on the demand for ED visits can be positive, negative or zero. Overall, we do not find empirical support for our health shock hypothesis.

The results from the test of the relative price hypothesis are more conclusive. Based on the results presented in section 7.2.3, we can reject all null hypotheses concerning the days of the week. The same can be done for the null hypothesis that *Dayafterholiday* has no effect on ED attendance. The only null hypothesis we fail to reject is the one concerning the effect of *Holiday* on ED admissions. Our findings imply that the number of ED admissions is significantly higher on a Monday and a day after a holiday while the number of ED visits is significantly lower on Saturdays and Sundays. This is in line with previous research that concludes that the day of the week is a strong predictor of the number of ED visits. More specifically, our results indicate that the number of ED admissions is highest on Mondays. This is in line with the findings of Diehl et al (21) and H Batal el al (22) from Sudbury, Canada and Denver, Colorado. However, this is inconsistent with the findings of MJ Côté et al (23) and Kam et al (24) in Pennsylvania and Korea that the number of admissions is highest on Sundays. All in all, as we can reject eight out of nine null hypotheses, we find strong support for the relative price hypothesis.

8.2 Theoretical explanations

As mentioned above, we do not find empirical support for the health shock hypothesis. This implies that we cannot say that an overall health shock will increase the number of ED visits. This may indicate that the assumptions made to identify the determinants for the ED attendance do not hold. The assumption that an increase in the demand for medical care simultaneously results in an increase in the demand for emergency care is central as we directly derive the determinants for ED attendance from the demand for medical care. However, even though Grossman's theory states that a health shock affects the demand for medical care, he does not derive the demand for emergency care specifically. As mentioned earlier, it is only when the demand for emergency care has reached a certain level that an ED visit will take place. This indicates that the perceived severity of the health reduction matters. Only when the perceived health reduction is large enough will it result in an ED visit. Although we do not reject the possibility that health status is not a determinant of ED attendance, we find it unlikely that the perceived health status do not impact the individual's decision to make an ED visit. Instead, we find it more likely that we have not managed to capture all types of health reductions through our choice of variables. We address the limitations in data in the following section.

The consequences of the assumptions made earlier also impact the relative price hypothesis. Although hypothesis is empirically supported, it is based on the assumption that leisure is valued higher than working hours. Research regarding how much individuals value each is limited, making it a strong assumption. If it fails to hold, the empirical results would be more difficult to interpret and no longer support the relative price hypothesis. Ultimately, it makes the validity of the theoretical framework questionable as the rejection of the null hypotheses could be due to other reasons than what is included in the framework.

The theoretical framework can also provide an explanation to why our results on the effect of day of the week are in line with some of the previous papers and conflicting with others. Based on the labor-leisure model, the value an individual attaches to leisure and work is dependent on whether he has reached his target income, as previously mentioned. If working hours is valued higher than leisure hours, the price of an ED visit will be relatively higher during working hours. Hence more patients would visit the ED during leisure hours. As the definition of leisure and how much individuals value this time vary from setting to setting, it could explain why previous research has found different effects of the day of the week. Another possible explanation is that the monetary and time price of an ED visit will vary depending on setting. If the monetary cost for health care is high in a specific setting, the opportunity cost of time will be a relatively less important element in determining the number of ED admissions.

8.3 Limitations in the data set

We believe that the insignificant results on the health shock hypothesis can be mainly attributed to the limitations in choice of variables. Overall, we suspect that phone calls to the Health Care Guide are not a comprehensive measure of health reductions and that the use of the Health

Care Guide might be limited. If the individuals that are captured by the phone calls vary systematically over time from those who are not captured by the phone calls, our results will be bias and possibly insignificant. The groups may differ in their tendency of calling the Health Care Guide and visiting the adult emergency department due to several reasons. Firstly, patients with more severe health reductions might be less inclined to call the Health Care Guide but more inclined to visits the ED than patients with less severe health reductions. Secondly, patients with complaints that are treated in separate emergency departments, such as gynecological complaints, might call the Health Care Guide but make an ED visit to another department. Thirdly, the tendency to seek emergency care may vary between patients suffering from complaints with more visible symptoms (that are more easily captured by a symptom-based service such as the Health Care Guide) and those with less obvious symptoms. Fourthly, by limiting our collection of phone calls to Uppsala County, there is also the risk of capturing health reductions in Uppsala County that lead to ED visits in another area. Although it would have been possible to exclude the phone calls made from Enköping municipality, there is a risk that patients from Enköping go to the ED at Uppsala University Hospital. This could yield bias and insignificant results as well since their health reductions would not be captured in our model if their phone calls to the Health Care Guide were excluded. All things considered, we have strong reasons to suspect that phone calls to the Health Care Guide are an imperfect measure of health reductions.

The flaws in our measure of health reductions may affect our results on the relative price hypothesis. If phone calls to the Health Care Guide fail to capture health reductions, either partly or entirely, there is a risk that our calendar variables capture it. If the risk of getting ill or injured is higher on some days than others, the variables for day of the week for example could capture the effects of health shocks. As a result, we cannot determine whether only relative price, only health shocks or a combination of both are determinants of ED attendance.

A result that is somewhat surprising is that we fail to reject the null hypothesis concerning holidays. A possible explanation could be that patients who would originally demand care from one of the substitutes to emergency departments (such as primary care centers) might demand more care at the emergency department when these substitutes are not available. As seen in section two, many care centers have limited opening hours during holidays. The limited availability of substitutes could therefore result in an increase in the demand for emergency care during holidays. However, as stated earlier, the relative price is higher during holidays and thus reduces the demand for emergency care during these days. The aggregate effect of a holiday on ED admissions depends on which of these two dominate. As this can vary depending on which holiday it is, the effect of a holiday can be either positive or negative on the number of ED visits. People may treat some holidays more or less similarly to working days. This is a possible explanation to why *Holiday* is insignificant on our regression. Although *Saturday* and *Sunday* are subject to these opposite effects as well, the effect of the relative price seems to be consistently dominating for these days.

8.4 Analysis of the subpopulations

Since we suspect that the phone calls to the Health Care Guide are imperfect and only capture a certain type of health reductions, we will compare the results of the regressions on the different subpopulations. We believe that the type of health reduction, in terms of both size and how quickly the reduction happens and evolves, may affect individuals' health seeking behavior. As seen in section 7.3, the R-squared is higher for the regression on patients in the category *Walking* (0.3944) than in the regression on patients arriving by ambulance (0.0416). As *Ambulance* is used as an approximation of a more severe health reduction, we believe that the difference in R-squared can be explained by the different types of health reductions the different subgroups experience. Important to note that is that the type of health reduction could have an effect on the role of the relative price. If patients arriving by ambulance have more severe health reductions, they might be less sensitive to the price of making an ED visit, as they are in need of more immediate care. Therefore, variables capturing the relative price could have less of an explanatory value for the subgroup *Ambulance*. Although the R-squared for the regression on patients sent home (0.2544) and for the regression on patients being admitted (0.2438) are rather similar. It could be the case that patients in the *Home* and *Admitted* category suffer from equally severe health reductions but vary in terms the treatment method. This would imply that they are affected equally much by the relative price which is why we can explain the same amount of variation in both groups. This provides further indication that not only the presence of a health reduction matter for the daily volume of ED patients but that the type of health reduction can be worthwhile to consider as well. This observation has a theoretical basis as well, as mentioned in section 8.2.

Worth noting is that the R-squared for all regressions on the subgroups are below 0.40. The variation in the number of ED visits we are able to explain is thus limited. This can be an indication that the determinants of ED attendance identified in this study are not exhaustive. It is possible that people's preferences for emergency care vary over time due to factors we have not controlled for. In particular, as the theoretical framework is based on an individual's preferences and resource constraint, we do not include interaction effects between individuals. Hence, there may be additional determinants of ED attendance on a population level. One example is the effect of bad media coverage of emergency care. Holding health status and relative price constant, articles portraying emergency care in a bad light may change people's preferences and thus affect how much emergency care they demand. Such interaction effects are something that is not captured in our theoretical framework.

8.5 The prediction model

The MAPE of our prediction model with *Calls1* to *Calls5* is 11.10%. This can be compared to the MAPE of 11.09% for the prediction model where phone calls are excluded. Hence, adding phone calls to the forecasting model do not increase the accuracy of the prediction and provides even more support to the suspicion that phone calls cannot be used to predict the number of ED admissions. Furthermore, as discussed in previous section, *Calls0* cannot be included in a model used in practice. However, including *Calls0* in the prediction model barely changes the prediction accuracy of the model (MAPE 11.12%). These results further emphasize the flaws of using phone calls to the Health Care Guide to capture health reductions. As we fail to capture health reductions, the prediction model is mainly based on calendar variables. However, these variables, such as day of the week, are not unique for each day but based on the entire 2014. This could explain why we are not able to predict values that are far below or above the average number of visits on that day of week as seen in figure 7.1 where the predicted number of patients do not vary as much as the observed number of patients.

Comparing our MAPE to the ones obtained in previous research, ours is rather high. Ekström et al, who have the most similar setting to ours, obtain a lower MAPE for six of the seven hospitals studied (31). They only use day of the week and the number of website visits to the Health Care Guide as independent variables. An explanation to why they obtain a lower MAPE than us could simply be that website visits are better at capturing overall health reductions than phone calls as they reach a wider audience. Similarly, this could explain why previous forecasting models with weather variables have obtained more accurate predictions. For example, HJ Kam et al (24) get a MAPE of 7.4%. It could be the case that weather variables are better at capturing health reductions than phone calls to the Health Care Guide. However, it is also possible that calendar variables have a greater explanatory value in their setting, Korea. Finally, the difference in accuracy between our prediction model and previous forecasting models could be due to the different empirical methods used. As mentioned earlier, ARMA models incorporate historical patterns in the structure of the model. If a population has been exposed to a health shock that lasts over several days, historical outcomes on the number of ED admissions could be a measure of health shocks. As we use linear regression, we aim to capture the duration of health shocks through our independent variables. We are not able to achieve this since we have not found a good enough measure of health shocks.

8.6 Generalizability of the results

It is important to separate the generalizability of the theoretical framework and the results from the operationalized hypotheses. Although the operationalization of the hypotheses allows us to test our theoretical framework, it imposes stronger limitations on the extent to which our findings can be generalized. This is the case for our finding that day of the week and days after a holiday are determinants of ED attendance. Following our previous assumptions, these results are only valid in settings where the time price constitutes a significant portion of the total price associated with an ED visit. In settings where the monetary costs of health care are high, the time cost may constitute only a minor fraction of the total cost and therefore not impact the demand for emergency care. In particular, in settings where health care is not publically financed to the same extent as in Sweden, calendar variables could irrelevant to include in prediction models. Instead, it would be the changes in monetary costs associated with an ED visit that would affect the daily volume of ED patients. Since our theoretical framework indicates that the relative price of an ED visit is a determinant for the number of daily ED admissions, and do not specify which of the time and monetary price should be dominant, its validity can be extended to settings that have different health care systems from Sweden's.

Furthermore, the reliability of the results from our hypothesis testing is limited by the chosen timeframe. People's preferences and behavior may change over a longer period of time due to changes in age, education and wage (factors we have assumed to remain constant). In particular, if wage and people's target income change over time, they may value leisure and working hours differently than today. Hence, our findings regarding the opportunity cost of time may no longer be valid for Uppsala County as demographical changes take place. The validity of our results is therefore dependent on routinely collected data that is updated continuously.

The extent to which our framework can be generalized is limited as well. As Grossman states, medical care is only one way of investing in health. For populations that invest in their health through other inputs than medical care or via other sorts of medical care than emergency care, an overall health shock will increase the demand for emergency care. Thus, the framework can only be extended to settings where the health seeking behavior and medical care preferences of the population do not deviate considerably from the population studied in this paper. For similar reasons, its validity could be questioned when analyzing the determinants for other patients groups that those studied in this thesis. Children or patients with psychological disorders for example may differ in their health seeking behavior. To strengthen the confidence in the generalizability of our framework it is therefore valuable to repeat the study on other populations.

9. Concluding remarks

Based on our theoretical framework we identify two determinants for daily ED attendance: the health status of individuals and the relative price of an ED visit. Of the two hypotheses tested for their impact on the demand for emergency care, only the relative price hypothesis gains empirical support. More specifically, we find that the day of the week and whether it is a day after a holiday affects the daily volume of ED admissions. The effect of holidays is less evident as the coefficient is only significant in the subgroups *Admitted* and *Walking*. We get no support for the health shock hypothesis that individuals' health status affects the number of ED visits. However, we believe that this is primarily a consequence of our choice of variables since it is supported by our theory. It is also unlikely that health reductions do not impact individuals' decisions to seek emergency care.

There are three main implications of our findings. Firstly, we find both theoretical and empirical support that calendar variables should continue to be included in future prediction models as they capture the opportunity cost of time. Secondly, although not supported by our data, our theoretical findings imply that measures capturing health shocks should be included as well. Thirdly, our analysis of the subgroups indicates that the type of health reduction, in terms of both size and how quickly the reduction happens and evolves, can be worthwhile to consider as it may affect the importance of the relative price of an ED visit. This is based on our finding that the majority of the calendar variables are insignificant in the regression on patients arriving by ambulance.

The main contribution of this thesis is the theoretical framework. The aim is to provide a theoretical foundation for identifying and analyzing the determinants of daily ED attendance. While different sets of variables have been used in previous forecasting models, a justification of the choice of variables based on theory has not been a priority. Although we do not affirm that the determinants of ED attendance identified in this study are exhaustive, the theoretical framework provides a solid platform from which to build upon on when choosing variables to include in future prediction models. Perhaps equally important, it provides a framework for analyzing and interpreting the findings in both future and previous studies aiming to forecast the daily volume of ED patients. In a wider perspective, it can provide hospital staff, healthcare administrators and policy makers with a more in-depth understanding of what drives the demand for emergency care. This is essential for the development of strategies aimed at mitigating the risk of ED overcrowding.

9.1 Further research

As the impact of health reductions on the demand for emergency care is supported by theory but we lack empirical support for it, our main suggestion for future research is to test whether health status is a determinant of daily ED attendance. We also recommend future prediction models to include measures that manage to capture different health reductions. It could be valuable to first conduct a more qualitative study of ED patients' behavior and investigate the course of events leading up to an ED visit. Such a study could help researchers in identifying appropriate measures of health reductions. For implementation purposes, it would be valuable if variables that allow predictions further into the future were found. Also, when used in practice is could be valuable to predict the fluctuations in demand within a given day, why we recommend future studies to examining this.

The theoretical framework could benefit from further investigation into the assumptions made as these limit the extension to which our findings can be applicable. Future research could for example investigate how leisure and labor is valued against each other more in-depth and examine the relationship between different providers of health care to determine whether the determinants for the demand for medical care and emergency care differ. Finally, the theoretical framework could be tested on other settings such as other health care providers, patient groups and geographical regions to examine its external validity.

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Appendix A – Holidays definitions

TABLE A LIST OF DAYS CATEGORIZED AS A HOLIDAY

Holiday	Date
New Year's Day	January 1
Twelfth Night	January 5
Epiphany	January 6
Maundy Thursday	The Thursday before Easter Sunday
Good Friday	The Friday before Easter Sunday
Holy Saturday	The day before Easter Sunday
Easter Sunday	The first Sunday after the first full moon after the spring equinox (March 22 - April 25)
Easter Monday	The day after Easter Sunday
Walpurgis Night	April 30
International Workers' Day	May 1
Ascension Day	39 days after Easter Sunday
Whitsun Eve	49 days after Easter Sunday
Pentecost	50 days after Easter Sunday
National Day of Sweden	June 6
Midsummer's Eve	The Friday during the period 19–25 June
Midsummer's Day	The Saturday during the period 20–26 June
All Saints' Eve	The day before All Saint's Day
All Saints' Day	The Saturday during the period 31 October–6 November
Christmas Eve	December 24
Christmas Day	December 25
Second day of Christmas	December 26
New Year's Eve	December 31

Table A List of days categorized as a holiday. The table presents the days for which the Holiday dummy variable takes on the value one.

Appendix B – Multicollinearity

TABLE B TESTING FOR MULTICOLLINEARITY

VARIABLE	VIF	1/VIF
Thursday	3.65	0.273924
Friday	3.41	0.293640
Wednesday	3.02	0.331043
Saturday	2.79	0.358540
Tuesday	2.25	0.444121
Sunday	2.11	0.474594
Calls1	2.07	0.484186
Calls2	1.98	0.504054
Calls4	1.97	0.508033
Calls3	1.95	0.511720
Calls0	1.93	0.518534
Calls5	1.88	0.532661
Dayafterholiday	1.07	0.937711
Holiday	1.03	0.968499
Mean VIF	2.22	

Table B Testing for multicollinearity. The table contains the results from the test of multicollinearity using the VIF command in STATA.

The numbers in the table is compared to the rule of thumb that variables that have a VIF value higher that 10 or a tolerance value (1/VIF) lower than 0.1 may need further investigation and multicollinearity could be a concern. As the VIF value of our variables is far below 10, the highest being 3.65, we conclude that multicollinearity does not constitute a problem in our data.

Appendix C – Descriptive statistics

In this section some descriptive statistics on the number of patients visiting the emergency department at Uppsala University Hospital and the number of phone calls to the Health Care Guide in Uppsala during 2012 and 2013 will be presented.

Visits to the ED at Uppsala University Hospital

The number of ED visits ranged between 93 and 197 per day during 2012 and 2013. The mean number of ED visits during the time period was 139. The number of ED visits was, on average, highest on Mondays and lowest on Saturdays. The average weekly variation in the number of ED visits is shown in figure C1.

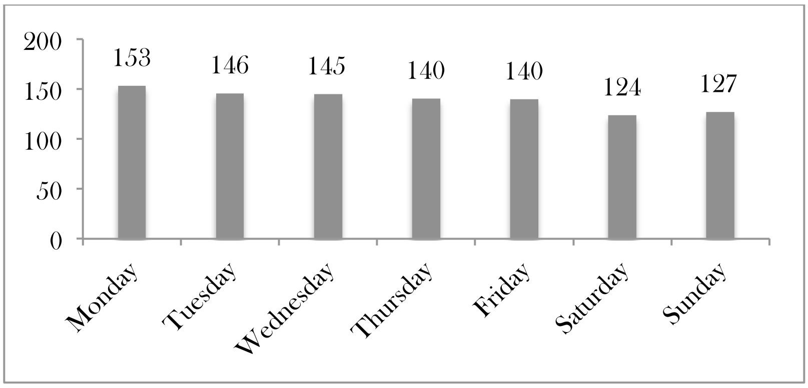

Figure C1 Weekly variations in ED visits. The figure illustrates the average number of patients with a recorded age over 18 years arriving to the ED at Uppsala University Hospital per day of the week during 2012 and 2013.

The number of ED visits was, on average, highest in May and lowest in February. The average monthly variation in the number of ED visits can be seen in figure C2.

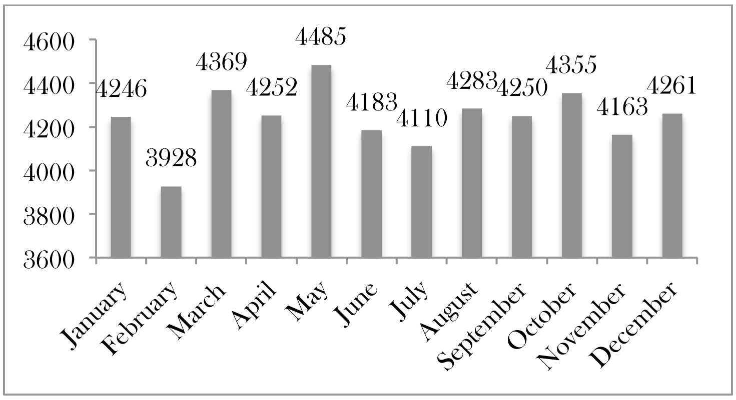

Figure C2 Monthly variations in ED visits. The figure illustrates the average number of patients with a recorded age over 18 years arriving to the ED at Uppsala University Hospital per month during 2012 and 2013.

The number of ED visits made by a person under the age of 18 years or by a person who's age have not been registered was on average 3 per day, representing a proportion of 2.3% of the total number of visits. They varied between 0 and 10 per day.

The most common way of arrival to the ED was walking followed by arriving by ambulance. The proportions of patients walking in to the ED and arriving by ambulance can be seen in figure C3.

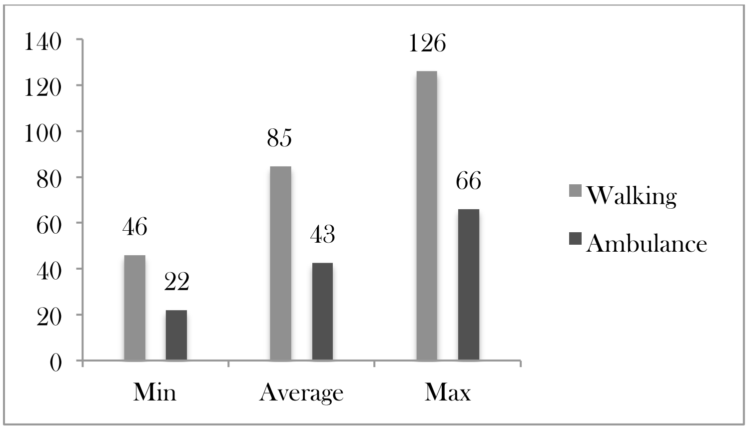

Figure C3 Number of patients arriving per day in the category Walking and Ambulance. The figure illustrates the minimum, average and maximum number of patients arriving in the two patients groups per day during 2012 and 2013.

The most common outcome after an ED visit was being sent home followed by being admitted to the hospital. The proportions of patients being sent home and patients being admitted to the hospital can be seen in figure C4.

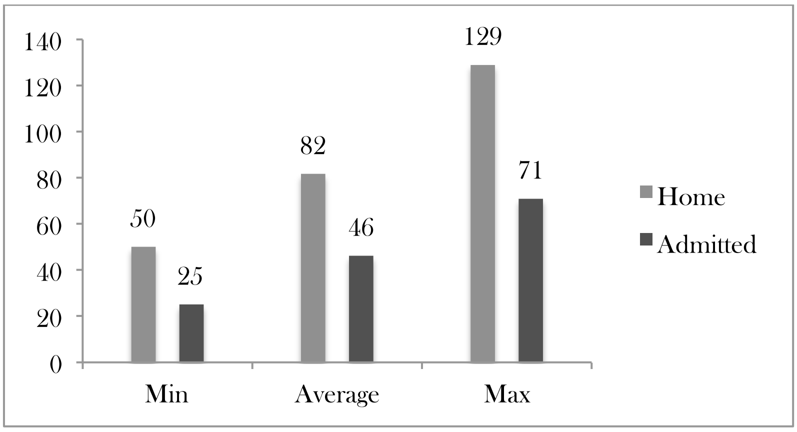

Figure C4 Number of patients arriving per day in the category Home and Admitted. The figure illustrates the minimum, average and maximum number of patients arriving in the two patients groups per day during 2012 and 2013.

Descriptive statistics of phone calls

The number of phone calls ranged between 99 and 310 calls per day in 2012 and 2013. The average number of phone calls during the time period was 198. The number of phone calls was, on average, highest on Sundays and lowest on Thursdays. The average weekly variation in the number of phone calls is shown in figure C5.

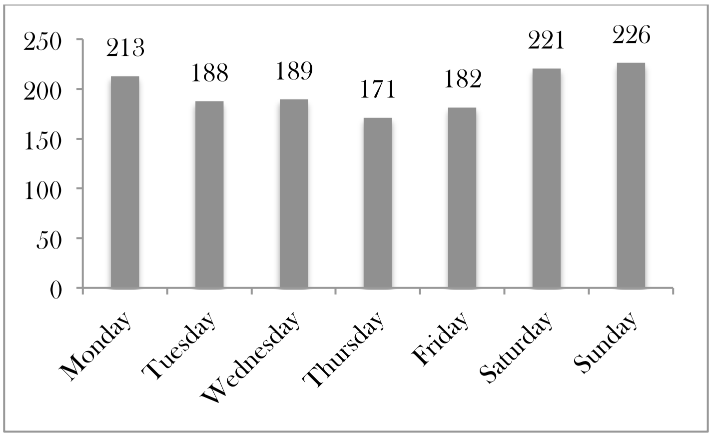

Figure C5 Weekly variations in phone calls to the Health Care Guide in Uppsala. The figure illustrates the average number of phone calls per day, concerning a person over the age of 18 years that have led to a medical chart during 2012 and 2013.

The number of phone calls was, on average, highest in January and lowest in November. The average monthly can be seen in figure C6.

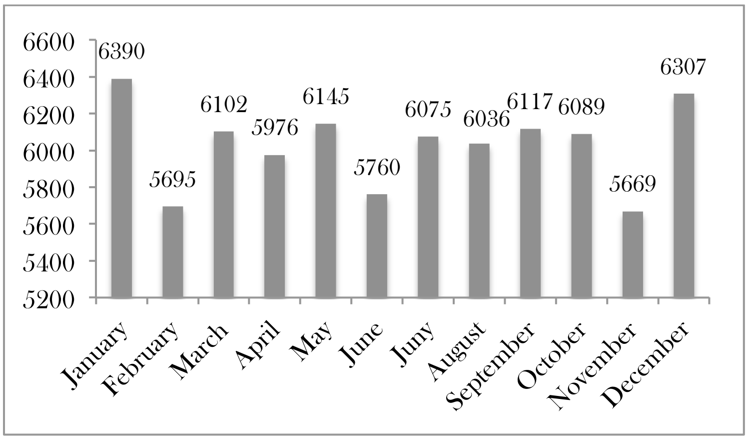

Figure C6 Monthly variations in phone calls to the Health Care Guide in Uppsala. The figure illustrates the average number of phone calls per month, concerning a person over the age of 18 years that have led to a medical chart during 2012 and 2013.

Our data also show that the number of phone calls in 2012 and 2013 that got the recommendation of going to the ED at Uppsala University Hospital varied between 1.82% and 16,28% of total calls with an average of 8.31%.

Appendix D – Hypothesis testing

TABLE D MAIN REGRESSION WITH DIFFERENT DAYS OF THE WEEK EXCLUDED

VARIABLES	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Calls0	0.0511**	0.0511**	0.0511**	0.0511**	0.0511**	0.0511**
	(0.0260)	(0.0260)	(0.0260)	(0.0260)	(0.0260)	(0.0260)
Calls1	0.00856	0.00856	0.00856	0.00856	0.00856	0.00856
	(0.0252)	(0.0252)	(0.0252)	(0.0252)	(0.0252)	(0.0252)
Calls2	0.00347	0.00347	0.00347	0.00347	0.00347	0.00347
	(0.0246)	(0.0246)	(0.0246)	(0.0246)	(0.0246)	(0.0246)
Calls3	0.0285	0.0285	0.0285	0.0285	0.0285	0.0285
	(0.0227)	(0.0227)	(0.0227)	(0.0227)	(0.0227)	(0.0227)
Calls4	-0.00963	-0.00963	-0.00963	-0.00963	-0.00963	-0.00963
	(0.0219)	(0.0219)	(0.0219)	(0.0219)	(0.0219)	(0.0219)
Calls5	-0.00584	-0.00584	-0.00584	-0.00584	-0.00584	-0.00584
	(0.0226)	(0.0226)	(0.0226)	(0.0226)	(0.0226)	(0.0226)
Holiday	-5.411	-5.411	-5.411	-5.411	-5.411	-5.411
	(3.476)	(3.476)	(3.476)	(3.476)	(3.476)	(3.476)
Dayafterholiday	13.56***	13.56***	13.56***	13.56***	13.56***	13.56***
	(3.016)	(3.016)	(3.016)	(3.016)	(3.016)	(3.016)
Tuesday	-	0.341	3.560	3.920	21.71***	19.26***
	-	(2.215)	(2.455)	(2.793)	(2.585)	(2.391)
Wednesday	-0.341	-	3.219	3.579	21.37***	18.92***
	(2.215)	-	(2.014)	(2.344)	(2.499)	(2.496)
Thursday	-3.560	-3.219	-	0.360	18.15***	15.70***
	(2.455)	(2.014)	-	(2.097)	(2.381)	(2.579)
Friday	-3.920	-3.579	-0.360	-	17.79***	15.34***
	(2.793)	(2.344)	(2.097)	-	(2.199)	(2.608)
Saturday	-21.71***	-21.37***	-18.15***	-17.79***	-	-2.446
	(2.585)	(2.499)	(2.381)	(2.199)	-	(2.039)
Sunday	-19.26***	-18.92***	-15.70***	-15.34***	2.446	-
	(2.391)	(2.496)	(2.579)	(2.608)	(2.039)	-
Monday	7.034***	7.375***	10.59***	10.95***	28.74***	26.29***
	(2.332)	(2.545)	(2.787)	(2.861)	(2.462)	(2.166)
Constant	130.1***	129.7***	126.5***	126.1***	108.3***	110.8***
	(7.049)	(6.941)	(6.938)	(6.826)	(6.914)	(6.931)
Observations	726	726	726	726	726	726
R-squared	0.358	0.358	0.358	0.358	0.358	0.358
Adj. R-squared	0.345	0.345	0.345	0.345	0.345	0.345

Table D Main regression with different days of the week excluded. The table contains the results of regressing the number of patients arriving at the ED per day on all the variables but one of the days of the week. Robust standard errors in parentheses and *** p<0.01, ** p<0.05, * p<0.1