HARVARD T.H. CHAN SCHOOL OF PUBLIC HEALTH

MASTERS THESIS

# Modeling the Obstetrics Ward at Tikur Anbessa Specialized Hospital, Ethiopia

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*in the*

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# Declaration of Authorship

I, Ben BIGELOW, declare that this thesis titled "Modeling the Obstetrics Ward at Tikur Anbessa Specialized Hospital, Ethiopia" and the work presented in it are my own. I confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this University.
- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where I have consulted the published work of others, this is always clearly attributed.
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
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# *Abstract*

Department of Global Health and Population

Master of Science

**Modeling the Obstetrics Ward at Tikur Anbessa Specialized Hospital, Ethiopia**

by Ben BIGELOW

The application of operations management techniques in the Ethiopian health system has been understudied. Additionally, although previous research has outlined limitations of paper-based records, few researchers have examined their potential utility for improving hospital operations. In this thesis, we used data collected from paper registries in an Ethiopian obstetrics ward to develop models of the ward's operations. With logistic regression models, we first attempted to identify predictors of lengthy stays and readmissions among women giving birth. Due to missing and incomplete data, few predictors were deemed significant. Time series methods for demand forecasting were applied to the data and evaluated with several error metrics. The forecasts had some limitations but were improvements over baseline methods. We conclude with recommendations on how the obstetrics ward could incorporate our models into their operations.

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# Chapter 1

# Introduction

## 1.1 Ethiopia

With a population of approximately 100 million, Ethiopia is one of the largest countries in Africa.[1] Over 3 million people live in the sprawling capital of Addis Ababa.[2] The country is divided into nine regions and two chartered cities, which are subdivided into zones.[3] (Table 1.1) Zones contain *woredas* (districts) and *woredas* contain *kebeles* (neighborhoods).

TABLE 1.1: Regions and cities of Ethiopia

| Regions | Chartered Cities |
|---|---|
| Afar | Addis Ababa |
| Amhara | Dire Dawa |
| Benishangul-Gumuz | |
| Gambela | |
| Harari | |
| Oromia | |
| Somali | |
| SNNPR | |
| Tigray | |

*Note.* SNNPR = Southern Nations, Nationalities, and Peoples' Region

Among countries in sub-Saharan Africa, Ethiopia is quite poor. In 2015, the World Bank estimated its per capita gross domestic product (GDP) to be $620, compared to $1,600 for the region.[4, 5] Of this, about 5% - or $27 per person - goes towards healthcare.[1, 6, 7] The government, however, has committed to increasing its spending on healthcare in order to address the country's disease burden.[1, 6] Ethiopia suffers from a mixture of communicable and non-communicable diseases. Although HIV/AIDS, tuberculosis, and respiratory infections cause 25% of deaths, complications from childbirth and nutritional deficiencies account for nearly 15%.[8]

For mothers in Ethiopia, childbirth is dangerous. The World Health Organization (WHO) estimated that the country's maternal mortality ratio was 353 per 100,000 live births in 2015.[9] That year, 11,000 women died giving birth.[9] Despite medical advances, the maternal mortality ratio hasn't changed much, though the causes of death have shifted.[10, 11, 12] Before 2000, nearly a third of maternal deaths were abortion-related; now, obstructed labor and hypertensive disorders cause 36% and 19% of deaths, respectively.[10]

The Ethiopian government recognizes the risks women face when giving birth. With its Health Sector Transformation Plan (HSTP), the Ministry of Health aims to cut the maternal mortality ratio in half by 2020.[13, 14] The previous five-year plan, the Health Sector Development Plan IV for 2011-2015 (HSDP IV), also prioritized maternal health.[13, 14] Both documents emphasize the role of information technology and management in healthcare reform. Nevertheless, current information systems have proven inadequate for generating and sharing data throughout the health system.[13]

The Ethiopian health system consists of three tiers. At the first level are health posts in *kebeles*, staffed by two female health extension workers; health centers, where doctors and health workers provide a broader range of curative services; and primary hospitals, with the capacity to perform caesarean sections, blood transfusions, and emergency surgeries.[6] At the second level are general hospitals, which train doctors and accept referrals from primary hospitals and health centers.[6] Finally, specialty hospitals provide tertiary care such as chemotherapy and medical imaging.[6] Tikur Anbessa Specialized Hospital (TASH), the teaching hospital affiliated with Addis Ababa University, is one such hospital.

## 1.2 Tikur Anbessa Specialized Hospital

One of the largest hospitals in Ethiopia and the only cancer referral center in the country, TASH treats hundreds of thousands of people in its outpatient departments every year.[15] It admits thousands more for inpatient services.[15] With over 600 beds, the hospital employs hundreds of doctors and nurses, many of whom trained at the Addis Ababa University College of Health Sciences.[15, 16, 17]

In the obstetrics and gynecology ward, it isn't unusual for six patients to share a room. The doctors and nurses help young women give birth; they treat old women with cancer. Most patients come from the *woredas* of Addis Ababa, but some arrive from rural towns and villages hundreds of miles away.

The ward operates under constraints common for health systems in developing countries. A dearth of qualified surgeons leads to long waiting lists for surgery. And once admitted, many patients have lengthy pre-operative stays. Operating rooms, like surgeons, are in short supply. The lack of physical and human resources can severely obstruct programs meant to improve maternal health.[18]

Inadequate information systems pose another challenge for the ward. Its current system consists primarily of paper-based records kept by the nurses and doctors. Paper records create several problems, including the difficulty of tracking errors and delays in retrieving information.[19] Kebede et al. discussed other problems that arise from the limited information technology in Ethiopian hospitals.[20] Despite these obstacles, the ward's management team is interested in using existing data sources to improve the efficiency of its operations.

## 1.3 Research motivation

Operations research, management science, and operations management share a similar objective: to design, understand, and improve processes and systems within an organization through the application of mathematical techniques.[21] Operations research and management methods have been adopted by health systems in high-income countries, but the extent to which they are used in low- and middle-income countries is unclear. Smith provides a comprehensive bibliography of operations research in both West and sub-Saharan Africa.[22, 23] In West Africa, 33 out of 279 studies related to health.[22] In sub-Saharan Africa, the number was 60 out of 300.[23] Smith identified 24 studies in Ethiopia using operations research, but only one related to health.[23]

In Smith's bibliography, he hypothesizes about the lack of operations research in Africa. The scarcity may be an illusion due to naming conventions: researchers and practitioners simply don't refer to operations research as operations research. Instead, they refer to specific modeling techniques, like linear programming or optimization.[23] For Ethiopia, this seems plausible. At least three theses by students at Addis Ababa University could be considered operations research. One assessed a quality management system in TASH's laboratory.[24] Another used data mining to study diarrheal diseases among children; the author tested the effectiveness of models for predicting diarrheal types and treatments.[25] The third examined demand management of emergency and referral services in Addis Ababa with simulation models.[17]

An earlier review of operations research in developing countries cited other factors impeding its implementation and adoption, including politics and a shortage of reliable data.[26] Despite these obstacles, recent collaboration between Yale University and the Ethiopian Health Management Initiative (EHMI) has shown promise in promoting operations research. Since its inception in 2008, EHMI has worked with public hospitals to improve their processes and has trained 120 hospital administrators.[27] In several papers, the researchers demonstrated quality improvements at hospitals with CEOs trained by the initiative; the improvements encompassed operational areas such as patient flow, inventory management, and medical records management.[28, 29, 30]

Bradley et al. make the case that health system research has neglected the role effective management plays in high-performing health systems.[31] To change this, they assert that we must focus on strengthening research that supports the role of management in improving health systems, particularly in resource-constrained settings. Operations management - from patient flow to bed management to information systems - forms the foundation of successful health systems, and is the focus of this thesis.

## 1.4 Thesis overview

As its title suggests, this thesis aims to answer one question: how can managers at TASH use existing data sources to anticipate the need for health services and resources, both at the patient and ward level? To answer this question, we present two analyses examining problems of interest to the obstetrics ward's management team.

Lengthy stays and unnecessary readmissions strain the ward's already limited resources. In Chapter 3, we apply logistic regression models to determine predictors of extended stays and readmission in women giving birth.

Accurate forecasts of daily admissions help hospital administrators anticipate the demand for beds, staff, and other resources. In Chapter 4, we use time series models to predict daily and weekly patient volume. We then assess the validity of these predictions with several different error metrics.

We conclude in Chapter 5 with an overview of our findings, a discussion of limitations, and some thoughts for future work.

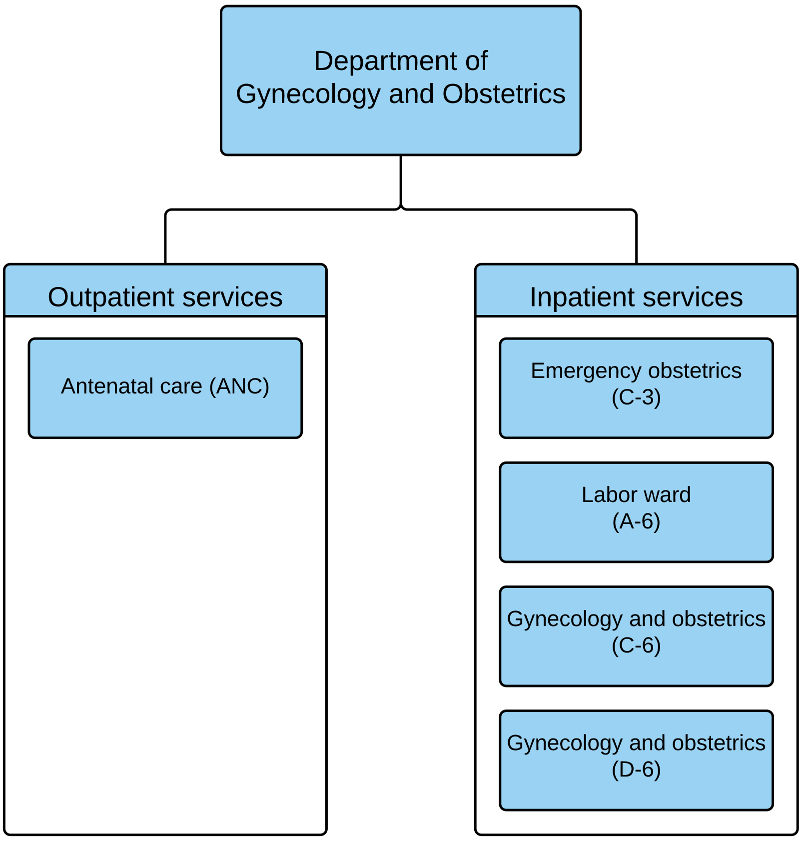
# Chapter 2

# Data Description

## 2.1 Statement on ethics

The institutional review boards for the Addis Ababa University School of Medicine and the Harvard-Longwood Medical Area approved this study (Protocol Number: IRB16-0993). All data collection and analysis complied with regulations established by both institutions.

FIGURE 2.1: Department organizational chart




## 2.2 Study setting and participants

We collected our data in the obstetrics and gynecology department at TASH. The department consists of one outpatient clinic and four inpatient wings:

C-6 and D-6, which contain general obstetrics and gynecology beds; A-6, the labor and delivery wing; and C-3, the emergency obstetrics wing. Most of the ward's workload involves labor and delivery. As the only cancer treatment center in Ethiopia, however, the ward regularly admits patients with cervical, ovarian, and other gynecological cancers.[15] Consequently, the ward reserves eight beds for oncology and chemotherapy patients. (Table 2.1)

TABLE 2.1: Distribution of beds between wings C-6 and D-6

| Wing | Bed type | Number of beds |
|---|---|---|
| C-6 | Obstetrics | 19 |
| | Gynecology | 7 |
| | Chemotherapy | 4 |
| | Sepsis | 3 |
| | Total | 33 |
| D-6 | Obstetrics | 14 |
| | Gynecology | 11 |
| | Oncology | 4 |
| | Total | 29 |

From August to September 2016, we collected data from the admission and discharge registries of wings C-6 and D-6. Nurses and residents maintain the registries, which track the information shown in Table 2.2. The two registries contained 3,005 entries for patients admitted between July 2015 and August 2016.

Table 2.2 shows the distribution of missing data. Although only 0.3% of entries are missing admission dates, nearly 10% of entries are missing the patient's medical records number (MRN) or discharge date. Without an MRN, it is difficult to tell whether an entry represents a unique admission or whether it "double-counts" another one.

TABLE 2.2: Missing data from the ward registries

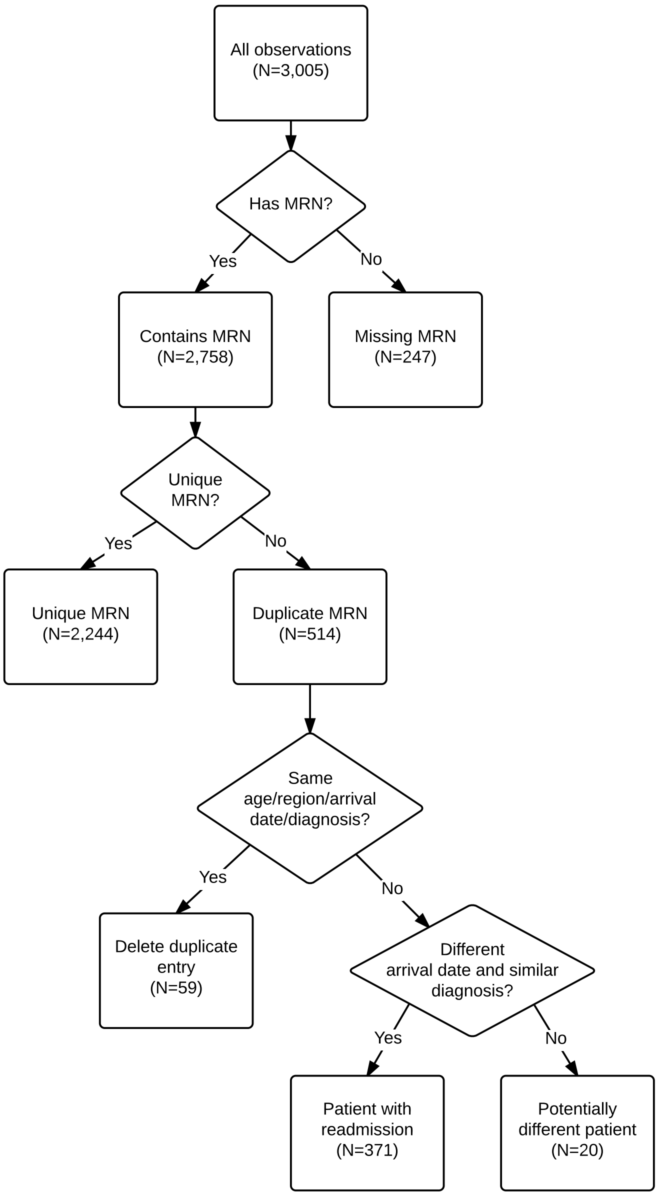
| | Observations missing (%) | |
|---|---|---|
| Variable | Before cleaning (N=3,005) | After cleaning (N=2,945) |
| Patient MRN | 247 (8.2) | 247 (8.4) |
| Age | 152 (5.1) | 141 (4.8) |
| City/region of residence | 80 (2.7) | 72 (2.4) |
| Admission date | 9 (0.3) | 8 (0.3) |
| Discharge date | 281 (9.4) | 244 (8.3) |
| Diagnosis and/or procedure performed | 46 (1.5) | 34 (1.2) |

*Note.* MRN = Medical records number

## 2.3 Data cleaning

Since the nurses and residents maintain the registries by hand, we first needed to clean the data. Between the two registries, there were 3,005 entries. Of these, 247 (8%) were missing patient MRNs. Of the entries containing an MRN, there were 514 (17%) instances where two or more entries had the same MRN.

FIGURE 2.2: Data cleaning algorithm




*Note.* MRN = Medical records number

According to the algorithm shown in Figure 2.2, we split the entries with duplicate MRNs into three groups. If two entries with the same MRN represented the same admission, we combined their information into a single entry. If the entries represented a patient's admission and subsequent readmission (e.g. for multiple rounds of chemotherapy), we kept the entries in the dataset and marked them with an indicator. Finally, if entries had the same MRN but differed markedly in other variables - for example, if one showed a patient's age as 20 and the other as 60 - we considered the entries to represent two distinct patients. After cleaning, the data had 2,945 entries. Table 2.2 shows the remaining extent of missing data.

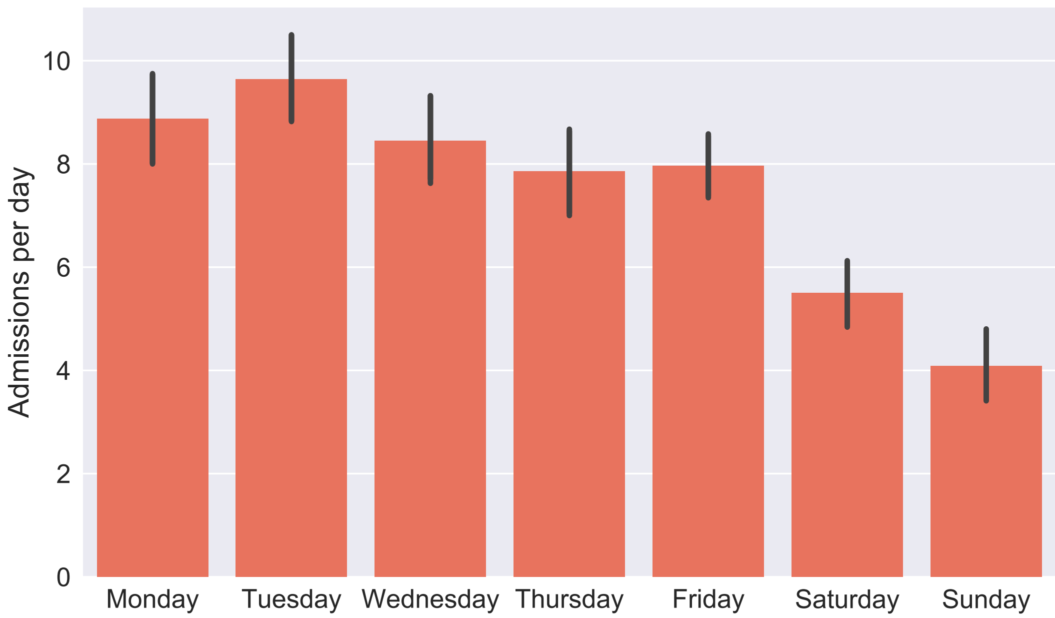
## 2.4 Variable derivation

Although the registries were sparse, we derived additional information from the variables themselves and from consultations with medical residents and faculty at TASH.

***Length of stay.*** We calculated the length of stay (LOS) by subtracting the admission date from the discharge date. For observations missing either date, the LOS was marked as missing.

***Weekend Admission.*** Hospital admission patterns tend to differ between weekends and weekdays; TASH conforms to this trend, as shown in Figure 2.3. Additionally, some evidence exists of a "weekend effect" in hospitals, where patients admitted during the weekend have worse outcomes than those admitted during the week. The magnitude of this effect in obstetrics is unclear, though one study found an association between weekend deliveries and the risk of perinatal mortality.[32, 33] To study this effect, we classified patients admitted on a Saturday or Sunday as weekend admissions. For observations without an admission date, this variable was marked as missing.

FIGURE 2.3: Average number of admissions by day of the week




*Note.* Black bars indicate the 95% confidence interval.

***Region.*** The registries record each patient's city or region of residence. (Table 2.2) Ethiopia has nine regions and two chartered cities, but the majority of patients (78%) came from Addis Ababa. Many fewer came from other regions in the country. Due to confidentiality considerations, therefore, we classified the region for each entry as "Addis Ababa" or "Outside Addis Ababa" with an indicator variable.

***Readmission.*** If two entries with the same MRN had admission dates within 30 days of each other, we classified the second entry as a readmission. Although we would prefer to use the difference between first discharge date and the subsequent admission date, data on a patient's discharge date was missing from nearly 10% of the data. The admission date, meanwhile, was almost never missing. (Table 2.2) For entries without an MRN, we marked readmission as missing.

***Discharge Diagnosis Category.*** Although the ward registries contained a descriptive diagnosis for patients, these diagnoses were not standardized. The majority of admissions were for two procedures: caesarean sections (often written as "C/S") and spontaneous vaginal deliveries ("SVD"). For other procedures, we worked with medical residents at TASH to categorize additional diagnoses and procedures. Our final list included: obstetrics, gynecology, oncology, chemotherapy, and "other". We designated entries without a clear diagnosis or with descriptions that did not fit well in the other categories as "other" (e.g. transfers, referrals).

***Pre-eclampsia.*** Hypertensive disorders cause a significant number of maternal deaths in Ethiopia; pre-eclampsia is one such disorder.[10] Observations with diagnoses of severe pre-eclampsia (SPE), moderate pre-eclampsia (MPE), and pre-eclampsia (PE) were marked with an indicator.

***Daily admissions.*** Using admission dates, we calculated the number of patients admitted on a given day and included this number as a variable.

***Multiple Births.*** Patients who gave birth to multiple children were typically identified in the registries. Their diagnoses included terms such as "twins" or "twin px" (where "px" is an abbreviation for "pregnancy"). We marked these entries with an indicator.

## 2.5 Data usage

The analyses in the following chapters use different combinations of the variables described above. For the length of stay and readmission models in Chapter 3, we included both the original and derived variables. But because identifying readmissions relies on MRNs - which are missing from 8% of the data - we chose to restrict our analysis to entries with valid MRNs.

In Chapter 4, identification issues are less important, since we're only interested in forecasting daily demand. For the forecasting models, we considered any data without an MRN to represent a unique admission to the ward. As shown previously, this is likely not entirely true, so the forecasting models could overestimate demand. However, since the data cleaning only identified 60 duplicate entries out of the 2,758 with a valid MRN, we believe the magnitude of upward bias will be negligible.

# Chapter 3

# Length of Stay and Readmission Among Women Giving Birth

## 3.1 Background

As the largest specialty hospital in Ethiopia, TASH admits patients who can't be treated in local or regional facilities. Although this speaks to the skill of the hospital's physicians, it creates operational difficulties. In the obstetrics ward, long waiting lists exist for procedures like cancer surgery. And once admitted, some patients remain in the ward for weeks. Consequently, the ward's management team is interested in understanding what factors contribute to lengthy stays and readmissions.

A patient's hospital stay represents a natural cost-benefit analysis. For women in developing countries, giving birth in a facility provides clear benefits. But for any given patient, it is difficult to determine when those benefits start to dwindle. In short, there is no "right" length of stay (LOS). A study of survey data across 92 low- and middle-income countries showed significant variation in postpartum LOS; the mean LOS ranged from less than 24 hours in some countries to more than 9 days in others.[34] The authors conclude that many women are discharged too soon after giving birth, and endorse the World Health Organization's (WHO) recommended LOS of at least one day after vaginal delivery and three days after a caesarean section.[34, 35] In Ethiopia, an analysis of caesarean deliveries found an average LOS of 5.9 days, although a quarter of patients were discharged in less than three days.[36]

But hospital stays, especially long ones, have risks. Hospital-acquired infections and other adverse events concern policymakers as well as hospital administrators in developing countries. When patients are readmitted for avoidable reasons, hospitals lose resources that could be better allocated. Patients can lose time, wages, or worse. In of 26 hospitals in 8 developing countries, Wilson et al. determined that 8% of patients experienced at least one adverse event; of these events, 30% resulted in death.[37] At TASH, Gebedou et al. found that 17% of obstetric and gynecological patients developed an infection.[38] Beside surgical site and urinary tract infections, vectors such as cockroaches also pose a threat to women in the hospital.[39, 38]

Long hospital stays expose patients to unnecessary risk, but shorter postpartum stays may not be any better. Liu et al. showed that a short LOS increased the risk of readmission among women giving birth in Canada.[40] Other research, however, found no significant harm from early discharge when adequate outpatient care was available.[41, 42, 43]

In addition to short stays, the delivery method may also affect patients' risk of readmission. Liu et al. found that women who had caesarean sections had a higher risk of readmission than those with spontaneous vaginal deliveries.[44] Research in Washington and Massachusetts reached similar conclusions.[45, 46]

Previous research at TASH examined outcomes among caesarean section patients; the focus, however, was on clinical measures such as complication rates, not operational measures like LOS or readmission rates.[47] To add to existing research, this analysis aims to determine whether the delivery method affects the risk of an extended stay among women giving birth in the obstetrics ward. Additionally, it examines whether the risk of readmission after childbirth varies by delivery method.

## 3.2 Methods

Data for this analysis came from admissions registries in the obstetrics ward. After cleaning the data as described in Chapter 2, the registries contained 2,945 entries for patients admitted between July 2015 and August 2016. We removed 247 entries which were missing patient MRNs. Of the remaining 2,698 entries, 1,828 (67.7%) were for admissions related to either a caesarean section or a vaginal delivery. The data had 5 entries for women over 50 related to childbirth. Given the improbability of childbirth at those ages, we considered these entries to be errors and removed them from our sample.

If a patient was admitted for childbirth, we included their other admissions during the study period. Consequently, we captured cases where a patient is admitted for reasons other than labor and then readmitted to give birth, in addition to instances when a patient gives birth and is readmitted for complications. Although 1,823 entries related specifically to childbirth, our final dataset had 1,886 entries. In total, 1,799 women were admitted at least once to the ward for childbirth. 1,529 women (85%) gave birth via caesarean section and 270 (15%) gave birth vaginally.

Table 3.1 shows the characteristics of our sample. The mean LOS among all women was 5.9 days, and 6.3 days among those who had caesarean sections. This is consistent with previous research on caesarean sections in Ethiopia.[36] Women delivering via either method had similar mean ages, 27.7 for caesarean section and 27.4 for vaginal deliveries. Approximately 12% of patients giving birth arrived from outside Addis Ababa, and 20% were admitted during a weekend. Half were discharged in four days or fewer, but a quarter of women remained in the ward for longer than a week. (Figure 3.1)

We examined two outcome variables: extended LOS for admissions related to childbirth and readmission after childbirth. Although policymakers

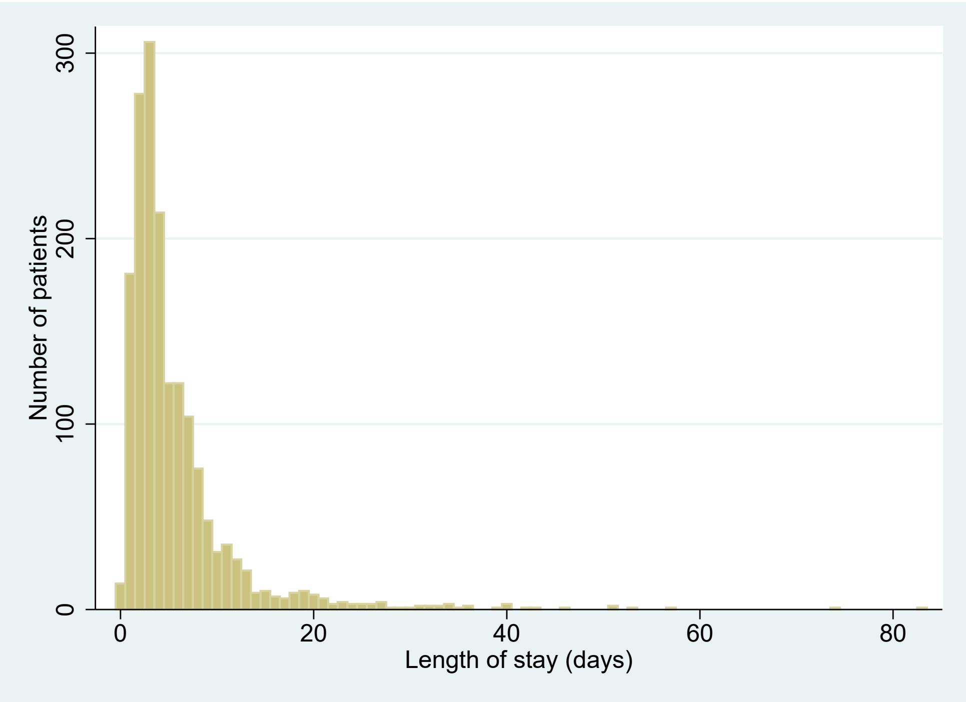
TABLE 3.1: Descriptive statistics for patients, by birth method

| | Caesarean Section (N=1,529) | | Vaginal Delivery (N=270) | | |
|---|---|---|---|---|---|
| | Mean | SD | Mean | SD | $t$-test |
| Age | 27.7 | 4.8 | 27.3 | 5.0 | -1.07 |
| Length of stay | 6.3 | 10.4 | 4.0 | 4.8 | -3.38*** |
| Daily admissions | 8.8 | 3.1 | 9.4 | 3.7 | 2.65** |
| | Percentage | | Percentage | | |
| Outside Addis Ababa | 11.2 | | 16.0 | | 2.21* |
| Multiple births | 1.0 | | 0.4 | | -0.92 |
| Preeclampsia | 0.6 | | 1.9 | | 2.15* |
| Weekend admission | 20.0 | | 22.6 | | 0.97 |
| Extended LOS | 10.7 | | 7.0 | | -2.13* |
| Readmission after childbirth | 1.7 | | 1.1 | | -0.90 |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

*Note.* SD = standard deviation

FIGURE 3.1: Length of stay distribution among sample population




*Note.* For visual clarity, we omitted one patient with a length of stay greater than 100 days.

may worry about postpartum stays that are too short, managers may be interested in stays that are too long. By narrowing the range of LOS, administrators can better manage variability in demand. For this reason, we defined an extended LOS as any LOS more than one standard deviation above our sample's mean LOS. Using this definition, approximately 10% of patients had an extended LOS. (Table 3.1) We classified admissions as readmissions after childbirth if they occurred within 30 days of a previous admission for either a caesarean section or vaginal delivery. Of the 1,799 patients, 30 (2%) were readmitted within 30 days after giving birth.

We used the independent variables described in Chapter 2, such as daily admissions and age, for each patient's first admission related to childbirth. The main variable of interest was an indicator for delivery method. Using logistic regression models, we estimated the effects of the independent variables on the risk of an extended LOS and readmission. We performed all analysis with Stata MP Version 14.2.[48] Results were considered significant at the $p$=0.05 level.

## 3.3 Results

### 3.3.1 Extended LOS

TABLE 3.2: Logistic regression results, extended LOS ($N = 1,665$)

| | Odds Ratio | 95% CI |
|---|---|---|
| Age | 1.06** | (1.02, 1.10) |
| Daily admissions | 1.01 | (0.95, 1.07) |
| Outside Addis Ababa | 1.14 | (0.69, 1.89) |
| Multiple births | 5.14* | (1.44, 18.39) |
| Pre-eclampsia | 4.47* | (1.42, 14.03) |
| Weekend admission | 1.08 | (0.68, 1.70) |
| Caesarean section | 1.52 | (0.90, 2.58) |
| Readmission after childbirth | 1.19 | (0.35, 3.98) |

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

*Note.* CI = confidence interval, $P(x > \chi^2)$=0.001

Table 3.2 shows our estimated coefficients for the first logistic regression model. Of the independent variables included in the model, only age, multiple births, and pre-eclampsia have a significant association with the risk of an extended LOS. Older patients seem to remain in the ward longer than younger ones; a one year increase in age is associated with a 6% increase in the risk of an extended LOS (95% CI: 1.02-1.10). Patients giving birth to more than one child are over 5 times more likely to have an extended LOS compared to patients giving birth to one child (95% CI: 1.44-18.39). Similarly, patients with pre-eclampsia have an odds ratio of 4.47 for an extended LOS (95% CI: 1.42-14.03). The model shows no significant difference in risk among patients based on daily volume or region of residence. Delivery method has no significant association with an extended LOS. With $P(x > \chi^2) = 0.001$, the model provides a significantly better fit to the data than an empty model.

### 3.3.2 Readmission after childbirth

Table 3.3 presents the regression results for readmission after childbirth. Due to multicollinearity, the indicators for multiple births, pre-eclampsia, and region were dropped from the model. Among the remaining covariates, none were significantly associated with the risk of readmission. Though positively associated with the risk of extended LOS, age did not affect the risk of readmission. We estimated that women giving birth by caesarean section have an odds ratio of 2.22 for risk of readmission, although this was not statistically significant (95% CI: 0.46-8.53). Finally, extended stays after childbirth showed no association with the risk of readmission. The likelihood ratio test of this model indicates that it provides no better fit to the data than an empty model. This is likely a result of insufficient statistical power, as only 30 women were readmitted after giving birth.

TABLE 3.3: Logistic regression results, readmission after childbirth ($N = 1,449$)

| | Odds Ratio | 95% CI |
|---|---|---|
| Age | 1.04 | (0.98, 1.10) |
| Daily admissions | 0.99 | (0.86, 1.14) |
| Outside Addis Ababa | 1.00 | * |
| Multiple births | 1.00 | * |
| Pre-eclampsia | 1.00 | * |
| Weekend admission | 1.01 | (0.39, 2.66) |
| Caesarean section | 2.22 | (0.52, 9.44) |
| Extended LOS | 1.17 | (0.35, 3.94) |

*Note.* CI = confidence interval, $P(x > \chi^2)$ = 0.610

## 3.4 Discussion

In this chapter, we used logistic regression models to analyze the risk of extended LOS and readmission among women giving birth at TASH. Caesarean sections were associated with an odds ratio of 1.52 (95% CI: 0.90-2.58) for the risk of extended LOS compared to vaginal deliveries after controlling for other factors. There is little evidence that daily patient volume has an effect on LOS. Similarly, women admitted during the weekend faced no higher risk of extended LOS than those admitted during the week.

Modeling LOS as a dichotomous variable is justifiable from an operational standpoint, but we nevertheless lose some information. Treating LOS as a continuous variable, therefore, could produce insights not captured by logistic regression models. And though our models cannot be interpreted causally, our results demonstrate the need for better data to understand factors driving LOS in the ward.

Managing the variation in LOS should be a priority for the ward's staff. When patients remain in the hospital for long periods of time, bed utilization increases and delays become more common. Although an extended stay may be necessary for certain patients, it suggests the presence of inefficiencies in hospital operations.

Due to insufficient power and multicollinearity among the variables, we could not establish any association between the included covariates and the risk of readmission. Our selection criteria may partly explain our model's limitations. Since we omitted entries without MRNs, we likely underestimated the true number of readmissions to the hospital. The ward's seemingly low readmission rate could also be an artifact of the data source. Inpatient registries don't capture women who give birth vaginally in the outpatient department. If someone was readmitted after an outpatient delivery, they would only show up once in the registry. Similarly, the readmission rates in the ward and the association of readmission with extended LOS suggest that more attention should be paid to the causes of readmission among patients giving birth.

Missing data, inconsistent data entry, and other problems with the ward registries limit what can be inferred about patients who are readmitted. Though individual faculty and residents may know why a patient is readmitted, better health information systems are necessary so that clean, reliable data can easily move among hospital staff and support their management practices.

# Chapter 4

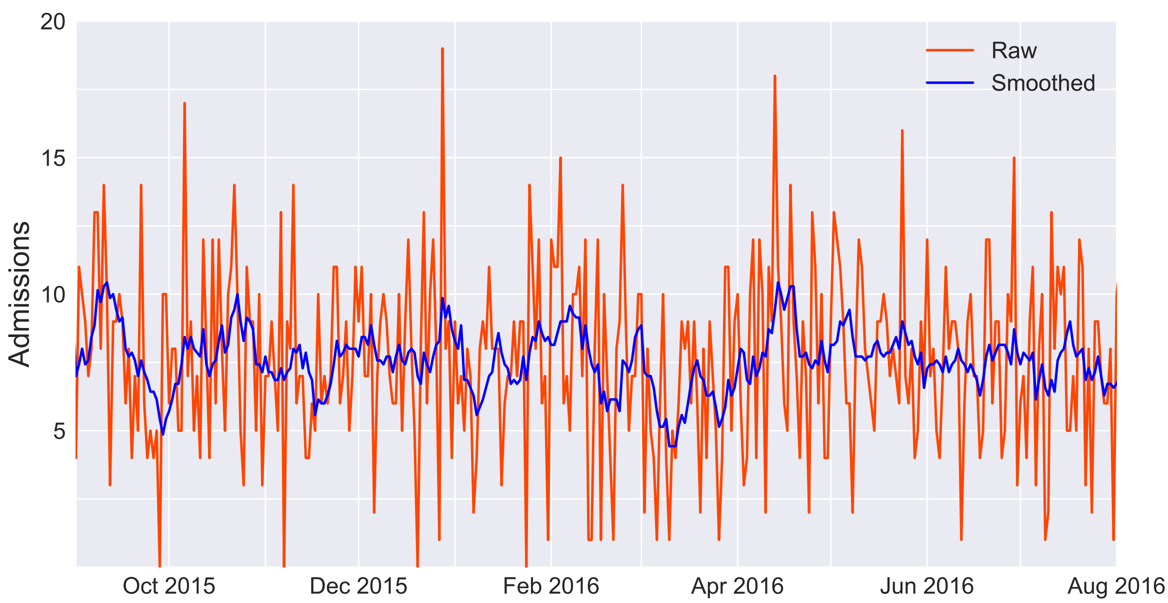
# Forecasting Patient Demand

## 4.1 Background

Demand forecasting is not a new problem in healthcare. For facilities trying to match supply to demand, forecasting represents a crucial part of the broader management infrastructure.[49] Accurate predictions of future demand help facilities operate efficiently. Poor forecasts strain staff and resources, leading to delays, errors, and suboptimal treatment.

In their paper, Soyiri and Reidpath survey forecasting methods and their application in healthcare.[50] They distinguish between objective statistical methods and subjective judgmental methods of forecasting.[50] Although statistical methods remove innate human biases from the forecasting process, expert input can often improve forecast accuracy. Other papers recommend that forecasts include subjective factors such as market demand, which statistical methods may ignore.[51]

FIGURE 4.1: Daily admissions to the obstetrics ward, raw and smoothed (7-day moving average)

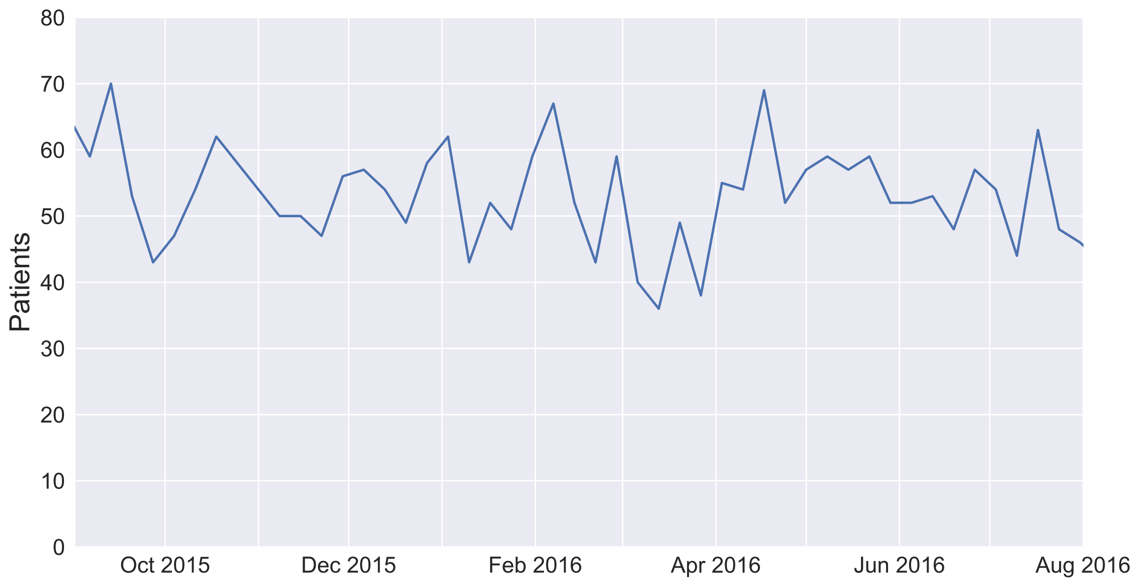


For effective management of a healthcare organization, forecasting should constitute an important part of the management control process. Ozcan outlines five steps that an organization should take for successful forecasting.[52] First, the organization should identify the goal of a forecast. Second, it should establish an appropriate time horizon. An obstetrics department, for example, might have a time horizon on the order of days to weeks. But the hospital as a whole might want to forecast demand years in advance to mold its strategy and guide its investments. Third, the organization should select an appropriate forecasting method, which depends on the problem being investigated and the resources available. Fourth, the organization must conduct the forecast. And finally, the organization should monitor the accuracy of the forecast. In addition to understanding the strengths and weaknesses of forecasting methods, managers in particular should be prepared to adapt their methods to changing circumstances.[53]

Hospital managers can choose from a variety of different forecasting models. These range from traditional moving averages and regressions to more sophisticated methods like neural networks.[54, 55] Despite the variety, Petropoulos et al. point out a germane paradox of choice.[56] With so many methods to choose from, modelers have difficulty answering a fundamental question: "what is the best method for *my* data?"[56]

In the following sections, we try to answer this question for the obstetrics ward at TASH. Daily patient volume is noisy. On some days, the ward admits few or no patients. On others, fifteen or more admissions swamp the 62-bed department. (Figure 4.1) Weekly patient volume oscillates with similar volatility. (Figure 4.2) Nevertheless, on average, admissions to the ward follow a predictable pattern by the day of the week. (Figure 4.3) By developing forecasting models for patient volume, we hope to demonstrate their value as management tools. We also incorporate several error metrics in order to understand the strengths and weaknesses of our forecasts.

FIGURE 4.2: Weekly admissions to the obstetrics ward



## 4.2 Methods

Using the data we collected at TASH, we aggregated patient arrivals at both the daily and weekly level. To forecast demand, we applied several basic time series models to the data. For model validation, we split our data into two parts, a training set and a testing set. The training set for daily forecasts consisted of admissions in August 2015. Admissions between September 2015 to August 2016 formed the testing set. At the weekly level, the training set spanned from August 2015 to January 2016, a period of sixth months. The subsequent six month period, from February to August 2016, formed the testing set.

Our analysis employs two models - a historical mean and a naïve model - as baselines and several others as comparisons. Most operations research and healthcare management textbooks cover these models in greater detail.[52, 57] We use $\hat{Y}$ to refer to projected values and $Y$ to refer to actual values of daily and weekly volume. We performed our analysis in the Python programming language.[58]

### *Historical mean*

$$\hat{Y}_{t+1} = \frac{\sum_{i=1}^{T} Y_i}{T} \tag{4.1}$$

The historical mean is the average of all admissions over some number of time periods, $T$. For this analysis, we used the testing set for both daily and weekly admissions to create the historical mean. This was the first baseline model against which others were evaluated.

### *Naïve forecast*

$$\hat{Y}_{t+1} = Y_t \tag{4.2}$$

$$\hat{Y}_{t+7} = Y_t \tag{4.3}$$

One of the simplest forecasting techniques is the naïve forecast, also called the one-step method. It predicts the value $\hat{Y}$ at time $t+1$ to be the actual value of $Y$ in the previous period $t$. For daily forecasts, we included a naïve forecast with a period of one day as well as one week. The latter model incorporates the cyclical pattern of weekly admissions, albeit in a crude way. (Figure 4.3) According to Ozcan, although naïve models have limited practical utility, their benefits include their low cost and ease of implementation.[52] For these reasons, we chose the naïve forecasting method as a second baseline model.

### *Moving average*

$$\hat{Y}_{t+1} = \frac{\sum_{i=t-N}^{t} Y_i}{N} \tag{4.4}$$

A naïve forecast only incorporates data from one previous period. A moving average (MA), however, considers data from an arbitrary number $N$ of previous periods. The predicted value $\hat{Y}$ in the period $t+1$ is the average of actual values during the previous $N$ periods, where $N$ is called the window size. For the weekly forecasts, we tested window sizes of 2, 3, and 4 weeks. For daily forecasts, we tested window sizes of 3, 5, and 7 days.

### *Exponentially-weighted moving average*

$$\hat{Y}_{t+1} = \alpha Y_t + (1-\alpha)\hat{Y}_t \tag{4.5}$$
$$\hat{Y}_0 = Y_0$$
$$\alpha = \frac{2}{1+N}$$

In addition to incorporating data from previous periods, the exponentially-weighted moving average (EWMA) discounts past values of $Y$ and $\hat{Y}$ according to a scaling factor $\alpha$. The scaling factor $\alpha$ can be written as a function of a window with $N$ periods. Unlike MA models, which weight all values of $Y$ in the window equally, EWMA models can apply more weight to the most recent values of $Y$. Data from last week, for example, is more relevant than data from three weeks ago. For daily and weekly forecasts, we tested the same windows as with the MA models.

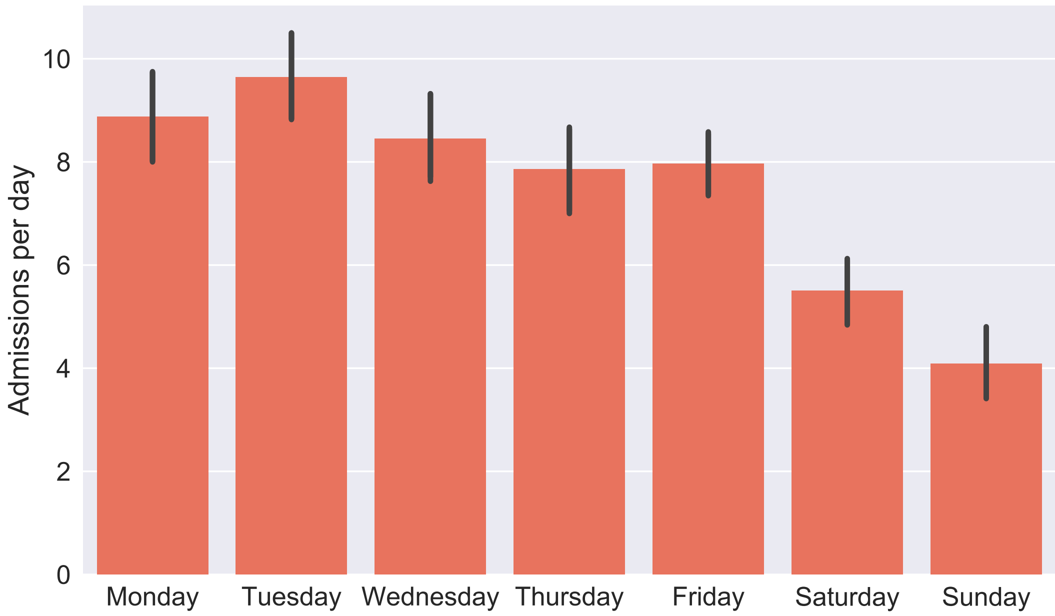
### *Daily and weekday/weekend average*

$$\hat{Y}_{t+1} = \bar{Y}_D \tag{4.6}$$
$$\hat{Y}_{t+1} = \bar{Y}_W \tag{4.7}$$

Daily admissions over the course of a week tend to follow a clear pattern, as shown in Figure 4.3. More patients are admitted during weekdays than weekends. To take advantage of this pattern, we added two more daily forecasting models to those described above. The first model calculates mean admissions $\bar{Y}$ by day $D$ of the week in the training set; it then applies those means to the testing set. The projected admissions on a Wednesday, for example, is just the average number of admissions on Wednesdays in the training set. The second model is similar, but uses the mean admissions $\bar{Y}_W$ during weekdays and weekends, respectively. We considered Monday through Friday to be weekdays and Saturday and Sunday to be weekends.

To evaluate forecast accuracy, we used three different error metrics: mean absolute deviation (MAD), mean forecast error (MFE), and mean absolute scaled error (MASE). (Equations 4.8, 4.9, and 4.10, respectively.) The MAD is simply the average absolute difference between predicted and actual values. Since it has the same units as the outcome variable, the MAD is easy to interpret. And unlike the root mean-square error, it doesn't disproportionately weight outliers.[59, 60] Its limitations, however, include scale-dependence; we can't use the MAD to compare forecasts of different magnitudes, e.g. daily and weekly volume.[59]

FIGURE 4.3: Average admissions, by day of the week




*Note.* Black bars indicate a 95% confidence interval.

$$MAD = \frac{1}{T}\sum_{t=1}^{T}|\hat{Y}_t - Y_t| \tag{4.8}$$

The MFE is the average difference between predicted and actual values. (Equation 4.9) Though it suffers from similar limitations as the MAD, the MFE incorporates the direction of our error. Therefore, the MFE also tells us whether our forecasts tend to over- or underestimate the actual values.[52]

$$MFE = \frac{1}{T}\sum_{t=1}^{T}(\hat{Y}_t - Y_t) \tag{4.9}$$

To compensate for the weaknesses of the MAD and MFE, we included the MASE, which penalizes errors equally regardless of size (i.e. it is scale invariant) or direction (i.e. it is symmetric).[59, 60] The MASE also accommodates data with zero values, unlike many metrics involving relative error.[59] This is important for forecasting daily demand, which can be zero. As shown in Equation 4.10, the MASE compares the MAD of any given forecasting method with the MAD of a naïve one-step model. An MASE value greater than one indicates that the forecasting method, on average, performs worse than a naïve one-step model. A value less than one indicates that the forecasting method performs better than a naïve model.

$$MASE = \frac{\frac{1}{T}\sum_{t=1}^{T}|\hat{Y}_t - Y_t|}{\frac{1}{T-1}\sum_{t=2}^{T}|Y_t - Y_{t-1}|} \tag{4.10}$$

## 4.3 Results

Table 4.1 shows the error metrics for our weekly forecasting models. With an MASE of 0.76, the constant historical mean performs better than other forecasting methods. The next best model for weekly forecasts, the 3-week moving-average, has an MASE of 0.82. All of the models, however, have MASE values below 1, indicating that they perform better than the naïve one-step model.

Among the models, the historical mean also minimizes the MAD. On average, its predictions of weekly volume are off by 6.5 patients; by comparison, the ward admitted an average of 54 patients a week in the testing set. Its MFE, however, is approximately three times larger than those for other models. The negative MFE values indicate that all of our forecasting methods tend to underestimate actual demand. (Table 4.1)

TABLE 4.1: Error metrics for weekly forecasting models

| | | | **MA** | | | **EWMA** | | |
|---|---|---|---|---|---|---|---|---|
| | *Mean* | *Naïve* | *2 weeks* | *3 weeks* | *4 weeks* | *2 weeks* | *3 weeks* | *4 weeks* |
| MAD | 6.51 | 8.52 | 7.89 | 6.96 | 7.33 | 7.73 | 7.43 | 7.28 |
| MFE | -1.89 | -0.59 | -0.63 | -0.69 | -0.54 | -0.61 | -0.62 | -0.62 |
| MASE | 0.76 | 1.00 | 0.92 | 0.82 | 0.86 | 0.90 | 0.87 | 0.85 |

*Note.* MAD = mean absolute deviation, MFE = mean forecast error, MASE = mean absolute scaled error, MA = moving average, EWMA = exponentially-weighted moving average

The errors for daily forecasts tell much the same story. Table 4.2 and Table 4.3 present the results from our models of daily volume. The simple mean performed better than the MA and EWMA methods; its MASE was 0.73, whereas the MASE was 0.76 and 0.79 for the best MA and EWMA models, respectively. On a daily time scale, however, the constant historical mean was not the best forecasting method. Both the daily average and the weekday/weekend average model performed better than the historical mean. The MASE for the weekday/weekend model was 0.67, compared to 0.73 for the historical mean, an improvement of six percentage points relative to a naïve model. In general, our daily forecasts had lower MASE values than the weekly forecasting methods.

In the testing set, the ward admitted an average of 7.7 patients per day. By comparison, the MAD ranged from 2.44 for the weekday/weekend model to 3.67 for the naïve one-step model. Again, the MFE values for all models were negative, indicating consistent underestimation of actual daily volume. Although the three models based on simple historical averages performed better than the other models, their MFEs reflect a stronger bias towards underestimation than the MA and EWMA models.

TABLE 4.2: Error metrics for daily forecasting models

| | | | | Naïve | |
|---|---|---|---|---|---|
| | *Mean* | *Daily* | *Weekend* | *1 day* | *7 days* |
| MAD | 2.68 | 2.57 | 2.44 | 3.67 | 3.26 |
| MFE | -0.13 | -0.40 | -0.33 | -0.03 | -0.07 |
| MASE | 0.73 | 0.70 | 0.67 | 1.00 | 0.89 |

*Note.* MAD = mean absolute deviation, MFE = mean forecast error, MASE = mean absolute scaled error

TABLE 4.3: Error metrics for daily forecasting models (con.)

| | MA | | | EWMA | | |
|---|---|---|---|---|---|---|
| | *3 days* | *5 days* | *7 days* | *3 days* | *5 days* | *7 days* |
| MAD | 3.19 | 3.06 | 2.80 | 3.15 | 2.99 | 2.90 |
| MFE | -0.02 | -0.03 | -0.04 | -0.03 | -0.03 | -0.04 |
| MASE | 0.87 | 0.84 | 0.76 | 0.86 | 0.82 | 0.79 |

*Note.* MAD = mean absolute deviation, MFE = mean forecast error, MASE = mean absolute scaled error, MA = moving average, EWMA = exponentially-weighted moving average

## 4.4 Discussion

In the previous section, we applied multiple forecasting methods to admissions data from the obstetrics and gynecology ward at TASH. To evaluate the models' predictions, we calculated three standard error metrics for out-of-sample forecasts, the MAD, MFE, and MASE. By incorporating the magnitude and direction of errors, each metric provided a different perspective on the quality of our forecasts.

On a weekly time horizon, a historical average could reduce forecasts errors by a quarter, compared to the naïve one-step method. Models on both the weekly and daily time horizon had MASE values below 1, suggesting that basic forecasting models could facilitate better staff scheduling and improve bed management. The MFE, however, illustrates that the models still suffer from bias towards underestimation.

Some limitations temper the results of our analysis. First, we assumed that entries in the admissions registries without MRNs represent unique patients. As we noted in Chapter 2, there are likely some duplicate data among the entries missing MRNs. This could mean that we overestimate the true number of daily and weekly admissions. We anticipate, however, that any differences in forecast accuracy would be minor.

Second, we only considered a handful of basic forecasting methods. Many other techniques exist and have been applied elsewhere. In one study, Jones et al. applied neural network models to daily patient volume at three emergency departments.[55] If we had several years worth of admissions data, auto-regressive methods or models incorporating seasonality could improve on the forecasts of our current models. Fourier transforms, for example, could illuminate demand cycles overlooked by simple moving averages.

Third, our forecasting methods may not be strictly comparable in an apples-to-apples sense. At the daily level, the weekday/weekend model is both a single-step and multi-step forecasting method; it can predict patient volume days or even weeks in the future. This statement holds for other historical averages as well. The MA and EWMA models, however, can only make predictions for one time period ahead.

Despite these limitations, our analysis holds two key points for managers in the obstetrics ward. Forecasting models - even simple ones - could be better than none at all. And if these models can account for cyclical admission patterns, like the weekend/weekday model, they are likely to be even more useful. Healthcare possesses a remarkable degree of regularity. In the absence of epidemics, the demand for health services exhibits a limited volatility when compared to industries like energy or technology. By integrating forecasting into their standard operations, managers at TASH could use data already at their disposal to improve the efficiency and resilience of a ward or department.

# Chapter 5

# Conclusion

In the previous chapters, we demonstrated how basic statistical methods could be applied to admissions data at TASH. In Chapter 3, we used logistic regression models to identify factors associated with extended stays and readmission among women giving birth. Although the delivery method did not seem to affect the risk of either outcome, our study population was a convenience sample from existing registries. Selection bias and missing data limit the inferences we can draw from our models. In Chapter 4, we used forecasting methods to project demand for health services. The models have their weakness, but their predictions of patient volume - particularly on a weekly time horizon - were quite reasonable. By selecting three different error metrics, we could better evaluate their deviations and biases.

In this thesis, we explored the utility of existing data in the obstetrics and gynecology ward at TASH. What staff can obtain from the admissions registries depends largely on the quality of specific variables and what the data are used for. When data are recorded consistently - as with patients' admission date - the registries can support some analysis of ward operations. But when data are missing and incomplete, the registries may paint an unclear picture of the ward.

Operations management could improve the efficiency of wards at TASH, but the existing information system needs to be strengthened. To enable the adoption of operations management methods at TASH, we propose the following steps:

1 **Improve the quality of data collection.**

As demonstrated in Chapter 2, missing and inconsistent data exist in the admissions registries. The ward's management team should aim to improve the quality of data collected by nurses, residents, and staff.

2 **Improve existing information systems.**

Our analysis illustrated the limitations of paper-based records. Still, strategies to improve paper-based record systems have been developed by other researchers.[61] In their review of paper registries in four countries, including Ethiopia, Westley et al. recommend that only essential data be collected and that registries be designed to fit local needs.[61] By critically examining current recording processes, managers can better understand how data collection contributes to broader organizational goals.

3 **Train senior staff and managers in operations management.**

Hospitals in Ethiopia have already benefited from the adoption of operations management techniques.[28, 30, 31] Much of the training, however, has only targeted executives.[27, 28, 30] For operations management to become standard practice, all managers should be trained in the methodology.

4 **Integrate operations management techniques into broader hospital management.**

Compared to operations management methodology, traditional management techniques often lead to suboptimal decisions.[62] Kolker presents numerous examples of this.[62] By adopting operations management techniques, hospitals can improve both their financial health and quality of care.[28, 30, 31, 63, 64] For such changes to take root, however, physicians and hospital leaders must not only adopt these techniques, but also integrate them into day-to-day operations.

We believe the recommendations are a good starting point for improving operations in the obstetrics ward. We expect that such changes will pay significant dividends for both patients and providers at TASH.

# Bibliography


[1] World Health Orgnization. *WHO | Ethiopia*. URL: `http://www.who.int/countries/eth/en/` (visited on 03/20/2017).

[2] Central Statistical Agency. *Census Tables - Addis Ababa*. 2007. URL: `http://www.csa.gov.et/index.php/census-report/census-tables/category/301-census-tables` (visited on 03/29/2017).

[3] Federal Democratic Republic of Ethiopia. *Regional States - Ethiopian Government Portal*. URL: `http://www.ethiopia.gov.et/regional-states` (visited on 03/29/2017).

[4] World Bank. *Ethiopia Country Report*. URL: `http://www.imf.org/external/pubs/ft/weo/2016/01/weodata/weorept.aspx?pr.x=40&pr.y=1&sy=2016&ey=2019&scsm=1&ssd=1&sort=country&ds=.&br=1&c=644&s=NGDPD%2CNGDPDPC%2CPPPGDP%2CPPPPC&grp=0&a=` (visited on 03/20/2017).

[5] The World Bank. *GDP per capita (current US$) | Data*. 2015. URL: `http://data.worldbank.org/indicator/NY.GDP.PCAP.CD?locations=ZG&view=chart` (visited on 03/29/2017).

[6] African Health Observatory. *Comprehensive Analytical Profile: Ethiopia*. URL: `http://www.aho.afro.who.int/profiles_information/index.php/Ethiopia:Index` (visited on 03/20/2017).

[7] The World Bank. *Health expenditure per capita (current US$) | Data*. 2014. URL: `http://data.worldbank.org/indicator/SH.XPD.PCAP` (visited on 04/01/2017).

[8] World Health Orgnization. *Ethiopia: WHO statistical profile*. Jan. 2015. URL: `http://www.who.int/gho/countries/eth.pdf` (visited on 03/20/2017).

[9] UNPD UNICEF UNFPA. *Trends in Maternal Mortality: 1990-2015*. 2015. URL: `http://www.who.int/reproductivehealth/publications/monitoring/maternal-mortality-2015/en/` (visited on 03/26/2017).

[10] Yifru Berhan and Asres Berhan. "Causes of Maternal Mortality in Ethiopia: A Significant Decline in Abortion Related Death". In: *Ethiopian Journal of Health Sciences* 24.0 Suppl (Sept. 2014), pp. 15–28. ISSN: 1029-1857. URL: `http://www.ncbi.nlm.nih.gov/pmc/articles/PMC4249203/` (visited on 01/04/2017).

[11] Yifru Berhan and Asres Berhan. “Review of Maternal Mortality in Ethiopia: A Story of the Past 30 Years”. In: *Ethiopian Journal of Health Sciences* 24.0 Suppl (Sept. 2014), pp. 3–14. ISSN: 1029-1857. URL: `http://www.ncbi.nlm.nih.gov/pmc/articles/PMC4249207/` (visited on 01/04/2017).

[12] A. Abdella. “Maternal Mortality Trend in Ethiopia”. en. In: *Ethiopian Journal of Health Development* 24.1 (Jan. 2010), pp. 115–122. ISSN: 1021-6790. DOI: `10.4314/ejhd.v24i1.62953`. URL: `http://www.ajol.info/index.php/ejhd/article/view/62953` (visited on 01/20/2017).

[13] African Health Observatory. *Ethiopia: Analytical summary - Health system outcomes*. URL: `http://www.aho.afro.who.int/profiles_information/index.php/Ethiopia:Analytical_summary_-_Health_system_outcomes` (visited on 03/27/2017).

[14] WHO Regional Office for Africa. *WHO Country Cooperation Strategy - 2012-2015 - Ethiopia*. Tech. rep. Brazzaville, Republic of Congo: World Health Organization, 2013. URL: `http://apps.who.int/iris/bitstream/10665/136003/3/ccs_ethiopia.pdf` (visited on 03/27/2017).

[15] International Network for Cancer Research and Treatment. *Tikur Anbessa (Black Lion) Hospital*. 2010. URL: `http://www.inctr.org/network-magazine/current-edition/partner-profile/tikur-anbessa-black-lion-hospital/` (visited on 03/29/2017).

[16] Addis Ababa University College of Health Sciences. *Background of Tikur Anbessa Hospital | College of Health Sciences*. 2017. URL: `http://www.aau.edu.et/chs/tikur-anbessa-specialized-hospital/background-of-tikur-anbessa-hospital/` (visited on 03/29/2017).

[17] Woldegebriel Shewit. “Service Quality Improvement through Integrated Demand Management in the Ethiopian Healthcare Sector”. Thesis. Addis Ababa University, Jan. 2016. (Visited on 03/21/2017).

[18] Phyllida Travis et al. “Overcoming health-systems constraints to achieve the Millennium Development Goals”. In: *The Lancet* 364.9437 (2004), pp. 900–906.

[19] Maxwell O Akanbi et al. “Use of electronic health records in sub-saharan africa: progress and challenges”. In: *Journal of medicine in the tropics* 14.1 (2012), p. 1.

[20] Sosena Kebede et al. “Educating leaders in hospital management: a new model in Sub-Saharan Africa”. In: *International Journal for Quality in Health Care* (2009), mzp051.

[21] Daniel B McLaughlin and Julie M Hays. *Healthcare operations management*. Health Administration Press, 2008.

[22] David K. Smith. "A bibliography of applications of operational research in West Africa". en. In: *International Transactions in Operational Research* 15.2 (Mar. 2008), pp. 121–150. ISSN: 1475-3995. DOI: 10.1111/j.1475-3995.2008.00625.x. URL: http://onlinelibrary.wiley.com.ezp-prod1.hul.harvard.edu/doi/10.1111/j.1475-3995.2008.00625.x/abstract (visited on 03/21/2017).

[23] David K. Smith. "A bibliography of applications of operational research in sub-Saharan Africa". en. In: *International Transactions in Operational Research* 18.2 (Mar. 2011), pp. 149–182. ISSN: 1475-3995. DOI: 10.1111/j.1475-3995.2010.00795.x. URL: http://onlinelibrary.wiley.com.ezp-prod1.hul.harvard.edu/doi/10.1111/j.1475-3995.2010.00795.x/abstract (visited on 03/21/2017).

[24] Beshah Daniel. "Assessment on implementation of quality management system and their challenges in Tikur Anbessa Specialized Hospital Laboratory, Addis Ababa, Ethiopia". Thesis. Addis Ababa University, June 2014. (Visited on 03/21/2017).

[25] Muluneh Endalew. "Exploring the prevalence of diarrheal disease using data mining technology". PhD thesis. Addis Ababa University, June 2011. URL: http://etd.aau.edu.et/bitstream/123456789/2759/3/Muluneh%20Endalew.pdf (visited on 03/21/2017).

[26] D. Kemball-Cook and D. J. Wright. "The Search for Appropriate O.R.: A Review of Operational Research in Developing Countries". In: *The Journal of the Operational Research Society* 32.11 (1981), pp. 1021–1037. ISSN: 0160-5682. DOI: 10.2307/2581856. URL: http://www.jstor.org.ezp-prod1.hul.harvard.edu/stable/2581856 (visited on 03/21/2017).

[27] Yale University. *Ethiopia | Yale Global Health Leadership Institute*. URL: http://ghli.yale.edu/where-we-work/ethiopia (visited on 03/30/2017).

[28] Elizabeth Bradley et al. "Hospital quality improvement in Ethiopia: a partnership–mentoring model". In: *International Journal for Quality in Health Care* 20.6 (Dec. 2008), pp. 392–399. ISSN: 1353-4505. DOI: 10.1093/intqhc/mzn042. URL: https://academic-oup-com.ezp-prod1.hul.harvard.edu/intqhc/article/20/6/392/1791411/Hospital-quality-improvement-in-Ethiopia-a (visited on 03/19/2017).

[29] Kari Hartwig et al. "Hospital management in the context of health sector reform: a planning model in Ethiopia". en. In: *The International Journal of Health Planning and Management* 23.3 (July 2008), pp. 203–218. ISSN: 1099-1751. DOI: 10.1002/hpm.915. URL: http://onlinelibrary.wiley.com.ezp-prod1.hul.harvard.edu/doi/10.1002/hpm.915/abstract (visited on 03/19/2017).

[30] Sosena Kebede et al. "Educating leaders in hospital management: A pre-post study in Ethiopian hospitals". In: *Global Public Health* 7.2 (Feb. 2012), pp. 164–174. ISSN: 1744-1692. DOI: 10.1080/17441692.2010.542171. URL: http://www-tandfonline-com.ezp-prod1.hul.harvard.edu/doi/abs/10.1080/17441692.2010.542171 (visited on 03/19/2017).

[31] Elizabeth H. Bradley, Lauren A. Taylor, and Carlos J. Cuellar. "Management Matters: A Leverage Point for Health Systems Strengthening in Global Health". In: (June 2015). URL: https://papers-ssrn-com.ezp-prod1.hul.harvard.edu/abstract=2621436 (visited on 03/19/2017).

[32] Jonathan M. Snowden and Aaron B. Caughey. "Is there a weekend effect in obstetrics?" en. In: *BMJ* 351 (Nov. 2015), h6192. ISSN: 1756-1833. DOI: 10.1136/bmj.h6192. URL: http://static.www.bmj.com.ezp-prod1.hul.harvard.edu/content/351/bmj.h6192 (visited on 01/02/2017).

[33] William L. Palmer, A. Bottle, and P. Aylin. "Association between day of delivery and obstetric outcomes: observational study". en. In: *BMJ* 351 (Nov. 2015), h5774. ISSN: 1756-1833. DOI: 10.1136/bmj.h5774. URL: http://www.bmj.com.ezp-prod1.hul.harvard.edu/content/351/bmj.h5774 (visited on 01/02/2017).

[34] Oona M. R. Campbell et al. "Length of Stay After Childbirth in 92 Countries and Associated Factors in 30 Low- and Middle-Income Countries: Compilation of Reported Data and a Cross-sectional Analysis from Nationally Representative Surveys". eng. In: *PLoS medicine* 13.3 (Mar. 2016), e1001972. ISSN: 1549-1676. DOI: 10.1371/journal.pmed.1001972.

[35] *WHO recommendations on postnatal care of the mother and newborn*. Tech. rep. World Health Organization, Oct. 2013. URL: http://apps.who.int/iris/bitstream/10665/97603/1/9789241506649_eng.pdf?ua = 1 (visited on 01/21/2017).

[36] Nebreed Fesseha et al. "A national review of cesarean delivery in Ethiopia". en. In: *International Journal of Gynecology & Obstetrics* 115.1 (Oct. 2011), pp. 106–111. ISSN: 1879-3479. DOI: 10.1016/j.ijgo.2011.07.011. URL: http://onlinelibrary.wiley.com.ezp-prod1.hul.harvard.edu/doi/10.1016/j.ijgo.2011.07.011/abstract (visited on 01/30/2017).

[37] R. M. Wilson et al. "Patient safety in developing countries: retrospective estimation of scale and nature of harm to patients in hospital". en. In: *BMJ* 344 (Mar. 2012), e832. ISSN: 0959-8138, 1468-5833. DOI: 10.1136/bmj.e832. URL: http://www.bmj.com.ezp-prod1.hul.harvard.edu/content/344/bmj.e832 (visited on 01/02/2017).

[38] M Gedebou et al. "Hospital-acquired infections among obstetric and gynaecological patients at Tikur Anbessa Hospital, Addis Ababa". en. In: *Journal of Hospital Infection* 11.1 (Jan. 1988), pp. 50–59. ISSN: 01956701. DOI: 10.1016/0195-6701(88)90039-4. URL: http://linkinghub.elsevier.com/retrieve/pii/0195670188900394 (visited on 01/21/2017).

[39] Birkneh Tilahun et al. "High load of multi-drug resistant nosocomial neonatal pathogens carried by cockroaches in a neonatal intensive care unit at Tikur Anbessa specialized hospital, Addis Ababa, Ethiopia". In: *Antimicrobial Resistance and Infection Control* 1 (2012), p. 12. ISSN: 2047-2994. DOI: 10.1186/2047-2994-1-12. URL: http://dx.doi.org/10.1186/2047-2994-1-12 (visited on 01/21/2017).

[40] Shiliang Liu et al. "Length of hospital stay, obstetric conditions at childbirth, and maternal readmission: A population-based cohort study". In: *American Journal of Obstetrics and Gynecology* 187.3 (Sept. 2002), pp. 681–687. ISSN: 0002-9378. DOI: 10.1067/mob.2002.125765. URL: http://www.sciencedirect.com/science/article/pii/S0002937802001886 (visited on 01/02/2017).

[41] Kenneth D. Mandl et al. "Maternal and Infant Health: Effects of Moderate Reductions in Postpartum Length of Stay". In: *Archives of Pediatrics & Adolescent Medicine* 151.9 (Sept. 1997), pp. 915–921. ISSN: 1072-4710. DOI: 10.1001/archpedi.1997.02170460053009. URL: http://jamanetwork.com.ezp-prod1.hul.harvard.edu/journals/jamapediatrics/fullarticle/518501 (visited on 01/09/2017).

[42] Paula Braveman et al. "Early Discharge of Newborns and Mothers: A Critical Review of the Literature". en. In: *Pediatrics* 96.4 (Oct. 1995), pp. 716–726. ISSN: 0031-4005, 1098-4275. URL: http://pediatrics.aappublications.org/content/96/4/716 (visited on 01/09/2017).

[43] Mehdi Kehila et al. "Early postpartum discharge: outcomes and risk factors of readmission". fre. In: *The Pan African Medical Journal* 24 (2016), p. 189. ISSN: 1937-8688. DOI: 10.11604/pamj.2016.24.189.9371.

[44] Shiliang Liu et al. "Risk of Maternal Postpartum Readmission Associated With Mode of Delivery:" en. In: *Obstetrics & Gynecology* 105.4 (Apr. 2005), pp. 836–842. ISSN: 0029-7844. DOI: 10.1097/01.AOG.0000154153.31193.2c. URL: http://content.wkhealth.com/linkback/openurl?sid=WKPTLP:landingpage&an=00006250-200504000-00025 (visited on 01/30/2017).

[45] Mona Lydon-Rochelle et al. "Association Between Method of Delivery and Maternal Rehospitalization". In: *JAMA* 283.18 (May 2000), pp. 2411–2416. ISSN: 0098-7484. DOI: 10.1001/jama.283.18.2411. URL: http://jamanetwork.com.ezp-prod1.hul.harvard.edu/journals/jama/fullarticle/192686 (visited on 01/30/2017).

[46] Eugene Declercq et al. "Maternal Outcomes Associated With Planned Primary Cesarean Births Compared With Planned Vaginal Births:" en. In: *Obstetrics & Gynecology* 109.3 (Mar. 2007), pp. 669–677. ISSN: 0029-7844. DOI: 10.1097/01.AOG.0000255668.20639.40. URL: http://content.wkhealth.com/linkback/openurl?sid=WKPTLP:landingpage&an=00006250-200703000-00014 (visited on 01/29/2017).

[47] E Tadesse, M Adane, and M Abiyou. "Caesarean section deliveries at Tikur Anbessa Teaching Hospital, Ethiopia." eng. In: *East African medical journal* 73.9 (Sept. 1996), pp. 619–622. ISSN: 0012-835X. URL: http://europepmc.org/abstract/med/8991247 (visited on 01/30/2017).

[48] StataCorp. *Stata Statistical Software*. Version MP Release 14.2. URL: http://www.stata.com/.

[49] William P. Pierskalla and David J. Brailer. "Chapter 13 Applications of operations research in health care delivery". In: ed. by BT Handbooks in Operations Research and Management Science. Vol. 6. Operations Research and The Public Sector. DOI: 10.1016/S0927-0507(05)80094-5. Elsevier, 1994, pp. 469–505. URL: http://www.sciencedirect.com/science/article/pii/S0927050705800945 (visited on 03/04/2017).

[50] Ireneous N. Soyiri and Daniel D. Reidpath. "An overview of health forecasting". In: *Environmental Health and Preventive Medicine* 18.1 (Jan. 2013), pp. 1–9. ISSN: 1342-078X. DOI: 10.1007/s12199-012-0294-6. URL: http://www.ncbi.nlm.nih.gov/pmc/articles/PMC3541816/ (visited on 03/04/2017).

[51] A. J. Beech. "Market-based demand forecasting promotes informed strategic financial planning". eng. In: *Healthcare Financial Management: Journal of the Healthcare Financial Management Association* 55.11 (Nov. 2001), pp. 46–54, 56. ISSN: 0735-0732.

[52] Yasar Ozcan. *Quantitative Methods in Health Care Management*. URL: https://books-google-com.ezp-prod1.hul.harvard.edu/books/about/Quantitative_Methods_in_Health_Care_Mana.html?id=zPeCLkDcIlAC (visited on 03/21/2017).

[53] M. J. Côté and S. L. Tucker. "Four methodologies to improve healthcare demand forecasting". eng. In: *Healthcare Financial Management: Journal of the Healthcare Financial Management Association* 55.5 (May 2001), pp. 54–58. ISSN: 0735-0732.

[54] Abdur Rais and Ana Viana. "Operations Research in Healthcare: a survey". en. In: *International Transactions in Operational Research* 18.1 (Jan. 2011), pp. 1–31. ISSN: 1475-3995. DOI: 10.1111/j.1475-3995.2010.00767.x. URL: http://onlinelibrary.wiley.com.ezp-prod1.hul.harvard.edu/doi/10.1111/j.1475-3995.2010.00767.x/abstract (visited on 03/17/2017).

[55] Spencer S. Jones et al. "Forecasting Daily Patient Volumes in the Emergency Department". en. In: *Academic Emergency Medicine* 15.2 (Feb. 2008), pp. 159–170. ISSN: 1553-2712. DOI: 10.1111/j.1553-2712.2007.00032.x. URL: http://onlinelibrary.wiley.com.ezp-prod1.hul.harvard.edu/doi/10.1111/j.1553-2712.2007.00032.x/abstract (visited on 03/04/2017).

[56] Fotios Petropoulos et al. "'Horses for Courses' in demand forecasting". In: *European Journal of Operational Research* 237.1 (Aug. 2014), pp. 152–163. ISSN: 0377-2217. DOI: 10.1016/j.ejor.2014.02.036. URL: http://www.sciencedirect.com/science/article/pii/S0377221714001714 (visited on 03/17/2017).

[57] Frederick S. Hillier and Gerald J. Lieberman. *Introduction to Operations Research*. McGraw-Hill, 1995. ISBN: 0-07-841447-4.

[58] Guido van Rossum. *Python*. Version 3.5.1. URL: https://www.python.org.

[59] Rob J. Hyndman and Anne B. Koehler. "Another look at measures of forecast accuracy". In: *International Journal of Forecasting* 22.4 (Oct. 2006), pp. 679–688. ISSN: 0169-2070. DOI: 10.1016/j.ijforecast.2006.03.001. URL: http://www.sciencedirect.com/science/article/pii/S0169207006000239 (visited on 03/02/2017).

[60] Philip Hans Franses. "A note on the Mean Absolute Scaled Error". In: *International Journal of Forecasting* 32.1 (Jan. 2016), pp. 20–22. ISSN: 0169-2070. DOI: 10.1016/j.ijforecast.2015.03.008. URL: http://www.sciencedirect.com/science/article/pii/S0169207015000448 (visited on 03/02/2017).

[61] Eva W Westley et al. "Strengthening paper health register systems: strategies from case studies in Ethiopia, Ghana, South Africa and Uganda". In: *Journal of global health* 6.2 (2016).

[62] Alexander Kolker. *Healthcare Management Engineering: What Does This Fancy Term Really Mean?: The Use of Operations Management Methodology for Quantitative Decision-Making in Healthcare Settings*. Springer Science & Business Media, 2011.

[63] Eugene Litvak and Maureen Bisognano. "More patients, less payment: increasing hospital efficiency in the aftermath of health reform". In: *Health Affairs* 30.1 (2011), pp. 76–80.

[64] Eugene Litvak and Harvey V Fineberg. "Smoothing the way to high quality, safety, and economy". In: *New England Journal of Medicine* 369.17 (2013), pp. 1581–1583.