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THESIS

ASSOCIATION BETWEEN EMERGENCY DEPARTMENT WAIT TIME AND MEDICATION PRESCRIPTION PATTERNS

by

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March 2020

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13. ABSTRACT (maximum 200 words)

In my thesis, I study whether a patient experiencing longer wait times in the emergency department (ED) is more or less likely to receive a medication, a non-prescription drug, or intravenous therapy (IV). Using survey data from the National Center for Health Statistics (NCHS), I analyze a sample of 98,451 ED visits from 2012 to 2016. My key variable is wait time, measured as a series of indicator variables for each quartile of the wait time distribution. My three outcome variables are: (1) indicator for receiving a medication, (2) indicator for receiving a non-prescription drug, and (3) indicator for whether an IV was given. I use four models for all three outcomes by including the following control variables in my analysis: (1) demographic information of the patients such as age, sex and race, (2) payment method, and (3) clinical characteristics such as pain scale and symptoms. I also include dummy variables for each respective year to capture any macro-trends. I find that patients in the 4th quartile of wait time have lower odds of receiving a medication, patients in the 3rd quartile have lower odds of receiving a non-prescription drug, and patients in the 2nd, 3rd, and 4th quartile have lower odds of being given an IV. Many control variables are also correlated with my outcomes, such as age, sex, race, pain scale, and symptoms. My results have implications for optimal staffing of triage units in hospitals, advancing work flows efficiencies, and cutting waste.

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ASSOCIATION BETWEEN EMERGENCY DEPARTMENT WAIT TIME AND MEDICATION PRESCRIPTION PATTERNS

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ABSTRACT

In my thesis, I study whether a patient experiencing longer wait times in the emergency department (ED) is more or less likely to receive a medication, a non-prescription drug, or intravenous therapy (IV). Using survey data from the National Center for Health Statistics (NCHS), I analyze a sample of 98,451 ED visits from 2012 to 2016. My key variable is wait time, measured as a series of indicator variables for each quartile of the wait time distribution. My three outcome variables are: (1) indicator for receiving a medication, (2) indicator for receiving a non-prescription drug, and (3) indicator for whether an IV was given. I use four models for all three outcomes by including the following control variables in my analysis: (1) demographic information of the patients such as age, sex and race, (2) payment method, and (3) clinical characteristics such as pain scale and symptoms. I also include dummy variables for each respective year to capture any macro-trends. I find that patients in the 4th quartile of wait time have lower odds of receiving a medication, patients in the 3rd quartile have lower odds of receiving a non-prescription drug, and patients in the 2nd, 3rd, and 4th quartile have lower odds of being given an IV. Many control variables are also correlated with my outcomes, such as age, sex, race, pain scale, and symptoms. My results have implications for optimal staffing of triage units in hospitals, advancing work flows efficiencies, and cutting waste.

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LIST OF ACRONYMS AND ABBREVIATIONS

CDC	Centers for Disease Control and Prevention
ED	Emergency Department
IV	Intravenous Therapy
LOGIT	Logistic Regression
NAMCS	The National Ambulatory Medical Care Survey
NCHS	National Center for Health Statistics
NHAMCS	The National Hospital Ambulatory Medical Care Survey
OR	Odds Ratio

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Through my journey, I would be remiss if I did not thank God for seeing me through seemingly difficult patches of life, including my thesis journey. I felt overwhelmed and stressed on multiple occasions, but I always found a way to stay grounded and push through, knowing everything was going to work out in the end.

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I. INTRODUCTION

A. RESEARCH TOPIC

My research studies the correlation between wait times and the likelihood of providers prescribing medications and IV to emergency department (ED) patients. I accomplish this by using survey data from the National Center for Health Statistics (NCHS) and analyzing a sample of 98,451 individuals from 2012 to 2016. I use four models to find any association my key indicator variable and control variables have on three separate outcome variables.

I accomplish my research by analyzing three outcome variables against the same four models. My outcome variables include: (1) Outcome #1 indicator for any medication received by a patient; (2) Outcome #2 indicator for a non-prescription drug being received by a patient; (3) Outcome #3 indicator for an IV being given to a patient. These outcome variables are discussed in detail in Chapter III. My control variables include demographic information, payment method, and clinical characteristics.

B. BACKGROUND

The baby boomer generation is currently entering retirement years, meaning this generation has reached Medicare eligibility in the U.S. By 2030, 20% of the U.S. Population will be 65 or older (Silverman, 2018). Additionally, the baby boomer generation average five or more medications (Brownlee et al., 2019). Due to this, healthcare demand in the U.S. is growing, but waste in the healthcare system has also grown. At the same time, more patients are utilizing EDs as their primary source of care at higher rates. For example, a 2011 study showed that ED visits increased 45% from 1998 to 2009 (He et al., 2011). In a separate study by the University of Maryland School of Medicine patients are observed to be receiving 50% of their medical care in the U.S. by EDs (2017). These facts are alarming and indicate an increased and growing demand from patients to get their medical needs met by an ED.

In addition to the growing demand placed on EDs, there is also a growing deficit in physicians. Current projections expect physician shortages to reach 40,800 to 104,900 by

2030 (Feldstein, 2019). This shortage becomes most evident when patients begin recognizing longer than average wait times. Current wait times to schedule an appointment to see a physician range across the country. For example, in Dallas patients wait 12 days to see their physician, but in Boston the wait time is 45 days (Feldstein, 2019). These data points (physician shortage and varying wait times) imply the healthcare industry is not operating at peak or optimal efficiency levels. In fact, current waste in the healthcare system is estimated to be $760 to $935 billion/year (Shrank et al., 2019). These findings give credence to research projects like mine that are capable of identifying areas of patient care that may be improved in a coordinated effort to operate more efficiently and effectively.

Based on these facts, there is an expected increase in the future with respect to demand on ED providers and their staffs. This increased demand requires EDs to be proactive in finding measures to becoming more efficient in order to meet future demands. In my thesis I analyze whether increased demand of the ED staff (proxied by emergency department wait time) is associated with changes in medication prescription patterns. Such analysis can potentially offer insights for improved resource management.

Due to the growing opioid crisis in the United States, the majority of studies relating to my analysis are opioid-specific. These studies do aid in the literature review process for my work, and do provide interesting data points for trends that exist in the prescribing behaviors of opioids, but not much exists on my three outcome variables. My hope is that the results from my study warrant further research in order to better understand how variables such as wait time and clinical characteristics such as whether a patient arrived by an ambulance affect the probability of a patient being prescribed a medication.

In the current U.S. healthcare system there is a trend occurring where more patients are seeking to receive their medical care needs from EDs. Due to this trend, my thesis starts by analyzing the likelihood of a patient receiving a medication while visiting an ED. In an article by Zeis (2016) a survey was sent to ED staffs to discover how they limit what they call “avoidable” visits for patients. The number two response (56% of respondents) is for EDs to limit prescriptions for opioids, and the number seven response (36% of respondents) included a way of tracking patients that seek opioid drugs (Zeis, 2016). These types of responses tell me that patients (in this case patients seeking opioids) use EDs to get their prescription drug needs met. My thesis looks at variables that have a relationship with a drug being prescribed for the same purpose, to discover if there are variables that help healthcare professionals understand various methods or ways to minimize these "avoidable" visits.

Another takeaway from Zeis (2016) is that 15% of respondents claimed that inadequate ED staff is a cause of inefficiencies. These shortages create bottlenecks that results in EDs becoming overworked and possibly unable to meet all of the demands of patients. I believe the results from my analysis offer tangible takeaways for healthcare professionals to use in order to counter these potential bottlenecks and/or modify workflow processes in their manpower programs. This is accomplished by utilizing my findings and tailoring programs to their localized data.

C. HOW CAN MY RESEARCH BENEFIT THE MILITARY?

The military system currently provides a significant healthcare benefits package to Active Duty, Dependents, and Retirees. Retired military personnel live longer than previous generations which turns into greater demand on the military health system overall. I previously discussed civilian specific growth trends, and in my analysis I assume the military health system will see the same growth in patient demand. The goal of my thesis is to identify variables that directly affect all medical providers, both inside and outside of the military health system. I aim to better understand relevant variables capable of helping providers focus their efforts, and bring these efficiencies and future initiatives to fruition.

The findings in my thesis have the ability to benefit military healthcare professionals in multiple ways. For example, I believe these findings can support healthcare professionals in identifying possible efficiencies in triaging patients. Also, my results offer insight into demographic variables that can be used in a localized manner to project and plan manpower needs, based on local demographics for a healthcare facility. For example, in my findings I identify unique characteristics for age, sex, race, and ethnicity all of which aid healthcare professionals to better understand their patients and plan for their needs. This can include creative solutions to meet patient needs such as implementing alternative methods of providing care to these patients (e.g., e-visit vs face-to-face). Lastly, the macro-trends evident in my findings will aid in projecting future demand on the military health system.

D. RESEARCH OBJECTIVE

In my analysis I study the association between wait times and the likelihood of a patient receiving a medication, receiving a non-prescription drug, and an IV being given. These three outcomes are analyzed against my key indicator variable wait time, controlling for demographic information, payment method, and clinical characteristics of a patient. Finally, I also include year fixed effects in my regressions to control for any macro-trends in prescription behaviors in EDs.

In my thesis, I analyze three medication outcomes: (1) Outcome #1 whether a patient received medication of any kind during the ED visit; (2) Outcome #2 whether a patient received a non-prescription drug during the visit; and (3) Outcome #3 whether a patient was given an IV during the visit. For each outcome, I address the following questions.

1. Is there an association between patient wait time and probability of receiving medication?

2. What are the other determinants of the medication outcomes?

3. What are the macro-trends over the five years of data of the medication outcomes?

I use logistic regressions to estimate the relationships between the three medication outcomes and my key independent variable of wait time. My control variables include demographic information, payment method, clinical characteristics, and year indicators.

E. DATA USED

My data comes from the National Center for Health Statistics (NCHS), an organization that falls within the Center for Disease Control (CDC). NCHS sends each respective state in the U.S. a survey, who in turn sends these surveys to hospitals with an

ED in order to solicit responses. I use data for years 2012 to 2016 in my analysis. The survey is called the National Hospital Ambulatory Medical Care Survey (NHAMCS). The data in these surveys is reported at the individual/patient level for my 98,451 total observations, but there are no unique identifiers to track individual patients from one year to the next.

F. SCOPE AND METHODOLOGY

To analyze the NHAMCS data I run multivariate logit models focusing on relevant variables identified based on my literature review and my key explanatory variable of wait time. In my first outcome variable (Outcome #1) I test the hypothesis that patients who wait longer are more likely to receive a medication. My data does not give me specific information on number of work hours worked by providers so I proxy longer wait times by splitting them into quartiles. The quartiles of time allow me to capture potential nonlinear relationship between wait time and the likelihood of a patient being prescribed any medication.

My Outcome #2 is the probability of a patient receiving a non-prescription drug and Outcome #3 is the probability of an IV being given to a patient. I include these two latter outcome variables in my research to get additional insights on whether the association between wait time and medication outcomes might differ depending on different aspects of medication as I compare the results of each respective outcome.

G. FINDINGS

My findings show that patients in the 4th quartile of wait time have lower odds of receiving a medication, patients in the 3rd quartile have lower odds of receiving a non-prescription drug, and patients in the 2nd, 3rd, and 4th quartile have lower odds of being given an IV. In all three outcome variables there is a decreased likelihood for a patient to receive a medication, receive a non-prescription drug, and be given an IV due to wait times longer than 8 minutes.

I also find many control variables that are correlated with all three outcomes such as age, sex, race, ethnicity, payment method, pain scale, and symptoms. For example, in

Outcome #1 patients experiencing severe pain and patients with pain and fever symptoms are 2.168 and 1.776 times more likely to receive a medication, respectively. In Outcome #2 these two variables are still good indicators of increasing the likelihood of receiving a non-prescription drug, but so is heart and chest pain (not heartburn) who are 1.686 times more likely. These findings and more are discussed in further detail in Chapter IV.

This thesis includes the following chapters organized as follows: Chapter II is my literature review focusing on the following areas: (1) previous research on NHAMCS and NAMCS data and their findings; (2) prior research on the effectiveness of prescribing policy programs and their findings. Chapter III covers in detail the data and method used to run my analysis. Chapter IV has my descriptive summary statistics table as well as the results of my logistic regressions for my three outcome variables. This chapter also discusses the key findings from my quantitative analysis. Lastly, Chapter V covers my conclusion from my analysis and recommendations to include my thoughts on what further research should be done in the future.

II. LITERATURE REVIEW

A. OVERVIEW

Over the last few decades much research and focus has been placed on the opioid epidemic happening in the United States. Due to this epidemic, much research exists surrounding opioid-specific drugs and the prescribing patterns associated with them, but I do not find any prior research specific to my primary outcome (determinants of any drug prescribed). I find this research on opioid drugs helpful because I am able to see and compare results of their determinants and mine using similar variables. Additionally, my literature review includes helpful research that uses the same survey dataset (NHAMCS/NAMCS). One of the main recommendations from opioid related research is a recommendation for hospitals to use a medication prescribing policy program. These policies are aimed at raising awareness and curbing the opioid epidemic. I dive into conflicting results of these programs to better understand if they influence the likelihood of any drug being prescribed. I conclude with a summary of the main takeaways from my literature review.

B. PREVIOUS RESEARCH ON NHAMCS AND NAMCS SURVEY DATA

1. Findings on Pain, Symptoms, Sex, Race, and Ethnicity

The initial focus of my literature review is prior research conducted on survey data from NHAMCS and NAMCS database, the same (or comparable) data I use in my study. The following articles look at a patient's primary complaint (i.e., pain scale and symptoms) as well as demographic characteristics such as age, sex, race, and ethnicity. I believe pain and symptom characteristics make up the bulk of interest in determinants of doctors prescribing a drug since they are primarily made up of traits patients have as they enter the ED. These traits provide useful and meaningful insight into aggregate trends in the U.S. healthcare system. For example, if patients (over time) show an increased likelihood of claiming higher pain levels, or specific symptoms show up in higher frequency, this type of information is helpful to know if they influence type of treatments received during an ED visit.

Lin et al. (2019) identify variables that increased the likelihood of an opioid being prescribed. They find that opioid medications are more likely to be prescribed when a patient noted both pain and depression as a symptom. The main takeaway from this research is that the pain and depression symptoms appear to increase the likelihood that an opioid was prescribed during a visit (Lin et al., 2019). Depression is of primary interest for providers of opioid drugs due to suicide related incidences, but it is not a characteristic used in my research. Instead, I focus on the patients reported pain levels and symptoms in my research to see if these initial patient reporting characteristics could be signals or determinants of a prescription or non-prescription drug being prescribed, and/or whether any of them have a relationship with an IV being given.

Another finding in the Lin et al. (2019) study is that white males between the age of 46–64 are more likely to be prescribed a narcotic analgesic. This type of finding suggests to ED's that patients falling into this category (white male, aged 46–64) may have unique underlying symptoms or conditions that increase their likelihood of being prescribed a narcotic. A separate study by Qureshi (2017) finds no relationship between race (White, Black, or Other). But, Qureshi does find that that when looking at the gross total amount of opioids prescribed, White males aged 50–64 do receive the most opioid prescriptions. Based on Lin et al. and Qureshi's research, there appears to be indications that White males in the age range of 50s to 60s receive a larger portion of opioid prescriptions but that does not translate into higher prescribing rates. Lin et al.'s and Qureshi's findings do conflict with one another. Lin et al. finds that race (being White) increases the likelihood of being prescribed a medication but Qureshi's findings state there is no relationship between this outcome and race.

Again, the focus of these studies are opioid-specific, but in my analysis I look at gender and race to see if there are any significant differences between the groups over the five years of data. I do not expect to find exactly similar results because my research is not opioid-focused. My research analyzes the effects demographics (sex, race, and ethnicity) have as a determinant of any drug or non-prescription drug being prescribed, or an IV being given. Additionally, I include payment type (i.e., private insurance, self-pay, Medicare, Medicaid, and other-pay) as a trait that each patient would have to see if any have a significant relationship with my outcome variables.

The next finding comes from Ashman et al. (2019) who finds that females have a higher visit rate to physicians than males, as well as infants and the elderly. To define the infant and elderly population this study excludes those aged 1–64. This is interesting because previous articles mention older White males as receiving the most opioid drug prescriptions, but this article suggests females have higher visit rates. While this study does not analyze the likelihood of a female being prescribed a medication based on higher visit rates, it does explain why they make up a higher percentage of visits in my analysis. The question remains, since females have a higher visit rate, does that make them more likely to receive a medication, receive a non-prescription drug, or be given an IV?

Additionally, Ashman et al. (2019) find that chronic conditions (e.g., cancer, kidney disease, diabetes) make up the majority of visits to the physician, for a total of 37% of all visits. Ashman et al. find that these types of conditions are higher for adults than children, which is expected since many chronic conditions appear in older patients. This finding on chronic conditions driving higher physician visits might also indicate that these same patients are more likely to need a prescription or non-prescription drug. The last finding from this study is that children's visits usually stem from new problems or some kind of preventative care whereas adults are usually visiting physicians for pre- or post-surgery care needs (2019). Based on Ashman et al.'s article, I believe the best method for analyzing determinants for my three outcome variables is to focus on pain scales and symptoms. I do not analyze specific pre- or post-surgery conditions of patients in my analysis.

Rasu & Knell (2018) also looked into factors that increase the likelihood of an opioid being prescribed and find that as a patient's age increased, opioid use also increased. This study is similar to the Lin et al. study, but varies slightly in age ranges. In the Rasu study they find opioid use increased for those aged 35–49 and are more than 1.37 times more likely to be prescribed an opioid when compared to the reference group aged 18–34. They also find that this likelihood decreases after the age of 65, where it becomes 0.61 times less likely than the reference group (2018). In my thesis I analyze any relationship age has with our three outcome variables to see if aging affects the probabilities. Rasu &

Knell also find a higher opioid prescribing rate for patients reporting symptoms of general chronic pain, specific to the southern region of the U.S. The reporting symptom is of interest in my research as I look at the main reported symptoms that may increase or decrease the likelihood of a drug being prescribed.

Lastly, the Rasu & Knell study finds that patients of Hispanic ethnicity and those who used private insurance are less likely to receive a prescription for an opioid drug (2018). This is a unique finding to the Rasu & Knell study, and it is something I evaluate further in my analysis as I include Hispanic and payment type in my research. Rasu & Knell's findings seem to suggest that patients that claim Hispanic are less likely to be prescribed an opioid. My analysis looks at three separate outcome variables in an attempt to see if there is in fact any type of relationship between a patient being Hispanic to be compared against the Rasu & Knell findings. I also dive further into payment type to see if there are any trends or relationships between various sources of payment (private insurance, self-pay, Medicare, Medicaid, and other-pay).

The results of the previous authors and research are evaluated against my findings, but I do not expect the exact same results since my study is not opioid-specific. However, there may be similar findings worth noting such as race, ethnicity, payment method, or patients reported symptoms, all of which are evaluated in my analysis.

2. Findings on Patient Wait Time / Length of Visit

Qureshi (2017) finds that patients who have a longer wait time, or length of stay, are more likely to be prescribed an opioid drug. Qureshi analyzes total time patients spend with a physician and finds that a patient with a length of visit over 30 minutes is more likely to be prescribed an opioid. I believe this finding is interesting and it is useful to use as a comparison to the findings in my research.

While these times are somewhat different (wait time versus length of visit) it may indicate that certain patients are willing to wait longer or stay with a provider longer in order to get a prescription need met. I make this comment because Qureshi's study also indicates that the overall average time a patient spends during their visit is 11–20 minutes (2017). Again, I believe this finding suggests that patients who are seeking an opioid or any drug related need, may be willing to wait longer than average since Qureshi also finds that those with visit lengths over 30 minutes are more likely to be prescribed an opioid. This is of keen interest to my analysis as it points to the fact that wait times can in fact have an impact on whether a patient received a medication.

C. EFFECTIVENESS OF PRESCRIBING POLICY PROGRAMS

1. Findings Suggest Minimal (if any) Effectiveness from Programs

An additional theme I find in my literature review involves the effectiveness of prescribing policies within the healthcare system. Menchine et al. (2017) conduct analysis on such policy programs in their critique of a previous study completed by Barnett et al. (2017). Menchine et al. suggests Barnet et al. incorrectly interpreted their key findings, which suggests that emergency physicians are key drivers of the opioid epidemic (Barnett et al. 2016). The main takeaway from the Barnett et al. study is that physicians over-prescribe opioid drugs (more likely to prescribe, meaning a higher prescribing pattern would be evident) whereas Menchine et al.'s team does not agree with these findings.

In Menchine et al.'s study, they state that Barnett et al.'s team incorrectly concluded that clinical providers prescribe too many opioids, because their analysis is biased. Menchine et al. goes on to say that Barnett et al.'s study may have lacked clear detail on the factors that truly impact higher prescribing rates of opioid drugs to patients. According to Menchine et al. (2017), emergency room visits only account for 5% of all opioids prescribed. Additionally, he states that "together these data suggest that interventions in the emergency department to reduce prescribing have a low potential to reduce long-term opioid use" (Menchine et al., 2017, p. 1895). This study finds that the variance between provider types (i.e., low-versus-high intensity prescribers of opioids) only varies by 0.35%. This is a very small and almost negligible variance between the two provider types analyzed by Menchine et al.

The "interventions" are of primary interest to me as I am looking at factors that increase or decrease the likelihood of a patient receiving a medication. I can infer from this study that these interventions had minimal effect on long-term opioid use. This study also stresses the fact that opioid prescription reduction should not be focused solely on emergency departments as they only make up a small portion of the prescriptions written. The bottom line is that clinicians appear to be prescribing medications consistently, with or without an intervention program to curtail opioid prescribing patterns. I carry this assumption in to my study as my data does not include prescribing policies as an option to analyze.

2. Findings Suggest "Hope" for Programs (inconclusive)

In contrast to Menchine et al. another article and analysis from Sowicz et al. finds the following: "variability in clinician, facility, and region-level prescribing patterns suggests that interventions to curtail high prescribing of opioids can be designed with the hope of affecting change on one or more levels" (Sowicz et al., 2018, p. 1832). This research appears to indicate that if a hospital uses a prescribing policy, it can in fact affect prescribing patterns of providers. This is interesting because of its contrary findings to that of Menchine et al.'s study.

The results from Sowicz et al. show that varying types of clinical providers may in fact have behaviorally different probabilities in prescribing medications if they are trained via some kind of prescribing policy. What I have already seen in prior research is that clinician type (physician versus non-physician) is irrelevant to prescribing patterns (i.e., no effect on the likelihood of a drug being prescribed). The research of Sowicz et al. (2018) suggests the "hope" that interventions like a prescribing policy could have an effect on prescribing patterns of clinical providers, which I interpret as inconclusive. The fact that Sowicz et al. use the word hope in their findings suggest that the possibility exists that prescribing policies could have a positive influence on curbing over-prescribing drugs (such as opioids). I take this finding as merely a possibility, not overwhelming evidence that programs such as these impact prescribing behaviors.

3. Findings Suggest Program Decreases Opioid Prescriptions

The third article under this prescribing policy program section is written by Chacko et al. (2017) and once again contradicts Menchine et al.'s findings and supports Sowicz et al. Chacko et al. finds that these types of programs have a clear effect on decreasing the overall prescription rates of opioid drugs. Chacko et al. goes on to acknowledge that success of such programs would help to curb the epidemic facing the United States, but this assumes prescribing policy programs are effective in changing clinical providers prescribing behaviors. Again, the results of this study are opioid-specific, so I take these results into consideration as a possible intervention method that might positively or negatively influence prescribing behaviors.

Given the results of this study, factors such as comparing EDs with and without this type of policy should be considered in future studies that choose to expand on the results seen in my research. This would require a control and treatment group—comparing EDs with and without some kind of prescribing policy—to then compare the prescribing rates of all clinical providers over time. Unfortunately, my dataset does not include any variable or method of tracking whether an ED had this type of program in place, so it not included in my models.

D. SUMMARY

The study conducted by Lin et al.'s team show indications that certain pain and symptom variables increase the likelihood of a drug (opioid) being prescribed. In my analysis I control for pain scale indicators as well as symptoms reported by patients to see if they affect my outcome variables. Additionally, multiple articles above find differential results based on age, sex, and race. For example, Qureshi (2017) did not find any correlation between race (White, Black, or Other) and a drug being prescribed, but did find that males aged 50–64 are prescribed the most opioid drugs. Also, women have higher visit rates to a physician than men (Ashman et al. 2019) but it is unclear if that corresponds with higher likelihoods of a drug being prescribed, so these traits are included and compared to in my analysis. With respect to the results of infants and elderly visit rates exceeding those between ages 1 and 64, my analysis evaluates any relationship between age and my three outcomes.

When I review literature on prescription policy related programs I find mixed results and conclusions. Based on these findings, I loosely interpret this data as indicating that additional prescription prescribing oversight programs have minimal impact on the likelihood of a patient being prescribed a medication. These findings are interesting for my analysis, but I assume this type of intervention has minimal to zero effect on prescribing patterns of providers. I believe omitting this type of observation does not bias my results, but I recommend future researchers include this type of observation in future studies to further assess whether it could impact prescribing patterns. I do acknowledge the possibility that such programs may have or may not have been in place at the respective EDs in my dataset, but it is not possible to identify since the surveys I analyze do not include such observations.

III. DATA AND METHODOLOGY

This chapter describes the data I use in my analysis, to include the three outcome variables, key independent variables, and various control variables to predict each outcome.

A. DESCRIPTION OF DATA AND SAMPLE POPULATION

The data set that I analyze is from the National Center for Health Statistics (NCHS), which operates within the Center for Disease Control (CDC). In 2002 NCHS started a nationwide survey called the National Hospital Ambulatory Medical Care Survey (NHAMCS). This survey is sent to each respective state who are responsible for soliciting inputs form its hospitals within their state. The surveys are collected at the state level, the sent to the CDC/NCHS. Each observation represents a unique ED visits. It is possible that the same patient made multiple visits to the ED, in which case the patient would appear multiple times in the data. Data received by NCHS goes through multiple consistency and quality control checks with coding error rates ranging between 0.1 and 1.5% when sampled (NHAMCS, 2016). For my thesis research I combine and analyze calendar years 2012–2016 which includes 98,451 total observations across five years.

The surveys are sent to about 450 hospitals each year, of which approximately 250 random hospitals submit responses, and these are recorded in micro-data files available from the NCHS website. Due to privacy and confidentiality concerns, this dataset does not include unique identifiers for patients or hospitals since it is a public use dataset. Meaning, there is no way to observe a single unique identity (patient or hospital) over the five years of data. Each respective state collects the survey, then randomly assign a unique 3-digit number known as a code to each hospital so end-users of the data have no way of knowing which hospital it is analyzing. Therefore, it is impossible to analyze this publicly available data for specific geographic locations by zip code, nor is it possible to track any individual patient or hospital through the years.

B. KEY VARIABLES

Based on the literature review and personal objectives of this thesis I have come up with the following outcome and independent variables to use in my analysis. In the following sections I briefly explain the three outcome variables: Outcome #1 (any medication), Outcome #2 (non-prescription drug), and Outcome #3 (IV). I also explain how I analyze the key independent variable, wait time, as measured with indicators for the quartiles of the wait time distribution. Following that I discuss the control variables that are broken up into five categories: demographic information, payment method, clinical characteristics, and year. Each respective outcome variable is analyzed in my regression models with the same key independent variable (wait time) and control variables (previously mentioned) to maintain uniformity and easily compare results of each respective variable against various outcomes.

1. Outcome Variables

This research analyzed three different outcome variables described below.

a. Outcome #1 - Medication (Probability of receiving a medication)

Outcome #1 is a binary outcome that captures whether a patient received any medication (yes or no response on the survey) during his ED visit. In the survey if a patient received any medication it would be marked as "yes," which has a value of 1 in the dataset. Alternatively, if the patient does not receive any medications during their visit to the ED it would be marked as "no," which carried a value of 0 in the dataset. This outcome variable is binary, so a patient either received a medication or did not. I do not distinguish between drug class (prescription vs non-prescription) with this outcome variable. It includes any type of medication given. I have inserted Table 1 as a reference point so readers can easily refer back to the definition and summary statistics for my first outcome variable.

Table 1. Outcome #1 Medication, Dependent Variable Summary

Dependent Variable		**Variable Definition**			
Medication		= 1 if patient received a medication during ED visit or discharge; otherwise = 0			
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Medication	98,451	.816	.387	0	1
Were Medications Prescribed		**Frequency**		**Percent**	
No (=0)		18,041		18.32	
Yes (=1)		80,451		81.68	
Total		98,451		100.00	

As seen in Table 1 the majority of patients were prescribed a medication (81.68% of the sample size population). Outcome #1 is not focused on differentiating between types of drug class, instead the purpose is to look at all drug types.

b. Outcome #2 - Non-Prescription Drugs (Probability of receiving a non-prescription drug)

Outcome #2 is also a binary outcome that captures whether a patient received any drug labeled as non-prescription during their ED visit. In the survey dataset up to 30 different types of medication are tracked and coded in the dataset. If a patient is given any non-prescription drug it is labeled as "non-prescription" or "prescriptions and non-prescription." Meaning, a patient that received any non-prescription drug may have also received a prescription drug.

I generate a new variable to capture these observations in order to analyze the probability of any non-prescription drug being prescribed. I have inserted Table 2 as a reference point so readers can easily refer back to the definition and summary statistics for my second outcome variable.

Table 2. Outcome #2 Non-prescription, Dependent Variable Summary

<table>
<tr><th colspan="2">Dependent Variable</th><th colspan="4">Variable Definition</th></tr>
<tr><td colspan="2">Non-Prescription</td><td colspan="4">= 1 if patient received a non-prescription drug during ED visit or at discharge; otherwise = 0</td></tr>
<tr><th>Variable</th><th>Observations</th><th>Mean</th><th>Std. Dev.</th><th>Min</th><th>Max</th></tr>
<tr><td>Non-Prescription</td><td>98,451</td><td>.533</td><td>.499</td><td>0</td><td>1</td></tr>
<tr><th colspan="2">Was a Non-Prescription Drug Received</th><th colspan="2">Frequency</th><th colspan="2">Percent</th></tr>
<tr><td colspan="2">No (=0)</td><td colspan="2">45,941</td><td colspan="2">46.66</td></tr>
<tr><td colspan="2">Yes (=1)</td><td colspan="2">52,510</td><td colspan="2">53.34</td></tr>
<tr><td colspan="2">Total</td><td colspan="2">98,451</td><td colspan="2">100.00</td></tr>
</table>

As seen in Table 2 a little more than half of all patients receive a non-prescription drug (53.33% of the sample population). Contrary to Outcome #1, Outcome #2 focuses on the likelihood of a patient receiving a non-prescription drug during their visit to the ED vs receiving any medication.

c. Outcome #3 - IV Fluids (Probability of an IV being given to a patient)

Outcome #3 is a binary outcome that captures whether a patient received any IV (yes or no response on the survey) during their ED visit. In the survey if a patient received an IV it would be marked as "yes," which carries a value of 1 in the dataset. Alternatively, if the patient does not receive an IV during their visit to the ED it would be marked as "no," which carries a value of 0 in the dataset. I have inserted Table 3 as a reference point so readers can easily refer back to the definition and summary statistics for my third outcome variable.

Table 3. Outcome #3 IV Fluids, Dependent Variable Summary

<table>
<tr><th colspan="2">Dependent Variable</th><th colspan="4">Variable Definition</th></tr>
<tr><td colspan="2">IV Fluids</td><td colspan="4">= 1 if IV was given during ED visit; otherwise = 0</td></tr>
<tr><th>Variable</th><th>Observations</th><th>Mean</th><th>Std. Dev.</th><th>Min</th><th>Max</th></tr>
<tr><td>IV Fluids</td><td>98,451</td><td>.264</td><td>.441</td><td>0</td><td>1</td></tr>
<tr><th colspan="2">Was a Non-Prescription Drug Prescribed</th><th colspan="2">Frequency</th><th colspan="2">Percent</th></tr>
<tr><td colspan="2">No (=0)</td><td colspan="2">72,419</td><td colspan="2">73.56</td></tr>
<tr><td colspan="2">Yes (=1)</td><td colspan="2">26,032</td><td colspan="2">26.44</td></tr>
<tr><td colspan="2">Total</td><td colspan="2">98,451</td><td colspan="2">100.00</td></tr>
</table>

As seen in Table 3, 26.4% of patients are given an IV during their visit. This is a much smaller percentage of patients when compared to Outcome #1 and #2, but a patient given an IV is also a much different intervention than receiving a type of medication.

2. Independent Variable

The key independent variable I use in this study is the patient's wait time. Patients wait time is recorded in minutes in the survey data. As stated in Chapter I, the primary purpose of this analysis is to understand whether overworked providers are more or less likely to prescribe medication to a patient. In order to get a better understanding of wait time and whether it has any relationship to various outcomes in care, I include it as the key independent variable for all three outcomes previously discussed.

I use the wait time recorded in the surveys as a proxy for whether the emergency department is under high patient demand (overworked) or not. Patients who had to wait longer than the average are considered to be seen by overworked EDs, whereas patients seen earlier than the average wait time are not. The method I choose to break up and analyze wait time is in quartiles, therefore each respective category of wait time has an equal share of 25% of the total observations. This allows me to analyze differences in various wait times, as well as easily address my original goal to understand if longer than average wait times have a significant relationship to any of my outcomes. I proxy longer wait times by looking at patients seen in the 3rd and 4th quartiles of wait time as seen in Table 4.

Table 4. Key Independent Variable, Wait Time Summary

Wait Time Category	Waiting time to see a provider (MD/DO/PA/NP) in minutes. Median (Interquartile Range)				
1st Quartile	3 (5) minutes				
2nd Quartile	14 (6) minutes				
3rd Quartile	30 (13) minutes				
4th Quartile	84 (68) minutes				
Overall	20 (39) minutes				
Variable	**Observations**	**Mean**	**Std. Dev.**	**Min**	**Max**
Wait Time	98,451	41.733	71.975	0	1,440

My intent with wait time is to analyze the entire dataset of observations (98,451 total observations) in a categorized wait time methodology. This method allows me to categorize wait times in the primary quartiles in which they fall (1st Quartile 0–25%, 2nd Quartile 25–50%, 3rd Quartile 50–75%, and 4th Quartile 75–100% of observations). I believe this method is necessary in order to capture the true effect (if any) that various wait times have on patients for each respective outcome variable. As seen in the summary statistics, wait times are very skewed to the right with some patients waiting for a very long time before seeing a provider. The categorical variable has two advantages over the continuous variable: (1) it can capture potential nonlinear relationship between wait time and the outcomes; (2) it minimizes potential estimation problems due to outlier.

3. Control Variables

The wide range of control variables used in this study help me identify potential determinants of doctors prescribing a drug, outside of my key independent variable wait time. The following paragraphs cover main categories I use in my research: demographic information, payment method, clinical characteristics, and years. The summary statistics for all of these control variables are in Table 5.

a. Demographic Information

The tables in Chapter IV reflect the four types of models run for each respective outcome variable, with demographic information being added in Models 2, 3, and 4. The category of demographic information includes the following: age, age-squared, female, White (reference group), Black, Asian, Race-Other, and Hispanic. I consider these variables to be very helpful due to the fact that most of the studies I reviewed in my literature review also include them.

Age and age-squared are helpful in my analysis for all three outcomes because it gives me insight into how significant age affects each outcome. For example, does aging greatly increase the likelihood a patient will receive a medication or be given an IV? Additionally, including patient's sex is standard practice for studies similar to mine, and is helpful for comparison purposes. Recalling an earlier question I posed in the literature review, if females are more likely to visit physicians are they also more likely to receive a medication, receive a non-prescription drug, and/or be given an IV when compared to males? I answer this question based on my results in Chapter IV.

I also include race and ethnicity since it appears to be a standard practice based on the results of my literature review. My race variables include: White, Black, Asian, and Race-Other. The first three are self-explanatory, if the patient answered yes to any of the three questions (White, Black, or Asian) then the observation would record one single race. If the patient responded with any of the following they are put into the Race-Other variable: American Indian/Alaska Native (AIAN), Native Hawaiian/Other Pacific Islander (NHOPI), more than one race reported, or if the patient left it blank.

b. Payment Method

As seen in Chapter IV, I add payment method to Models 3 and 4. I include payment method to analyze whether any relationship exists between patients' payment method and my outcome variables. I create indicator variables for the different types of payment methods used. The reference group for this variable is any patient who used private insurance. The remaining payment method for a patient are as follows: self-pay (patient paid out of pocket), Medicare, Medicaid or CHIP, or other payment method. The last category of others includes the following: worker's compensation insurance, no charge to the patient, charity, or unknown.

c. Clinical Characteristics

I add clinical characteristics in Model 4 for each respective outcome. Clinical characteristics include indicators for the following: if the patient was seen in the last 72 hours, patient arrived by ambulance (a rough proxy for severity of illness), patient reports an experience of severe pain (pain scale > 5 on a scale 1–10), a binary indicator capturing unknown or missing pain scale (since over 1/3 of patients have missing information on pain scale), patient reporting heart or chest pain (not heartburn), and patients reporting pain and fever. The primary goal of these characteristic is to help understand any relationship of a pain or symptom that patients arrive to the ED with, and how they affect the outcomes in my models.

All of the variables in this section are captured in a binary fashion for regression analysis. For example, if the patient was seen in the ED within the last 72 hours, arrived by an ambulance, and reports a pain scale greater than 5 on a 10-point scale, the value in the dataset would be =1. Additionally, with respect to how patients filled out their pain scale when they arrived at the ED, any patient that left it blank or had an unknown response are put into a separate variable for my analysis (pain scale unknown / left blank).

There are a number of ways to capture various types of symptoms in this dataset, but I choose to create two new variables to analyze specific traits. These included the following two variables: 1) heart or chest pain (not heartburn); and 2) symptoms of pain and fever. My intent is to understand whether these types of specific ailments, present at patients' arrival to the ED, could potentially have a relationship to being receiving a medication, receiving a non-prescription drug, and/or being given an IV. I believe these types of symptoms are relatively common and my data had sufficient observations of these traits so they are worth analyzing with my three outcome variables.

d. Year

I have included dummy variables for years in all four models (Model 1, 2, 3, and 4). The reference group is year 2012, so each respective following year is compared to 2012. The purpose of including these variables is to capture macro-trends that may be present over time. For example, are ED's more or less likely to prescribe a medication, or a non-prescription drug, or give a patient an IV in 2016 vs 2012? This information should be useful in understanding the macro-trends that are present in the U.S. healthcare system. If prescribing rates are increasing over time it could lead to future research into potential unknown drivers of this increase over time.

C. METHODS

1. Logistic Regression Model

I use a quantitative approach to analyze my data, through logistic regression analysis (LOGIT) with odds ratio (OR) to represent the effects of my key indicator and control variables on my three outcome variables. The primary purpose of using this type of model is to evaluate variables that increase or decrease the likelihood of a patient receiving a medication for Outcome #1. I also study two other outcomes, namely Outcome #2 indicator for a non-prescription drug being received and #3 indicator for whether an IV was given, both of which use the same LOGIT OR regression for analysis.

I apply the same process and methodology for all three outcomes, as I analyze them using the same four models (Model 1, 2, 3, and 4). As seen in the outcome tables in Chapter IV, Model 1 only includes my key independent variable of wait time, which is in quartile categories and year indicators to capture macro-trend. This is the basic analysis to see the overall (net) relationship between wait time and my three outcome variables.

The next step for Model 2 is to add in the demographic information: age, age-squared, female, White, Black, Asian, Race-Other, and Hispanic. The intent here is to review basic demographic information to see if any of them have a significant relationship to my outcomes variables. It also allows a comparison to Model 1 to see if the relationship between wait time and medication outcomes changed significantly when taking into account patient demographics. This model helps to establish any baseline significance of various demographic traits which I can then compare to as I add in additional variables in Models 3 and 4.

My next step for Model 3 includes variables from the previous two models, but it also adds in payment methods. The patient's payment method is an interesting variable to observe between all three outcomes as it paints a picture of the type of patient seeking various types of care. For example, do Medicare patients have a statistically significant relationship indicating they are more likely to receive an IV, but not a medication or a non-prescription drug? The results of Model 3 should be of keen interest to the U.S. government as the primary financial burden falls upon the government to fund Medicare and Medicaid programs. Understanding trends within the ED and its respective patients could lead to future cost-saving initiatives.

The fourth and final model for all three outcomes is Model 4, and it builds on the prior models by adding in clinical characteristics, to see their effects on my outcome variables. Once again, finding trends between the various outcomes could help ED staff better understand their patients. For example, if a patient arrives by ambulance are they more likely to receive an IV, but less likely to be prescribed any drug/medication? If so, why is that the case? This final model does help me to understand how certain characteristics, usually present as the patient is admitted to the ED, could lead to higher or lower likelihoods of a patient receiving a medication, receiving a non-prescription drug, or given an IV.

D. SUMMARY

The primary focus of my research is to analyze any determinant that can increase or decrease the probability of a patient receiving a medication, receiving a non-prescription drug, and/or being given an IV. Due to this focus I believe logistic regressions in odds ratio (LOGIT OR) is the appropriate model in this context. Data used from NHAMCS come as individual years but I want to analyze potential determinants based on a longer time horizon, hence the 5 years of combined data. It is possible to analyze individual years for outcomes, but I believe I have captured macro-trends over time by including dummy variables for year, omitting 2012, and focusing on whether 2013, 2014, 2015, and 2016 had a higher or lower probability of prescribing over 2012. The results are discussed in Chapter IV.

IV. RESULTS

This chapter discusses the results from the four models for each respective outcome described in Chapter III. The results for these logit regressions are presented in table format for each respective outcome, starting with medications, then non-prescriptions, then IV fluids. I conclude this chapter with a summary of key takeaways.

A. DESCRIPTIVE STATISTICS

The summary table of descriptive statistics can be seen in Table 5 starting with the first column that summarizes the entire sample size of 98,541 observations. Going from left to right, I have included 3 categories of summary statistics: Whole Sample, Patient Without a Medication, and Patient with a Prescription. There are a total of 18,041 observations in the patient without a prescription column. Consequently, there are a total of 80,410 observations in the patient with a prescription column. Meaning, patients that received any type of medication make up 81.7% of the whole sample, whereas patients that do not receive any medication make up the remaining 18.3% of the whole sample. This indicates that a high majority of patients receive a medication during their visit to the ED.

Table 5. Descriptive Statistics (Summary Table)

	Whole Sample		Patient does not receive a Medication ("No" response)		Patient does receive a Medication ("Yes" response)	
Variable Description	Mean	Std.Dev.	Mean	Std.Dev.	Mean	Std.Dev.
Outcome						
Patient Received a Medication?	.817	.387	N/A	N/A	N/A	N/A
Patient Received a Non-Prescription Drug?	.533	.498	N/A	N/A	.653	.476
Patient Given an IV?	.264	.441	.091	.288	.303	.459
Demographic Info						
Age	37.970	24.11	36.406	26.061	38.321	23.636
Female	.550	.498	.529	.499	.554	.497
White	.602	.490	.605	.489	.601	.490
Black	.198	.399	.190	.392	.200	.400
Asian	.017	.131	.020	.14	.017	.128
Race - Other	.183	.387	.185	.388	.182	.386
Hispanic	.162	.368	.169	.375	.160	.367
Payment Method						
Private Insurance	.352	.478	.347	.476	.353	.478
Self-Pay	.135	.342	.116	.321	.140	.347
Medicare	.187	.390	.197	.398	.185	.388
Medicaid or CHIP	.350	.477	.358	.479	.348	.476
Pay - Other: Workers Comp, No Charge, Charity, Unknown	.115	.320	.121	.326	.114	.318
Clinical Characteristics						
Seen in Last 72 Hours	.039	.194	.047	.211	.037	.189
Patient Arrived by Ambulance	.157	.364	.172	.377	.154	.361
Experience Severe Pain (pain scale >5)	.357	.479	.206	.404	.391	.488
Pain Scale Unknown / Left Blank	.267	.442	.326	.469	.253	.435
Heart/Chest Pain (not heartburn)	.052	.223	.045	.208	.054	.226
Pain and Fever	.187	.390	.116	.320	.202	.402
Total Observations	98,451		18,041		80,410	

Note: Omitted reference groups include male, White, private insurance, and year 2012 for their respective categories.

1. Whole Sample Descriptive Statistics

One of my main takeaways from the whole sample column is that 81.7% of the patients in my sample population received a medication. If you look at the column which includes all patients that received a medication, 65.3% of them received a non-prescription drug. Lastly, 30.3% of these patients received an IV.

The next interesting statistic that stands out is the mean percentage of patients who received an IV. As seen in Table 5, for patients that do not receive a medication, only 9.1% receive an IV vs 30.3% for those patients that received a medication. This is a large variance, but it is not too alarming since patients that get an IV put in during an ED visit are more likely to receive some kind of medication with it. I would assume that the smaller 9.1% population that received an IV, as shown in the middle column, may have been in the ED for symptoms such as dehydration, where the hydrating effect of an IV is sufficient for purposes of care for that visit. That is just an assumption, but it is worth exploring why those who do not receive a medication appear to be less likely to receive an IV based on my analysis of the descriptive statistics table.

The next takeaway from this table is the age across the three categories. Specifically, when looking at the mean age for patients that do not receive a medication, their age is ~36. Conversely, patients that receive a medication have a mean age of ~38. While they are relatively close in age, the variance of 2 years is somewhat interesting as it could be associated with general changes all adults experience as they get older. Based on these summary statistics, it appears to indicate that generally younger patients may be less likely to receive a medication during their ED visit.

When looking at the clinical characteristics in the descriptive statistics table there are two variables worth discussing. The first one is the pain scale variable for patients that report severe pain (>5). Patients who report this level of pain make up a larger portion among patients who receive a medication totaling 39.1% of this sample, versus 20.6% of the population from patients that do not receive a medication. This shows me that a larger portion of patients that receive a medication come in reporting higher levels of pain versus those patients that do not receive any medication. Looking at the next pain scale variable are those patients that left it blank or pain scale is unknown. For patients that do not receive a medication, 32.6% of this sample left pain scale blank or checked unknown, whereas for patients that receive a medication, 25.3% of this sample left pain scale blank or checked unknown. This appears to indicate that patients that end up receiving a medication are more likely to report higher levels of pain. This appears to be true since 39.1% of patients who receive a medication also reported high levels of pain, versus 20.6% of the sample of patients who do not receive a medication. Additionally, it could indicate that patients that leave pain scale blank or unknown are not seeking medication during their ED visit.

2. Macro-Trends in Wait time and Medication Received

In this section I discuss macro-trends for the following: (1) wait time trend (2012-2016); and (2) percentage of patients that receive a medication and the percentage of patients that receive a non-prescription drug. Figure 1 represents the wait time trend over the five years of data. The main takeaway for this macro-trend is that wait time does appear to be decreasing over time, a good indication that EDs are already finding ways to become more efficient in decreasing the mean and median wait time a patient has prior to being seen. There is a slight uptick in wait time from 2012 to 2013, but it decreases in the following years.

Figure 1. Mean and Median Wait Time Trend (2012–2016, in minutes)

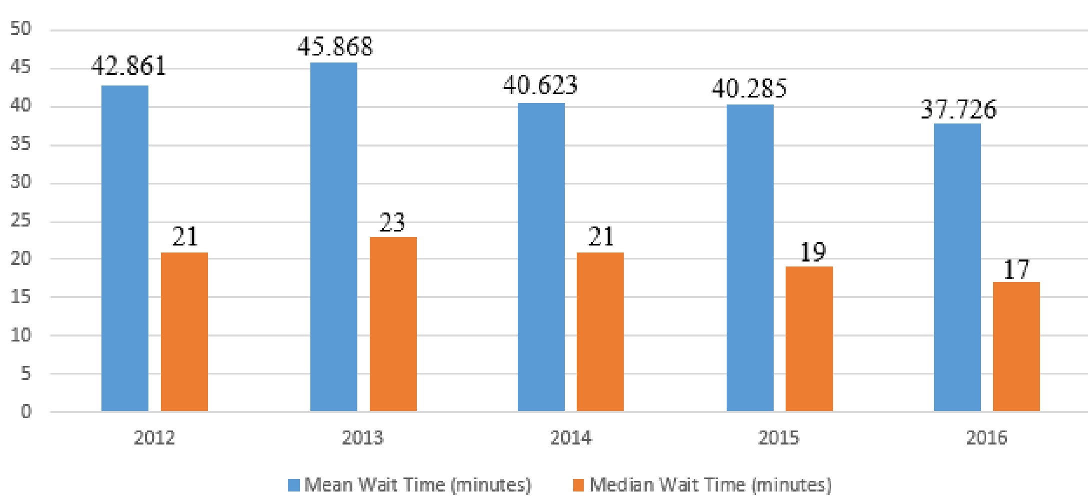
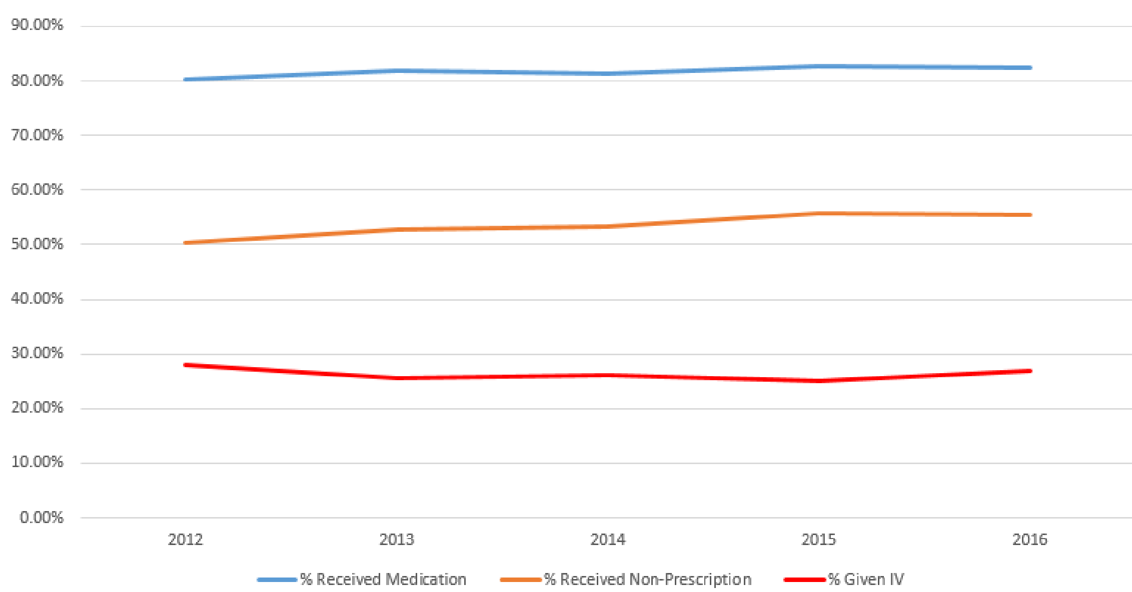


Figure 2 has two lines reflecting the macro-trends over the years 2012–2016 with respect to the percentage of patients that receive: (1) any medication; (2) a non-prescription drug; and (3) an IV. The trend for Outcome #1 and #2 increases, meaning a higher percentage of patients receive a medication and a non-prescription drug, respectively. Conversely, when looking at Outcome #3 there is a slight decrease in the percentage of patients that receive an IV, most noticeably in years 2012 and 2015 when ~25% of patients received an IV vs 28% in 2012. In my multivariate results section, I discuss the macro-trends of all three outcome variables in greater detail within the four models. Figure 2 is a snapshot of the summary statistics results for Outcome #1, Outcome #2, and Outcome #3.

Figure 2. Percentage (%) of Patients Receiving any Medication and a Non-prescription Drug



B. MULTIVARIATE RESULTS

The three outcomes described in my research are analyzed and presented separately in the following sections. All three outcome variables include the same four models discussed in Chapter III. Model 1 includes the quartile categories for wait time, Model 2 adds demographic information, Model 3 adds in payment method, and Model 4 adds in clinical characteristics. All four models include my key independent variable for wait time (in quartiles) as well as the year variables to compare macro-trends in the three outcomes.

1. Outcome #1 – Probability of Receiving a Medication

Table 6 presents the findings from the four models for Outcome #1 (medication) an indicator variable for any medication received by a patient. The key independent variable wait time, measured as a series of indicator variables for each quartile of the wait time distribution (1^{st}, 2^{nd}, 3^{rd}, and 4^{th} quartiles) is insignificant for Models 1, 2, and 3 but becomes statistically significant in Model 4. The 4^{th} quartile of wait time in Model 4 shows patients who waited longer than 48 minutes have lower odds to receive a medication (by 6%), after controlling for patient's demographic, insurance, and clinical characteristics. Conversely, the remaining categories of wait time and remaining three models do not show any relationship between wait time and a patient receiving a medication during a visit to the ED. Below I discuss some of the other main takeaways from this regression as there are statistically significant variables that appear to have a relationship with Outcome #1 (medication).

Table 6. Outcome #1: Logistic Regression (Odds Ratio) Probability of Receiving a Medication

Variable	**(Model 1)**	**(Model 2)**	**(Model 3)**	**(Model 4)**
Wait Time (minutes)				
1^{st} Quartile (0-8)	1.000 (.)	1.000 (.)	1.000 (.)	1.000 (.)
2^{nd} Quartile (9-20)	1.040 (0.024)	1.045 (0.025)	1.043 (0.025)	1.020 (0.024)
3^{rd} Quartile (21-47)	0.993 (0.023)	0.997 (0.023)	0.993 (0.023)	0.965 (0.023)
4^{th} Quartile (48-1,440)	1.000 (0.023)	0.985 (0.023)	0.981 (0.023)	0.940^{**} (0.022)
Demographic Information				
Age		1.031^{***} (0.001)	1.031^{***} (0.001)	1.020^{***} (0.001)
Demographic Information (cont.)				

Variable	**(Model 1)**	**(Model 2)**	**(Model 3)**	**(Model 4)**
Age-Squared		1.000^{***} (0.000)	1.000^{***} (0.000)	1.000^{***} (0.000)
Female		1.091^{***} (0.018)	1.091^{***} (0.018)	1.017 (0.017)
White		1.000 (.)	1.000 (.)	1.000 (.)
Black		1.050^{*} (0.023)	1.047^{*} (0.023)	1.062^{**} (0.024)
Asian		0.870^{*} (0.053)	0.873^{*} (0.053)	0.913 (0.056)
Race - Other		1.016 (0.023)	1.029 (0.024)	1.054^{*} (0.025)
Hispanic		0.999 (0.024)	0.992 (0.024)	0.977 (0.023)
Payment Method				
Private Insurance		1.000 (.)	1.000 (.)	1.000 (.)
Self-Pay			1.137^{***} (0.032)	1.097^{***} (0.031)
Medicare			0.939^{*} (0.028)	0.944 (0.029)
Medicaid or CHIP			1.024 (0.021)	1.013 (0.021)
Pay-Other			0.906^{***} (0.026)	0.908^{***} (0.026)
Clinical Characteristics				
Seen in Last 72 Hours				0.760^{***} (0.031)
Patient Arrived by Ambulance				0.924^{***} (0.022)
Experience Severe Pain (pain scale >5)				2.168^{***} (0.048)
Pain Scale Unknown or Left Blank				1.007 (0.020)
Heart/Chest Pain (not heartburn)				1.180^{***} (0.047)
Pain and Fever				1.776^{***} (0.045)
Year				
2012	1.000 (.)	1.000 (.)	1.000 (.)	1.000 (.)
Year (cont.)				

Variable	(Model 1)	(Model 2)	(Model 3)	(Model 4)
2013	1.099*** (0.027)	1.101*** (0.027)	1.100*** (0.027)	1.102*** (0.027)
2014	1.072** (0.026)	1.078** (0.026)	1.077** (0.026)	1.080** (0.027)
2015	1.167*** (0.030)	1.174*** (0.030)	1.178*** (0.031)	1.157*** (0.031)
2016	1.146*** (0.030)	1.146*** (0.030)	1.149*** (0.030)	1.161*** (0.031)
Observations	98,451	98,451	98,451	98,451

Note: Omitted reference groups include male, White, private insurance, and year 2012 for their respective categories.

Exponentiated coefficients; Standard errors in parentheses

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

a. Demographic Information Results for Outcome #1 (Medication)

The demographic information variables are discussed in this section and the significant relationships these demographic variables have with Outcome #1 (medication), seen in Table 6. There are mixed effects for Models 2, 3, and 4 for the following demographic information variables: age, female, Black, Asian, and Race-Other. The only variable in this outcome that shows no relationship to a patient receiving a medication is Hispanic. Additionally, age, Black, and Race-Other are the only variables that appear in Model 4. The variables that show significant relationships across multiple models are reviewed next.

The age of a patient shows significance across Models 2, 3, and 4. The results indicate that older patients are more likely to receive medication but the rate of increase is not linear. The effect appears to be minimal, but this is expected based on similar findings in previous research discussed in the literature review section mentioning older individuals are more likely to be prescribed opioid drugs.

An indicator for female patients also has mixed effects. For example, in Model 2 and 3, we can see that female patients are 1.091 times more likely to receive a medication versus males. What is interesting is that there appears to be no significance in Model 4 for females when the clinical characteristics that captures experiences of pain are added into the model. Still, this is an interesting finding as the literature review suggests females have higher visit rates, and the descriptive summary statistics (Table 5) also shows females receive more medications in the whole sample population. The regression suggests that the higher probability of female receiving medication in the literature is correlated with differences in pain experiences by gender.

The next sub-category of variables I discuss are the race and ethnicity variables. I previously mentioned that Hispanic shows no significant relationship to medication, but there is a significant relationship for Black, Asian, and Race-Other. For patients that report being Black, all three models show they are 1.047-1.062 times more likely to receive a medication. Conversely, patients that report being Asian have lower odds to receive a medication (by 12.7-13%) in Models 2 and 3, with no significance in Model 4. The final variable in this section Race-Other shows a significant relationship in Model 4, reflecting these patients are 1.054 times more likely to receive a medication.

b. Payment Method Results for Outcome #1 (Medication)

The payment method variables are discussed next for Models 3 and 4 on Outcome #1. The results from these Models show that patients that are self-pay, Medicare, and pay-other have a statistically significant relationship with Outcome #1. The main takeaway is that Medicare is only significant in Model 3, showing lower odds to receive a medication (by 6.1%) compared to patients with private insurance, but is insignificant in Model 4. The remaining two significant variables (self-pay and pay-other) are discussed next.

The interesting results for self-pay patients from Models 3 and 4 indicate these patients are 1.097-1.137 times more likely to receive a medication, when compared to patients with private insurance. This means that a patient that pays for their healthcare needs out of their own pocket are more likely to receive medication than a patient with private insurance. This could be due to the fact that these self-pay patients are more selective about when they go to the ED, so when they do they are seeking a medication to take care of their respective symptoms. This is just my hypothesis, but worth considering in future research.

The next category of pay is pay-other, which includes all observations of patients that use workers' compensation insurance, no charge situations, charity, or unknown payment method. These patients, when compared to private insurance patients, have lower odds to receive a medication (by 9.2-9.4%) during their visit to the ED.

c. Clinical Characteristics Results for Outcome # 1 (Medication)

The clinical characteristics variables are discussed next for Model 4 on Outcome #1. The results from this model are very interesting in my opinion because it shows the following variables to have a significant relationship to a medication being received by a patient: seen in the last 72 hours, patient arrived by ambulance, experience severe pain (>5), heath/chest pain (not heartburn), and pain and fever symptoms.

The first variable is whether a patient has been seen in that respective ED within the last 72 hours, and if the patient responded with yes they have lower odds to receiving a medication (by 24%). In addition to this variable if the patient arrived by ambulance, they also have lower odds to receive a medication (by 7.6%). Both of these findings are interesting but it is unclear to me why this would be the case. Normally, I would assume that a patient with repeat visits to the ED would be doing so due to ongoing issues that require some form of treatment, like a medication. Or, these repeat visits could be due to patients returning with similar symptoms and providers see an original prescription and instruct patients to continue with their original medication. Additionally, I think whenever a patient arrives by ambulance they too would be in higher need of a medication. But, the results of my analysis prove otherwise.

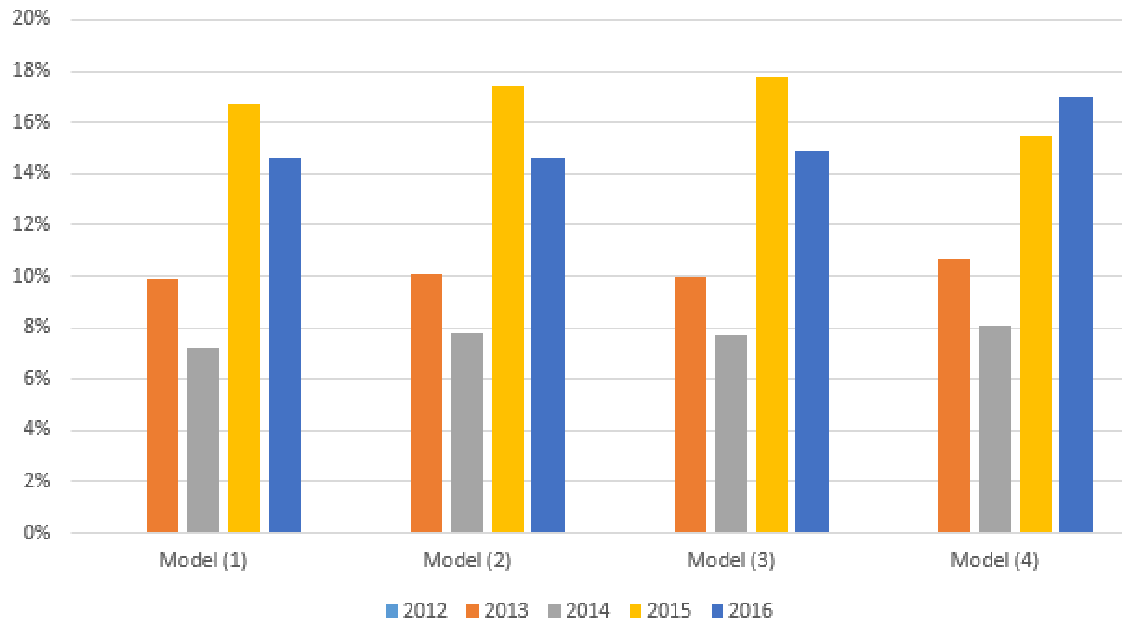
This next variable is very interesting; it includes patients that reported experiencing severe levels of pain (>5 on a 10-point scale). A patient that marks a pain scale higher than 5 is 2.17 times more likely to receive a medication. I think the obvious takeaway from this finding is that patients in severe levels of pain are most likely seeking care at the ED to alleviate the symptoms, and are legitimately in need of medication. It is interesting to see how these results compare to Outcome #2 where I analyze this same variable and its relationship to non-prescription drugs. Patients that left a blank or unknown response to pain scale when they entered the ED do not appear to show any significant relationship with Outcome #1.

The next two variables are symptomatic behaviors of patients: those reporting heart/chest pain (not heartburn) and separately those reporting pain and fever. Both variables indicate a higher likelihood of a patient receiving a medication. For those patients reporting heart/chest pain (not heartburn) they are 1.18 times more likely to receive a medication. For patients reporting pain and fever, they are 1.776 times more likely to receive a medication. I believe these results are similar to patients reporting severe levels of pain, where they are in some kind of imminent need of aid to alleviate their respective symptoms and seeking medications at the ED appears to be their solution.

d. Macro-Trends in Years for Outcome #1 (Medication)

The final observation I analyze in Table 6 are the results shown in the prescribing patterns from 2012 to 2016. In the table, 2012 is the omitted year group, so all subsequent years show an increased likelihood of a medication being received. This means that over time, EDs appear to be more likely to prescribe a medication when compared to previous years. But, it must be noted that the trend does not appear to consistently increase as 2014 appears to be lower than 2013, and 2016 is lower in models 1, 2, and 3 when compared to 2015. Figure 3 shows the trend for 2013–2016, when compared to the base year 2012.

Figure 3. Outcome #1 Probability of Receiving a Medication Macro-Trend 2013–2016 (2012 is reference year)



When comparing the latter two years (2015 and 2016) to the reference year 2012, a patient is 114.6-1.178 times more likely to receive a medication in the latter years. This is an interesting finding as it appears to suggest that over time, ED's are more likely and patients are more likely to receive a medication, assuming they have comparable patient population (since Model 4 controls for underlying patient characteristics). This could be due to varying factors such as an aging population, affects from the Affordable Care Act (ACA), or defensive medicine by providers. These findings warrant additional research on prescribing rates over time to identify causes and solutions to slow the trend.

2. Outcome #2 – Probability of Receiving a Non-prescription Drug

Table 7 presents the findings from the four models for my second outcome variable an indicator variable for whether the patient received a non-prescription drug. The key independent variable wait time (broken into quartiles) is now statistically significant in the 3rd quartile (21-47 minutes) in all four models. The results for the 3rd quartile of wait time shows that a patient waiting 21–47 minutes have lower odds to receiving a non-prescription drug (by 3.8-4.2%) when compared to the reference category quartile 1 (patients who wait 0–8 minutes). These findings suggest that as patients wait longer (when compared to the 1st quartile of wait time), the likelihood of them receiving a non-prescription drug decreases, at least for the 3rd quartile of wait time.

Table 7. Outcome #2: Logistic Regression (Odds Ratio) Probability of Receiving a Non-prescription Drug

Variable	**(Model 1)**	**(Model 2)**	**(Model 3)**	**(Model4)**
Wait Time (minutes)				
1st Quartile (0-8)	1.000 (.)	1.000 (.)	1.000 (.)	1.000 (.)
2nd Quartile (9-20)	0.967 (0.018)	0.967 (0.018)	0.967 (0.018)	0.965 (0.018)
3rd Quartile (21-47)	0.962* (0.017)	0.962* (0.017)	0.962* (0.017)	0.965* (0.018)
4th Quartile (48-1,440)	0.986 (0.018)	0.975 (0.018)	0.975 (0.018)	0.969 (0.018)
Demographic Information				
Age		1.012*** (0.001)	1.012*** (0.001)	1.003** (0.001)
Age-Squared		1.000*** (0.000)	1.000*** (0.000)	1.000* (0.000)
Female		1.085*** (0.014)	1.085*** (0.014)	1.028* (0.014)
White		1.000 (.)	1.000 (.)	1.000 (.)
Black		1.010 (0.017)	1.011 (0.017)	1.017 (0.018)
Asian		1.150** (0.057)	1.148** (0.057)	1.189*** (0.060)
Race - Other		1.094*** (0.019)	1.096*** (0.020)	1.116*** (0.020)
Hispanic		1.113*** (0.021)	1.111*** (0.021)	1.096*** (0.021)
Payment Method				
Private Insurance		1.000 (.)	1.000 (.)	1.000 (.)

Variable	**(Model 1)**	**(Model 2)**	**(Model 3)**	**(Model4)**
Payment Method (cont.)				
Self-Pay			0.997 (0.020)	0.973 (0.020)
Medicare			0.951* (0.022)	0.942* (0.022)
Medicaid or CHIP			0.996 (0.016)	0.982 (0.016)
Other - Pay			0.965 (0.022)	0.966 (0.022)
Clinical Characteristics				
Seen in Last 72 Hours				0.819*** (0.027)
Patient Arrived by Ambulance				1.170*** (0.022)
Experience Severe Pain (pain scale >5)				1.608*** (0.025)
Pain Scale Unknown or Left Blank				0.980 (0.016)
Heart/Chest Pain (not heartburn)				1.686*** (0.051)
Pain and Fever				1.744*** (0.031)
Year				
2012	1.000 (.)	1.000 (.)	1.000 (.)	1.000 (.)
2013	1.100*** (0.021)	1.103*** (0.021)	1.104*** (0.021)	1.111*** (0.021)
2014	1.123*** (0.021)	1.124*** (0.022)	1.124*** (0.022)	1.131*** (0.022)
2015	1.230*** (0.025)	1.234*** (0.025)	1.234*** (0.025)	1.224*** (0.025)
2016	1.217*** (0.025)	1.218*** (0.025)	1.218*** (0.025)	1.242*** (0.026)
Observations	98,451	98,451	98,451	98,451

Note: Omitted reference groups include male, White, private insurance, and year 2012 for their respective categories.

Exponentiated coefficients; Standard errors in parentheses

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

a. Demographic Information Results for Outcome #2 (Non-prescription)

The demographic information variables are discussed next for all three models on Outcome #2. Similar to Outcome #1, there are mixed results across Models 2, 3, and 4 for the following demographic variables: age, female, Asian, and Race-Other. Notably, the race variable Black is not statistically significant in any of the models for Outcome #2, whereas it is in Outcome #1. Also, previously Hispanic had no relationship to Outcome #1, but it appears highly significant in the models from Outcome #2.

An indicator for female patients also has mixed effects in Outcome #2, similar to findings in Outcome #1. In Models 2, 3, and 4 the regression suggest a female patient has a higher probability of receiving a non-prescription drug. This shows that female patients are 1.028-1.085 times more likely to be prescribed a medication vs males, the same or similar results as Outcome #1. Model 4 is the only variance from Outcome #1 as it previously showed no relationship when controlling clinical characteristics, but it does show a relationship in Outcome #2. These results continue to indicate that females do have a slightly higher likelihood of receiving any medication and/or a non-prescription drug, compared to males.

The next sub-category of variables includes race and ethnicity. In Outcome #1 a Hispanic patient does not show any significant relationship, but that is not true for the models in Outcome #2. In fact, a Hispanic patient is 1.096-1.113 times more likely to receive a non-prescription drug. These findings are interesting because it appears to indicate the possibility that Hispanic patients are more likely to be seen in the ED for a non-prescription drug need.

In almost all models, an Asian patient is 1.15-1.189 times more likely to receive a non-prescription drug when compared to White patients. This is in direct contrast to Outcome #1 where they have lower odds to receive a medication. Similar to the Hispanic variable, this could indicate that more people of Asian race are likely to seek non-prescription drug needs from the ED. Similar results are seen with patients of other races, who are 1.094-1.116 times more likely to receive a non-prescription drug when compared to White patients.

b. Payment Method Results for Outcome #2 (Non-prescription)

The payment method variables are discussed next for Models 3 and 4 on Outcome #2. The results from these models show that Medicare patients have lower odds to receive non-prescription drug compared to privately insured patients (by 4.9-5.8%). In the previous sections for Outcome #1 patients who use self-pay and pay-other show a significant relationship to receive any medication, but they have similar odds of receiving non-prescription drugs as privately insured patients.

c. Clinical Characteristics Results for Outcome #2 (Non-prescription)

The clinical characteristics variables are discussed next for Model 4 on Outcome #2. Similar to the results from Outcome #1, the results of the models run with Outcome #2 show the same variables have a significant relationship with receiving a non-prescription drug: seen in the last 72 hours, patient arrived by ambulance, experience severe pain (>5), heath/chest pain (not heartburn), and pain and fever symptoms.

The first variable is whether a patient has been seen in that respective ED within the last 72 hours, and in this outcome model these patients have lower odds to receive a non-prescription drug (by 18.1%). This is in comparison to the lower odds in Outcome #1 (by 24%). If the patient arrived by ambulance, they are 1.17 times more likely to be receive a non-prescription drug. This is contrary to Outcome #1's results indicating patients that arrive by ambulance have lower odds of receiving a medication (by 7.6%). These results are interesting because the likelihood of a patient being prescribed any drug versus a non-prescription drug goes in the opposite direction if they arrive by ambulance. Meaning, if a patient arrives by ambulance, I would predict that they would be more likely to leave the ED with a non-prescription drug. This could indicate that the majority of patients that arrive by ambulance are in higher demand of non-prescription drugs. It is unclear why that is the case, but it is something worth considering in future research.

This next variable looks at a patient that reports experiencing severe levels of pain (>5 on a 10-point scale). Similar to Outcome #1, patients that report these higher levels of pain are also more likely to receive a non-prescription drug. While the likelihood in this outcome is lower than Outcome #1's results, it is still high overall as these patients are

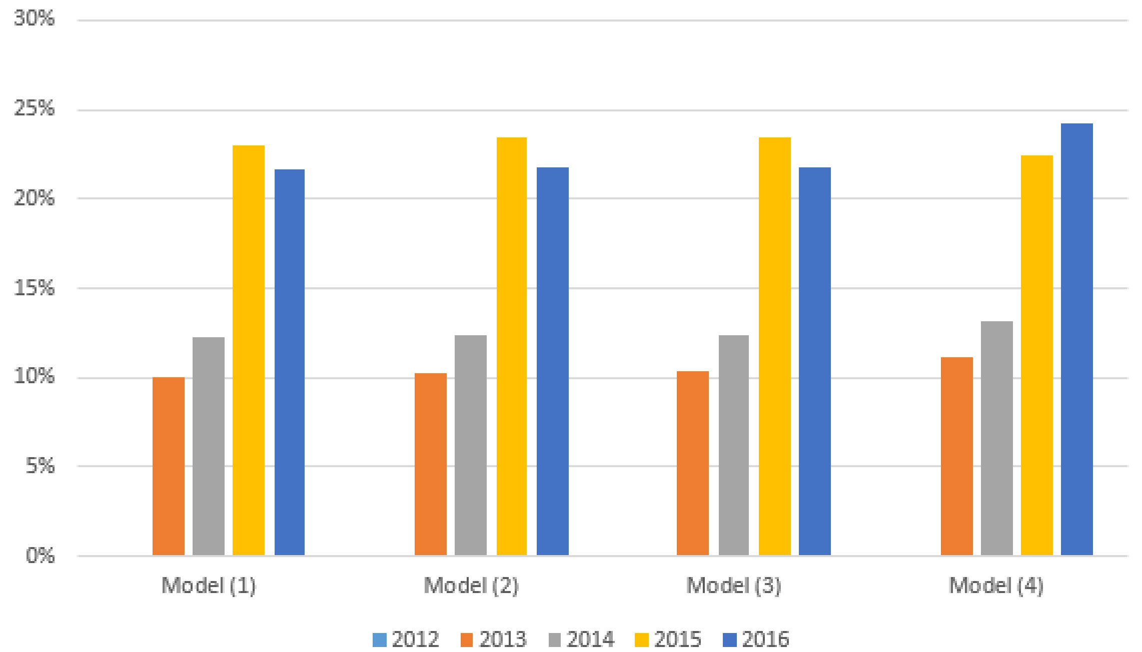
1.608 times more likely to receive a non-prescription drug. It makes sense to me that patients that come in to the ED with high or severe levels of pain are more likely to receive some kind of drug intervention. I assume in most cases a patient presenting with high levels of pain likely leave the ED with a Tylenol or Motrin like drug. A patient that left a blank or unknown response to pain scale when they entered the ED do not appear to show any significant relationship to Outcome #2, similar to Outcome #1.

Patients reporting heart/chest pain (not heartburn) are 1.686 times more likely to receive a non-prescription drug, compared to Outcome #1 where they are only 1.18 times more likely to receive any medication. This suggests the possibility that more patients with heart or chest pain symptoms have higher need of non-prescription drug means, or these non-prescriptions could be used in higher frequency for other reasons. Another possible reason for some patients could be they need surgery, not a medication. For patients reporting pain and fever, they are 1.744 times more likely to receive a non-prescription drug, similar to Outcome #1's results of (1.776 times more likely). These results, along with Outcome #1's, indicate symptom types do play a role in prescribing behaviors in whether a patient receives any medication and/or a non-prescription drug.

d. Macro-Trends in Years for Outcome #2 (Non-prescription)

The final observation worth analyzing from this table is the results shown in the prescribing patterns from 2012 to 2016. Similar to Outcome #1, 2012 is the omitted year group and there continues to be a trend that each subsequent year has a higher likelihood of a patient receiving a non-prescription drug. There are consistent increases from 2012 to 2013, 2013 to 2014, then 2014 to 2015 where it drops slightly from 2015 to 2016 for all models except Model 4. Figure 4 reflects the increased likelihood of a non-prescription drug being prescribed for each year, and each model.

Figure 4. Outcome #2 Probability of Receiving a Non-prescription Drug Macro-Trend 2013–2016 (2012 is reference year)



The trend for a patient receiving a non-prescription drug increases as seen in year 2016 where a patient is 1.217-1.242 times more likely to receive a non-prescription drug. Outcome #1 and #2 both show an increased likelihood of a patient receiving a medication or a non-prescription drug, a consistent macro-trend in prescribing behaviors over time.

3. Outcome #3 – Probability of an IV Given to Patient (IV)

Table 8 presents the findings of the four models for my third and final Outcome #3 (IV), assessing the likelihood of an IV being given to a patient. I expect the results for these models to vary from the first two outcomes, primarily due to the fact that a patient given an IV is a different intervention than receiving a medication or non-prescription drug like the first two outcomes.

The key independent variable wait time (broken into quartiles) is statistically significant in all four models of this outcome. In all four models, longer wait time (when compared to the 1st quartile 0–8 minutes) is associated with lower likelihoods of an IV being given to a patient. This may be due to the fact that patients that are in most need of an IV are seen immediately, possibly in the 1st quartile of wait time. This might explain why patients who wait longer have lower odds to be given an IV. The range of results for wait time reflects lower odds of being given an IV: by 12.5-19.7% in the 2nd quartile, by 17.5-27.3% in the 3rd quartile, and by 19.6-29.2% in the 4th quartile; when compared to the 1st quartile of wait time. I believe this reflects the nature of the patients' symptoms as they enter the ED, and likely associated with the fact that patients in need of an IV may likely receive it immediately upon arrival, or at least more likely to receive it in the first 8 minutes.

Table 8. Outcome #3: Logistic Regression (Odds Ratio) Probability of an IV Being Given

Variable	**(Model 1)**	**(Model 2)**	**(Model 3)**	**(Model 4)**
Wait Time (minutes)				
1st Quartile (0-8)	1.000 (.)	1.000 (.)	1.000 (.)	1.000 (.)
2nd Quartile (9-20)	0.803*** (0.016)	0.825*** (0.017)	0.826*** (0.017)	0.870*** (0.019)
3rd Quartile (21-47)	0.727*** (0.015)	0.758*** (0.016)	0.762*** (0.016)	0.825*** (0.018)
4th Quartile (48-1,440)	0.708*** (0.014)	0.739*** (0.016)	0.745*** (0.016)	0.804*** (0.018)
Demographic Information				
Age		1.055*** (0.001)	1.056*** (0.001)	1.055*** (0.001)
Age-Squared		1.000*** (0.000)	1.000*** (0.000)	1.000*** (0.000)
Female		1.150*** (0.017)	1.150*** (0.018)	1.108*** (0.017)
White		1.000 (.)	1.000 (.)	1.000 (.)
Black		0.816*** (0.017)	0.841*** (0.017)	0.823*** (0.018)
Asian		1.080 (0.061)	1.106 (0.062)	1.109 (0.064)
Race - Other		0.868*** (0.018)	0.890*** (0.019)	0.876*** (0.019)
Demographic Information (cont.)				

Variable	**(Model 1)**	**(Model 2)**	**(Model 3)**	**(Model 4)**
Hispanic		1.080*** (0.024)	1.113*** (0.025)	1.087*** (0.025)
Payment Method				
Private Insurance		1.000 (.)	1.000 (.)	1.000 (.)
Self-Pay			0.822*** (0.020)	0.816*** (0.021)
Medicare			1.139*** (0.028)	1.100*** (0.028)
Medicaid or CHIP			0.846*** (0.016)	0.807*** (0.015)
Pay - Other			0.846*** (0.022)	0.824*** (0.023)
Clinical Characteristics				
Seen in Last 72 Hours				0.986 (0.039)
Patient Arrived by Ambulance				2.357*** (0.047)
Experience Severe Pain (pain scale >5)				1.041* (0.019)
Pain Scale Unknown or Left Blank				0.980 (0.020)
Heart/Chest Pain (not heartburn)				2.470*** (0.076)
Pain and Fever				2.799*** (0.054)
Year				
2012	1.000 (.)	1.000 (.)	1.000 (.)	1.000 (.)
2013	0.890*** (0.019)	0.895*** (0.020)	0.896*** (0.020)	0.890*** (0.020)
2014	0.909*** (0.020)	0.929** (0.021)	0.930** (0.021)	0.928** (0.021)
2015	0.843*** (0.019)	0.856*** (0.020)	0.854*** (0.020)	0.842*** (0.020)
2016	0.924*** (0.021)	0.931** (0.022)	0.934** (0.022)	0.939** (0.023)
Observations	98,451	98,451	98,451	98,451

Note: Omitted reference groups include male, White, private insurance, and year 2012 for their respective categories.

Exponentiated coefficients; Standard errors in parentheses

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

a. Demographic Information Results for Outcome #3 (IV)

The demographic information variables are discussed next for all three models on Outcome #3. There appears to be mixed results across Model 2, 3, and 4 for the following demographic variables: age, female, Black, Race-Other, and Hispanic. The only variable in this outcome that shows no significant relationship to an IV being given is Asian.

The age of a patient shows significance across Models 2, 3, and 4. The results indicate that as patients get older they are more likely to be given an IV. Even though Outcome #3 looks at a completely different outcome result (medication being given) I find it interesting that the odds ratios of age on Outcome #3 are higher than in Outcome #1.

The indicator variable for female has higher odds of being given an IV in Models 2, 3, and 4. This shows that female patients are 1.108-1.15 times more likely to receive an IV than males. These odds ratios are higher than those reported in Outcome #1 and Outcome #2 models, which is interesting because a female patient has a higher likelihood of being given an IV and a higher likelihood in some previous outcome models of receiving a medication or non-prescription drug. This is something I note in my recommendations section as an area of potential future research to understand why females tend to have higher visit rates to physicians, higher likelihoods of receiving a medication, and in some models higher likelihood of receiving a non-prescription drug.

The next sub-category of variables I discuss are the race and ethnicity variables. The only race that shows no significance is Asian, the first outcome where Asian does not have a significant relationship in any of the models. For a patient that reported being Black, all three models have lower odds of being given an IV when compared to the reference group White (by 15.9-17.7%). Additionally, patients of other races have lower odds of being given an IV (by 11–13.2%) when compared to the reference group. Lastly, Hispanic patients are 1.08-1.113 times more likely to be given an IV during their visit to the ED. It is interesting to see that most race categories (when compared to the reference group) have lower odds to be given an IV, but the Hispanic ethnicity shows a higher likelihood of being given an IV.

b. Payment Method Results for Outcome #3 (IV)

The payment method variables are discussed next for Models 3 and 4 on Outcome #3. The results from these models show that patients that are self-pay, Medicare, Medicaid or CHIP, and pay-other have a statistically significant relationship with Outcome #3. There are a few interesting findings for payment method, the main one being that a Medicare patient is the only variable with an increased likelihood of being given an IV. Medicare patients are 1.1-1.139 times more likely to be given an IV when compared to a private insurance patient. This may be due to the average age, health, and condition of patients that are on Medicare versus private insurance. Either way, this is an interesting finding that could warrant future research, especially if patients of Medicare are experiencing above average demand for an IV. The remaining three significant variables (self-pay, Medicaid or CHIP, and pay-other) are discussed next.

The interesting result for a self-pay patient from Models 3 and 4 shows this type of patient has lower odds of being given an IV when compared to a private insurance patient (by 17.8-18.4%). This means that a patient that pays for their healthcare needs out of their own pocket have lower odds to being given an IV than a patient with private insurance. The remaining two payment methods have nearly similar results as self-pay. Medicaid or CHIP and pay-other patients both have lower odds of being given an IV (by 15.4-19.3% and 15.4-17.6%, respectively), when compared to privately insured patients. It is interesting to see that only Medicare patients have a higher likelihood of being given an IV compared to the other groups.

c. Clinical Characteristics Results for Outcome #3 (IV)

The clinical characteristics variables are discussed next for Model 4 on Outcome #3. The results from this model show the following variables to have a significant relationship to an IV being given: patient arrived by ambulance, experience severe pain (>5), heath/chest pain (not heartburn), and pain and fever symptoms. One thing to note is that the variable seen in the last 72 hours is not statistically significant like it is for Outcome #1 and #2.

A patient that arrived by ambulance is much more likely to be given an IV. In fact, they are 2.357 times more likely to be given an IV. This may not be too surprising considering most patients that arrive via an ambulance probably have a very serious issue, and most EMT's are trained as a first step in triage to administer an IV when necessary. I assume the reason this variable has such a higher likelihood of a patient being given an IV is due to the fact that patients that arrive by ambulance are likely considered to be a higher risk and IV's are given at least as a precautionary measure.

A patient that claims severe levels of pain (>5 on a scale of 10) are only 1.041 times more likely to be given an IV. I would have thought this would have been higher, similar to those patients arriving by an ambulance, but it goes to show that even though a patient comes in with a high pain scale does not necessary mean they are highly likely to receive an IV. Lastly on pain scale, patients that left a blank or unknown response to pain scale when they entered the ED do not appear to show any significant relationship with Outcome #3.

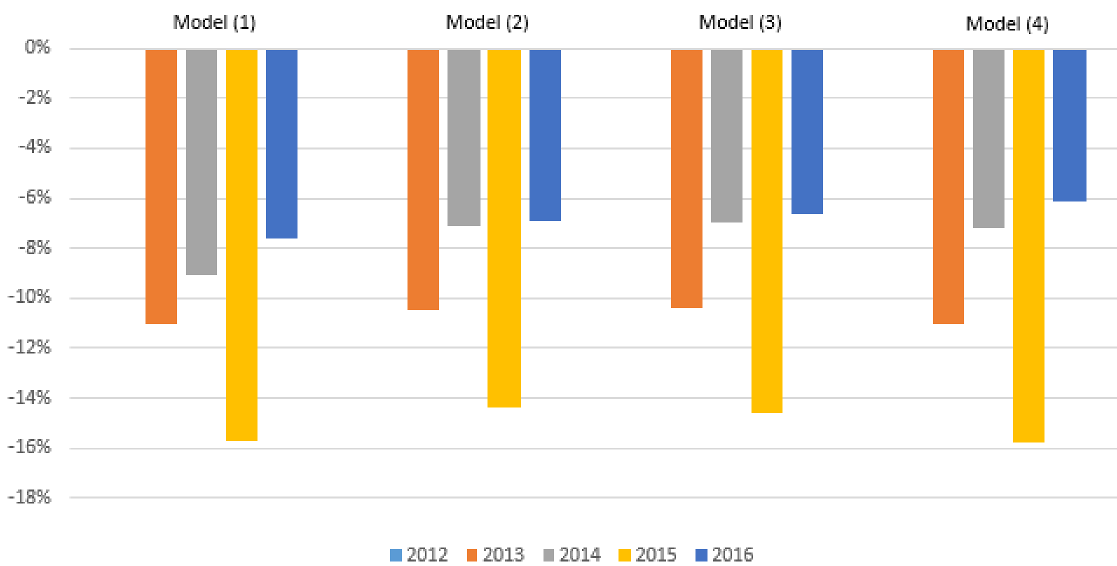
The next two variables are symptomatic behaviors of patients: those reporting heart/chest pain (not heartburn) and separately those reporting pain and fever. Both variables indicate a much higher likelihood of an IV being given. A patient reporting heart/chest pain (not heartburn) are 2.47 times more likely to be given an IV than a patient without such pain. For a patient reporting pain and fever, they are 2.799 times more likely to be given an IV. These are very interesting findings because they both hint toward possible triage procedures that could be in place for certain symptoms reported by patients, especially when they lead to higher likelihoods of an IV being given.

d. Macro-Trends in Years for Outcome #3 (IV Fluids)

The final observation worth analyzing from this table are the results shown in the prescribing patterns from 2012 to 2016. In the table, 2012 is the omitted year group, so all subsequent years show a decreased likelihood of an IV being given. This is in direct contrast to the trends we saw in Outcome #1 and #2, where there is a clear increase in prescribing behavior for ED visits. The results for Outcome #3 shows me that for every year after 2012, there is a lower likelihood of an IV being given. The range of values in

2013 lower odds (by 10.5-11%), in 2014 lower odds (by 7–9.1%), in 2015 lower odds (by 14.4-15.8%), and lastly in 2016 lower odds (by 6.1-7.6%), when compared to 2012. Figure 5 reflects the macro-trend results.

Figure 5. Outcome #3 Probability of an IV Given Macro-Trend 2013–2016 (2012 is reference year)



One possible explanation for the overall decreased likelihood of an IV being given to a patient could be associated with reimbursement rates. Meaning, lower fees paid by insurance providers could theoretically deter EDs from administering them as often. Recall that all payment methods had a lower likelihood of an IV being given, with the exception of Medicare. This is one possible explanation, but again something worth considering in future research.

C. KEY FINDINGS

In this sub-section, I summarize my key findings on wait time, then briefly touch on some interesting control variables that had an effect on the outcomes I analyzed.

The reason I am conducting this research is to understand the effects wait time has on my three outcome variables. In Outcome #1, Model 4 shows me the first sign that there is a statistically significant relationship for patients that have longer wait times. When a patient waited longer than 48 minutes to be seen they have lower odds of receiving a medication (by 6%) seen in Table 6. While this is encouraging, the four models done for Outcome #1 does not show overwhelming evidence of wait time affecting the likelihood of a patient being prescribed any medication. In Outcome #2, wait time shows more signs of having a significant relationship to receiving a non-prescription drug. This is true for all models at the 3rd quartile of time (21-47 minutes) where patients have lower odds of receiving a non-prescription drug (by 3.8-4.2%). This could be due to more serious patients having shorter wait times.

The final outcome looked at is whether a patient has higher or lower odds to being given an IV (Outcome #3). In Outcome #3 wait time has a significant relationship in all four models when predicting the probability of a patient being given an IV. As patient wait time increases beyond the 1st quartile, the likelihood of getting an IV decreases in all four models. Clearly, Outcome #3 (IV) shows the most significant relationship with my key independent variable (wait time).

Based on my literature review and results of my regressions, I agree that age does appear to have a significant relationship to increasing the likelihood of receiving a medication (Outcome #1). I also find a relationship exists between age and my other two outcome variables (Outcome #2 and #3). Sex, race, and ethnicity appear to have mixed effects based on the outcome variable being analyzed. The ones that stand out the most include Models 2 and 3 from Outcome #1 that show females are 1.091 times more likely and Asian patients have lower odds to receiving a medication (by 12.7-13%). Females are also up to 1.085 times more likely to receive a non-prescription drug in Outcome #2.

As previously stated, an Asian patient has lower odds of receiving a medication in Outcome #1, but in Outcome #2 they are 1.148-1.189 times more likely to receive a non-prescription drug. Also, a Hispanic patient has no relationship with Outcome #1, but shows a highly significant relationship in Outcome #2 where they are 1.0896-1.113 times more likely to receive a non-prescription drug. These results appear to indicate that both Asian and Hispanic patients have a higher probability of visiting an ED for non-prescription drug needs.

The next key finding looks at interesting takeaways from payment methods. A Medicare patient has a lower odd of receiving a medication in Model 3 Outcome #1 (by 6.41%). Medicare patients also have lower odds by 4.9-5.8% to receive a non-prescription drug in Outcome #2, seen in Model 3 and 4. This is interesting because it may indicate the type of symptoms or reasons Medicare patients seek care in the ED if they are less likely to be seen for a medication or non-prescription drug. Conversely, Medicare patients are the only ones in Outcome #3 with a higher odd of being given an IV (1.1-1.139 times more likely) compared to a private insurance patient. Again, this finding is interesting due to the fact that Medicare is such a large government funded program and for some reason a Medicare patient has the highest odds of being given an IV.

The clinical characteristics variables show the highest probabilities out of all the variables in my regressions. For example, in Outcome #1 patients experiencing severe pain are 2.168 times more likely to receive a medication, and patients with pain and fever symptoms are 1.776 times more likely. In Outcome #2 these two variables are still good indicators of increasing the likelihood of receiving a non-prescription drug, but so is heart and chest pain (not heartburn) who are 1.686 times more likely. Lastly, for Outcome #3 the variables that stood out the most include: whether the patient arrived by ambulance, patients with heart/chest pain, and those with pain and fever symptoms; all of which are twice as likely to be given an IV (2.357, 2.47, and 2.799 times more likely, respectively).

V. CONCLUSION AND RECOMMENDATIONS

A. CONCLUSION

I started this research project based on personal experiences I have had, both in the military and civilian healthcare systems. I have experienced long wait times myself, and witnessed EDs on multiple occasions that appeared under-staffed and overworked. I use the NHAMCS data to analyze my key indicator variable of wait time and find some interesting key findings as seen in Chapter IV. I am able to find models and outcomes that indicate when wait time increases and decreases the likelihood of an outcome (e.g., patient receiving a medication, receiving a non-prescription drug, or being given an IV). I also identify macro-trends in ED drug prescribing rates that have increased over the years, and a pattern of decreasing likelihood of an IV being given over that same time period.

In my thesis, my goal includes finding answers the to the following questions.

1. Is there an association between patient wait time and probability of receiving medication?

2. What are the other determinants of the medication outcomes?

3. What are the macro-trends over the five years of data of the medication outcomes?

My research evolved from just analyzing wait time against Outcome #1 (medications) to a more robust analysis on the odds of a patient receiving a non-prescription drug (Outcome #2) and the odds of an IV being given (Outcome #3). The findings for my three outcomes and the four models I use within each, suggest there are multiple variables with significant relationships to each respective outcome. These findings have the ability to aid and educate healthcare professionals in understanding how demographic information, patient payment method, and clinical characteristics affect the probability of a patient receiving a medication, a non-prescription drug, and/or being given an IV. My hope is that these same healthcare professionals can extrapolate results from my study pertinent to their area of expertise and find new workflow efficiencies or cost-saving initiatives that can positively influence the healthcare community.

With regard to Outcome #1 (probability of receiving a medication) the data shows that patients who wait longer than 48 minutes (4^{th} quartile) have lower odds to receiving a medication. I also find age, female, Black, and Race-Other patients have an increased likelihood of being prescribed a medication whereas Asian patients have a decreased likelihood in various models for this outcome. When looking at a patient's payment method, those who are self-pay have an increased likelihood of being prescribed a medication whereas those in the pay-other variable have a decreased likelihood. In the clinical characteristics section, a patient experiencing severe pain, with symptoms of heart/chest pain (not heartburn), or pain and fever symptoms are all more likely to be prescribed a medication. Conversely, a patient seen in the last 72 hours, or if they arrived by an ambulance, have lower odds to receiving a medication.

With regard to Outcome #2 (probability of receiving a non-prescription drug) patients in the 3^{rd} quartile of time (21-47 minutes) show a decreased likelihood of receiving a non-prescription drug in all four models. In Model 4 the 3^{rd} quartile of wait time shows lower odds of receiving a non-prescription drug. I also find age, female, Asian, Race-Other, and Hispanic patients have an increased likelihood of receiving a non-prescription drug. When looking at a patient's payment method, a Medicare patient is the only significant relationship in this outcome and they show a decreased likelihood of receiving a non-prescription drug when compared to a private insurance patient. In the clinical characteristics section, a patient that arrived by ambulance, experiences severe pain, has symptoms of heart/chest pain (not heartburn), or symptoms of pain and fever are all more likely to receive a non-prescription drug. Conversely, a patient seen in the last 72 hours has lower odds to receiving a non-prescription drug.

With regard to Outcome #3 (probability of an IV being given) patients in the 2^{nd}, 3^{rd}, and 4^{th} quartiles of wait time all show a decreased probability of being given an IV. I also find age, female, and Hispanic patients have an increased likelihood of being given an IV. Conversely, a Black or a Race-Other patient have lower odds of being given an IV. In payment methods a Medicare patient is the only one with an increased likelihood of being given an IV whereas self-pay, Medicaid or CHIP, and other-pay are all less likely to be given an IV. In the clinical characteristics section, a patient that arrives by ambulance, experiences severe pain, has symptoms of heart/chest pain (not heartburn), or symptoms of pain and fever are all more likely to be given an IV.

B. RECOMMENDATIONS

Moving forward, I recommend researchers take my results and identify a finding that is applicable to their situation and research it further. I find the results of wait time to be most interesting in Outcome #3 due to the decreased likelihood of an IV being given, and with all three quartiles being statistically significant in that outcome. In all three outcomes I also find that clinical characteristics have the largest effects, a finding that is also worth nothing for potential future research. I list some specific recommendations from my other findings below.

1. **Follow-up on the macro-trends seen in 2012–2016 with more recent years of data to see if the trend is still increasing.** In my analysis it is evident that prescribing behaviors for medication and non-prescription drugs has increased from 2012 through 2016. Future research can look further into why this is true for the years I have analyzed, or continue by researching the most recent three-to-five years of data available to see if the trend is still present. I also recommend looking further into the probability of an IV being given, which shows a decreased likelihood in the macro-trend analysis over the years. Contrary to the results of higher prescribing patters of medications, I find that over time IV's are not as likely to be given. I make the assumption that the reason could possibly be related to reimbursement rates, but that would mean providers are either more or less critical in their assessments of a patients need for an IV. It is unclear in my analysis why this trend appears to be decreasing, but I do hope it is due to medical providers being more efficient and accurate in assessing when a patient actually needs an IV vs being driven by things like reimbursement rates (regardless of necessity).

2. In my analysis female patients have a higher likelihood in all three of my outcomes, but why? I believe the findings for female patients warrants future research and analysis based on multiple findings in my research. In the literature review, I point out the fact that females have higher visit rates to physicians than males. In my data I am able to show that females also have a higher likelihood of receiving a medication and non-prescription drug, as well as having a higher likelihood of being given an IV. Once I control for pain experiences in Model 4, the higher likelihood of female receiving medication disappear for Outcome #1, but not in Outcome #2. I find these results very intriguing and worth future research and analysis. If this trend continues, I believe there is a possibility to better understand the drivers to see if there are alternative methods to better meet the healthcare needs of a female patient. For example, e-visits could be more widely available for certain female related medical visits which would decrease demand for a face-to-face visit. This is just one example idea worth pursuing in future research targeted towards understanding these findings for a female patient in my study.

3. **Continue further research in clinical characteristics such as ambulance arrival, pain scale, and symptoms to better understand patients as they arrive.** This type of continued research has the potential to aid in triage methodologies or projecting manpower needs. In more than one outcome my data shows how variables such as ambulance arrival, patients experiencing severe pain, symptoms of heart/chest pain or pain and fever can all significantly increase the likelihood of a patient receiving a medication or being given an IV. My research just scratched the surface on types of symptoms that could be looked at, but these findings do suggest that healthcare professionals can capture this type of data prior to treatment and potentially plan for a plan of care based on probabilities. I make this statement in general terms as I understand every patient is different. But, I believe healthcare professionals can use these types of findings to analyze their own patient database, see the most recurring clinical characteristics, find trends in hours, days, weeks, or months that these characteristics ebb and flow, then apply workflow or manpower solutions appropriately.

Given the findings throughout my thesis, I believe follow on research could warrant relevant results for the medical community to consider. I have listed some example recommendations above, but my hope is that the healthcare community continually strives to understand its patients through analysis of variables such as demographic information, payment method, and clinical characteristics. I have shown in my analysis that these types of variables do in fact have significant relationships with predicting outcomes such as the likelihood of a patient receiving medication or being given an IV. My findings have the potential to aid in the following: establish new and more efficient triage of procedures, build awareness within the healthcare community on variables that are driving higher prescription rates, and creating manpower plans based on localized data. The healthcare industry is faced with daunting challenges in the future. The United States healthcare system improves with every small step taken towards advancing work flow efficiencies, cutting waste, and improving the overall quality of care. I hope that the results of my thesis play a role in influencing one such small step.

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