Quality of Healthcare in US Hospitals
Factors Associated with CMS HAC-POA Fall Rates Among the Elderly Population

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بسم الله الرحمن الرحيم

الحمد لله الذي بنعمته تتم الصالحات

DEDICATIONS

This study is fully dedicated to my family, without them nothing would be possible. Each and every one of them has demonstrated the trait of perseverance and dedication to every mission and every task they were put against.

I therefore dedicate this study to my mother, Magda, who exemplified these attributes to me and my sisters every day of our lives, and whose pristine morals are engraved within me. I dedicate this study to my father, Mohsen, who exercises perseverance every day, where he himself went through the same process of completing his PhD, at the same age as I did, while practicing medicine, and having three daughters (just as I do). I dedicate this to my sisters Reham and Miral, who have tirelessly and unquestionably supported me, my husband and daughters, and whose love is my eternal support. I dedicate this to my grandfather, Mohamed, who was the first self-funded Egyptian to receive his PhD degree from Austria, and although we never met, his inspiration has guided me for over 40 years. I dedicate this to my grandmother, Gameela, who as a widow raised exceptional leaders in the Egyptian society, where my aunts and uncle have been pioneers in their fields while also completing their PhD or other graduate degrees through her guidance and support. Although; Safinaz, Ismail and Farida are not here to see this achievement, they have fully shaped me to become as determined as they had been. I dedicate this study to my aunt Eman and uncle Ezz for supporting me unconditionally where your prayers were integral to completing this thesis. I dedicate this study to my cousins; Bassam, Gameela and Ismail and their families, who show me every day that working hard is not an option, but an attitude in life.

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ABSTRACT

Recognizing the necessity for quality in hospital care, and the importance of reducing the rate of elderly inpatient falls, this thesis conducts an exploratory analysis using multivariate statistical regression on national hospital-level data of injurious falls, from the Centers for Medicare and Medicaid Services (CMS), recorded after implementing the Hospital Acquired Conditions-Present on Admission quality initiative. This observational study attempts to identify possible correlations between falls and 24 independent variables, to guide further research to explore reasons for any identified relationships.

Inpatient fall rates have been studied previously, but typically only one or two possible explanatory variables were considered, and data on only a limited number of hospitals was used. This study considered 1,000+ large hospitals nationwide, using data from six open-source datasets. The use of large databases helped identify statistically significant effects, while using data on multiple independent variables reduced problems of confounding. The independent variable categories were: 1. Nursing staff; 2. Occupancy rate; 3. Hospital size; 4. Average Length of Stay; 5. Diagnosis Related Groups (DRG); 6. Hospital quality score; 7. Hospital location; 8. Hospital type; and 9. Magnet award status.

This study developed a new variable, the propensity to fall index (PTFI). The PTFI was created from CMS's top 100 DRGs through a multistep backwards weighted regression process, to identify DRGs significantly associated with high or low fall rates. PTFI was consistently

associated with increased fall rates (as hypothesized). The study's interim results suggest possible future research on the linkage between diagnoses and fall rates.

Other variables consistently associated with increased fall rates were average length of stay for Medicare patients (ALSM) (as hypothesized) and number of hospital Medicare beds (HSMB) (opposite to our initial hypothesis). Finally, the interaction of hospital bed occupancy with average length of stay of Medicare patients (HTBO x ALSM) was associated with decreased fall rates (opposite to our initial hypothesis). One possible reason for this is if hospitals with both a high average length of stay and high occupancy were more likely to keep patients in bed. Results will hopefully stimulate additional research on factors associated with fall rates in hospitals.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

CHAPTER 1:

Centers for Medicare and Medicaid Services (CMS)

Hospital Acquired Conditions-Present on Admission (HAC-POA)

Diagnosis Related Group (DRG)

Average length of stay (ALOS)

End-Stage Renal Disease (ESRD)

Social Security Administration (SSA)

Health and Human Services (HHS)

National Health Expenditure (NHE)

Congressional Budget Office (CBO)

Gross Domestic Product (GDP)

National Conference of State Legislatures (NCSL)

Affordable Care Act (ACA)

Hospital Insurance Trust Fund (HI)

Amyotrophic Lateral Sclerosis (ALS)

Deficit Reduction Act (DRA)

Inpatient Prospective Payment System (IPPS)

Centers for Disease and Control and Prevention (CDC)

Agency for Healthcare Research and Quality (AHRQ)

National Quality Forum (NQF)

International Classification of Diseases, Ninth Revision (ICD-9)

National Council on Aging (NCOA)

Catheter-associated urinary tract infection (CAUTI)

Urinary-Tract Infection (UTI)

National Healthcare Safety Network (NHSN)

Vascular catheter-associated infection (VCAI)

Surgical site infection (SSI)

Deep Vein Thrombosis (DVT)

Pulmonary Embolism (PE)

Venous Thromboembolism (VTE)

CHAPTER 2:

HAC Reduction Program (HACRP)

Institute of Medicine (IOM)

Institute for Healthcare Improvement (IHI)

National Institutes of Health (NIH)

The National Database of Nursing Quality Indicators (NDNQI)

National Trauma Data Bank (NTDB)

Intensive Care Unit (ICU)

National Council on Aging (NCOA)

Hospital Consumer Assessment of Healthcare Providers and Systems (HCAHPS)

Certified Registered Nurse Anesthetist (CRNA)

Licensed Practical Nurses (LPN)

Licensed Vocational Nurses (LVN)

Nurse Practitioners (NP)

Registered Nurses (RN)

CHAPTER 3:

American Nurses Credentialing Center (ANCC)

Board of Vocational Nursing and Psychiatric Technicians (BVNPT)

Certified Nurse Assistant (CNA)

National Quality Strategy (NQS)

American Hospital Association (AHA)

Rural Health Information Hub (RHIH)

THESIS INTRODUCTION

The Centers for Medicare and Medicaid Services (CMS) has identified the importance of improving the existing quality of healthcare in hospitals, emphasizing the vulnerable elderly population, and has stated that a significant challenge facing this population is; falls. Research has shown that falls have a large negative psychological, financial and social impact on the entire US population. CMS has been able to document an improvement in fall rates among the elderly but has *not* identified factors associated with that decrease.

Recognizing the necessity for quality in hospital care, and the importance of reducing the rate of inpatient falls among the elderly population, *this thesis aims to conduct an exploratory analysis of readily available national hospital-level data of injurious falls recorded after implementing the HAC-POA quality initiative policy, through an observational study to identify factors that are statistically associated with differing fall rates from hospital to hospital, as a guide to further research to explore the reasons for any identified relationships.*

To accomplish this goal, multivariate statistical regression analysis will be applied to a large national database CMS on Hospital Acquired Conditions-Present on Admission (HAC-POA) to identify possible correlation(s) and statistically significant associations between the rate of injurious falls and the variables identified in the study.

Research Question: What factors are associated with the rate of injurious falls for Medicare hospital inpatients 65 years and older in CMS's HAC-POA datasets?

The topic of fall rates among inpatient populations has been tackled in previous published studies. However, most such studies considered only one or two possible explanatory variables, using data from a limited number of hospitals. By comparison, this study considers numerous independent variables, using data on rates of injurious falls at over three thousand hospitals nationwide. The use of a large nationwide database should facilitate the identification of statistically significant effects, while the use of data on multiple independent variables should reduce problems of confounding.

With fall rates being the dependent variable of the study, several independent variables were previously studied in the literature while others were developed for purposes of this study. The categories of independent variables to be considered include: 1. Nursing staff per patient, and level of nursing qualifications; 2. Bed occupancy; 3. Diagnosis Related Group (DRGs); 4. Average length of stay (ALOS); 5. Hospital quality as measured through patient experience; 6. Hospital characterization as urban vs. rural areas; 7. Hospital type (religious, non-profit, voluntary, or proprietary); 8. Hospital size; and 9. Magnet award status.

Notably, the publicly available version of the CMS database does not provide data on some variables that would have been desirable to include in the study (e.g., the actual diagnoses of patients who fell, and their ages). Where possible, these limitations are addressed through the use of proxy variables, such as DRGs and ALOS as a proxy for severity of stay. Two-variable interaction effects will also be considered; for example, having Magnet status or a high level of nursing staff may be more important at hospitals with a longer ALOS (reflecting a more vulnerable patient population).

Of course, some variables that turn out to be associated with high or low fall rates may not be immediately actionable (e.g., urban vs. rural location). However, such results will hopefully stimulate additional research to explore in greater detail which factors are associated with low fall rates in hospitals, in support of continued improvement in fall-related incidents among the vulnerable elderly population.

CHAPTER 1

INTRODUCTION

1.1 BACKGROUND

Since the post-war baby boom, it has been identified that in the future there will be a large elderly population. To be exact, the "baby boomers" per the United States Census Bureau are currently between the ages of 53 and 71 (Colby and Ortman, 2014). There are "early" boomers (those born between 1946 and 1955) and "late" boomers (born between 1956 and 1964). This generation has been pictured as a "pig-in-a python", due to their massive numbers, which have reached 78 million (Cavanaugh, 2012). The Census Bureau reported that by 2029 all the baby boomers will have reached age 65, leading them to account for more than 20 percent of the entire US population, and by 2056 the boomers will account for a larger fraction of the population than those younger than 18 years of age (Colby and Ortman, 2014). Figure 1 represents the "explosive" power and impact of baby boomers on both Social Security and Medicare, recognizing that they also realize their forceful "boom" on both systems.

Figure 1: Baby Boomers. (Darkow. J. 2010)

It is crucial that as a society, to prepare for the aging of the baby boomers. The ability to meet their needs is required that (especially the basic ones), while maintaining the systems currently in place and not having them collapse under the pressure of their rising numbers. With the coming of age at 65 comes the perks of being eligible for Social Security and Medicare services.

Medicare, a Center for Medicare and Medicaid Services (CMS) branch, is defined as “the federal health insurance program for people who are 65 or older, certain younger people with disabilities, and people with End-Stage Renal Disease (permanent kidney failure requiring dialysis or a transplant, sometimes called ESRD)” (What’s Medicare? 2017). Medicare consists of four parts: Part A (hospital insurance); Part B (medical insurance); Part C (Medicare advantage plans); and Part D (prescription drug coverage). This study will focus only on the services provided by CMS, specifically Parts A and B.

The other branch of CMS is Medicaid, which is defined by the Social Security Administration (SSA) as “a jointly funded, Federal-State health insurance program for low-income and needy people. It covers children, the aged, blind, and/or disabled and other people who are eligible to receive federally assisted income maintenance payments” (Social Security Administration, 2017). The department of Health and Human Services (HHS) reported that those eligible for Medicaid are required to fall under a specific level of income, so they are “some low-income people, families and children, women who are pregnant, the *elderly* (emphasis added), and people with disabilities, and in some states the program covers all low-income adults below a certain income level” (2014).

It is worth noting that Medicaid eligibility is *not* based on age, but on level of income, while Medicare is based on age and/or severe disability regardless of the level of income. Since there are situations where an individual can qualify for both services at the same time, this study will cover both Medicare and Medicaid services offered to the elderly, to ensure that all baby boomers have a fair chance at attainable, affordable, quality healthcare. A summary of Medicare Parts A and B is listed in Table 1.

Table 1: Summary of Medicare Parts A and B

Part A: Hospital Insurance	**Part B: Medical Insurance**
Most premiums have already been paid through payroll taxes while working.	Most premiums are paid monthly.
Assist in inpatient coverage in: hospitals, critical access hospitals, skilled nursing facilities (not custodial or long-term care), hospice care and some home healthcare.	Assist in coverage of: doctors' services, outpatient care, some other medical services (those not covered by Part A) such as some services of physical and occupational therapists, and some home healthcare.
The above benefits are granted based on certain conditions.	The above benefits are covered when they are medically necessary.

1.2 RESEARCH MOTIVATION

By 2015, the latest year with reported outcomes, Medicare had been serving more than 46 million elders, who accounted for approximately 15 percent of the US population (AOA, 2016). CMS (CMS, 2017) reported that for the year 2016; Medicare spending increased 3.6 percent which accounted for 20 percent of the total National Health Expenditure (NHE) reaching $672.1 billion and is projected to grow 5.4 percent in 2017. Also, in 2016, Medicaid spending climbed 3.9 percent, accounting for 17 percent and $565.5 billion of the total NHE. The Congressional

Budget Office (CBO) projected in 2007 that the total spending on healthcare will increase the Gross Domestic Product (GDP) from 16 to 25 percent by 2025 and would almost double to 50 percent by 2082, whereas the net federal spending on Medicare and Medicaid will grow from four to 20 percent of the GDP from 2007 to 2025, according to the National Conference of State Legislatures (NCSL, 2008). CMS also declared that health spending by federal, state and local governments is forecast to surpass that by all private payers (e.g., businesses, households, etc.) between 2016 and 2025, with 5.9 percent covered by government payers (compared to 5.4 percent by private payers) (CMS, 2017).

The CBO is projecting an increase in net Medicare spending (i.e., mandatory spending minus income from premiums and other offsetting receipts) from $590 billion in 2017 to $1.2 trillion in 2027 (Cubanski and Neuman, 2017). This increase is driven in large part by the demand of the baby boomers for Medicare services, and funding by the government to subsidize the premiums of those enrolled in the lower income Marketplace bracket, which is coverage provided through the Affordable Care Act (ACA) (CMS, 2017). The ACA formed the health insurance Marketplaces by creating state based, competitive, private health insurance markets where individuals and small businesses are able to perform a “one-stop shop” for coverage they need and are able to afford and pay for independently (CMS, 2017). Figure 2 shows Medicare’s actual net spending from 2010 to 2016, and projected net spending from 2017 to 2027, both in dollar terms and as a percentage of GDP and the federal budget (Cubanski and Neuman, 2017).

CMS is *the nation’s largest health regulator and payer* and it is also the *primary insurer for nearly all older adults* in the US and the *single largest purchaser of healthcare* (AOTA, 2010).

In the wake of the above projections, CMS thus understands the necessity to prepare for the mammoth number of clients it will be expecting for years to come. Unfortunately, the CBO anticipates that during the next thirty years, the growth of healthcare costs per beneficiary (adjusted for demographic changes) will exceed the growth of GDP per person and will probably be spent mainly on major healthcare programs, rather than on the elderly population (CBO, 2016). Therefore, understanding the current sources of revenue for Medicare and their sustainability and how they are expected to maintain the coverage for the aging is important.

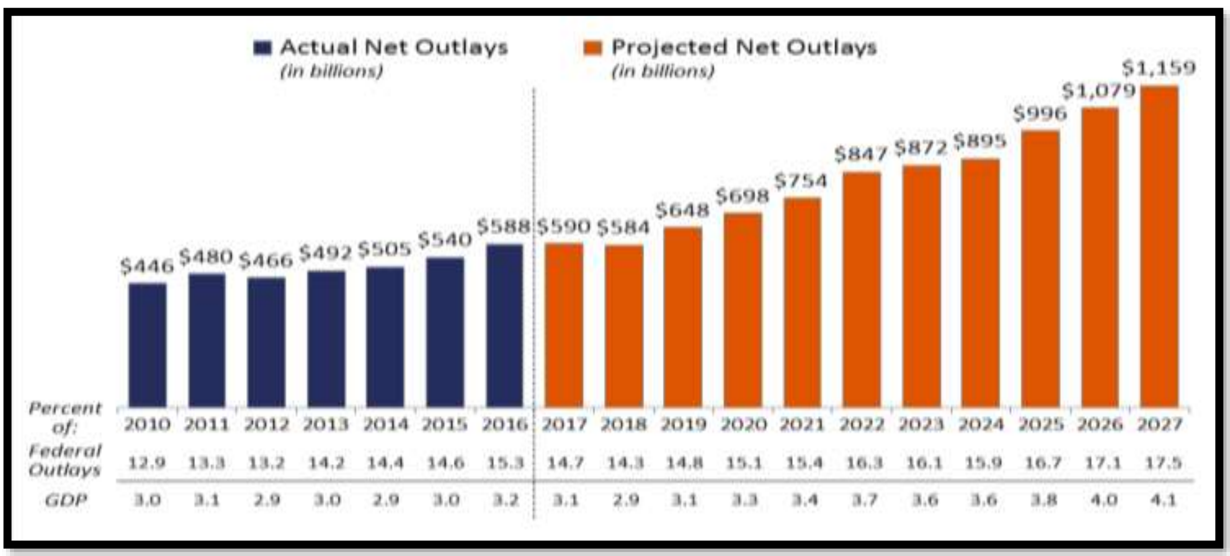


Figure 2: Actual and Projected Net Medicare Spending, 2010-2027 (Cubanski and Neuman, 2017)

Figure 3 indicates the three main sources of revenue for Medicare: general revenues for services (45 percent); payroll taxes (36 percent); and beneficiary premiums (13 percent). Other sources include transfers from the states, taxation of Social Security benefits, and interest. In what follows, the emphasis will be on Part A which is called the Hospital Insurance Trust Fund (HI) due to its focus on inpatient hospital stays and also serves as the revenue source for Part A which is the scope of the study. Part B pays specific non-hospital medical expenses, e.g. doctors' office visits, blood tests, X-rays, and outpatient hospital care (eHealth Medicare, 2017).

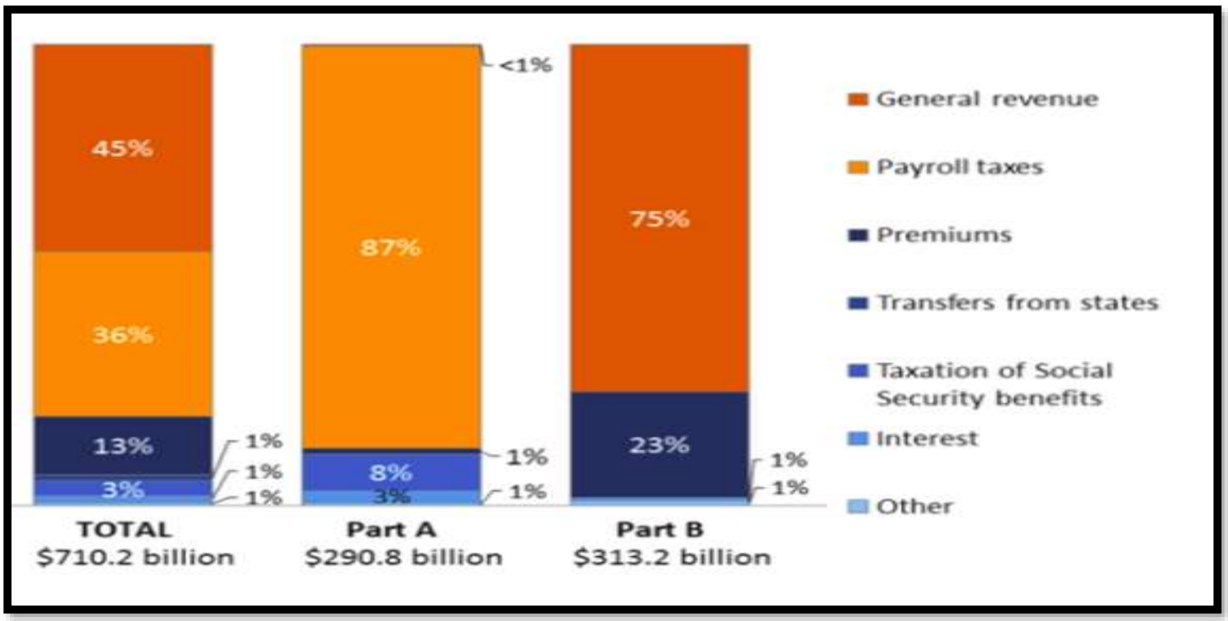


Figure 3: Sources of Medicare Resources (Cubanski and Neuman, 2017

Part A, or HI, covers inpatient care, which is care provided in a hospital setting (inpatient hospital stay sites are identified as acute-care hospitals, critical-access hospitals, inpatient rehabilitation facilities, long-term care, and facilities partaking in a qualified clinical research study), a skilled nursing facility, hospice care, and in some situations a home. When reaching age 65, a United States citizen or a legal permanent resident of at least five continuous years generally qualifies automatically for Medicare Part A, if the individual is collecting retirement benefits from the SSA or the Railroad Retirement Board. On the other hand, if the individual has a disability or suffers from ESRD or amyotrophic lateral sclerosis (ALS), then s/he is eligible for Medicare Part A prior to age 65 (eHealth Medicare, 2017).

Upon understanding the finances of Medicare, it is essential to understand the mechanics of the HI Trust Fund; in the event that the annual income of the HI trust fund exceeds the spending on benefits, the assets of the trust increase, *but* when the annual spending on benefits exceeds the income of the trust fund, then it is in a state of asset depletion. Depletion in this context refers to "decreasing seriously or exhausting the abundance or supply of" (Dictionary, 2017). In fact, the largest funding arm in the system, the HI fund, has been in depletion state (expenditure exceeding non-interest income) since 2008 (SSA, 2016). As of 2015, the reserve reached approximately $194 billion, falling from slightly more than $197 billion in 2014 (SSA, 2016). Figure 4 shows the Medicare fund is currently estimated to exhaust its reserves by 2029 due to lower payroll tax receipts and a slowing rate of reduction in inpatient utilization (Cubanski and Neuman, 2017); by 2029, the HI fund will be able to cover only 88 percent of its costs (SSA, 2016) (Van De Water, 2017), and will not be sufficient to cover all costs ever again (SSA, 2016).

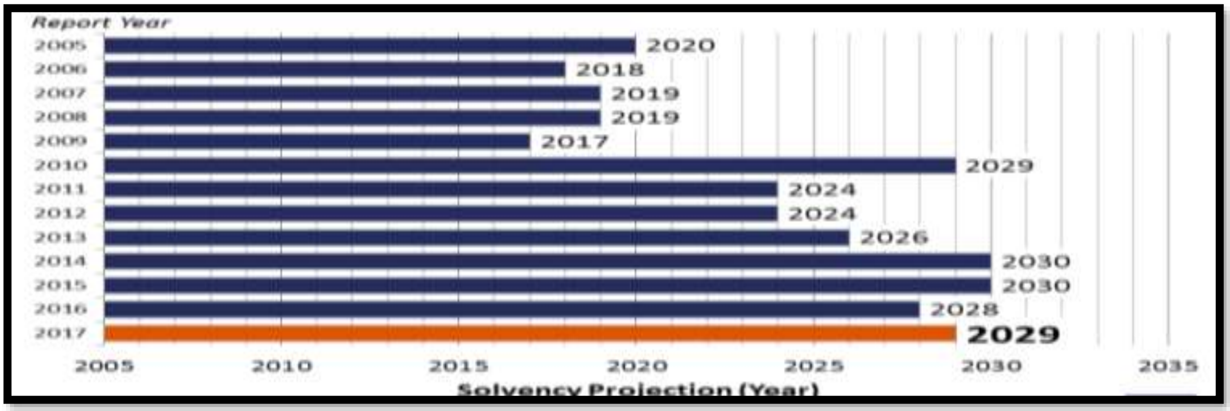


Figure 4: Solvency Projections of the Medicare Part A Trust Fund, 2005-2017 (Cubanski and Neuman, 2017)

1.3 RESEARCH RATIONALE

Given the financial situation of Medicare, and the vulnerability of the elderly population, there is a sense of obligation to provide both high-quality and cost-effective care (CMS, 2015). Therefore, programs have been created to align quality of care with quantity of care provided to patients, with the goal of reducing healthcare cost without compromising quality.

CMS has been redefining its programs to suit the requirements of controlling both the quality and the quantity of care. In particular, the Deficit Reduction Act (DRA) of 2005 Section 5001 (c) (CMS, 2017) called for a “quality payment adjustment system” (NCSL, 2008), also known as the Inpatient Prospective Payment System (IPPS). The IPPS was initially implemented in 1983 to reward efficient hospitals, with the idea that those hospitals would be awarded single payments equal to the average costs of treating patients with specific diagnoses, versus the “actual” case payment (CMS, 2008). A significant goal of the IPPS was to “improve the quality and reliability of care provided to people with Medicare” (CMS, 2008). Notably, prior to issuing the DRA in 2005, Medicare was unable to legally enforce financial repercussions on hospitals to encourage them to improve their performance, but since this Act was approved Medicare has been able to identify and track data related to inpatient admissions to general acute-care hospitals using at least two Diagnosis Related Group (DRG) codes, where an acute-care hospital "is a level of healthcare in which patients are treated for brief but severe episodes of illness, for conditions that are the result of disease or trauma, and during recovery from surgery, these hospitals have facilities, medical staff and all necessary personnel to provide diagnosis, care and treatment of a wide range of acute conditions, including injuries" (Hospitals Today, 2000). DRGs are identified as payment units for Medicare hospitals, as they were established to support Medicare's hospital reimbursement system, which classifies the patient and the hospital treating him/her (case mix) and the costs associated with this patient's care (CMS, 2016).

The requirements of these codes were adopted from CMS's DRA of 2005, section 5002 (c), and represent conditions with one or more of the following features (AHA, 2010) (CMS, 2016):

1. "High cost, high volume, or both";

2. "Assigned to a higher paying DRG when present as a secondary diagnosis";

3. "Could have reasonably been prevented through the application of evidence-based guidelines."

Applying these criteria led to the designation of the Hospital Acquired Conditions – Present on Admission (HAC-POA) indicator. CMS mandated that relevant hospitals start applying the POA indicator codes and identifying all primary diagnoses (main events causing hospitalization) and secondary diagnoses on discharge claims, effective October 1st, 2007 (CMS, 2016). Generally, a secondary diagnosis code, also known as “other diagnoses,” is defined as “conditions that coexist at the time of admission, or develop subsequently, and that affect the patient care for this current episode of care” (ACDIS, 2015). In lay terms, they are conditions that need to be cared for, monitored, and considered during the medical stay of the patient, but are not the main reason s/he is admitted.

A POA indicator is identified as “a condition present at the time the order for inpatient admission occurs” (CMS, 2016). Thus, CMS explains that a POA condition could be “(1) a condition occurring during an outpatient encounter (e.g., emergency department, observation, or outpatient surgery), (2) all claims involving inpatient admissions to IPPS general acute-care hospitals or other facilities, including all principal and secondary diagnoses and (3) any external cause of injury” (CMS, 2016).

To develop the list of conditions subject to this mandate, CMS consulted with the Centers for Disease and Control and Prevention (CDC), and upon analyzing conditions from the list of “never events” (“specific medical errors which should never have happened”), *multiple* HAC were identified and nominated to undergo a reduced payment program (NCSL, 2008); see also the Agency for Healthcare Research and Quality (AHRQ, 2016). Dr. Ken Kizer, chief executive officer of the National Quality Forum (NQF) in 2001 described “never events” as “events easily identifiable and measurable, could lead to death or a substantial disability and could have been preventable." As of 2011, the most recent revision of the never-event list included seven categories with 29 events (AHRQ, 2016).

In 2008, CMS announced 10 relevant HACs and by 2015 (the time of the final updated list), four more conditions had been added (CMS, 2015). The first eight conditions listed below were chosen specifically because they could lead to complications of the illnesses or injuries that initially caused the hospitalization, leading to higher payments by Medicare and/or the patient (NCSL, 2008):

1. *Object inadvertently left in after surgery*
2. *Air embolism*
3. *Blood incompatibility*
4. *Catheter associated urinary tract infection*
5. *Pressure ulcer (decubitus ulcer)*
6. *Vascular catheter associated infection*
7. *Surgical site infection-Mediastinitis (infection in the chest) after coronary artery bypass graft surgery*
8. *Certain types of falls causing* ***only*** *the following traumas*
    - *Fracture*

- *Joint dislocation*
- *Head injury*
- *Crushing injury*
- *Burn*
- *Electric shock*

9. Surgical site infections following certain orthopedic surgeries

10. Surgical site infections following certain bariatric surgery for obesity

11. Certain manifestations of poor control of blood sugar levels

12. Deep vein thrombosis or pulmonary embolism following total knee replacement and hip replacement procedures.

13. Surgical site infection following cardiac implantable electronic device

14. Iatrogenic pneumothorax with venous catheterization

Upon establishing the list of conditions deemed preventable, the use of the POA indicators was mandated for all discharges occurring on or after October 1st, 2008, by which time all acute-care inpatients arriving at relevant hospitals, and presenting one or more secondary condition(s), were required to be identified and diagnosed upon arrival and documented in the POA indicator. This report is submitted at discharge to CMS and verifies that the patient did not acquire these conditions as an inpatient, and therefore the preexisting conditions were treated and billed as secondary diagnoses. Therefore, by October 1st, 2008, hospitals would no longer receive any additional payments for any of the identified HAC if they were not recorded as being POA, leading to financial losses on payments related to any of the 14 HACs reported by hospitals (CMS, 2017). To identify the cause of hospitalization, CMS assigns unique codes based on the conditions of the arriving patient (Garrett, 2009).

As another example of a CMS policy targeting HAC, in 2010, an additional payment policy was established as part of the Patient Protection and ACA mandated by Section 3008, known as the HAC Reduction Program (HACRP). The HACRP allows CMS to apply financial penalties in addition to denying payments to hospitals. The HACRP also permits payment adjustments according to risk-adjusted quality measures. Cook Medical (2015) had published a report on HACRP and how this initiative affects the payments made to acute care hospitals for inpatient care only. In the event that a hospital's performance score drops to the lowest 25 percent among all reporting hospitals, which is identified on a scale of one (best) to 10 (worst) (KHN, 2014), hospitals scoring 7+ will suffer a one percent yearly reduction from CMS reimbursements. This reduction is in addition to the payments lost due to the identified HACs, which CMS will refuse to pay. Given the acute financial impact this policy has on hospitals, and its financial intimidation, it is difficult to disassociate the impacts of the HAC-POA policy and the HACRP policy. On the other hand, these two policies are ***not*** directly related, due to their different applications, measurements and outcomes (CMS, 2017).

Notably, the DRA HAC-POA rates do not include *any* case-mix adjustments for patient populations, due to the significance of these conditions and the belief that they should never occur, regardless of patient population or circumstances (CMS, 2017). Moreover, CMS reserves the right to deny any *additional* payments for providers that fail to comply with the reporting regulation. This denial would be exercised if claims were to be submitted at a higher (costlier) DRG, resulting in billing charges exceeding those due when the correct codes were provided.

Simply put, *IF* a provider submits a claim for a preventable condition, and this condition was *not* reported initially as being POA, then the provider will *not* receive payment for the higher DRG, and CMS will withhold *ALL additional* payments related to this condition; i.e., payment is made with no consideration for the HAC secondary diagnoses (only for the primary diagnoses). On the other hand, if a condition was identified as POA, then payment will be made for that specific diagnosis.

The International Classification of Diseases, Ninth Revision (ICD-9-CM Version 32), was initially used to code the conditions, with a joint effort between healthcare providers and coders to achieve complete and accurate documentation, code assignment, and reporting of diagnoses and procedures. In the event of issues arising when diagnosing a POA condition, such as information being inconsistent, not listed, or imprecise, then the provider is required to handle the matter and resolve it (Garrett, 2009) (CMS, 2014). This quality initiative policy has the potential to improve and enhance the health system and incentivize hospitals to prevent these scenarios in order to maintain payment from CMS (NCSL, 2008).

1.4 RESEARCH SCOPE

Although the HAC-POA initiative is intended to decrease payments to hospitals while increasing quality provided by the hospitals, this study is not able to focus on all of the conditions identified. This section will further examine the facilities where the HAC-POA conditions occur, and consequently analyze the various conditions that have been identified and their impact on the targeted aging population to determine which condition will be selected for further analysis and study. Notably, the POA requirement for HAC payment applies *only* to hospitals covered by the IPPS. These hospitals include all short-term care facilities, whereas the following hospitals are ***exempt*** from the POA requirements (CMS, 2017):

1. “Critical Access Hospitals”
2. “Long-term Care Hospitals.”
3. “Cancer Hospitals”
4. “Children's Inpatient Facilities”
5. “Religious Non-Medical Health Care Institutions”
6. “Inpatient Psychiatric Hospitals”
7. ‘Inpatient Rehabilitation Facilities”
8. “Veterans Administration/Department of Defense Hospitals”

To clarify, long-term care hospitals are identified as facilities with “inpatient stay of 25 days or more, to patients transferring from the intensive/critical care unit and require additional extended (i.e. long term) care, specializing in treating patients with multiple serious conditions, and necessitate additional time and care to return home, and for services such as respiratory therapy, head trauma treatment, and pain management" (CMS, 2017). This is to be distinguished from another usage of "long-term care," usually referring to home or an assisted-living facility that is "custodial (i.e. assist with feeding, dressing, in addition to healthcare provided)", which is not covered by Medicare (CMS, 2017).

The HAC-POA conditions chosen were initially identified via a study conducted by Kandilov et al. (2014) which discussed the impact of HACs on Medicare Program Payments. This study reviewed the leading six HACs and their outcomes and impacts (other conditions are not discussed here due to their relatively rare occurrence rate and/or lesser impact):

- "Stage III and IV pressure ulcers";
- "Falls and trauma;";
- "Catheter-associated urinary tract infection";
- "Vascular catheter-associated infection";
- "Surgical site infection following spinal fusion or re-fusion, arthrodesis of shoulder or elbow or other repair of shoulder or elbow"; and
- "Deep vein thrombosis and pulmonary embolism following total or partial hip replacement or resurfacing, or total knee replacement."

Condition 1: Stage III and IV Pressure Ulcers

Lyder and Ayello (2008) noted that pressure ulcers occur when “capillaries supplying the skin and subcutaneous tissues are compressed enough to impede perfusion, leading ultimately to tissue necrosis.” The National Pressure Ulcer Advisory Panel reported an incidence rate of “0.4 to 38 percent in hospitals, compared to 2.2 to 23.9 percent in skilled nursing facilities and from zero to seventeen percent for home health agencies.”

Lyder et al. (2001) reported fifteen percent of the elderly are likely to experience pressure ulcers, specifically within the first four weeks of their hospital stay. Lyder and Ayello (2008) noted that in most cases, pressure ulcers do not cause deaths, but do lead to a deterioration in the health of the patient, which can cause significant functional impairment, and in very few cases death. The main morbidities associated with pressure ulcers, in addition to possible death, are; “pain, depression, local infection, anemia, osteomyelitis, sepsis, gas gangrene and necrotizing fasciitis” (Brem et al. 2010). Brem et al. (2010) also mentioned that those who develop pressure ulcers during hospital stays are likely to remain an average of 10.8 days more than those who do not, therefore resulting in higher costs and increased probability of infection. Russo and Elixhauser (2006) had estimated the treatment cost of pressure ulcers to be approximately $38,000, based on a hospital cost and utilization project study. Notably, Oot-Giromini et al. (1989) reported that the “cost of treating pressure ulcers is 2.5 times the cost of preventing them.” Brem et al. (2010) indicated that if preventative measures were carried out, 87 percent of pressure ulcers would not occur.

Lyder et al. (2012) subsequently acquired data on hospital developed pressure ulcers in Medicare patients at the national and state level directly from their medical records and focused on the relationship between pressure ulcers and related deaths. A main outcome of this study identified that the elderly who are at a higher risk for acquiring pressure ulcers during hospital stays are those "with existing chronic conditions, such as congestive heart failure, pulmonary disease, cardiovascular disease, diabetes and obesity, as well as those on steroids." Lyder et al. (2012) reported that Medicare spending on pressure ulcers in 2007 for approximately 257,000 cases was 11 billion dollars, with nearly $43,000 for each case of stage III or IV pressure ulcers. Since 2007, the elderly population and the costs for treatment have increased (Lyder et al., 2012), but the rate of pressure ulcers and associated death rate have decreased gradually from almost 11,500 deaths in 1990 to nearly 9,000 deaths in 2001 (Redelings et al., 2005).

Condition 2: Falls and Trauma

The National Council on Aging (NCOA, 2016) reported that falls are "*the leading cause of fatal injury and the most common cause of nonfatal trauma-related hospital admissions among older adults*". Statistics on falls summarized by the NCOA (2016) are as follows:

- "one-third of Americans aged 65+ falls each year";
- "every 11 seconds, an older adult is treated in the emergency room for a fall; every 19 minutes, an older adult dies from a fall"

- “falls among the elderly result in more than 2.8 million injuries treated in emergency departments annually, including over 800,000 hospitalizations and more than 27,000 deaths”; and
- “the financial toll for older adult falls is expected to increase as the population ages and may reach almost $68 billion by 2020.”

Falls do not cause only physical constraints in the event of an injury, such as hip fractures, broken bones, or head traumas (NCOA, 2017), but also psychological and financial tolls on the affected individuals. O’Loughlin (1993) reported that falling once doubles the probability of falling again. The fallen become more fearful of being mobile, dreading another fall, which leads to remaining in their home and losing their independence, becoming depressed, isolated, and lonely.

Unlike pressure ulcers, the rate of falls is expected to increase along with its financial burden, since falls have a high prevalence rate to begin with compared to pressure ulcers and cause high rates of death and non-fatal injuries in the elderly. Three to 20 percent of elderly inpatients are predicted to fall at least once during their hospital stays, and at least a third of those are expected to develop some sort of injury, which can lead to death (Oliver et al., 2010). Wu et al. (2010) calculated that one fall in a hospital without a serious injury would add an extra $3,500 to the expected cost of a hospital stay, while falls with serious outcomes can cost in excess of $27,000 over and above a normal hospital stay.

AHRQ (2013), NCOA (2016), the Hospital and Health Networks (Butcher, 2013), and other organizations have initiated efforts to minimize the rate of falls. However, given that the elderly often have other comorbidities that interfere with their gait and balance, it has proven to be a challenge to improve the rate of falls within this fragile population. An in-depth discussion and analysis on the elderly population and the causes of their falls as inpatients will be provided in chapter 2.

Condition 3: Catheter-Associated Urinary Tract Infection (CAUTI)

The CDC (2018) defined a CAUTI as a urinary-tract infection (UTI) “where an indwelling urinary catheter (IUC) was in place for >2 calendar days on the date of event, with day of device placement being Day 1, *and* an indwelling urinary catheter was in place on the date of event or the day before. If an indwelling urinary catheter was in place for > 2 calendar days and then removed, the date of event for the UTI must be the day of discontinuation or the next day for the UTI to be catheter-associated.” National Healthcare Safety Network (NHSN) (2018) reported that CAUTI account for 30 percent of the total acute care hospital infections with approximately 500,000 CAUTIs a year, with an estimated medical cost of $758 per incident adding up to more than $340 million in total and accounting for 13,000 deaths yearly. Gomolin and McCue (2000) noted that CAUTIs are also responsible for approximately 40 percent of nosocomial infections in hospitals, which lead to 10 - 27 percent of bacteriuric outcomes in the patients, out of which four percent escalate to becoming bacteremic, with the majority of such patients being elderly, leading to a 25 percent chance of mortality due to septicemia (Kunin, 2006). Similar to falls, the cost of preventing CAUTIs is expected to rise with the increase in population age and size, accounting for approximately $0.3 trillion of all health expenses (Jacobsen et al., 2008). Fortunately, however, the incidence rate of CAUTI remains low for the time being, compared to rates of falls and pressure ulcers.

Condition 4: Vascular Catheter-Associated Infection (VCAI)

VCAI, which is also known as bloodstream infection caused by a catheter, has existed since the early years of the twentieth century (Shah et al., 2013). Fletcher (2005) notes that these common infections can lead to health complications, including death in 25 percent of all incidents. These infections have led to high treatment costs and extended hospital stays. There are limited publications on this condition and its effect on the elderly, but Fletcher (2005) has estimated an incidence rate of infection of 16 percent of all catheterization incidents. Schmid (2001) noted that infections of this sort were estimated to cause 88,000 fatalities out of two million infection patients in 1999; these deaths led to an estimated loss of $4.6 billion.

Condition 5: Surgical Site Infection (SSI) following spinal fusion or re-fusion, arthrodesis of shoulder or elbow or other repair of shoulder or elbow

The CDC (2010) defined SSI as; “an infection that occurs after surgery in the part of the body where the surgery took place. Surgical site infections can sometimes be superficial infections involving the skin only. Other surgical site infections are more serious and can involve tissues under the skin, organs, or implanted material." Similar to VCAI, few publications related to the elderly suffering from this condition are available, so no comparison can be fairly made.

Condition 6: Deep vein thrombosis (DVT) and pulmonary embolism (PE), also known as venous thromboembolism (VTE), following total or partial hip replacement or resurfacing, or total knee replacement

DVT is described as a blood clot which can form in one or more of the deep veins, usually in the legs, where one or more of these clots can travel into the lungs and cause PE, which eventually leads to death (Dunleavy. B.P., 2015). Geldhof et al. (2014) noted that age and renal weakening cause the incidence rate for vein thrombosis to increase, with an average of two cases per 1000 patients. Specifically, DVT and PE have a higher rate in the elderly, four to six times more than the younger population. Consequently, the death rate caused by DVT and PE increases with age and comorbidities (Geldhof et al. 2014). Ozaki and Bartholomew (2012) use the terms "common" and "lethal disorder" when describing DVT and PE. The CDC estimated one million people suffer from these conditions (CDC, 2018), while Beckman et al. (2010) gave a more conservative number of 300,000 to 600,000 a year, with the difference being accounted for the difference in age and race (Beckman et al., 2010). Beckman (2010) reported that DVT and PE are usually fatal and 10 percent to 30 percent of those who are affected by this condition die within the first month of diagnosis (CDC, 2016), with approximately 100,000 dying a year (everyday guide to DVT) costing an estimated $10 billion in medical costs yearly (CDC, 2016).

Table 2 summarizes the conditions discussed above, to highlight the effect of falls and trauma compared to the other events:

Table 2: Summary of Leading Six Hospital Acquired Conditions

Condition	Rate of Incidences	Financial Burden
Pressure ulcers	In 2007: 257,000 cases In 2001: 9,000 deaths	$11 billion, $43,000 per case
Falls and Trauma	2.8 million injuries and 27,000 deaths	***$68 billion*** by 2020 Each case adds an extra $3,500 to $27,000 to the bill
CAUTI	Estimated 450,000 cases and 13,000 deaths a year	$340 million, $758 each case
VCAI	2 million cases, 88,000 deaths	$4.6 billion
SSI	No data	No data
DVT	1 million cases, 100,000 deaths	$ 10 billion

1.5 RESEARCH STATEMENT

This chapter has served as the introduction of the study and provided an explanation of how the elements were selected. In particular, it provides a view into the future of the biggest health insurer in the US (CMS), the impact of the growing elderly population on its financial foundation, and how the elderly population’s physical and medical conditions may affect the entire American economy and society. The CMS HAC-POA policy was identified as a meaningful baseline for this study to start observing the rates of falls, since this quality initiative was intended to help reduce the financial impact of HAC on CMS’s budget and spending, while also reinforcing the importance of quality in healthcare.

This policy, HAC-POA, has focused on specific events that were proven to harm the US healthcare system, and its quality outcomes, as they were deemed “never events.” From these events, 14 HAC-POA conditions were identified as conditions that CMS would not reimburse (either if an inpatient acquires them during his/her hospital stay, or if the patient had arrived with one of these conditions, but the hospital failed to list it as a POA).

According to the literature, the focus on injurious falls was chosen based on its prevalence compared to other conditions comparable in severity. Based on the analysis of the six leading HACs, it has been concluded that “falls and trauma” are the most alarming due to the high incidence rate, the elevated rate of fatalities, and the negative financial, psychological and social impact this condition imposes on communities.

CHAPTER 2

LITERATURE REVIEW

In this chapter, an in-depth literature review will be presented on the scope of the research and the relevant attributes. The research scope, as mentioned in the conclusion of the previous chapter, attempts to identify the factors possibly related to injurious falls, how they can affect healthcare quality of HAC-POA indicators, and in particular their effect on the rate of falls among the elderly in CMS facilities (acute-care settings). Initially, the outcome of this policy was not identified, as being positive or negative, until AHRQ published in a national scorecard in 2016 that HAC rates have declined (AHRQ, 2016). Although this report was widely, positively received, neither AHRQ nor CMS have been able to publish the causes for this reduction, and although this study will *not* be able to determine causes for the reported decrease, the motivation to understand factors possibly associated with injurious fall rates on the hospital level is high.

In this chapter, a thorough literature review is conducted, and studies linked to the keywords of the scope (falls, elderly, hospitals, rates, HAC, POA, quality, healthcare) will be identified and evaluated for usage. These keywords were either combined or separate during the search. Due to the relatively new literature within the scope of the study, all US publications in the years 2000 to 2017 were considered, and older relevant ones were cited, as needed. Publications from countries other than the US were generally excluded from the search, to eliminate effects of different regulations and drug usage from other countries, unless those publications provided uniquely valuable information (e.g., when US literature was not located).

2.1 RESEARCH ELEMENTS

Multiple concepts are introduced in this thesis, and later woven together to create a cohesive understanding of the causes of falls among the elderly. To understand these concepts, each one is first discussed individually, as follows:

- Quality and its impact on healthcare,
- The population: Elderly,
- The condition: Falls,
- The medical setting: CMS facilities
- The variable data sources: CMS reports
- The aim of the research
- The challenges of the research
- The significance of the research

2.2 QUALITY OF HEALTHCARE

2.2.1 DEFINE - QUALITY OF HEALTHCARE

In the US, the focus on quality in healthcare has been developing for almost a century (Marjoua and Bozic, 2012). One of the main pioneers for introducing quality fundamentals to healthcare was Ignaz Semmelweis, who argued that hands need to be washed when handling patients or functioning in a medical care establishment, while another pioneer, Ernest Codman, presented the idea of “standardization” in hospitals and applying “healthcare assessments” (Berwick and Fox, 2016). Notably, Codman focused on “the end results of healthcare” (Berwick and Fox, 2016), and as described by another infamous quality founder, Avedis Donabedian, he also “enhanced accountability” in healthcare facilities and to the public (Berwick and Fox, 2016). Berwick and Fox noted that quality standards and healthcare requirements have continued to evolve, best-practice principles have been identified, rewards for good performance have been developed, reprimands for poor performance initiated, and methods and tools for performance evaluation and implementation have been established (Marjoua and Bozic, 2012).

The recognized father of quality assurance in healthcare was Avedis Donabedian (Best and Neuhauser, 2004, Ayanian and Markel, 2016). Slightly more than 50 years ago, in 1966, Donabedian published the most cited article in the history of health-services research; “Evaluating the Quality of Medical Care” (Donabedian, 1966). This article remains a cornerstone of quality in healthcare and public health.

Donabedian introduced the fundamental concept of quality in healthcare, featuring three components. The first component is structure (the attributes of the settings in which care is provided). Structure includes elements such as resources, staff, and equipment. The second component is process, which is defined as how care is expected to be practiced and how it is received by the patient. Process is related to the interactions among and between practitioners and patients. The third component is outcome, identified as the effect of care (Mosadeghrad, 2012). The Donabedian structure, also known as the quality triad, is represented in Figure 5 (Grossbart and Agrawal, 2012).

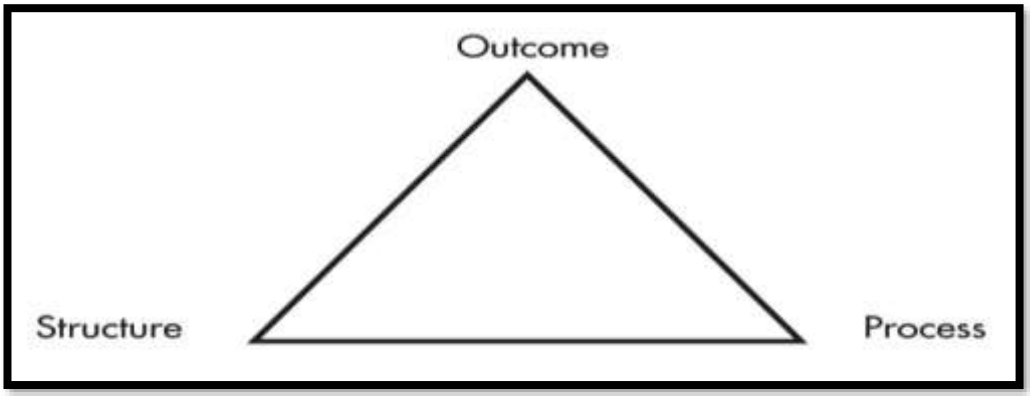


Figure 5: Donabedian Quality Triad (Grossbart and Agrawal, 2012)

Øvretveit (1992) identified three facets, which are required for healthcare quality: professional quality; client quality; and management quality. Professional quality was identified as being able to professionally handle the consumer requirements with the suitable techniques and procedures for the situation. Client quality was defined as the sense of service fulfilment and satisfaction which the client (patient or resident) has when being treated in a medical establishment. Finally, management quality was described as providing healthcare services efficiently and effectively.

Also, in 1992, the Health Services Research Group published another definition for healthcare quality, which is “the capacity to achieve legitimate medical and nonmedical goals set by the patient with the assurance of the physicians or the capability of meeting the customer’s needs for patients having sensible, understandable, and reasonable expectations of healthcare" (Basinski et al., 1992).

The Institute of Medicine (IOM, 2001) defined quality in the healthcare system as "the degree to which health services for individuals and populations increase the likelihood of desired health outcomes and are consistent with current professional knowledge." Additionally, in 2007, the director of the AHRQ defined quality as "getting the right care to the right patient at the right time – every time" (Clancy, 2007). Using this definition, AHRQ has been steadily improving the quality, safety, efficiency, and effectiveness of healthcare (Clancy, 2007).

Additionally, one of the most influential publications in the history of healthcare, which helped to create support for quality improvement in the US, was "To Err is Human: Building a Safer Health System" (IOM, 1999). This report highlighted the importance of safety, and the necessity of embedding safety measures and systems into the healthcare system to prevent the occurrence of errors, which have led to almost 100,000 deaths yearly and cost the US an average of $25 billion annually (IOM, 1999). This founding report emphasized the need to create procedures and standards within healthcare establishments to allow for accountability and common safe practice among medical facilities.

An additional dimension to quality improvement is measurement and accountability, to ensure that the system in fact functions as it is designed to function, the system delivers the intended outcomes, and the outcomes are repeatable when the same scenario occurs. Applying the measurement tools and processes of quality improvement within the healthcare system is crucial, since they assist in identifying deviations from intended goals and correcting them. AHRQ added six attributes to the definition of quality in healthcare (AHRQ, 2016) to allow for a broader view of quality:

1. Safety: patients not to be harmed by care helping them.
2. Patient-centered: care is tailored to each individual need
3. Timely: reduce wait and delay for the patient
4. Effective: practice evidence-based care
5. Efficient: reduce waste
6. Equitable: all patients to be treated equally

2.2.2 THE MANY FACES OF QUALITY IN HEALTHCARE

TriStar Horizon Medical Center (2010) noted that the IOM has discussed multiple aspects of "what is quality healthcare?" Some are subjective, since patients have advocated that quality could be assessed by how long it takes to meet with a doctor, or by being treated respectfully by the doctor and the hospital staff, or, even more importantly, having the patient and his/her family spend substantial time with the physician. Another aspect of quality in healthcare is based on objective evidence-based clinical care. To determine whether the desired outcomes (more lives saved, increased satisfaction, etc.) are taking place, Horizon suggested that quality of care could be measured by specific indicators such as data from the patient medical records, converted to rates or percentages to demonstrate the level of care in a medical establishment (e.g., percentage of heart-attack patients who are prescribed aspirin at discharge); a patient can easily access such indicators and use them as a basis for comparison to choose the “best” facility to visit (TriStar Horizon Medical Center, 2010). These indicators can either be process indicators (e.g., timeliness of care) or outcome indicators (e.g., mortality rates, infection rates, complication rates). A patient can also evaluate the quality of a facility by the awards and national accreditations it has achieved (TriStar Horizon Medical Center, 2010).

2.2.3. CONCEPTUALIZE – QUALITY OF HEALTHCARE

As mentioned previously, since healthcare is extremely complex and specialized, utilizing quality and performance evaluation metrics can assist individuals with their healthcare decisions, and provide context for state and national policy discussions regarding healthcare programs and investments, while emphasizing where and how the system can further be improved (Claxton et al., 2015). Admittedly, though, the best approach to understand a system, how it functions, and how to evaluate it; is by seeing it at work. One of the pioneering frameworks for this was the Donabedian quality triad, shown earlier in Figure 5 (Grossbart and Agrawal, 2012). In that framework, the three elements (structure, process and outcome) are portrayed with equal weight, which “allows for equilibrium in the model” (Grossbart and Agrawal, 2012).

The elements depend on each other. For example, structure identifies the characters of the model or system (the physicians, hospitals, other professionals, and other facilities). It provides information on level of education, describes the facilities, and evaluates the state of the medical records and how they are maintained, in addition to assessing the relationships among the clinicians (e.g., is the mammography equipment up to date and well maintained? are the radiologists well-trained and board certified?).

Once the structure is deemed solid, next would be the actual process of medical care. The quality of the process is determined not only by having the right people and facilities, but also by having the correct actions implemented correctly (e.g., was a mammogram done for a woman at risk for breast cancer?). Finally, the outcome portrays the level of care provided (e.g., did the mammogram discover a tumor? did the woman get better? was her disease or disability reduced or prevented? was it reduced as much as it could have been, given what is scientifically possible?). It is important to measure the outcomes of care, to compare the pre- and post-process levels (Grossbart and Agrawal, 2012). Next step is to either improve the intervention, so that the outcome is what is projected, or maintain the intervention, if it delivers the projected outcome. These three components are considered the foundation to providing care that is consistently safe, timely, effective, efficient, equitable, and patient-centered (IOM, 2001).

It has been recognized by the community of researchers and the developers of healthcare-quality improvement that there is a need to design systems and to thus transform the abundant verbal descriptions of quality of care into a model format, where it is necessary to rely not only on verbal definitions but also on fundamental tools and conceptual models to demonstrate what the defined system represents and how the success or failure of the system designed is measured. This transformation will help demonstrate the connections between the existing and/or future attributes of the system and their relation to each other. Models also demonstrate the technical functions of care and the interactions of clinicians with patients, all in a common environment. Clemente et al. (2014) defined the technical level within a model, and how it demonstrates the capability of the health services and the skill at which appropriate care is performed, as follows: "quality of the systems is also defined by the quality of the relationships between the structure and its users, and between the ability of the staff and the physicians to gain confidence and show empathy, tact, and sensitivity toward the patient" (Clemente et al., 2014).

When creating a conceptual model, it is vital to apply a meaningful tool/method to conceptualize the factors associated with the event being analyzed. When studying falls, it is essential that the factors leading to this event are identified, in order to determine the appropriate improvement methods. To achieve this goal, a widely used quality-improvement mechanism—the cause-and-effect diagram is utilized, also known as an Ishikawa or fishbone diagram, due to its shape. The Institute for Healthcare Improvement (IHI) has been applying the cause-and-effect diagram to numerous healthcare projects, and describes it as follows: "it helps teams understand that there are many causes that contribute to an effect, it graphically displays the relationship of the causes to the effect and to each other and it helps to identify areas for improvement" (IHI, 2018). CMS (2014) has additionally supported its use as a quality-improvement tool, as a way to focus on the cause of an issue (e.g., why falls occur) and not just on the symptoms (falls).

Figure 6 is a fishbone diagram created by the University of Texas-Southwestern. This diagram displays five “branches”: 1. People: who fall (the elderly) and why they fall; 2. Processes (i.e., rules and procedures): why circumstances can lead to falls; 3. Equipment: contributing to falls of the elderly; 4. Environment: the area where the people are located, and how the environment can contribute to falls; and 5. Process: medical procedures to which the elderly are subject to, and how they can contribute to falls.

Utilizing the elements in the fishbone model, an additional, more comprehensive conceptual model can also be created, by applying the Donabedian model. This model would enable us to view a compilation of elements that can affect falls within the three different components of the quality triad as shown in Figure 7. Elements listed in the model were gathered from the literature and will be further explained in this chapter. It is also worth noting that numerous elements listed in this triad will not be further investigated due to the lack of data resources supporting them.

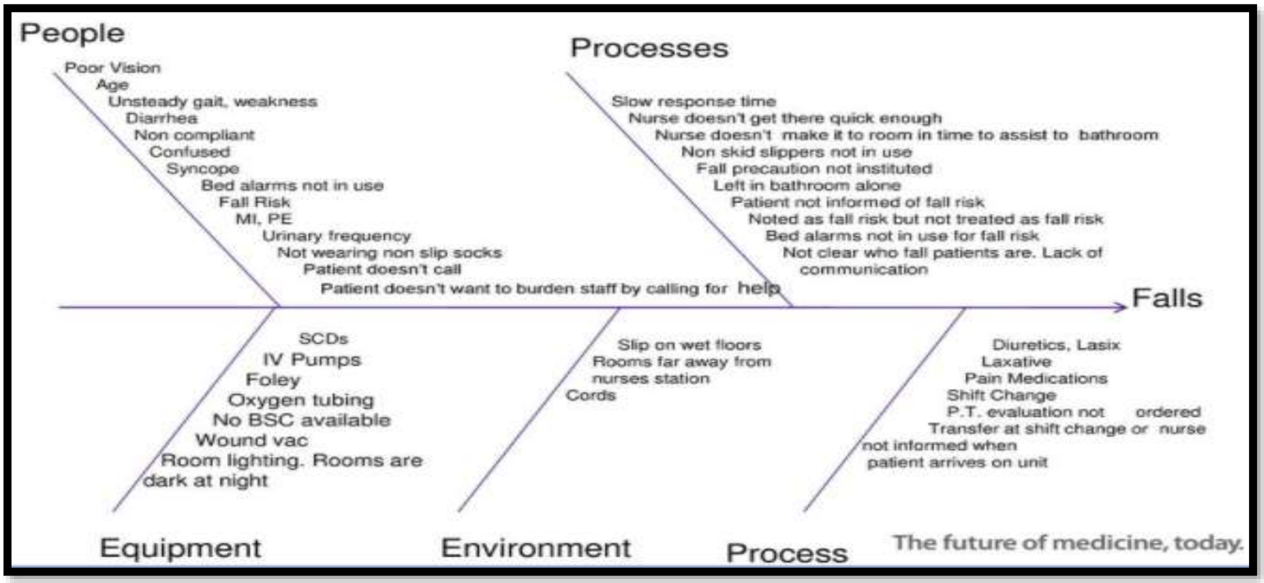


Figure 6: Fishbone Diagram: Contributing factors to falls (Webster, 2011)

Having offered extensive information and history on quality in healthcare and understanding how to visualize it through models and frameworks, the upcoming section 2.3 will focus on understanding the population of the study, and their wide impact on the US economy and its healthcare system.

Following the presentation on the elderly, next it is important to understand one of the biggest challenges faced in the current healthcare facilities; namely, the fact that fall rates have become one of the biggest threats to the quality of the US health system and its clients. Although falls were introduced briefly, earlier when discussing the HACs with high incidence rate, next a more in-depth look at this issue with be presented in section 2.4.

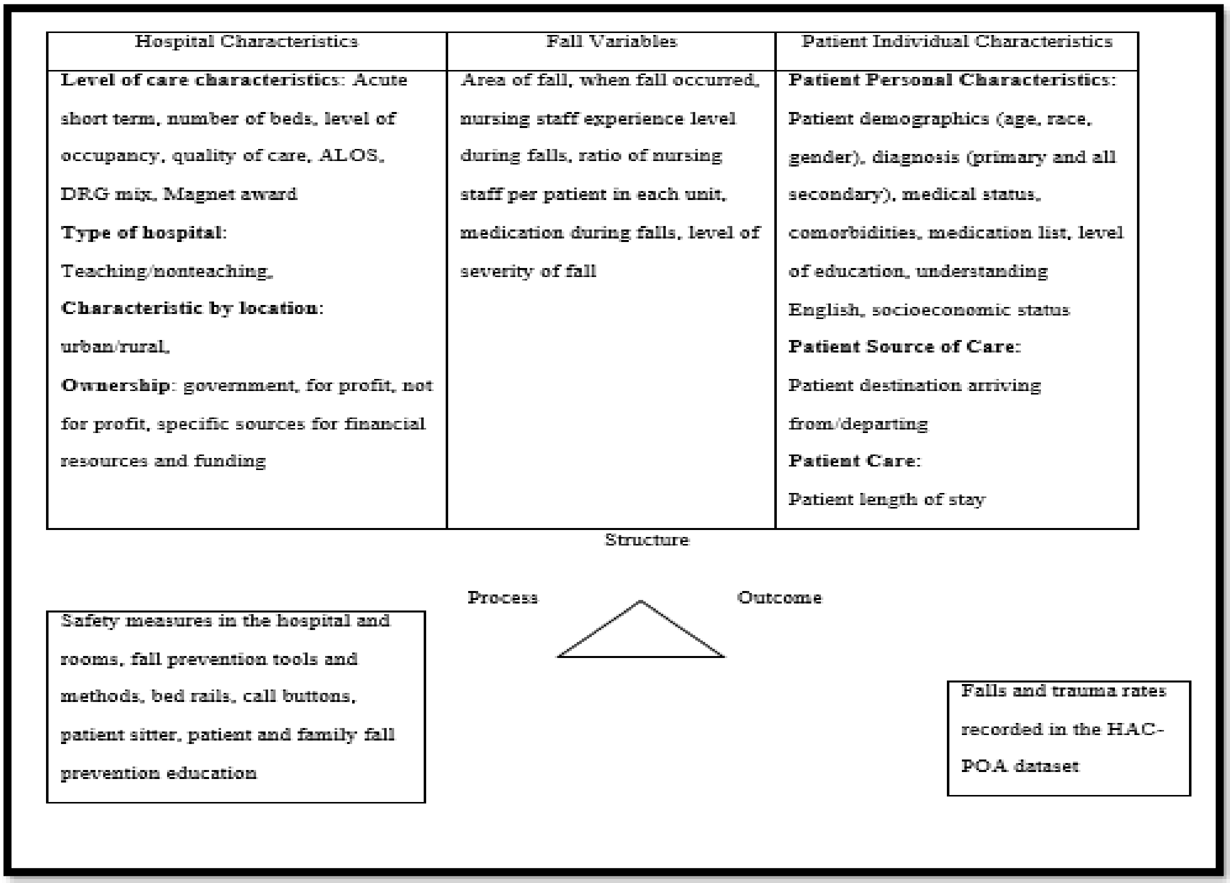


Figure 7: Applying the Donabedian Model as a Conceptual Model to the Study of Falls

2.3 POPULATION: THE ELDERLY

The definition of the term “elderly” is unfortunately not consistent, but most definitions agree that it applies to those who are 65+ years old. Nevertheless, a full review of the definitions for this population will be conducted, where it provides a better understanding as to why they are more prone to falls than others.

The Medical Dictionary defines the elderly as “individuals over 65 years old who have functional impairments” and/or “any adult over 75 years old” (Medical Dictionary, 2003). Orimo et al. (2006) defined the term as “a chronological age of 65 years old or older, …those from 65 through 74 years old are referred to as ‘early elderly’ and those over 75 years old as ‘late elderly’.” The US Census Bureau’s statistical brief defined the elderly as those 65+ years in age (Hobbs and Damon, 1995). The Bureau has also reported that during the 20th century, those 65+ years have tripled compared to the previous century. As of 2050, the elderly population is expected to reach approximately 80 million in the US, where one in five people will be 65+ years, with the spike occurring mostly between the years 2010 and 2030 (Hobbs and Damon, 1995). The **N**ational Institute on Aging of the National Institutes of Health (NIH, 2006) noted that those 85+ years are the fastest growing population in the US, with Figure 8 representing the average annual growth rate in the percentage of the elderly population from 1910 -2050 (Hobbs and Damon, 1995).

A significant and alarming challenge per Gordy and Trunkey (2014) is that the older population (60+, 65+ and 85+) has been increasing since 1900 and will steadily continue to increase until 2050. Compared to the entire population, those aging are expected to increase from an average of five percent to 22 percent of the population between 1900 and 2050. Gordy and Trunkey (2014) also reported that in 2002, 36 percent of personal healthcare expenses were spent by the 13 percent of the population who were elderly, with falls contributing heavily to these expenses.

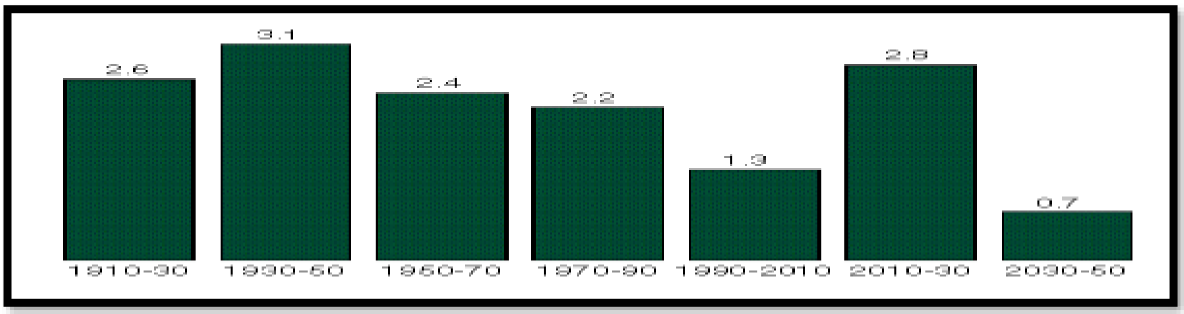


Figure 8: Average Annual Growth Rate in Percentage of the Elderly Population (Hobbs and Damon, 1995)

2.4 THE CONDITION: FALLS AND TRAUMA

It is serious challenge when attempting to understand the term “falls,” which has numerous definitions, making it difficult to know which definition is used *when* and *why,* and which medical settings adopt which definition. With the high rate of incidents and events reported as “falls,” confirming the reliability of these reports is important. Do authors refer to the same events as falls? How consistent are the events used to define a fall? Is it confirmed that the definition of a fall is consistent throughout the literature? Well…the short answer is no!

With “falls” not being defined consistently, this causes speculation about the incidence rates reported, since it is usually not clear which definition is being used by the reporting individual (whether that is the patient, or a member of the medical staff). It might have been expected that a fall can simply be identified and defined; instead, the multitude of definitions make it difficult to compare studies against each other and has led to a need for a universally used meaning. Moreover, there is no definition on which all or most researchers and scientists agree; rather, each author seems to define the motion based on his or her own circumstances and requirements at the time. A fall can be described as an involuntary shift from the position the person was originally in; this shift can be a complete descent to the ground, or merely leaning over due to tripping. AHRQ (2013) described finding a consistent definition to be “problematic.” To understand the multitude of definitions of the term “falls” that are used in medical reports, see Table 3 below.

Table 3: Definitions of falls

Author	Year of Publication	Definition
The Merriam-Webster Dictionary - 11 definitions with this being the targeted meaning	First known use was recorded before 12th century	“To drop or descend under the force of gravity, to hang freely, to drop oneself to a lower position, to come or go as if by falling.”
The Kellogg Group	1987	“A fall is an event which results in a person coming to rest inadvertently on the ground or other lower level and other than as a consequence of the following: sustaining a violent blow, loss of consciousness, sudden onset of paralysis, as in a stroke, an epileptic seizure.”
Tinetti et al.	1988	“An event which results in a person coming to rest unintentionally on the ground or other lower level, not as a result of a major intrinsic event (such as stroke) or overwhelming hazard.”
Nevitt et al.	1991	“Falling all the way down to the floor or ground or falling and hitting an object like a chair or stair.”
Lach et al.	1991	“An unexpected loss of balance resulting in coming to rest on the floor, the ground, or an object below knew level.”
The Cochrane Review (Buchner et al.)	1993	“Unintentionally coming to rest on the ground, floor or other lower level.”
Means et al.	1996	“…Any involuntarily change from a position of bipedal support (standing, walking, bending, reaching, etc.) to a position of no longer being support by both feet, accompanied, by, (partial or full) contact with the ground or floor.”
Berg et al.	1997	“…Losing your balance such that your hands, arms, knees, buttocks or body touch or hit the ground or floor.”
Kannus et al	1999	“An unexpected, sudden descent from an upright, sitting, or horizontal position, the descent height being less than or equal to one meter.”

Carter et al.	2002	"…Inadvertently coming to rest on the ground or other lower level with or without loss of consciousness and other than as the consequence of sudden onset of paralysis epileptic seizure, excess alcohol intake or overwhelming external force."
Cesari et al.	2002	"…A sudden loss of gait causing the hit of any part of the body to the floor."
Tideiksaar	2002	"…Any event in which a person inadvertently or intentionally comes to rest on the ground or another lower level such as a chair, toilet or bed."
The International Classification of Diseases-9 (World Health Organization)	2007	"An unexpected event where a person falls to the ground from an upper level or the same level."
The National Database of Nursing Quality Indicators (NDNQI) (Staggs. et al.)	2015	"A patient fall is an unplanned decent to the floor with or without injury to the patient. Include falls when a patient lands on a surface where you wouldn't expect to find a patient. All unassisted and assisted falls are to be included whether they result from physiological reasons (fainting) or environmental reasons (slippery floor). Also report patients that roll off a low bed onto a mat as a fall"

The above definitions are a compilation of various authors, and a collection by Zecevic et al. (2006). Unfortunately, determining how each person identifies falls is not possible. Since there is no specific medical term that all medical staff use in their charts, this study it will be assumed that the falls reported have a consistent meaning and all fall events will be accepted.

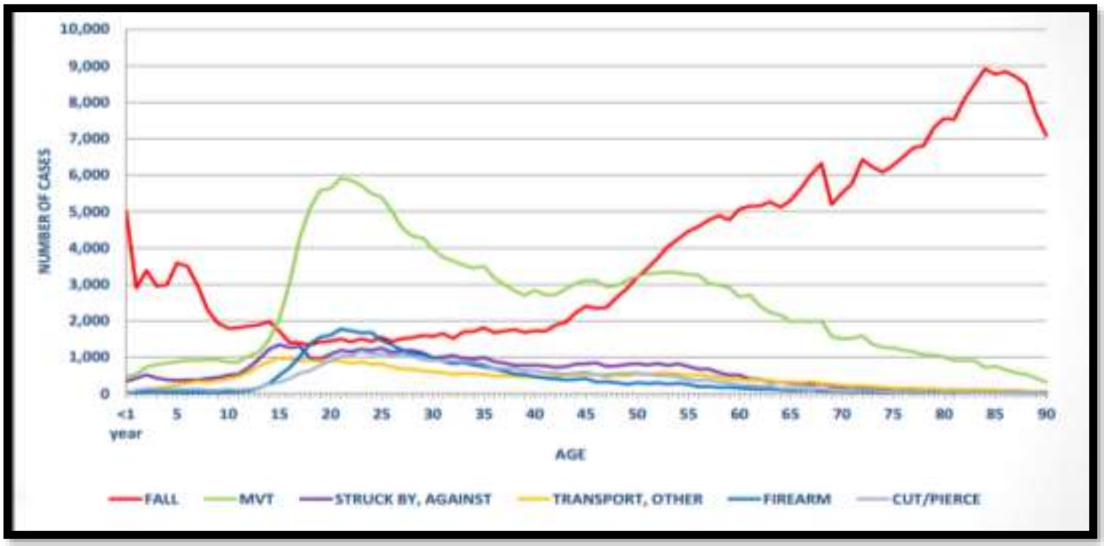


Figure 9: Incidents by Selected Mechanism of Injury and Age (NTDB, 2016)

Looking closely at the definition of falls, there are also culturally accepted synonyms, such as slips and trips, where a slip is defined as "sliding of the support leg," and a trip is the "impact of a swinging leg with an external object or a body part." While both can cause someone to fall, these two words illustrate different events and involve different causes for loss of balance (Zecevic et al., 2006).

Realizing the difficulty of defining a fall among scientists, it is clear how confusing it is for laypeople, especially the elderly, to report falls to medical staff during their stay in the hospital. Therefore, there is a need to understand how, why, when and where falls occur, and how they can be prevented from happening.

Quigley and White (2013) reported that falls and their injuries are the most common reported adverse events among all inpatients (three to 20 percent of inpatients falling once or more).

Specifically, according to data from 1998 to 2010, the rate of falls has increased from 28 percent to 36 percent for the elderly (Cigolle et al., 2015). Notably, falls among the elderly cost Medicare more than $31 billion in 2015 (Bergen et al., 2016). A fall injury costs an average of $30,000 per hospital visit, and these costs increase with the age of the patient (CDC, 2016). By 2017, 33 percent of the elderly in the US are expected to report a fall every year, compared to 25 percent in 2016, making falls the ***number one cause for both fatal and nonfatal injuries among the elderly*** (NCOA, 2017). The National Trauma Data Bank (NTDB, 2016) reported that falls were the *only* cause, out of six studied causes of injuries, to increase with age, as shown in Figure 9.

The NTDB (2016) also mentioned that falls accounted for approximately 44 percent of all trauma and injury cases, with a higher incidence rate in the elderly, and accounted for the largest number of deaths caused by injuries (an average of 6,500 deaths for those 65+), with females having a higher fall frequency than males in this age group (Currie, 2008). Dalton et al. (2015) published an extensive history on falls for the elderly, finding that falls account for 75 percent of all blunt trauma, and resulted in the longest median length of stay in hospitals and in the intensive-care unit (ICU) compared to all other injury types (four and three days, respectively).

The information presented below provides a more complete picture on this issue:

- With the elderly accounting for a third of the entire population; the National Council on Aging (NCOA) (2016) cited falls as the first ranking cause for fatal and nonfatal injuries in the United States for adults 65+ years in 2005.

- The first national estimates of the elderly population with fall-related injuries linked to restricted activity or doctor visits indicated that over 15,000 people 65+ years died from injuries related to unintentional falls (CDC, 2008).
- In 2014, the elderly experienced 29 million falls, accounting for seven million injuries for that year, and approximately 27,000 fatalities (CDC, 2016).
- An estimated 2.8 million people 65+ years old were treated in emergency departments for nonfatal injuries from falls, with 800,000 of these patients hospitalized (Bergen et al. 2016; CDC, 2017).
- 20 to 30 percent of falls result in moderate to severe injuries such as bruises, hip fractures, or head traumas (Bell et al., 2000).
- In 2013, a study on the falls by the elderly in US hospitals estimated 300,000 falls, with almost 26 percent of the falls resulting in injuries (Bouldin et al., 2013).

2.4.1 CAUSES AND PREVENTION/REDUCTION TOOLS FOR FALLS

The literature has documented that falls do not “just happen” (NIH, 2013). There are underlying causes that are heavily affected by existing risk factors due to age. Causes for falls are identified as intrinsic (an event or condition causing the sudden loss of postural control), or extrinsic (caused by an environmental factor). Taylor et al. (2005) noted that the intrinsic and extrinsic fall risk factors can be either injurious or non-injurious. Figure 10 presents examples of fall risk factors and causes, where Rubenstein and Josephson (2006) listed intrinsic and extrinsic risk factors of falls in their study. Notably these factors largely represent the common fall factors also being listed in this study.

Abraham and Cimino-Fiallos (2017) listed multiple factors leading to falls and trauma among the elderly, including "previous medical diagnoses (e.g., cerebrovascular accidents/transient ischemic attacks), arthritis, fractures, dementia, diabetes, vitamin D deficiency, anemia, arrhythmias, neuropathy), impaired vision/hearing, recent hospital discharge, higher body mass index, poor sleep/obstructive sleep apnea, and urinary incontinence and alcohol use."

The NCOA (2017) listed the following five causes for falls, which include both intrinsic and extrinsic causes:

- Balance and gait are affected due to a decrease in "coordination, flexibility and balance" because of idleness compared to the level of activity during earlier years in life (intrinsic)
- Vision strength drops as limited light enters through the retina, leading to difficulty in seeing items and the surrounding environment
- Medications with side effects cause dizziness, or dehydration, or have adverse reactions if taken together
- Environment within the home would require safety proofing to ensure smooth mobility paths and protected settings for residents, such as "loose rugs, clutter on the floor or stairs, carrying heavy or bulky things up or down stairs, not having stair railings and not having grab bars in the bathroom" (extrinsic cause) (NIH, 2013)

- Chronic conditions, which occur in more than 90 percent of the elderly, can lead to low levels of function including psychological and physical incompetence (intrinsic cause)

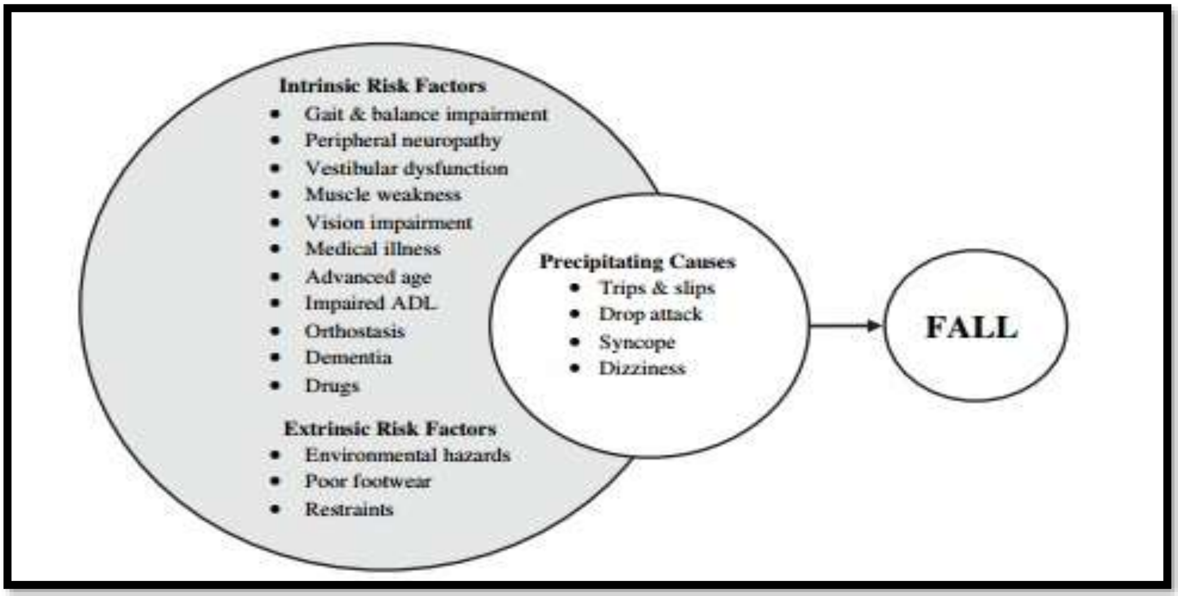


Figure 10: The Multifactorial and Interacting Causes of Falls (Rubenstein and Josephson, 2006)

Another cause leading to falls can be associated with the individual's "postural hypotension" (NIH, 2013), which is a dip in blood pressure when a person moves from an inactive to active position (intrinsic cause). Also, those suffering from the deficiency of vitamin D are at a higher risk of falls and fractures, and by taking a vitamin D supplement (Annweiler et al., 2010), the risk can be reduced (Barclay, 2014; Ringe, 2012; Janssen et al., 2002; Shuler et al., 2014). Annweiler et al. explained that vitamin D has an effect on the "postural adaptations - i.e., muscles and central nervous system." These authors assume that supplements could be the explanation for decreased fall and bone-fracture rates (Annweiler et al., 2010).

Once the individual and/or his/her caregivers are aware of the impact of these risk factors on the safety of the aging person, precautions can be taken, and prevention methods and tools can be implemented in the living environment to attempt to reduce and hopefully eliminate falls and their impact on the individual and society. As the setting of this study will be in hospitals, it is necessary to identify the causes and prevention tools discussed by Hitcho et al. (2004) that relate to this setting. The highest rate of falls in hospitals occurs during "the night, in the patient's room while being unassisted." The most common cause for falling in Hitcho's study was, losing balance, while the highest incidence of falls occurred during an event of moving/relocating ("ambulation") of the patient (e.g., moving to/from the bathroom, to/from the bedside commode, moving out of the bed for cleaning or moving to reach for an item (Hitcho et al., 2004). The most common intervention used was "assignment of patient to special rooms (i.e., video surveillance or placement close to the nurses' station)" (Hitcho et al., 2004). Some of the common causes of falls in hospitals per Hitcho et al. (2004) include: being unable to maintain balance when mobile; slipping or tripping while moving; losing consciousness either partially or completely; inability to maintain posture due to muscle weakness; unreliable sources of body support; and effects of sedation. The prevention methods that Hitcho et al. (2004) proposed emphasized increasing staff assistance during patient ambulation, providing managed toileting schedules where staff assistance is available, and providing mobility assistance such as walkers or canes to help prevent falls.

Another significant study (O'Connor, 2016) utilized quality tools and Lean Six Sigma methodology to determine the causes for falls in hospitals and prevent them, confirming the causes mentioned in the previous study by Hitcho et al. (2004). O'Connor compiled causes for falls into six categories: "1. fall risk assessment issues, 2. handoff communication issues, 3. toileting issues, 4. call light issues, 5. educational and organizational culture issues, and 6. medication issues." Prevention methods implemented to tackle the causes related to this study were as follows: "conducted two daily huddles related to bathroom falls and offering help with toileting every two hours, realizing the demographics of the patients and providing suitable levels of help when required, a 'no one walks alone' policy is applied and hourly support is provided to use the bathroom and switching positions in the bed, creating educational material to portray success stories and to promote best practices to reduce/eliminate falls and finally, realizing the effect of medications on the patients and attempting to modify the administration time to better suit the life style of the patient during the hospital time and recommended a high level of staff inclusion and support during the daily routine of the patient."

Aside from academic studies conducted to understand the causes of falls and applying prevention interventions to measure the change in fall rates, it is necessary to identify those major healthcare-quality entities which have also been involved in defining the reasons for falls and creating tools to prevent them. The Joint Commission (2015) issued a Sentinel Event Alert discussing the prevention of falls and fall-related injuries in healthcare facilities. The focus of this report was on falls with injuries; the most prevalent causes identified were "inadequate assessment, communication failures, lack of adherence to protocols and safety practices, inadequate staff orientation, supervision, staffing levels or skill mix, deficiencies in the physical environment and lack of leadership." The findings of this report align well with the other literature and publications discussed earlier. The causes and prevention tools identified in this report have also been incorporated into data and toolkits for falls available from AHRQ, ECRI Institute, Institute for Clinical Systems Improvement, IHI, Joint Commission Center for Transforming Healthcare, and Veterans Affairs National Center for Patient Safety.

On the other hand, not all literature notes the effectiveness of fall prevention tools and methods. Waters et al. (2015) studied four conditions, one of which was falls and their associated injury levels among inpatients (from July 1st of 2006 to December 31st of 2010, which overlaps briefly with the HAC-POA policy). Waters' study reported a decline in fall rates, but the authors were not able to identify a relationship between that insignificant decline in falls and the HAC policy. Oliver (2018) has extensively studied the methods and tools currently applied for fall prevention and has argued that the tools and methods should not be applied in a cookie-cutter manner. In particular, Oliver (2018) argued that although bed and chair sensors are cost-effective, their effectiveness has yet to be proven. Moreover, he theorized that when used on distressed, disoriented elderly suffering from dementia, they could have a negative impact on their inpatient experience, with disrupted or lack of sleep, which could cause falls possibly leading to deaths. Janeczko interviewed King (Janeczko, 2017) who explained that since nurses are usually the staff members penalized for falls, there is effectively an incentive for nurses to restrict patients and prevent them from moving freely. King said, "It's not about protecting the patients, it's about protecting themselves, to stop the message." This may not be in the best interest of patients, if it results in deconditioning due to lack of exercise, or if it results in falls occurring after discharge because patients have not been prepared adequately, known as "post-hospital syndrome"

(Growdon et al., 2017). In fact, Growdon described the use of restraints as an "epidemic of immobility among hospitalized older adults". Brown et al. (2009) reported that inpatients remained in their beds for more than 95 percent of their time in the hospital. Growdon stated that it is now more common in hospitals to use bed and chair alarms as a means to prevent falls, leading to unintended consequences of the inpatients feeling "in jail". This concern was also highlighted by Inouye et al. (2009), who added that some of the unintended consequences of bed restraints can be delirium, agitation, asphyxiation, and death, among others.

In conclusion, it was discovered that most of the causes for falls at home or in a hospital are significantly similar, and prevention/reduction tools are heavily reliant on identifying the causes and tailoring the solutions to them.

Realizing the rate of falls led us to question if they are defined correctly, which consequently indicated the numerous definitions of falls in the medical field. Determining that there is a common theme of descent and position alteration, which can be injurious or not, makes us relatively confident that when falls are reported, the reporting individuals mean *almost* the same thing. Notably, as of now, there is unfortunately no consistent fall-prevention policy used across the board in all medical settings. For this study, however, the data sources discuss only injurious falls causing the six specific outcomes; fracture, dislocation, head injury, crushing injury, burns and/or electric shock, which may reduce the ambiguity about what counts as a fall, since relatively minor incidents will be excluded.

The rising cost of falls socially and financially has demanded that multiple entities become involved in fall prevention. These include healthcare professionals, policymakers, public-health authorities, social-service providers, families, and caregivers of older adults. Therefore, in the next two subsections, the social and financial hardships imposed by falls will be discussed.

2.4.2 SOCIAL IMPACT OF FALLS

The impact of falls on the elderly can manifest in feeling pain for an extended period of time from the bruises or cuts. The elder can be subject to a “10-15 percent reduction in life expectancy” if the fall causes a hip fracture, which would in turn result in loss of independence and lack of self-confidence, resulting in loss of willingness to perform activities, leading to significant reduction in mobilization and movements (University of Indiana, 2004). Those who experience multiple fall events struggle with the highest levels of depression and decreased physical functions and a sense of humiliation from thinking they might fall again and get hurt.

The University of Indiana (2004) stated that concerns about the financial demands and costs of healthcare increase the level of anxiety about falls among all individuals involved. One result of this anxiety is that family members become more fearful that another fall event can occur, leading to overbearing protectiveness of the elder, which comes at the cost of eliminating or limiting their own activities to spend time assisting the aging member.

2.4.3 FINANCIAL IMPACT OF FALLS

Falls are second to motor-vehicle accidents as the largest contributor to the economic burden of injuries in the US, costing $100 billion annually (University of Indiana, 2004). In the elderly population, falls and their outcomes are *the* main contributor to the economic burden of injuries (Heinrich et al., 2010).

Falls can cause injuries or not; injuries in turn can cause both direct and indirect financial impacts. Direct costs can include medical costs (e.g., for inpatient care and pharmaceuticals) and non-medical costs (e.g., for informal care and transportation). Indirect costs account for the productivity lost due to the fallen person being either completely absent from work or decreasing work hours or load (Heinrich et al., 2010). The direct medical costs of falls in older adults in the year 2000 totaled $0.2 billion for fatal falls, and $19 billion for nonfatal fall injuries (Stevens et al., 2006). Indirect costs accounted for 16 to 33 percent of the total costs incurred to manage falls (Heinrich et al., 2010). According to the latest report (giving 2015 outcomes), direct medical costs totaled an estimated $640 million for fatal and $31 billion for non-fatal injuries (Burns and Stevens, 2016).

Table 4 is a representative illustration of the costs incurred (direct versus indirect) related to falls in the elderly population (Heinrich et al., 2010).

Table 4: Cost Incurred by the Elderly Due to Falls (Heinrich et. al., 2010)

Study	Cost components: Direct costs: IP/ED	OP	LTC	NU	Other: M	Other: NM	Indirect Costs	Costs per country and year: NCU in million (year of pricing)	USD PPP in million	Share of total healthcare expenditure (GDP) in %	Costs per inhabitant in USD PPP
All											
USA											
Stevens et al.	+/+	+	N.S.	+	+	+	-	19,200 USD (2000)	19,200	1.5 (0.20)	547
Kochera	N.S	-/+	+	+	N.S.	N.S.	-	16,398 USD (2000)	16,398	1.3 (0.17)	467
Mathers & Weiss	-/+	-	-	-	-	-	-	505 USD (1993)	505	0.06 (0.01)	15
Englander et al.	+/+	+	+	+	+	+	+	20,246 USD (1994)	20,246	2.2 (0.29)	607
Rice et al.	+/+	+	+	+	+	+	+	9,799 USD (1985)	9,799	2.3 (0.23)	345
Long- Term Care											
USA											
Carroll et al	+/-	-	+	-	-	-	-	4,200 to 5,700 USD (2003)	4,200 to 5,700	0.25 to 0.34 (0.04 to 0.05)	117 to 159
Community											
USA											
Carroll et al	+/-	+	-	-	+	-	-	5,328 to 6,174 USD (1997)	5,328 to 6,174	0.49 to 0.57 (0.06 to 0.07)	155 to 179

ED costs of emergency department, GDP gross domestic product, IP costs of inpatient care, LTC costs of long-term care, M medical costs, NCU national currency unit, NM non-medical costs, N.S. not specified, that is no or insufficient information, I.E. no or insufficient information, NU costs of ambulatory nursing care, OP costs of outpatient care (including outpatient clinic), PPP purchasing power parities

2.5 MEDICAL SETTING: CMS ACUTE-CARE HOSPITALS

As previously noted, the HAC-POA quality initiative was developed for inpatients in acute-care settings. This policy is also known as a "quality payment adjustment system," and payments for this system are handled under the IPPS, which pays acute-care hospitals for their performance based on quality outcomes.

2.6 MEASUREMENTS: VARIABLES OF STUDY

The final element of this research is to identify the specific variables to study, define them, and understand their impact in healthcare, and their relevancy to possible factors related to falls in hospitals. The variables to be collected and analyzed are deemed potentially relevant to falls based on the literature and will be analyzed during the period after implementation of the CMS HAC-POA policy.

The 2010-2015 National Scorecard on Rates of Hospital-Acquired Conditions published by AHRQ (2016) as part of the Partnership for Patients' goal of reducing HAC, noted that from 2010 to 2015, the rate of HACs in inpatient acute-care settings has *decreased by 21 percent*, saving approximately $28 billion in costs and 125,000 patient lives (AHRQ, 2016). A report in December 2016, published the reduced rates of HAC, noting that there was a cumulative total of three million fewer incidents over the five-year period between 2011 to 2015 compared to the baseline year of 2010 (AHRQ, 2016), where falls accounted for 2.9 percent of the total of three million incidents avoided. This study provides an examination on variables supported by literature, and also novel variables that the literature has identified as interesting, but no one has analyzed yet. Multiple factors discussed in the literature will be explored to identify their relevance to this study and their availability in the datasets.

2.6.1 VARIABLE IDENTIFICATION

Since the publication of the IOM (1999) report, many research bodies have published continuous-improvement publications targeting patient safety, such as Consumers Union (2009), which discussed the need for more work on safety and establishment of protocols for a "healthcare system free of preventable medical harms." There are various causes for medical errors and adverse outcomes, those which are dependent on the facility and its functions e.g. the nurses, the equipment, etc. and those which are dependent on the patients and their own features and characteristics (e.g., gender, race, religion, socioeconomic status). While the most commonly studied quality-of-care factors are patient satisfaction, low medical-error rate, low mortality level, low rates of adverse events, high level of patient care reported, etc., there are other factors that contribute to the creation and improvement of these intuitively appealing elements. In search for relevant literature on elements affecting the quality of care in healthcare, only publications after the year 2000 are referenced, to provide the necessary relation between the newly adopted quality measures and the 1999 IOM report.

2.6.2 VARIABLE DETERMINATION

AHRQ, CMS, and other agencies have concluded that HAC-POA quality initiative is on the right track and is accomplishing its goal of reducing incidents, and financial impact, specifically for falls. Nevertheless, they did identify a challenge since the actual variables contributing to this reduction have not been identified yet (AHRQ, 2016). Although there is a realization of increased safety measures in hospital settings, other effects and causes need to be studied to ensure continued improvement for this initiative.

2.6.2.1 VARIABLE EXPLORATION

Hospitals need to be aware of who is more prone to falls (e.g. based on gender and age), to enable the facility to provide and prepare the necessary requirements to avoid falls as much as possible, and preparing to understand the possible variables possibly related to falls during hospital stays, one variables was examined and proven not to be pronounced in the literature was; the difference in the elderly age range.

Older adults start off at the age of 65 years, but another range, called the “oldest old,” are those above 75 or 85 years old, depending on the publication. Notably, there is limited research performed on these specific age ranges and their effect on fall rates. Grundstrom et al. (2012) reported the scarcity of studies for this age range. They focused mainly on whether those who are 85+ are at a higher risk of falling compared to those who are “younger,” and found that if individuals have an “excellent overall health status” they do not appear to be at a greater risk for falling than those who are younger. Abraham and Cimino-Fiallos (2017) also investigated falls among the elderly and the causes, injuries, and how to manage falls when they occur. This investigation, similar to that by Grundstrom et al. (2012), concluded that those who are among the healthiest of the oldest old (85+) do not necessarily exhibit a higher risk of falls compared to those who are 65+. On the other hand, Fuller (2000) concluded that the fall risk increases with age, especially for those who are 75+ or older, and a similar study by the IOM (1992) noted that at older ages (85+), over 60 percent of falls lead to deaths, with men accounting for the highest mortality rate. Stevens (2005) supported the view that those 85+ are at a higher risk for falls than those 65-74, by a factor of “four to five times.”

Exploring the relation of gender to falls in those who are over 70 years old, Currie (2008) documented that females are more prone to falls, but fatalities are more likely in men, while Grundstrom et al. (2012) reported that males were at a higher risk of falling compared to females among those 85+ years old. This variability in findings suggests that the same policies and requirements should be used for all ages and genders to prevent falls, since there is no clear evidence as to which subpopulations of the elderly are more prone to falls. Therefore, most publications on falls have generalized their procedures to apply to the general age range of 65+ or younger and applied the same precautions to both genders. Although these elements were identified as potentially significant in the literature, this study is unable to continue this analysis based on gender or age due to a limitation in the datasets analyzed.

An additional variable explored was the quality of resources the healthcare facilities receive based on their geographical location and its possible impact on fall rates. Hitcho et al. (2004) and Everhart et al. (2014) reported on the relative commonality of fall studies conducted in different geographical settings in long-term care and rehabilitation settings compared to acute-care inpatient settings and recommended further analysis and understanding of conditions that can be correlated to falls during hospital stays. Hitcho et al. (2004) focused on an urban, academic hospital. Another study on fall prevention in hospitals targeted the data of four urban facilities (two academic medical centers, and two teaching community hospitals) in Boston, Massachusetts (Dykes et al., 2010), while Allison et al. (2000) compared quality outcomes in teaching versus non-teaching hospitals and reported an association of better quality with teaching hospitals. Similar findings for teaching hospitals were also reported by Ayanian and Weissman (2002). Given that the data utilized for this study does not distinguish between academic facilities and others, this attribute will not be applied in this analysis.

Finally, one of the few sources that provided feedback on performance measures to use in this study is Guiding Metrics.com (2014). Although not CMS-specific, this source published an article discussing "The Hospital Industry's 10 Most Critical Metrics." This article was written specifically for companies in the hospital industry and what they should be *watching* in the performance of the medical facilities they are conducting business with, which is a similar relationship between CMS and the hospitals it deals with, since CMS and the businesses require improvement to be measured and identified.

The 10 most critical metrics discussed by Guiding Metrics.com are listed as: 1. Average Length of Stay (ALOS), 2. Time to Service, 3. Hospital Incidents, 4. Patient Satisfaction, 5. Physician Performance, 6. Patient Readmission Rate, 7. Inpatient Mortality Rate, 8. Operating Margin, 9. Bed Occupancy Rate and 10. Asset Utilization Rate. Notably, although some of these metrics do not relate to this study, a few of them are in fact identified as variables in Chapter 3.

2.6.3 VARIABLE SOURCES

This study relies exclusively on open source datasets. The main datasets are extracted from CMS, while other publicly available sources were investigated and referenced where applicable. In this chapter, elements of CMS and other databases identified as potentially relevant to this study shall be summarized. Chapter 3 will then discuss the dependent variable and specific independent variables used in the analysis.

2.6.3.1 FALLS DATASET

The CMS dataset on rates of injurious falls and trauma (CMS,2019) must be connected to additional CMS datasets to create a meaningful relation between the fall rates reported and the factors related to these fall rates at the time of the study. The HAC-POA fall rates datasets are presented in a 24-month period, with the first dataset reporting the falls outcome of this policy spanning from July 1st, 2010, to June 30th, 2012, with the final dataset published covering July 1st, 2013 to June 30th, 2015. For the purposes of this study, and given the current available data for other variables, the following guidelines shall apply:

- A dedicated period of time will be assigned, which will depend on the longest period of time covered by all the CMS datasets used in this analysis. This study will initially analyze the first dataset published, which is from the third quarter of 2010 to the second quarter of 2012 (two years) and will follow with a secondary analysis using the 2013-2015 dataset to compare the relationships of the variables and the HAC-POA fall rates.

- CMS Data Files on Falls and Trauma (Medicare and HAC) which portray the fall rates per hospital (rate/1000 discharges) will be used following elements for period 7/1/2010 to 6/30/2012 (within this period, approximately 5,000 hospitals are registered but some do not report fall rates). The following elements represent the columns in this dataset:
    - Hospital ID Number (all the variables shall be cross referenced by the hospital name and ID number in this analysis)
    - Measure Name: Falls and Trauma
    - Rate of falls per 1,000 Discharges: CMS calculates the rate of falls in this database by accounting for the number of patient falls during the specified period of time in the hospital (numerator), dividing by the number of eligible discharges at that hospital (denominator), and multiplying the outcome by 1,000. In this study the specified period is two years (CMS, 2017).
    - Data presenting the fall and trauma rates are identified by Provider ID/Hospital ID/Provider Number. The Provider ID = Hospital ID = Provider Number.

2.6.3.2 HOSPITAL COST REPORTS DATASET

CMS's hospital cost reports (CMS,2019) published data on the following characteristics (for years 1994 to 2016). It is worth noting that since these files are annual, the year analyzed against the falls and trauma files will be that providing data for a full calendar year (i.e., 2011 for the primary analysis and 2014 for the secondary analysis). Elements available in the dataset include:

- Provider number (separate sheet links the provider number with Hospital ID)
- Beginning of fiscal year
- End of fiscal year
- Hospital name
- State
- Total certified hospital beds ("total number of beds in Medicare and/or Medicaid certified areas within a facility"), where beds are "maintained for lodging inpatients, including beds in intensive care units, coronary care units, neonatal intensive care units, and other special care inpatient hospital units" (CMS, 2009).
- Total hospital bed days available: ("all licensed beds", CMS, 2009)
- Total hospital Medicare days
- Total hospital days (number of days being admitted to the hospital)
- Total hospital employees on payroll
- Total hospital Medicare discharges
- Total hospital discharges
- Urban or rural hospital provider

The definition of total hospital bed days available has been controversial. It was determined by CMS that although a hospital can have a portion of its acute-care beds *occupied* as swing and/or observation beds (not acute care), they remain *available* and are counted as such. Taking this into account, available beds include both those “in use and housed in patient rooms or wards” (CMS, 2009) and those that can be brought into a room that currently does not have a bed in it (e.g., a storage room) (IMA, 2003).

2.6.3.3 PROVIDER OF SERVICE DATASET

CMS data files (CMS,2019) on provider of service list attributes including, but not limited to: the ownership type of the facility; and the staffing levels. Although various types of staff members and levels are listed (e.g., residents, physician assistants, anesthesiologists, social workers, etc.), this study will focus only on the nursing staffing level, since the literature has confirmed the relationship between falls and nursing staff compared to other medical staff levels, and no other level of staff member (e.g., physician or physician assistant) would have the same direct and continuous relationship with the patient as nurses. King et al. (2016) noted that staff nurses in the hospital setting are the most influential in terms of decreasing fall rates among elderly inpatients. King also reported that the NQF in 2004 had assigned nursing as a quality indicator related to patient falls, where nursing is now viewed as the primary responsible factor to reduce or eliminate falls.

Similar to the cost reports, the provider of service lists are also published annually, thereby the year analyzed against the falls and trauma files will be that providing data for a full calendar year (i.e., 2011 for the primary analysis and 2014 for the secondary analysis).

Ownership types of the hospitals listed are:

- Church
- Private (not for profit)
- Private (for profit)
- Federal
- State
- Local
- Hospital district/authority
- Other

Likewise, staffing levels for nurses are given as follows:

- Total number Certified Registered Nurse Anesthetist (CRNA) (total of fulltime equivalent CRNA employed by a provider)

- Total number of Licensed Practical Nurses (LPN) and Licensed Vocational Nurses (LVN) (total of fulltime equivalent LPN/LVN employed by a provider)

- Total number of Nurse Practitioners (NP) (total of fulltime equivalent NP employed by a provider)

- Total number of Registered Nurses (RN) (total of fulltime equivalent RN employed by a provider**)**

2.6.3.4 ADDITIONAL DATASETS

Additional datasets applied to this study will include CMS's IPPS (CMS, 2019) provider summary for the top 100 DRGs. This data set is available in the Acute IPPS file, which is part of the Medicare Fee-For-Service Payment folder. This dataset presents the annual top 100 DRGs, and each provider/hospital which has these DRGs coded in their records for that year. Each annual dataset presents over 3,000 hospitals, listing more than seven million DRGs in total, which account for more than 60 percent of the total Medicare IPPS discharge diagnoses of that year (CMS, 2017). Each data set lists the following:

  - DRG code and its definition

  - Provider ID and information

  - Total discharges for each DRG

An additional source for datasets is CMS's Hospital Compare, which is a quality scoring tool used by CMS to evaluate all the US hospitals against seven specific quality performance variables. These variables are: 1. Mortality, 2. Safety of care, 3. Readmission, 4. Patient Experience, 5. Effectiveness of care, 6. Timeliness of Care and 7. Efficient Use of Medical Imaging (Medicare.gov, 2018). These seven categories represent 57 specific elements used to determine the overall scoring of the hospital. The overall score is presented on a scale of stars (from one to five), with one star being the worst quality performance and five stars being excellent quality performance.

To make an educated decision on possible variables to apply to this study, a deeper look into the definitions of these variables, how they are rated in the medical environment, and how they can affect the rate of injurious falls will be made. Table 5 represents the Hospital Compare measures by categories (Medicare.gov, 2018).

Table 5: Hospital Compare Measures by Categories (Medicare.gov, 2018)

Variable (number of elements scored for this variable)	**Description of the Variable Elements**	**Relevance of Variable to the Study**
Mortality (7)	Death rate for heart attack patients	**Probably irrelevant:** Discusses the death rate of patients, which is not relevant to this study of injurious falls, since causes of death may be largely unrelated to causes of falls.
	Death rate for coronary artery bypass graft (CABG) surgery patients	
	Death rate for chronic obstructive pulmonary disease (COPD) patients	
	Death rate for heart failure patients	
	Death rate for pneumonia patients	
	Death rate for stroke patients	
	Deaths among patients with serious treatable complications after surgery	
Safety of Care (8)	Central line-associated bloodstream infections (CLABSI)	**Potentially relevant:**

	Catheter-associated urinary tract infections (CAUTI)	Although safety of care is potentially relevant to fall rates, aggregate scores (e.g., star rankings) for safety are not available. Using all eight elements for safety as separate independent variables could result in false positives, and in any case most of the specific elements listed for safety are related mainly to infection control, not to fall safety.
	Surgical site infections from colon surgery (SSI: Colon)	
	Surgical site infections from abdominal hysterectomy (SSI: Hysterectomy)	
	Methicillin-resistant Staphylococcus Aureus (MRSA) Blood Laboratory-identified Events (Bloodstream infections)	
	Clostridium difficile (C.diff.) Laboratory-identified Events (Intestinal infections)	
	Rate of complications for hip/knee replacement patients	
	Serious complications	
Readmission (9)	Hospital return days for heart attack patients	**Potentially relevant:** Although readmission is potentially relevant to fall rates (since for example insufficient mobility while in the hospital may lead to greater risk of falls and readmission after discharge), aggregate scores (e.g., star rankings) for readmission causes are not available. As above, using all nine elements for readmission as separate independent variables could result in false positives.
	Rate of unplanned readmission for coronary artery bypass graft (CABG) surgery patients	
	Rate of unplanned readmission for chronic obstructive pulmonary disease (COPD) patients	
	Hospital return days for heart failure patients	
	Rate of unplanned readmission after hip/knee surgery	
	Rate of unplanned readmission for pneumonia patients	
	Rate of unplanned readmission for stroke patients	
	Rate of unplanned readmission after discharge from hospital (hospital-wide)	
	Rate of unplanned hospital visits after an outpatient colonoscopy	
Patient Experience (11)	Patients who reported that their nurses communicated well	**Relevant**: Discussed separately in next section.
	Patients who reported that their doctors communicated well	
	Patients who reported that they received help as soon as they wanted	
	Patients who reported that their pain was well controlled	
	Patients who reported that staff explained about medicines before giving it to them	
	Patients who reported that their room and bathroom were clean	
	Patients who reported that the area around their room was quiet at night	
	Patients who reported that they were given information about what to do during their recovery at home	
	Patients who understood their care when they left the hospital	

	Patients who gave their hospital a rating on a scale from 0 (lowest) to 10 (highest)	
	Patients who would recommend the hospital to their friends and family	
Effectiveness of Care (10)	Patients assessed and given influenza vaccination	**Probably irrelevant:** Many of the elements in this category represent effectiveness of care for healthcare workers, outpatients, and emergency department patients, who are not covered by this study.
	Healthcare workers given influenza vaccination	
	Outpatients with chest pain or possible heart attack who received aspirin within 24 hours of arrival or before transferring from the emergency department	
	Percentage of patients who left the emergency department before being seen	
	Percentage of patients who came to the emergency department with stroke symptoms who received brain scan results within 45 minutes of arrival	
	Percentage of patients receiving appropriate recommendation for follow-up screening colonoscopy	
	Percentage of patients with history of polyps receiving follow-up colonoscopy in the appropriate timeframe	
	Percent of mothers whose deliveries were scheduled too early (1-2 weeks early), when a scheduled delivery was not medically necessary	
	Patients who developed a blood clot while in the hospital who did not get treatment that could have prevented it	
	Percentage of patients receiving appropriate radiation therapy for cancer that has spread to the bone	
Timeliness of Care (7)	Average (median) time patients spent in the emergency department, before they were admitted to the hospital as an inpatient	**Probably irrelevant:** While timeliness of care for inpatients could be relevant to fall rates, this element again concerns timeliness of care for outpatient cohorts and emergency department patients, who are not covered by this study.
	Average (median) time patients spent in the emergency department, after the doctor decided to admit them as an inpatient before leaving the emergency department for their inpatient room	
	Average (median) number of minutes before outpatients with chest pain or possible heart attack who needed specialized care were transferred to another hospital	
	Average (median) number of minutes before outpatients with chest pain or possible heart attack got an ECG	
	Average (median) time patients spent in the emergency department before leaving from the visit	

	Average (median) time patients spent in the emergency department before they were seen by a healthcare professional	
	Average (median) time patients who came to the emergency department with broken bones had to wait before getting pain medication	
Efficient Use of Medical Imaging (5)	Outpatients with low-back pain who had an MRI without trying recommended treatments first, such as physical therapy	**Irrelevant:** Outpatient cohorts are not covered by this study. Moreover, excessive use of medical imaging is relevant to cost control, but not to fall rates.
	Outpatient CT scans of the abdomen that were “combination” (double) scans	
	Outpatient CT scans of the chest that were “combination” (double) scans	
	Outpatients who got cardiac imaging stress tests before low-risk outpatient surgery	
	Outpatients with brain CT scans who got a sinus CT scan at the same time	

The category of quality that this study will address is patient experience, also known as the Hospital Consumer Assessment of Healthcare Providers and Systems (HCAHPS) survey, which is believed to be most relevant to this study. This survey was created by CMS and AHRQ to maintain a standardized tool and data collection method to collect patients’ experiences and their feedback on the quality performance of hospitals during inpatient stays. This survey presents data on eleven topics and they are also scored in stars, similar to the Hospital Compare methodology (Medicare.gov, 2018).

Table 6 represents the HCAHPS’ survey eleven topics along with their definitions (Medicare.gov, 2018), and briefly discusses their relevance to this study.

Table 6: HCAHPS Survey Topics (Medicare.gov, 2018)

HCAHPS Topics	Relevance to this Study
1. Nurse communication: "Patients reported how often their nurses communicated well with them during their hospital stay. "Communicated well" means nurses explained things clearly, listened carefully to the patient, and treated the patient with courtesy and respect".	**Relevant**: Nursing has been identified as the primary factor affecting fall rates in hospitals (King, 2018). When nurses are able to communicate and explain the impact of, e.g. not leaving your bed without support, and maintaining a trust, relationship between the patient and nurses, falls are hypothesized to decrease.
2. Doctor communication: "Patients reported how often their doctors communicated well with them during their hospital stay. "Communicated well" means doctors explained things clearly, listened carefully to the patient, and treated the patient with courtesy and respect".	**Less Relevant:** Since nursing has been identified as the primary factor affecting fall rates in hospitals (King, 2018), it is anticipated that physicians have a limited effect on injurious fall rates.
3. Responsiveness of hospital staff: "Patients reported how often they were helped quickly when they used the call button or needed help in getting to the bathroom or using a bedpan".	**Relevant**: When patient calls and requests are responded to swiftly, falls are hypothesized to decrease, since patients may be less likely to leave their beds without assistance.
4. Pain management: "If patients needed medicine for pain during their hospital stay, the survey asked how often their pain was well controlled. "Well controlled" means their pain was well controlled and that the hospital staff did everything they could to help patients with their pain.	**Limited Relevance**: Pain management may in principle be related to falls (e.g., if excessive pain results in patients remaining immobile or bedridden) but seems at best to be tenuously related to fall rates.
5. Communication about medicines: "If patients were given medicine that they had not taken before, the survey asked how often staff explained about the medicine. "Explained" means that hospital staff told what the medicine was for and what side effects it might have before they gave it to the patient".	**Limited Relevance**: Communication about medicine may in principle be related to falls (e.g., if a patient is not informed that a particular medication may impair balance) but seems at best to be tenuously related to fall rates.
6. Discharge information: "the survey asked patients about information they were given when they were ready to leave the hospital. Patients reported whether hospital staff had discussed the help they would need at home. Patients also reported whether they were given written information about symptoms or health problems to watch for during their recovery".	**Irrelevant**: May be related to falls after discharge, but not to the time and location covered by this study.
7. Care transition: "Patients reported whether they and/or their caregivers understood the type of care the patient would need once the patient left the hospital.	**Irrelevant**: May be related to falls after a patient leaves the hospital, but not to the time and location covered by this study.

8. Cleanliness of hospital environment: “Patients reported how often their hospital room and bathroom were kept clean”.	**Probably irrelevant:** Arguably not related to fall rates.
9. Quietness of hospital environment: “patients reported how often the area around their room was quiet at night”.	**Probably irrelevant:** Arguably not related to fall rates.
10. Hospital rating: “After answering all other questions on the survey, patients answered a separate question that asked for a hospital rating”.	**Probably irrelevant:** Arguably too broad to be a good predictor of fall rates.
11. Willingness to recommend hospital: “The survey asked patients whether they would recommend the hospital to their friends and family”.	**Probably irrelevant:** Arguably too broad to be a good predictor of fall rates.

In conclusion of understanding the HCAHPS topics, two topics have been identified as relevant and will be included into the analysis. The first topic is: 1. nursing communication; which is a compilation of how inpatients described their interactions with nurses and how they “communicated well” with them. HCAHPS defines ‘communicated well’ as: “a. nurse explained things clearly, b. listened carefully to the patient, and c. treated the patient with courtesy and respect’ (Medicare.gov, 2018). The second topic is: the responsiveness of hospital staff and how quick patients received help; which HCAHPS defines as the swiftness of assistance when the inpatient: a. used the call button or b. needed help in getting to the bathroom or using a bedpan (Medicare.gov, 2018).

Notably, the information for the HCAHPS dataset is usually collected quarterly. Given that the first complete annual survey was published for the year 2014, it will be applied for the first dataset analysis, and the second full annual survey for 2016 will be applied for the second dataset analysis (Medicare.gov, 2019).

Finally, another data source which could have been accessed is the US Census dataset, which provides information on the population by county or state; e.g., demographics (race, gender, age), level of education, level of English spoken, etc. However, since data is available only at the county level, use of this data would require manually identifying the relevant data for the counties housing each hospital in the CMS datasets. This could be done by locating the variable(s) identified for the study, and then adding the values of those variables (e.g., percentage of each gender per county) manually to the dataset used in the analysis. Based on a random sample for a small state, with a limited number of counties, this proved to be labor intensive. Moreover, some demographic and socioeconomic data did not vary much between counties, while individuals or neighborhoods within a county may vary widely. Therefore, future research on health disparities related to falls is recommended.

2.7 RESEARCH AIM

The aim of this analysis is to:

Conduct an exploratory analysis of readily available national hospital-level data of injurious falls recorded after implementing the HAC-POA quality initiative policy, through an observational study to identify factors that are statistically associated with differing fall rates from hospital to hospital, as a guide to further research to explore the reasons for any identified relationships

In particular, this study will implement a regression analysis to identify possible correlation(s) and statistically significant associations between the rate of injurious falls and the variables identified in the study, with several supplementary analyses to ensure the robustness of the results across different model specifications and different time periods.

2.8 RESEARCH CHALLENGES

A significant challenge for this study was assuring that all falls reported had a common definition (the abundant fall definitions have been previously discussed). However, given the study's focus on injurious falls, the plethora of definitions can be assumed to be less problematic.

Also, given that CMS data is referenced, it is recognized that not all the population represented in the fall rates are 65+ (since Medicare allows individuals younger than 65 years to sign up based on specific conditions, as discussed earlier). Therefore, assumptions are made that the vast majority of falls are related to the elderly who are signed up for Medicare, since it is not possible to determine the exact percentage of the elderly population served by Medicare.

The next challenge was locating open access datasets relevant to the medical setting. It was important that the datasets provide variables related to the falls, so that numerous factors could be compared, allowing for a correlation to be identified (or not) between those factors and fall rates. Acquiring datasets with specific patient or incident related information proved to be a hardship, since these datasets must be purchased from CMS. Locating sufficient datasets with relevant information that overlapped for a considerable period of time to enable the analysis also proved a challenge.

Restrictions in the variables available meant that multiple confounding factors may exist, causing potential weaknesses in the study. The datasets of the HAC-POA are hospital/provider specific. This limits the ability to analyze patient-level data that could be involve confounding factors, such as patient demographics, pre-existing comorbidities affecting the status of the patient, high fall risk factors, patient medications (specifically drugs that can cause sleepiness and drowsiness), data on location and time of fall in the hospital, the description of the injury related to the fall, and number of falls recorded per unit.

Despite the limitations of this study, the interest remains in conducting a hospital-level analysis to understand the factors that are important at the facility level and their possible association to falls.

2.9 RESEARCH SIGNIFICANCE

The elements of this study and the research challenges have now been identified, leading to the importance of this study and why/how it is different from other studies performed to date on HACs.

The novelty of this study lies partially in its database, since utilizing a national database such as CMS has not been tackled before to this extent. In particular, all hospitals listed in the CMS datasets will be compared, therefore, maximizing the chance of finding statistically significant relationships. Moreover, the analysis does not focus on only one or two variables, but multiple variables studied together (in addition to their interactions), reducing the risk of confounding effects.

This exploratory analysis is considered to be beneficial, since understanding the correlations between falls and the multiple variables of this study would help guide future confirmatory research, and hence contribute to the knowledge base assisting facilities to be prepared for the elderly population and utilize their resources effectively to reduce fall rates.

CHAPTER 3

METHODOLOGY

This research study will utilize statistical means to investigate and quantify the contribution of the different potential factors on falls. Multivariate regression will be employed to meet the study's objective such that the influence of a given factor on falls can be identified and measured. In the literature review, critical factors were identified, and in order to conduct the statistical analysis, the anticipated critical factors and the fall indicators will be incorporated as variables. Further explanation of the variables, how they will be calculated, and what is expected from the analysis to deliver, follows in this chapter.

Initially, to conduct a regression analysis, the variables must be identified: the dependent variable, which in this study is the fall rate; and independent variables, which will be discussed shortly. The business dictionary defines a variable as: "a characteristic, number, or quantity that increases or decreases over time, or takes different values in different situations" (BD.com, 2018). Independent variables are recognized as "predictor or explanatory" variables, and are typically denoted by X (Alexopoulos, 2010). The dependent variable is defined as a "response or outcome" variable, and is typically denoted by Y (Alexopoulos, 2010). Note also that there are a number of independent variables that would have contributed to this study but are not available in the current databases; this is recognized as a challenge for this study and will be discussed in further detail.

3.1 DEPENDENT VARIABLE: FALL RATE

Hospital falls and trauma rates are readily available in the CMS HAC-POA database, where they are identified as the fall rates per 1,000 discharges. This database portrays the hospitals associated with the CMS reimbursement program, and which have also recorded the total number of falls which occurred between the third quarter in 2010 (July 1st) through the second quarter of 2012 (June 30th), which is exactly two years. Initially, in the provider of services files located in the CMS datasets, there were 4,905 hospitals that could have reported falls throughout the two years of study. However, 1,579 hospitals did not record fall rates; resulting in 3,326 hospitals with recorded fall rates per 1,000 discharges remain to be analyzed. An additional dataset covering the period between the third quarter of 2013 (July 1st) through the second quarter of 2015 (June 30th) will also be analyzed.

3.2 INDEPENDENT VARIABLES

3.2.1 VARIABLES JUSTIFICATION

In the literature, there are few comparable US studies focusing on falls and the variables leading to falls in CMS acute care settings. In the event that US studies were not located for a particular topic, non-US (e.g., Canadian) publications were cited. For this study, based on the literature, eight categories of variables have been chosen for analysis: nursing staff; hospital bed occupancy rate; proxy for severity of stay, represented by: ALOS and DRGs; scoring of hospital quality of care, represented by: nursing communication score and staff responsiveness score; hospital location as urban vs. rural; hospital type; hospital size; and Magnet award hospitals.

Referencing the conceptual model in Figure 7, the Donabedian model, the aforementioned variables will be highlighted to present the linkage between the conceptual model and the study's variables which can be accessed through open source datasets. Figure 11 highlights the division of the variables, based on availability for use in this study (highlighted in yellow) and those which would be recommended for future analysis if data is available (highlighted in green).

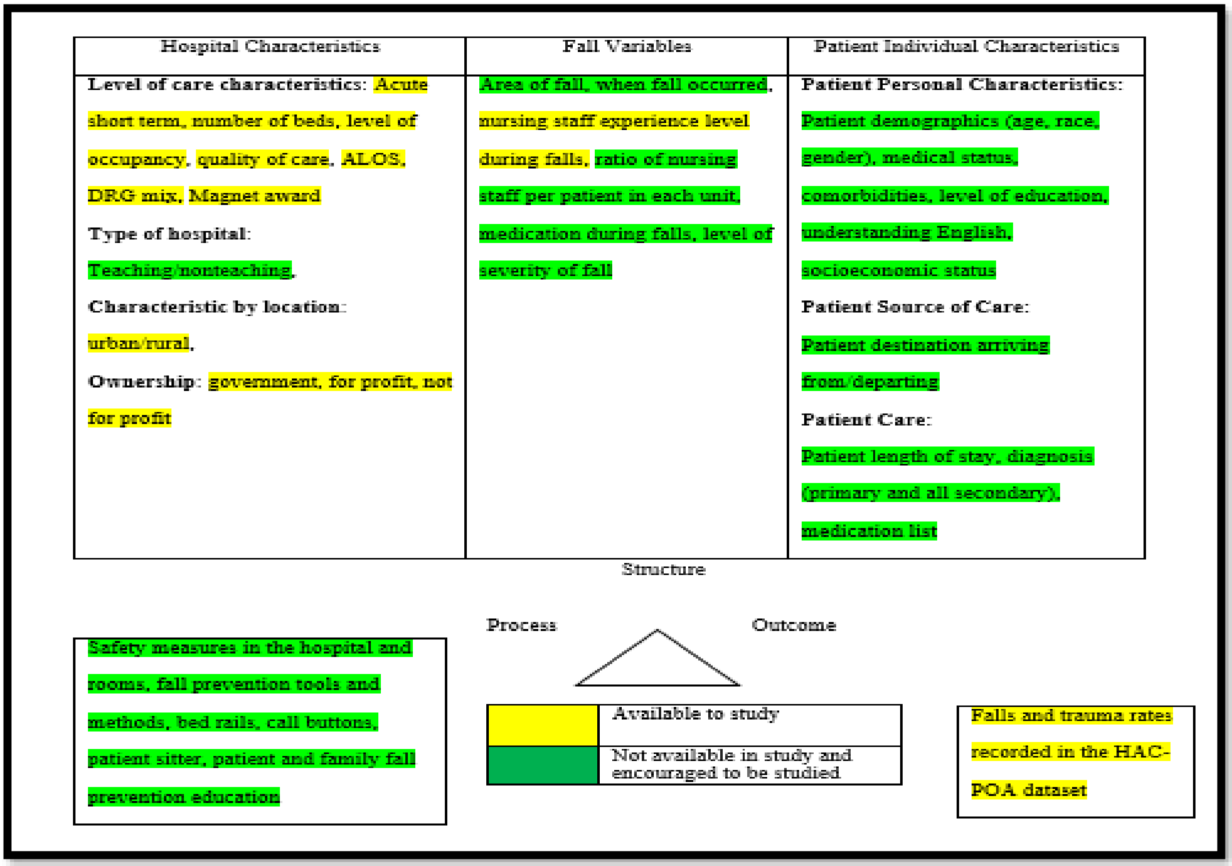


Figure 11: Donabedian Conceptual Model incorporating the Study's Variables

3.2.2 PREPARING THE VARIABLES FOR ANALYSIS

A compiled list of variable descriptions introduced in this study is presented in Table 7, where each variable is categorized as continuous, dichotomous or numeric, along with a short description. A more detailed explanation of each variable and the equations assigned to each will follow.

Table 7: Variable Descriptions

Variable	**Type**	**Short Description**
Dependent	Continuous	Patient falls per 1,000 discharges
Hospital falls and trauma rates per 1,000 discharges		
***Covariates**:*		
Hospital Factors:		
Hospital type	Dichotomous	1= other nonprofit voluntary, 0= other. 1= proprietary, 0 = other. 1= private nonprofit voluntary, 0 = other, 1= all nonprofit voluntary, 0= otherwise
Hospital location	Dichotomous	Urban/ Rural (1= urban, 0 = other)
Magnet status	Dichotomous	American Nurses Credentialing Center (ANCC) Magnet award (1= magnet, 0=other)
Hospital bed occupancy	Continuous	Rate of inpatient beds occupied during the period per all available beds in the hospital
Hospital size	Continuous	Number of beds available in each hospital
Quality of healthcare (HCAHPS Survey)	Ordinal	Star scoring (one star being the lowest ranked performance through to five stars being the highest ranked performance)
Hospital ALOS	Continuous	Rate of patient days per discharge
Hospital DRGs	Continuous	Rate of DRG per total discharges
Hospital nurse staffing		
Total nursing staff	Continuous	Total RN and LPN/LVN staff per bed
RN rate to all nursing	Continuous	Total RNs per total staff

3.2.2.1 HOSPITAL SIZE

Hospital size is identified by two elements: total number of hospital beds; and total certified (Medicare) hospital beds. Total hospital beds available identifies *all* existing beds in a hospital (which can be used *at any time*), while total hospital certified/Medicare beds represent existing beds in a hospital which can be used *at any time* and are assigned to Medicare (CMS, 2009). This study would hypothesize that larger hospitals, with large number of beds, would have significant funding sources to sustain their size, therefore allowing for better care and lower fall rates, compared to smaller size hospitals, which might not be able to prevent falls due to lack of funding and/or resources.

$$\text{HSBD} = \text{Total Hospital Beds} \quad \text{Equation 3.1}$$

$$\text{HSMB} = \text{Total Hospital Certified Beds} \quad \text{Equation 3.2}$$

3.2.2.2 NURSING STAFF

Nurse staffing and its effect on quality of care and inpatient falls has been discussed in numerous studies as a significant indication for quality of care (NQF, 2004). Multiple studies have also identified that nurse staffing levels are associated with the level of inpatient falls (Everhart et al., 2014); the higher the staffing level and number of nurses, the better or higher the quality of care offered to inpatients allowing for fewer falls. Among the many who published in this area are Aiken et al. (2002, 2003, 2008), Needleman et al. (2002), Mark et al. (2004), Sochalski (2004), Stanton and Rutherford (2004), Currie et al. (2005), and Kane et al. (2007), excluding publications dated pre-2000. The relationship of the nurse staffing to fall rates was also studied by Hitcho et al. (2004), who utilized data relevant to patients, fall situations, injury outcomes, and staffing levels in comparison to the fall rates of the inpatients in acute care hospitals. Interestingly, inpatient facilities with the highest nursing ratios recorded the highest fall incidence rates. Hitcho et al. assumed that their patient populations may have suffered from more extreme illnesses, or from poor ability to balance; thus, Hitcho et al. recommended accounting for patient condition. Additionally, a strong relationship between the nurse staffing availability and fall rate was identified and explained by Everhart et al. (2014) and AHRQ (2004).

In this study, the provider of services files in the CMS database give staffing levels for LPNs and LVNs, RNs, NPs, and CRNAs, where when more light was shed on the nurses’ responsibilities, the Board of Vocational Nursing and Psychiatric Technicians (BVNPT, 2016) have identified LVNs as entry-level care providers who perform basic nursing skills. LVNs perform under the supervision of either a RN or a doctor (BVNPT, 2016). The Charter College (2017) Nursing School reports that some states recognize LVNs as LPNs. Practical nursing.org (2017) likewise confirms the similarity between LVNs and LPNs.

By contrast, the RN is at a higher level than LVNs/LPNs. RNs are considered to be next in line after the physicians, which demonstrates the large area of responsibility that they cover (Nurse Journal.org, 2018). RNs can diagnose, treat, and prescribe medications to patients by generating a treatment plan to reach a healthy state and maintain it (Practical nursing.org, 2017). Although, as mentioned earlier, LVN/LPNs are directed by either RNs or the physicians, those who are experienced can “unofficially” access patients but must refer to the RN or physician they work with for a treatment plan (NurseJournal.org, 2018). While RNs help physicians, and treat patients, among other duties, they are unable to perform advanced medical care as NPs. NPs are more advanced in terms of the medical requirements s/he needs to meet, and also medical applications s/he can provide compared to RNs (Charter College, 2017). NPs are more specialized in their clinical training area. They are recognized as an addition to the physician and perform tasks such as diagnosing and treating patients while also focusing on specific areas such as family care or adult care (Allnursingschools.com, 2018).

Another specialty assisting nurses is a certified nurse assistant (CNA), who according to Nurse Journal.org (2018) is considered to be one of the most important members in a healthcare team. CNAs work directly with the patient and the medical team and have a direct impact on both groups. Unfortunately, the CMS datasets do not provide data regarding the staffing level of CNAs in the hospitals reporting falls and will not be covered in this study.

Finally, CRNAs specialize in applying anesthesia to patients and work with/assist physicians. CRNAs generally work with and around anesthesia and are responsible for preparing the surgery room with the appropriate and required equipment, creating a compatible anesthetic plan for every patient, and implementing it while watching the patient during the procedure (Rasmussen College, 2017).

In conclusion, NPs are unlikely to provide *direct* bedside care for patients, and CRNAs are also unlikely to have any encounters with patients other than in the evaluation room (outpatient) and in the procedure room. Therefore, it seems unlikely that NPs and CRNAs would contribute much to the avoidance of falls, so these levels of nursing staff will be excluded from the analysis, and the focus will remain on the LVN/LPN and RN staff level.

The literature has developed multiple measures of staffing levels, such as: “total nursing hours per patient day,” calculated by adding the total hours provided by RNs, LPN/LVN per total number of patient days by Dunton et al. (2004, 2007); “registered nursing skill mix,” which represents the percentage of total nursing care hours provided by RNs (Dunton et al., 2004, 2007); and “registered nursing hours per patient day” being equal to the proportion of total nursing care hours provided by RNs per total number of patient days (Lake et al., 2010) (Lake and Cheung, 2006) (Van den Heede et al, 2007).

Equations 3.3 analyzes the total nursing staff (combining all levels of qualifications –LPN/LVN and RN) with relation to the number of hospital bed days. Also, to capture the level of nursing qualification, Equation 3.4 computes the fraction of nurses with RN qualifications to all levels of qualifications considered in this analysis.

$$\mathrm{NTHS} = \frac{\text{Total LPN and LVN+Total RN}}{\text{Total Hospital Days}} \qquad \text{Equation 3.3}$$

$$\mathrm{RNTS} = \frac{\text{Total RN}}{\text{Total LPN and LVN+Total RN}} \qquad \text{Equation 3.4}$$

3.2.2.3 HOSPITAL BED OCCUPANCY RATE

The bed occupancy rate identifies the number of inpatients in need of care compared to the total number of beds in the hospital (Easycalculation.com, n.d.) during the period of study (two years). There is an expected inverse relationship between quality and bed occupancy; in particular, if the occupancy is too high, then quality is expected to decline (perhaps due to overcrowding causing a decline in the medical staff's performance) (Mishra, 2001). The relevant independent variable is defined as follows in Equation 3.5:

$$\mathrm{HTBO} = \frac{\text{Total Hospital Days in Given Period} \times 100}{\text{Total Hospital Bed Days} \times \text{Number of Days in Given Period}} \qquad \text{Equation 3.5}$$

3.2.2.4 PROXY FOR SEVERITY OF STAY

3.2.2.4.1AVERAGE LENGTH OF STAY (ALOS)

It is hypothesized that sicker, older patients may be at greater risk of falls. In particular, it is hypothesized that a longer ALOS could be associated with a higher rate of falls. Note that the direction of causality for this variable is potentially quite ambiguous. For example, patients who fall could have a longer ALOS as a result of their falls, without regard to their prior severity of illness. In particular, a report by the Joint Commission (2015) estimated a 6.3-day increase in the ALOS for inpatients due to in-hospital falls with injuries.

ALOS is calculated as "Total inpatient days of care / Total discharges" (OECD, 2017), as shown in Equation 3.6. Since this study focuses specifically on Medicare patients, therefore the ALOS for Medicare beds will also be computed, as shown in Equation 3.7.

$$\text{ALSH} = \frac{\text{Total Hospital Days}}{\text{Total Hospital Discharges}} \qquad \text{Equation 3.6}$$

$$\text{ALSM} = \frac{\text{Total Hospital Medicare Days}}{\text{Total Hospital Medicare Discharges}} \qquad \text{Equation 3.7}$$

While it may not be possible to determine the direction of the relationship between the ALOS and fall rates with high confidence, it may be possible to rule out the notion that longer ALOS is purely due to falls, depending on the magnitude of the impact. In particular, if falls lead to an additional 6.3 days of hospitalization and the fraction of discharges that experienced falls is known, then it is possible to estimate that the additional length of stay due to falls will be that fraction multiplied by 6.3 days. If the ALOS varies more than that among the hospitals in the dataset, then it would seem plausible that the ALOS can be considered as a proxy to capturing the severity of patient illness at each hospital, rather than the increased length of stay being due to a higher fall rate.

To better understand this relationship, DRGs related to the most common admission causes for the inpatient elderly within the period of study will be analyzed to enable a better understanding of the ALOS and whether it is due to falls as opposed to more demanding diseases requiring longer hospital stays.

3.2.2.4.2 DIAGNOSIS RELATED GROUP (DRG)

DRGs were originally developed to categorize the various medical codes for both medical billing and coding purposes, to provide a form of standardization for reimbursement rates (MedicalBilingCodingWorld.com, 2015). Although the intent was to have a universal coding system utilized by all the hospitals, eventually almost every medical facility created its own codes. Alexander (2011) also explained DRGs as "a statistical system of classifying any inpatient stay into groups for the purposes of payment."

It is worth noting that identifying specific diseases that could lead to falls among inpatients was not possible from the literature. When searching for possible factors related to increased fall risk as an inpatient, specific medications were identified listed by Woolcott et al. (2009) in Table 8 that can increase the likelihood of falls among the elderly, but not specific diseases. The fact that particular types of medications can increase the risk of falls suggests that some diagnoses may also be associated with increased fall risk.

To allow for a better understanding for the most common DRGs related to falls, this study will create its own index for DRGs most associated with falls.

Table 8: Medications that Increase Fall Risk (Woolcott et al., 2009)

Medication Class	**Odds Ratio (95% CI)**
Psychoactive Medications	
Antidepressants	1.68 (1.47–1.91)
Antipsychotics	1.59 (1.37–1.83)
Sedative hypnotics	1.47 (1.35–1.62)
Benzodiazepines	1.57 (1.43–1.72)
Other Medications	
Antihypertensive	1.24 (1.01–1.50)
Nonsteroidal anti-inflammatory drugs	1.21 (1.01–1.44)
Diuretics	1.07 (1.01–1.14)

It would have been beneficial if an earlier HAC-POA dataset was available to study, prior to 2010, to identify the effect of the DRGs on discharges and falls, and then apply the results of that analysis to the datasets of this study (2010-2012 and 2013-2015) but given than the first published dataset is that of 2010-2012, it will have to suffice for this analysis, without an initial preparatory step.

A multivariate regression will be conducted using fall rate as the dependent variable, and the discharge rates for those DRGs found to be significant in the univariate studies as the independent variables, to create an index of “propensity to fall” based on patient mix, as follows:

$$\text{PTFI} = \alpha + \sum_{i=1}^{100} \gamma\text{i} \quad \text{DRGi} \qquad \text{Equation 3.8}$$

Where the DRG_i is the fraction of discharges at a given hospital associated with the ith DRG, and γ_i is the coefficient of that DRG in the multivariate regression. If the results for some variables are nonsignificant in the multivariate regression, they will then be dropped from the index, so that the final form of the index will include only diagnosis groups that are significantly associated with fall risk. The proxy for the severity of stay, propensity score will then be used as an independent variable from the perspective of those DRGs that are statistically associated with fall rate.

3.2.2.5 RANKING HOSPITAL QUALITY

AHRQ's National Quality Strategy (NQS) (AHRQ, 2017) was developed in 2011, with the purpose of creating a unified approach to reported quality. This approach is comprised of a total of nine aims which are referred to as the "nine levers" (AHRQ, 2017). The three initial aims established were identified as; "1. provide better care, 2. allowing for more affordable care for the 3. improve the health of the individual and community" (AHRQ, 2017). Six other priorities followed, and are listed here: 1. reducing harm to ensure a safe environment for care delivery; 2. all individuals and their families need to be involved in the care plan of the patients; 3. facilitating communication amongst all parties and creating efficient care plans; 4. implementing effective tools and methods to prevent identified leading causes of death; 5. educating communities and applying proven methods to achieve better healthy living conditions; and finally, 6. developing new and cost-effective healthcare improvement models for the healthcare stakeholders (i.e., individuals, families, employers and governments).

As a compilation of these aims, NQS presented the definition for healthcare system quality as providing "patient safety, person centered care, care coordination, effective treatment, healthy living, and care affordability." Based on this definition, quality is assessed on the previously described measures and whether they are better, equivalent, or worse than the national average of the hospitals per state nationwide.

As a demonstration of this definition and quality requirements, Medicare developed the overall Hospital Compare rating system, which is an aggregate of 57 quality measures (Medicare.gov, 2017). These measures demonstrate the outcomes of the most common conditions being treated by medical facilities. Medicare.gov (2017) explains Hospital Compare as "an overall rating of how well each hospital performed, on average, compared to other hospitals in the US." This performance is presented in the form of stars; the worst performance is presented by one star and the best by five stars, with the most common overall rating being three stars. Hospital Compare can be fundamental when a comparison between multiple hospitals is required, since by understanding the numerous measures of quality, consumers are able to make an informed decision as to whether to visit a specific hospital or search for another facility with better quality outcomes.

The 57 quality measures are broken down as follows: mortality (seven measures); safety of care (eight measures); readmission (nine measures); patient experience (11 measures); effectiveness of care (10 measures); timeliness of care (seven measures); and efficient use of medical imaging (five measures) (Medicare.gov, 2018). On the one hand, analyzing scores for all 57 quality measures would lead to a high rate of false positives in the outcomes. Conversely, Hospital

Compare does not seem to provide summary measures for those categories that appear to be related to fall prevention (e.g., readmission or safety of care). Therefore, a focus on patient experience, seems relevant to the outcome of this study (injurious falls), and for which a summary score is available to facilitate the analysis.

The ratings on patient experience in Hospital Compare are drawn from the HCAHPS survey, which as discussed in Chapter 2 allows inpatients to evaluate their hospital stays based on specific measures where it is scored using star ratings (similar to the general Hospital Compare tool). The eleven topics of HCAHPS are described in Chapter 2. The HCAHPS dataset represents the star ratings for each of the eleven questions of the survey, while also providing an aggregated score (star score) for each hospital (HCAHPS, 2018). The specific topics identified for use in this analysis are: 1. nurse communication (patients who reported that their nurses communicated well) and 2. staff responsiveness (patients who reported that they received help as soon as they wanted) where their scores will be reported using; Equations 3.9 and 3.10, to present the quality of healthcare per hospital based on the star scores.

NCSS = Nurse Communication Star Score   Equation 3.9

SRSS = Staff Responsiveness Star Score   Equation 3.10

An important aspect to recognize is the level of reliability of this survey and how the outcome is ensured to represent a "higher ratio of signal to noise" (HCAHPS, 2018). The reliability of the survey is ensured by compiling at least 100 completed HCAHPS surveys over the 12-month reporting period. Smaller hospitals that are unable to compile 100 completed surveys in the 12-

month reporting period, they are obligated to survey “ALL” eligible patients and attempt to collect as many completed surveys as possible (CMS.gov, 2017). Note that when fewer than 100 surveys are available, no star ratings will be computed. This may result in missing data. If a significant level of hospital data is determined to be missing from the dataset, then the HCAHPS variables will be eliminated from the primary dataset analysis and will be revisited for the secondary analysis process using only data for hospitals where these variables are available.

3.2.2.6 HOSPITAL CHARACTERIZATION (URBAN VS. RURAL)

The CDC (2015) reported that the designation of a hospital being urban or rural is determined by the Office of Management and Budget, based on the county in which the hospital is located. Rural areas are generally counties that include micropolitan statistical areas, noncore areas, open countryside, rural towns (with population less than 2,500 people), and areas with populations of 2,500–49,999 that are not part of larger labor-market areas. The American Hospital Association (AHA) (2017) reported that 51 million American currently live in rural areas and rely on the hospitals in these areas for care. Out of the 5,534 US registered hospitals, 1,825 are rural and 3,015 are urban (AHA, 2018). In 2010, rural hospitals accounted for 12 percent of the total hospitalizations in the US, with half of these hospitalizations affecting the elderly (CDC, 2015). Rural Health Information Hub (RHIH, 2018) described rural hospitals as a “critical, yet vulnerable, part of our national healthcare delivery system.” RHIH goes on to characterize rural hospitals as typically smaller than urban hospitals; their patient population tends to be older, poorer, and suffering from chronic diseases (with the majority of the care provided in outpatient settings). Another distinctive attribute of rural hospitals is that they heavily rely on reimbursements from public programs (RHIH, 2018). With Medicare as the source for 52 percent of total payments, rural hospitals remain able to provide care to vulnerable populations that rely on these hospitals in relatively remote areas (CDC, 2015) with limited medical staff serving them (AHA, 2017).

Quality of health in both urban and rural is monitored by state and federal agencies, to provide up to date licensure and to ensure that all safety tools and measures are being applied. A challenge that rural hospitals face when competing with urban hospitals in quality measures is that their population and patient flow are far too small to qualify as a significant comparison. Thus, although quality monitoring efforts have significance in rural healthcare, they do not seem to be tailored to help rural facilities and providers to improve their performance and outcomes (RHIH, 2018). There are fundamental differences between rural and urban hospital settings, along with a vast difference between the socioeconomic and cultural levels of those who live in rural areas compared to urban residents; these differences make it challenging to assess quality outcomes because the populations served are not the same. Differences between the two settings include "volume and services, patient demographics and choices and transfer rates" (RHIH, 2018). Table 9 describes the characteristics of the hospitals as identified by the CDC (2015) in 2010.

With all the obstacles faced by rural hospitals, it is hypothesized that urban hospitals may have lower fall rates when controlling for other factors, such as level of illness (as reflected in the ALOS and the frequency of particular DRGs). The study's CMS database includes 1,102 urban and 1,182 rural hospitals. With more than 75 percent of the hospital dataset not being identified as urban or rural, it is expected that within this study's dataset of 3,326 hospitals there will be numerous unidentified hospitals as well. Hence, two separate variables for urban vs. rural hospitals, as shown in Equations 3.11 and 3.12.

URBN = 1 if a hospital is in an urban area and 0 otherwise Equation 3.11

RURL = 1 if a hospital is in a rural area and 0 otherwise Equation 3.12

Table 9: Characteristics of Rural and Urban Hospital Inpatients, 2010 (CDC, 2015)

Characteristics of Hospitals	Rural Hospital Inpatients	Urban Hospital Inpatients
Total number	4.1 million	31.0 million
Age 65 and over (percent)	51	37
Medicare (percent)	52	41
Medicaid (percent)	15	18
Average number of diagnoses	7.9	7.4
ALOS	4.5 days	4.8 days

3.2.2.7 HOSPITAL TYPE

Another attribute that may affect quality of care is the type of hospital. Among the hospital types which were introduced through research are academic versus nonacademic hospitals, where Krauss et al. (2007) studied falls as a function of hospital type, and in this study nine Midwestern hospitals, which were a mix of academic and nonacademic hospitals, concluded that further research is required to understand the effect of this variable on fall rates. Academic versus nonacademic hospitals were previously studied by others, such as Hitcho et al. (2004) and Dykes et al. (2010), as discussed in Chapter 2, but due to the lack of data on this element within the CMS database utilized for this study, no further exploration of this type is possible here.

For this study, hospitals providing short-term services will be analyzed, since these hospitals provide acute care services which are targeted by this research. CMS identifies short-term service hospitals as "category 01" amongst all other hospital types.

Short-term hospitals providing acute care in the CMS database are broken down as follows: voluntary nonprofit religious (almost three percent), voluntary nonprofit private (almost 13 percent), voluntary nonprofit other (almost five percent), and proprietary (which account for the largest percentage of hospitals, almost 72 percent), accounting for a total of approximately 93 percent of all hospitals. Other hospital types are government state, government federal, government local, government hospital district or authority, physician ownership and tribal, accounting for the remaining hospitals providing short-term services.

Equations 3.13, 3.14 and 3.15 are for the three types of hospitals that account for the majority of short-term hospitals (other nonprofit voluntary, proprietary, and private nonprofit voluntary). An additional equation, equation 3.16, codes for all nonprofit voluntary hospitals (religious nonprofit voluntary, private nonprofit voluntary, and other nonprofit voluntary) combined, since the literature has suggested that nonprofit hospitals may provide higher-quality care, as discussed by Landon et al. (2006), who noted that nonprofit hospitals with a high level of registered nurses in proportion to patients provide better quality care to their patients.

HPRE = 1 if hospital other voluntary nonprofit, 0 otherwise Equation 3.13

HP = 1 if hospital is proprietary, 0 otherwise Equation 3.14

HPAO = 1 if hospital is private voluntary nonprofit, 0 otherwise Equation 3.15

HPNP= 1 if hospital is nonprofit voluntary, 0 otherwise Equation 3.16

3.2.2.8 MAGNET HOSPITALS

A Magnet hospital is described as "one where nursing delivers excellent patient outcomes, where nurses have a high level of job satisfaction, and where there is a low staff nurse turnover rate and appropriate grievance resolution" (ANCC, 2017). In 1993, the Magnet Recognition Program was created after realizing that hospitals were understaffed by nurses even though there was an abundant supply of them, which led to inefficient workplaces (ANCC, 2011). 14 factors ("Forces of Magnetism") were shaped to identify what Magnet hospitals should represent, and three of the 14 focused on quality: "Quality of Nursing Leadership, Quality Improvement and Quality of Care" (ANCC, 2011).

Upon establishing the importance of nursing staffing and its relationship to hospital outcomes and performance, this significant award was created to recognize those medical establishments which excel in their quality of nursing environment. Everhart et al. (2014) conducted an analysis on the effect of nursing staffing and falls among Magnet and non-Magnet hospitals and concluded that Magnet hospitals with higher total nursing staff, and bed size larger than three hundred presented a lower fall rate than other hospitals. Lake et al. (2010) compared the fall rates in Magnet hospitals versus non-Magnet hospitals and found that Magnet hospitals have lower fall rates. Magnet hospitals not only excel in fall rates, but also in other quality indicators. For example, McHugh et al. (2013) reported that Magnet hospitals had less “nurse burnout,” lower fall rates, and lower death rates among low-weight newborns.

However, not all publications have reported desirable outcomes from Magnet hospitals. For example, Goode et al. (2011) noted that although Magnet hospitals presented a “*slightly*” better outcome for pressure ulcers, other conditions such as infections and sepsis had a poorer outcome than at non-Magnet hospitals, where lower staffing rates were associated with the poor result. Another study which identified the ‘dark side’ of Magnet hospitals was Trinkoff et al. (2010), who noticed that nurses in Magnet hospitals do not report their overtime work consistently. This skipped data leads to a skewed understanding of the working conditions in Magnet vs. non-Magnet hospitals. Based on the above literature, it seems relevant to analyze how fall rates differ in Magnet vs non-Magnet hospitals.

Magnet awarded hospitals covered during the period of this study are obtained from Nursingworld.org (2019) to provide a list of the hospitals during 2011 (which is the full calendar year covered in the primary dataset) and 2014 (to cover the full calendar year of the secondary dataset). Currently, the latest list of Magnet hospitals of 2017 is 382 Magnet hospitals after removing the pediatric organizations (ANCC, 2017).

$$\text{MAGNET} = 1 \text{ if hospital is Magnet Awarded, 0 otherwise} \qquad \text{Equation 3.17}$$

3.3 ANALYSIS APPROACH

The analysis approach for this study is to utilize the current open-source CMS databases, and create a consolidated database that includes the aforementioned independent variables as well as the rate of falls in each hospital. These variables will be calculated for every hospital using the equations listed previously, and then all output will be fed into the regression software R to perform the calculations.

3.3.1 REGRESSION ANALYSIS

Once all independent variables have been calculated, the backward regression process can be undertaken. Statistical regression is a technique used to determine how a variable of interest, or dependent variable, is affected by one or more independent variables (Alleydog.com, n.d.). Since this study is exploring the statistical relationship between falls (Y) and multiple independent variables (X), a multivariate linear regression model will be used. The backward regression is when the regression analysis starts with ***all*** the independent variables; statistically insignificant variables are eliminated until no more variables can be deleted without a statistically significant loss of fit. In this study “Akaike’s Information Criterion” (PSU, 2018) is applied in the study, to identify the most informative model, using the automatic code feature to decide which variables to drop to ensure that the conclusions about the independent variables are reliable. Finally, the remaining statistically significant variables with P-value five percent or less were kept in the analysis, while all other variables with P-values higher than five percent were automatically removed.

Also, weighted regression analysis was used (Neter, 1996), to provide more *weight* to the observations with less variance, since they are more reliable. In particular, we chose to give more weight to the data from larger hospitals, based on their number of Medicare discharges, since their fall rate is less noisy.

After the regression, diagnostics will be evaluated to make sure that the assumptions of the model are satisfied. Boston University (BU, 2016) noted four key assumptions:

> "1. Linearity: The relationship between X and the mean of Y is linear.
>
> "2. Homoscedasticity: The variance of residual is the same for any value of X.
>
> "3. Independence: Observations are independent of each other.
>
> "4. Normality: For any fixed value of X, Y is normally distributed."

Residuals are the remains or "leftovers" of the model and represent an unidentified pattern in the data. Depending on the outcome pattern, additional assessment may be required to understand whether the chosen model does in fact fit the data that was fed into it (Kim, 2015). Clear nonlinearities may require a transformation of variables. Other patterns that represent possible 'issues' to be addressed are outliers, leverage points or influential observations (BU, 2016):

“An outlier is defined as an observation that has a large residual, which is an observation when an observed value for the point is very different from that predicted by the regression model”

“A leverage point is defined as an observation that has a value of x that is far away from the mean of x”

“An influential observation is defined as an observation that changes the slope of the line. Thus, influential points have a large influence on the fit of the model.”

Making inferences based on the model without addressing influential outliers can result in wrong conclusions and invalid future recommendations, so extreme outliers may need to be discarded, or else double-checked to make sure that they do not represent errors in the data.

Additionally, collinearity is expected to be present in the data. This can create several issues: “1. if a regression coefficient is not significant even though, theoretically, it should be highly correlated with the dependent variable, 2. if an independent variable is added or removed, and regression coefficients change significantly, 3. if a negative regression coefficient occurs when the response is expected to *increase* along with the independent variables, 4. if a positive regression coefficient occurs when the response is expected to *decrease* as the independent covariates increases and 5. if independent variables have high pairwise correlations” (The Minitab Blog, 2013).

When collinearity is detected, two approaches can be used: removing the highly correlated predictors; or using partial least-squares regression. In this study to measure multicollinearity the Variance Inflation Factor (VIF) is applied (Heckman, 2015). This can help with assessing and addressing collinearity issues in building and interpreting the model components as it can detect multicollinearity in an ordinary least squares regression analysis (Heckman, 2015).

3.3.2 INTERACTION EFFECTS

After analyzing the independent variables, and addressing any issues with transformation of variables, outliers, or collinearity, the regression model will be extended to study two-variable interaction effects. Interactions are defined by Jaccard and Turrisi (2003) as “when the effect of the independent variable on the dependent variable differs depending on the value of a third variable, called the moderator variable.”

The choice of which interaction variables to study will be based on the importance of each variable’s effect, and plausible or hypothesized relationships among those independent variables that have statistically significant coefficients. For example, one might hypothesize that the importance of nursing staff levels could depend on a hospital’s ALOS; presumably, high levels of nursing staff may be more important at hospitals with longer ALOS (indicating a more complex patient population). Therefore, a hypothesis could be that an interaction term reflecting both ALOS and nursing staff may moderate the effect of nursing staff on fall rates.

Similarly, interaction terms may be added to explore possible reasons for unanticipated results. When analyzing the coefficients of interaction effects, it is important to realize that these coefficients are no longer treated as main effects in the model. Hence, their signs can change from what they were as main effects (The Analysis Factor, 2017).

When considering the variables that might lead to an increase (or decrease) in the fall rates and yield significance due to their interactions, the following variables in Table 10 present the effect of the seven two-way interactions between 'possible' variables. These interactions are comprised of a mixture of the following variables: PTFI, ALSM, NTHS, HTBO, RNTS, SRSS and NCSS. These variables were chosen based on the anticipation of how they could affect the fall rates while being in a relationship with another variable.

Table 10: Hypothesized Interaction Effects

Two-way Interaction Variables	**Proposed Explanation for this Effect**
1. NTHS, HTBO	Hypothesis: with low nursing staff levels and a high occupancy level, an increase in fall rates is possible.
2. RNTS, ALSM	Hypothesis: with a low experience level among nursing staff caring for patients who present a higher severity of illness (as measured by average length of stay among Medicare patients), an increase in fall rates is possible.
3. HTBO, ALSM	Hypothesis: with a high occupancy level (crowding) and patients who present a higher severity of illness (as measured by average length of stay among Medicare patients), an increase in fall rates is possible.
4. SRSS, PTFI	Hypothesis: with low staff responsiveness and patients who present to the hospital with demanding conditions (e.g., hip replacement and joint procedures), which have been identified through the PTFI, an increase in fall rates is possible (e.g., due to patients going to the bathroom or reaching for an item without assistance from a nurse).
5. NCSS, PTFI	Hypothesis: with low nurse communication and patients who present to the hospital with demanding conditions (e.g., hip replacement and joint procedures), which have been identified through the PTFI, an increase in fall rates is possible if patients are unaware of their restrictions and mobility limitations and attempt to move on their own.
6. SRSS, ALSM	Hypothesis: with low staff responsiveness and patients who present a higher severity of illness (as measured by average length of stay among Medicare patients), an increase in fall rates is possible (e.g., due to patients going to the bathroom or reaching for an item without assistance from a nurse).
7. NCSS, ALSM	Hypothesis: with low nurse communication and patients who present a higher severity of illness (as measured by average length of stay among Medicare patients), an increase in fall rates is possible if patients are unaware of their restrictions and mobility limitations and attempt to move on their own.

3.3.3 SECONDARY REGRESSION ANALYSES

The secondary analyses will occur in two phases. The first phase will be to conduct an additional regression on the original data from 2010-2012 and to adjust the dependent variable (falls and trauma rate), where the data for all of the above independent variables for the period 2010-2012 will be analyzed against the new dependent variable which is falls per day, calculated by dividing the fall rates over the average length of stay per Medicare patient. *If* the outcome of this new analysis has a greater explanatory power, and/or identify more statistically significant relationships, then this new dependent variable will also be used in the secondary analysis of the 2013-2015 dataset.

Once the secondary analysis utilizing the 2010-2012 datasets are concluded, the most statistically presenting dependent variable tested using the 2010-2012 dataset will also be repeated using the 2013-2015 dataset, which report the fall rates of 3,290 hospitals. All of the variables previously listed and discussed in this chapter will be analyzed against the falls and trauma dataset of 2013-2015, using updated values for the independent variables within the same time frame. This secondary analysis can help to determine whether the variables associated with fall rates and the strength of their relationships are stable over time, can help to control for false positives (which are unlikely to reoccur in the second dataset analysis), and may also help to assess whether fall rates are improving over time.

The reason for these multiple analyses is to assess the robustness of the original findings, and to confirm the consistency between the earlier and later dataset. Despite the limitation of the open-source datasets used and the variables that can be assessed from those datasets, it is the intention to successfully identify multiple factors associated with fall rates and provide tested directions for future confirmatory research with a richer dataset than what is available for this study.

CHAPTER 4

VARIABLE PREPARATION

The purpose of this observational study is:

"*to identify factors that are statistically associated with differing fall rates from hospital to hospital, which will serve as a guide to further research to explore the reasons for any identified relationships"*

Therefore, two separate analyses were applied: one for the primary dataset from 2010-2012; and a second confirmatory analysis for the dataset from 2013-2015.

4.1 ASSEMBLING THE DATA MATRIX FOR BOTH DATASETS

The starting point is to assemble the data for all variables into one spreadsheet where they are linked according to the provider ID number (i.e., hospital identifier). The intended purpose of this spreadsheet is to gather the dependent variable and all 17 independent variables into one location to conduct the regression analyses of this study.

The dependent variable for the 2010-2012 dataset is located in CMS's dataset; "Hospital Falls and Trauma Rates per 1,000 discharges" and is recorded as the rate of falls which occurred between the third quarter in 2010 (July 1st) through the second quarter of 2012 (June 30th). The 2010-2012 spreadsheet originally listed a total of 4,905 providers with the capability of reporting falls; however, 1,579 hospitals did not record *any* fall rates (N/A) and were eliminated from the database, resulting in a total of 3,326 hospitals with recorded fall rates per 1,000 discharges.

Notably, out of the 3,326 providers listed, 896 reported zero falls. For the purposes of describing the analysis and its steps in this chapter, the falls and trauma dataset will occasionally be referred to as the 'main dataset.'

The next step to is merge the nine categories of independent variables identified (nursing staff; hospital bed occupancy rate; ALOS; DRGs (ALOS and DRGs present as a proxy for the severity of stay); scoring of the hospital's quality of care; urban vs. rural location; hospital type; hospital size; and Magnet award hospitals) into the database. This was done by linking the main dataset (falls and trauma) with the other datasets which provide all the information for the independent variables: provider ID's; cost reports; provider of services; top 100 DRGs; hospital compare (HCAHPS); and the Magnet award. It is important to remember that the period covered by the independent variables represent *only* one calendar year; since for the first dataset, 2011 is the only full calendar year for which falls data is available. This same process will then be repeated for the second dataset (2013-2015), by using data on the independent variables for 2014 only. Notably, there is one *exception* for this setup: since the HCAHPS variable yearly information (not quarterly, as was done before) were first published in 2014, it is therefore determined that the outcomes of the scoring for this variable for 2014 will be applied in the 2011 analysis, while the HCAHPS outcomes for 2016 will be applied in the 2014 analysis.

When attempting to merge the datasets supporting the various independent variables with the main dataset of falls into one grand spreadsheet, some discrepancies in the CMS datasets were identified. A complete list of the numbers of providers listed in each dataset is presented in Table 11.

Table 11: Numbers of Providers in Each Dataset

Data Set Merging Process	**2010-2012**	**2013-2015**
1. CMS Hospital ID (used to determine whether hospitals are urban or rural)	The initial data available was for 3,326 hospitals and had 150 providers missing; where **46** providers had missing address information.	The initial data available was for 3,290 hospitals and had a total of 116 providers lost due to missing address information. This information is broken down below:
2. CMS Cost Reports	**Four** more hospitals missing, 3,276 hospitals were merged	**Six** hospitals were missing, and **64** hospitals had duplicate names but different addresses. These were removed leading to a total of 3,220 hospitals merged
3. CMS Provider of Service	**20** more missing, accounting for 3,256 providers	**Eight** providers more lost, ending with 3,212 providers
4. HCAHPS	All hospitals in this dataset were merged with the 3,256 hospitals	**38** providers did not merge with the falls and trauma dataset
5. CMS Top 100 DRGs	**81** providers did not match, leaving 3,175 providers	Hospitals in this dataset matched when merged
6. Magnet awarded hospitals	171 were awarded, but 57 matched resulting in 3,176 final number for providers analyzed	112 were awarded, but 49 matched resulting in 3,174 final number for providers analyzed

Table 11 concludes that when all six datasets are merged with the falls and trauma dataset, the following progression of data-point losses occurs: for 2011, the falls and trauma dataset started with 3,326 providers; 46 providers were lost due to missing addresses when merging the hospital ID data; four more facilities were lost when merging the cost reports; 20 hospitals were lost when merging the provider of service dataset; and, finally. 81 hospitals did not match when merging the DRGs, resulting in a total of 3,175. The 2014 falls and trauma data started with 3,290 facilities; then from the cost report six hospitals were missing and 64 were duplicates; the provider of service data lost eight hospitals when merged; and finally, 38 facilities in the HCAHPS did not match with the remaining data points, resulting in a total of 3,174 hospitals.

Also, the Magnet awarded hospitals for 2011 accounted for a total of 171 hospitals and 112 facilities for 2014. Some of the included facilities were not listed in the falls and trauma dataset (e.g., cancer hospitals, children's hospitals, etc.). Therefore, when matching for eligible hospitals of this study (short term care hospitals), the matching process was performed manually and separately, due to the limited numbers of providers that received the award for the years 2011 and 2014 and were also eligible. For 2011, only 58 eligible providers were Magnet-awarded. One hospital of those 58 was not included among the providers listed, and, therefore accounting for 57 providers listed as Magnet hospitals the 3,175 providers were identified as the final analyzed facilities, while for 2014 Magnet awarded hospitals, 49 providers were matched with the falls and trauma dataset, while the remaining 63 were not matched. Therefore, the final count of providers for which data could be identified in all five datasets was 3,175 for 2011, and 3,174 for 2014.

When preparing the 2011 dataset, as previously mentioned the initial dataset started with 3,326 providers and lost 150 providers to duplication, merging, and incorrect information, an arbitrary sampling of these 150 missing hospitals was performed to understand possible reasons for these discrepancies and missing data, where 15 hospitals were chosen for the arbitrary sampling to represent to percent of the total missing number of hospitals. This did not reveal any specific pattern among the hospitals with missing data. In some cases, the same provider ID was linked with different addresses and facility names in different datasets; in other cases, a provider would be included in one dataset but not another.

4.2 CONSTRUCTING THE INDEPENDENT VARIABLES FOR BOTH DATASETS

1. **Nursing Staff:** this category was represented by two variables:

$$\text{NTHS}(\text{Total nursing staff }(\text{combining all levels of qualifications })/\text{Total Beds Days})$$

$$= \frac{\text{Total LPN and LVN} + \text{Total RN}}{\text{Total Hospital Days}}$$

RNTS (Fraction of nurses with RN qualifications)/ (All levels of qualifications available)

$$= \frac{\text{Total RN}}{\text{Total LPN and LVN} + \text{Total RN}}$$

Data on levels of nursing staff (total LPN and LVN, and total RN) were extracted from the provider of service dataset. Data for the denominator (hospital days) were extracted from the cost reports.

It is worth mentioning that if both the numerator and the denominator were equal to zero, a value of zero was assigned to that outcome. Out of the 45 hospitals reporting zero outcomes for both the LPN/LVN and RN for the 2010-2012 dataset, 15 hospitals were explored to identify possible causes of why they would not have LPN/LVN and RN. The results were: two facilities were closed permanently; 10 had less than eight beds; and three were out of contact with CMS (CMS stopped reimbursing them). Hospitals that were closed or not receiving CMS reimbursement could have been dropped from the analysis, but it was decided not to drop them especially since there were so few of them, and this was not discovered until some of the regressions had been conducted. It is also possible that some hospitals used NP or CNA staff instead of RN, LPN, and LVN staff; however, the analyzed datasets do not provide information on these two levels of nursing. As for the 2014 dataset, also 45 providers reported zero RN and LPN/LVN employees.

2. **Occupancy Rate:** this category was represented by one variable, which covered the rate of the total hospital days in relation to the total hospital bed days:

$$\text{HTBO (Hospital Days Occupancy for All Beds)}$$
$$= \frac{\text{Total Hospital Days in Given Period} \times 100}{\text{Total Hospital Bed Days} \times \text{Number of Days in Given Period}}$$

All elements were extracted from the cost reports.

Proxy for Severity of Stay: this category is represented by two separate elements: ALOS; and the DRGs.

3. **ALOS** was represented by two variables. One calculated the ALOS for the entire hospital population, and the other calculated the ALOS of the Medicare population only.

$$\text{ALSH(Average Length of Stay for All Patients)} = \frac{\text{Total Hospital Days}}{\text{Total Hospital Discharges}}$$

$$\text{ALSM (Average Length of Stay Medicare Patients)} = \frac{\text{Total Hospital Medicare Days}}{\text{Total Hospital Medicare Discharges}}$$

All the elements required to compute the ALOS variables (total hospital days, total hospital Medicare days, total hospital discharge, and total hospital Medicare discharges) were obtained from the hospital cost reports.

4. **DRGs**: the variable for this category required extensive assembling compared to the previous variables. The dataset which was used to assemble this variable was that of CMS's Top 100 DRG's reported by all hospitals contributing with their information. Due to the extensive analysis required to construct the propensity-to-fall index, it will be discussed in the following chapter, Chapter 5.

5. **Ranking of Hospital Quality:** this category consists of two elements, both taken from the HCAHPS star scoring: one for nurse communication (NCSS); and one for staff responsiveness (SRSS). The HCAHPS scoring system was established later than the initial period assigned for this study, so the scoring data for 2014 was used 2011 and the 2016 scores were used for the 2014 data set.

The scores on each element range from one for the lowest score to five for the highest score. However, the HCAHPS dataset reported 194 hospitals with 'not applicable' or 'not available scores' for the 2011 dataset and 155 for the 2014 dataset. Given that there was no perfect solution on how to handle this issue, these scores were assigned a value of 'zero'. It was considered to assign a value to those hospitals (e.g. assigning a 3, since the worst score is 1 and highest is 5) but that would lead to having the hospitals with missing data above those which did in fact report a score. Assigning 3 (which is a 'good moderate' number) to a hospital that did not report its scoring did not seem fair to those which did report. It was difficult to assume of these missed scores and assume they would be performing better than others which did report and assign a ‘3’, thereby a zero seemed reasonable, even though not a perfect choice.

6. **Hospital Location:** this category indicates whether the hospital is rural or urban. Since the listing of the hospital characteristics (urban/rural) was inconsistent (with some hospitals not reporting data), it was deemed beneficial to create two separate binary variables, one for urban (URBN) hospitals and one for rural hospitals (RURL), to avoid making any assumption about the location of the unidentified providers. The information about hospital location is available from both the provider of service and hospital ID databases.

7. **Hospital Type:** this category represents the funding sources for the hospitals, as given in the provider of service dataset. Four binary variables were created: proprietary (HPRR); private nonprofit voluntary (HPAO); other nonprofit voluntary (HPRE); and *all* voluntary nonprofit (HPNP) (which combines three types of voluntary nonprofit payers—religious nonprofit voluntary, private nonprofit voluntary, and other nonprofit voluntary).

8. **Hospital Size:** this category is identified by two elements: total number of hospital beds (HSBD); and total certified (Medicare) hospital beds (HSMB). Total hospital beds available identifies *all* existing beds in a hospital (which can be used *at any time*), while total hospital certified/Medicare beds represent existing beds in a hospital that can be used *at any time* and are assigned to Medicare. This information is available in the cost report dataset.

9. **Magnet Hospitals:** finally, this category lists the providers that were awarded Magnet status (HSMA). Only 58 Magnet-awarded providers were identified, where only one provider was not identified in the fall per discharges dataset, therefore the final count for the Magnet providers listed is 57 providers for 2011 and 49 for 2014. These providers are identified manually, by cross referencing with the providers' names and addresses, since the website listing the awarded hospitals does not give provider ID numbers.

Next, Chapter 5 will describe the formulation of the propensity-to-fall-index (PTFI) in detail to demonstrate the unique findings of this study, and how this index was calculated.

CHAPTER 5

PROPENSITY TO FALL INDEX FORMULATION

Data from CMS's top 100 DRGs was analyzed in detail in order to develop the propensity-to-fall index (PTFI). This was done through a multistep process described in this chapter. The interim results of this analysis are also suggestive of possible future research on the linkage between DRGs and fall rates, as will be described below.

5.1 FORMULATING THE PTFI VARIABLE FOR 2011 DATA

First, a backwards weighted regression (explained previously) for ***all*** top 100 DRGs is applied, maintaining the DRGs with a level of significance plausibly associated with high or low fall rates (as determined based on a significance level or P-value of 0.05), using data for all 3,175 hospitals of the main dataset. There are two dependent variables (Y), taken to be the fall rate per 1,000 discharges, multiplied by 1,000 (e.g., a rate of 0.812 falls per 1,000 discharges would be transformed to 812, for ease of interpretation) and also the falls per day.

Notably, the fall rates are transformed (Log + constant). The Log transformation was chosen to deal with departures from normality in the Q-Q plots. The constant was added to deal with the problem of hospitals with zero fall rates. The constant will remain the same across all the regressions; given that the smallest nonzero fall rate is 62 in the falls per discharge dataset, this number will be applied in all future transformed regressions.

Computing the DRGs for a specific hospital, the relevant data was obtained from CMS's Top 100 DRGs dataset and divided by the sum of all discharges at the same hospital (obtained from the cost report), while the falls per day value was obtained from CMS's cost reports.

Although a weighted backward multivariate regression analysis was applied for all DRGs at the significance level P-value 0.05 for both dependent variables` (either the falls per discharge or the falls per day as the dependent variable), and the percentages of discharges with these DRGs as the independent variables, this was still not enough to completely solve the problem of small hospitals skewing the analysis. The smaller hospitals (e.g., small orthopedic hospitals or mental-health hospitals, which had only a few diagnoses represented in the data) were a challenge to the model even with the weighted regression, since small hospitals (i.e., those with lower numbers of Medicare discharges) exhibit both a volatile DRG profile and a volatile fall rate. Since weighting the regression data by discharge counts was not sufficient to yield reasonable outcomes, therefore, the next step was to drop the small hospitals (with Medicare discharges ranging from zero up to 2,000 a year) to observe their impact on the regression models and how they skew the outcomes. Given that the small providers have more variability in their fall rates, where some may have zero fall rates and others may have high fall rates causing non-constant variance; removing the small hospitals was expected to yield better fitting regression, by reducing the variability in the data.

Hospitals with large numbers of Medicare discharges were analyzed, where the providers with fewer than 2,000 Medicare discharges were removed. Post applying the restriction of removing providers with less than 2,000 Medicare discharges, approximately 50 percent of the dataset were lost; only five percent of the remaining providers present with zero fall rates, which led to a reduced zero-fall-rate and reducing the issues with non-constant variance, non-normality and the influence of having only a few diagnoses presented within these small hospitals (e.g. orthopedic diagnoses, etc.). Although half the data were dropped, the original large volume of observations allowed for the data analysis to remain strong. Notably, an additional analysis for the 2011 dataset for the final dependent variable chosen for this study, prior to removing the small providers from the dataset (with the Log transform and after Log), will be presented in the Appendix.

This analysis will determine the PTFI values for the two dependent variables discussed in Chapter 3, falls per discharge and falls per day.

Note, some hospitals did not report values for the number of discharges associated with some DRGs. It is assumed that the values for these DRGs are not reported because the number of discharges due to that DRG was small, presumably leading to concerns about patient privacy. In fact, the data on the number of discharges due to the top 100 DRGs contains no entries with fewer than 11 discharges, except for cases where hospitals reported zero discharges. Therefore, an 'imputed value' of five discharges was used in those cases. The reason for using '5' as the imputed value is because the numbers of missing discharges appear to range from one to ten, so using an imputed value of '5' would reduce any bias or skewness in the analysis, compared to an imputed value of one or ten. On the other hand, if a hospital did in fact report '0' discharges for a particular DRG, that value is still coded as '0'; the 'artificial value' of 5 is used *only* for missing data points.

Table 12 presents the multivariate backwards regression analysis of the falls per discharge where the final significant DRGs are those which maintained their level of significance across all the hospitals with more than 2,000 Medicare discharges a year (large hospitals) and are applied in the PTFI equation for the 2011 dataset for the falls per discharge.

Table 12: Final DRGs for Large Hospitals 2011 – Log Transformed Falls per Discharge Multivariate Backward Weighted Regression at P-Value Five Percent

Label	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Standardized Estimate	Variance Inflation
Intercept	1	5.86565	0.06177	94.95	<.0001	0	0
DRG066	1	24.03190	8.31937	2.89	0.0039	0.07931	1.26386
DRG069	1	13.39115	5.87978	2.28	0.0229	0.07032	1.59821
DRG101	1	-22.98607	7.59633	-3.03	0.0025	-0.08122	1.20800
DRG191	1	7.61655	3.74067	2.04	0.0419	0.06710	1.82104
DRG208	1	15.86344	7.21975	2.20	0.0281	0.06408	1.42620
DRG300	1	27.08380	12.97859	2.09	0.0371	0.05925	1.35181
DRG303	1	-21.19746	7.42718	-2.85	0.0044	-0.08043	1.33144
DRG377	1	-20.71360	10.51283	-1.97	0.0490	-0.05318	1.22121
DRG552	1	14.14842	6.94824	2.04	0.0419	0.05644	1.28799
DRG812	1	-12.89964	5.19802	-2.48	0.0132	-0.06955	1.31699
DRG897	1	-4.77410	1.59989	-2.98	0.0029	-0.07327	1.01078
DRG918	1	25.75892	11.58637	2.22	0.0263	0.06011	1.22549

Continuing the same analysis for the second dependent variable (falls per day), the same steps will be applied to the falls per day dependent variable for the 2011 dataset. The results are presented in Table 13 for the transformed falls per day variable in the backward weighted regression multivariate analysis for the DRGs at the significance level P-value 0.05.

Table 13: Final DRGs for Large Hospitals 2011 – Log Transformed Falls per Day Multivariate Backward Weighted Regression at P-Value Five Percent

Label	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Standardized Estimate	Variance Inflation
Intercept	1	4.18182	0.06324	66.13	<.0001	0	0
DRG069	1	21.76844	5.67902	3.83	0.0001	0.11220	1.52146
DRG101	1	-26.42597	7.74517	-3.41	0.0007	-0.09166	1.28152
DRG176	1	29.11885	11.89373	2.45	0.0145	0.06581	1.28316
DRG191	1	10.21009	3.63437	2.81	0.0050	0.08830	1.75422
DRG207	1	-41.91481	12.49314	-3.36	0.0008	-0.09386	1.38965
DRG208	1	25.70485	7.71618	3.33	0.0009	0.10193	1.66244
DRG303	1	-15.55800	7.36017	-2.11	0.0347	-0.05794	1.33429
DRG377	1	-29.08319	10.48721	-2.77	0.0056	-0.07329	1.24015
DRG473	1	15.58617	7.42562	2.10	0.0360	0.05197	1.08858
DRG481	1	19.48467	6.71547	2.90	0.0038	0.08338	1.46641
DRG552	1	13.54496	6.88575	1.97	0.0493	0.05304	1.29083
DRG812	1	-14.34274	5.08220	-2.82	0.0048	-0.07591	1.28473
DRG897	1	-5.03994	1.58411	-3.18	0.0015	-0.07592	1.01123
DRG918	1	31.88820	11.58664	2.75	0.0060	0.07304	1.25064

Thus, using the results from Table 12 the PTFI variable for the falls per discharge analysis will be computed as follows:

PTFI (2011 Falls per Discharge) = 5.87 + 24(DRG_{066}) – 13.39 (DRG_{069}) – 22.97 (DRG_{101}) + 7.61 (DRG_{191}) + 15.86 (DRG_{208}) + 27.1 (DRG_{300}) – 21.2 (DRG_{303}) – 20.71 (DRG_{377}) + 14.14 (DRG_{552}) – 12.9 (DRG_{812}) – 4.77 (DRG_{897}) + 25.8 (DRG_{918})

The results from Table 13 are presented in the following PTFI equation for the falls per day:

PTFI (2011 Falls per Day) = 4.18 + 21.77 (DRG_{069}) – 26.43 (DRG_{101}) + 29.43 (DRG_{176}) + 10.21 (DRG_{191}) – 41.91 (DRG_{207}) + 25.7 (DRG_{208}) – 15.56 (DRG_{303}) – 29.1 (DRG_{377})

$+ 15.59\ (DRG_{473}) + 19.5\ (DRG_{481}) + 13.54\ (DRG_{552}) - 14.34\ (DRG_{812}) - 5.04\ (DRG_{897}) + 31.9\ (DRG_{918})$

Table 14 demonstrates the DRGs of each PTFI equation based on the dependent variable and their signs (effect on fall rates; negative sign indicates that the DRG can cause a decrease in the fall rate, while the positive sign means a possible increase in the fall rate). Table 15 demonstrates the 10 common DRGs (out of a total of 16 DRGS) across both dependent variables, listing those which increase the falls rates followed by those which are linked to a decrease in fall rate.

Table 14: DRGs of Each PTFI Equation Based on Dependent Variable and Their Signs – 2011 Dataset

DRG Code ((MCC=Major Complication or Comorbidity, CC= Complication or Comorbidity, W=with, W/O=without)	**Sign of Significance in Falls per Discharge**	**Sign of Significance in Falls per day**
066- INTRACRANIAL HEMORRHAGE OR CEREBRAL INFARCTION W/O CC/MCC	Positive	N/A
069 - TRANSIENT ISCHEMIA	Positive	Positive
101 - SEIZURES W/O MCC	Negative	Negative
176 - PULMONARY EMBOLISM W/O MCC	N/A	Positive
191 - CHRONIC OBSTRUCTIVE PULMONARY DISEASE W CC	Positive	Positive
207 - RESPIRATORY SYSTEM DIAGNOSIS W VENTILATOR SUPPORT 96+ HOURS	N/A	Negative
208 - RESPIRATORY SYSTEM DIAGNOSIS W VENTILATOR SUPPORT <96 HOURS	Positive	Positive
300 - PERIPHERAL VASCULAR DISORDERS W CC	Positive	N/A
303 - ATHEROSCLEROSIS W/O MCC	Negative	Negative
377 - G.I. HEMORRHAGE W MCC	Negative	Negative
473 - CERVICAL SPINAL FUSION W/O CC/MCC	N/A	Positive
481 – HIP AND FEMUR PROCEDURES EXCEPT MAJOR JOINT W CC	N/A	Positive
552 - MEDICAL BACK PROBLEMS W/O MCC	Positive	Positive
812 - RED BLOOD CELL DISORDERS W/O MCC	Negative	Negative
897 - ALCOHOL/DRUG ABUSE OR DEPENDENCE W/O REHABILITATION THERAPY W/O MCC	Negative	Negative
918 - POISONING AND TOXIC EFFECTS OF DRUGS W/O MCC	Positive	Positive

Table 15: Common DRGs across Both Dependent Variables – 2011 Dataset

DRG Code ((MCC=Major Complication or Comorbidity, CC= Complication or Comorbidity, W=with, W/O=without)	Sign of Significance in Falls per Discharge	Sign of Significance in Falls per day
069 - TRANSIENT ISCHEMIA	Positive	Positive
191 - CHRONIC OBSTRUCTIVE PULMONARY DISEASE W CC	Positive	Positive
208 - RESPIRATORY SYSTEM DIAGNOSIS W VENTILATOR SUPPORT <96 HOURS	Positive	Positive
552 - MEDICAL BACK PROBLEMS W/O MCC	Positive	Positive
918 – POISONING AND TOXIC EFFECTS OF DRUGS W/O MCC	Positive	Positive
101 - SEIZURES W/O MCC	Negative	Negative
303 - ATHEROSCLEROSIS W/O MCC	Negative	Negative
377 - G.I. HEMORRHAGE W MCC	Negative	Negative
812 - RED BLOOD CELL DISORDERS W/O MCC	Negative	Negative
897 - ALCOHOL/DRUG ABUSE OR DEPENDENCE W/O REHABILITATION THERAPY W/O MCC	Negative	Negative

Some of the DRGs associated with an increase in falls are supported by the literature. For example, chronic obstructive pulmonary disease (DRG 191 in Table 14) would be expected to have a high fall rate since it is associated with a worsening of dyspnea perception and loss of balance (Roig et al., 2011). Transient ischemia (DRG 069 in Table 14) is also expected to cause an increase in falls, since it can cause temporary blindness and dizziness (Mayo Clinic, 2019) so if a patient is admitted with this DRG and attempts to be mobile, s/he might fall as a result, with no specific cause for the other observed associations.

The next step is to conduct the analysis and prepare the PTFI variable for spreadsheet 2014 and compare the outcomes of the analysis and examine the DRGs which present as significant compared to those of 2011.

5.2 FORMULATING THE PTFI VARIABLE FOR DATASET 2014

The analysis for this year will also incorporate only the large hospitals (those with more than 2,000 Medicare discharges a year), building on the 2011 analysis on all providers (shown in the Appendix) vs. large hospitals only. That is because limiting the dataset to those providers with large numbers of Medicare discharges resulted in less variability and better residual plots.

Table 16 presents the transformed multivariate backward weighted regression for the falls per discharge analysis for the DRGs with those at the significance level P-value 0.05, while Table 17 presents the transformed multivariate backward weighted regression for the falls per day analysis for the DRGs with those at the significance level P-value 0.05.

Table 16: Final DRGs for Large Hospitals 2014 – Log Transformed Falls per Discharge Multivariate Backward Weighted Regression at P-Value Five Percent

Label	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Standardized Estimate	Variance Inflation
Intercept	1	5.69630	0.07341	77.60	<.0001	0	0
DRG064	1	16.79996	6.43857	2.61	0.0092	0.07387	1.31848
DRG149	1	-59.68155	20.35328	-2.93	0.0034	-0.09492	1.72390
DRG312	1	17.97733	6.25178	2.88	0.0041	0.09365	1.74463
DRG315	1	49.47481	21.13286	2.34	0.0194	0.06125	1.12608
DRG394	1	36.10686	14.45539	2.50	0.0126	0.06934	1.26783
DRG481	1	20.71206	6.80655	3.04	0.0024	0.08533	1.29361
DRG602	1	-39.49108	18.80937	-2.10	0.0359	-0.05638	1.18629
DRG640	1	-19.82858	7.91977	-2.50	0.0124	-0.06820	1.22062
DRG684	1	-39.83129	18.06283	-2.21	0.0276	-0.05891	1.17418
DRG853	1	27.82769	11.38760	2.44	0.0146	0.08688	2.07935
DRG871	1	-6.44790	1.53594	-4.20	<.0001	-0.15425	2.22098
DRG917	1	44.16003	13.76935	3.21	0.0014	0.08866	1.25724

Thus, using the results from Table 16 the PTFI variable for the falls per discharge analysis will be computed as follows:

PTFI (2014 Falls per Discharge) = 5.7 + 16.8(DRG_{064}) – 59.7 (DRG_{149}) – 17.9 (DRG_{312}) + 49.5 (DRG_{315}) + 36.1 (DRG_{394}) + 20.7 (DRG_{481}) – 39.5 (DRG_{602}) – 19.8 (DRG_{640}) – 39.8 (DRG_{684}) + 27.8 (DRG_{853}) – 6.4 (DRG_{871}) + 44.2 (DRG_{917})

Table 17: Final DRGs for Large Hospitals 2014 - Log Transformed Falls per Day Multivariate Backward Weighted Regression at P-Value Five Percent

Label	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Standardized Estimate	Variance Inflation
Intercept	1	4.10557	0.06763	60.70	<.0001	0	0
DRG208	1	23.77201	7.94145	2.99	0.0028	0.08310	1.26948
DRG246	1	-28.91468	14.38686	-2.01	0.0446	-0.08190	2.73541
DRG247	1	16.07085	5.95283	2.70	0.0070	0.11151	2.81056
DRG303	1	-34.92336	15.29629	-2.28	0.0226	-0.05786	1.05788
DRG394	1	45.55174	13.27125	3.43	0.0006	0.08796	1.08179
DRG469	1	45.05315	14.42924	3.12	0.0018	0.08129	1.11659
DRG602	1	-36.84192	18.41507	-2.00	0.0456	-0.05289	1.15108
DRG640	1	-22.17645	7.74421	-2.86	0.0042	-0.07669	1.18149
DRG870	1	-30.12141	9.13236	-3.30	0.0010	-0.08728	1.15345
DRG917	1	44.95927	13.58344	3.31	0.0010	0.09076	1.23859

The results from Table 17 are presented in the following PTFI equation for the falls per day:

$$\text{PTFI (2014 Falls per Day)} = 4.11 + 23.77\,(DRG_{208}) - 28.91(DRG_{246}) + 16.1\,(DRG_{247}) - 34.9\,(DRG_{303}) + 45.55\,(DRG_{394}) + 45.1(DRG_{469}) - 36.8\,(DRG_{602}) - 22.2\,(DRG_{640}) - 30.12\,(DRG_{870}) + 44.9\,(DRG_{917})$$

Table 18 demonstrates the DRGs of each PTFI equation based on the dependent variable and their signs. Table 19 demonstrates only four (out of a total of 18 DRGS) common DRGs across both dependent variables, listing those which increase the falls rates followed by those which are linked to a decrease in fall rate.

Unlike the outcomes of the 2011 DRGs, the common outcomes of the DRGs across both dependent variables, in Table 19, are not numerous. However, in order to demonstrate a more rigorous analysis, the 2014 DRGs dataset will also be applied using the 2011 intercept and coefficients.

Table 18: DRGs of Each PTFI Equation Based on Dependent Variable and Their Signs – 2014 Dataset

DRG Code ((MCC=Major Complication or Comorbidity, CC= Complication or Comorbidity, W=with, W/O=without)	**Sign of Significance in Falls per Discharge**	**Sign of Significance in Falls per day**
064 - INTRACRANIAL HEMORRHAGE OR CEREBRAL INFARCTION W MCC	Positive	N/A
149 - DYSEQUILIBRIUM	Negative	N/A
208 - RESPIRATORY SYSTEM DIAGNOSIS W VENTILATOR SUPPORT <96 HOURS	N/A	Positive
246 - PERC CARDIOVASC PROC W DRUG-ELUTING STENT W MCC OR 4+ VESSELS/STENTS	N/A	Negative
247 - PERC CARDIOVASC PROC W DRUG-ELUTING STENT W/O MCC	N/A	Positive
303 - ATHEROSCLEROSIS W/O MCC	N/A	Negative
312 - SYNCOPE AND COLLAPSE	Positive	N/A

315 - OTHER CIRCULATORY SYSTEM DIAGNOSES W CC	Positive	N/A
394 - OTHER DIGESTIVE SYSTEM DIAGNOSES W CC	Positive	Positive
469 - MAJOR JOINT REPLACEMENT OR REATTACHMENT OF LOWER EXTREMITY W MCC	N/A	Positive
481 - HIP AND FEMUR PROCEDURES EXCEPT MAJOR JOINT W CC	Positive	N/A
602 - CELLULITIS W MCC	Negative	Negative
640 - MISC DISORDERS OF NUTRITION, METABOLISM, FLUIDS/ELECTROLYTES W MCC	Negative	Negative
684 - RENAL FAILURE W/O CC/MCC	Negative	N/A
853 - INFECTIOUS AND PARASITIC DISEASES W O.R. PROCEDURE W MCC	Positive	N/A
870 - SEPTICEMIA OR SEVERE SEPSIS W MV 96+ HOURS	N/A	negative
871 - SEPTICEMIA OR SEVERE SEPSIS W/O MV 96+ HOURS W MCC -	Negative	N/A
917 - POISONING AND TOXIC EFFECTS OF DRUGS W MCC	Positive	Positive

Table 19: Common DRGs across Both Dependent Variables – 2014 Dataset

DRG Code ((MCC=Major Complication or Comorbidity, CC= Complication or Comorbidity, W=with, W/O=without)	**Sign of Significance in Falls per Discharge**	**Sign of Significance in Falls per day**
394 - OTHER DIGESTIVE SYSTEM DIAGNOSES W CC	Positive	Positive
917 - POISONING AND TOXIC EFFECTS OF DRUGS W MCC	Positive	Positive
602 - CELLULITIS W MCC	Negative	Negative
640 - MISC DISORDERS OF NUTRITION, METABOLISM, FLUIDS/ELECTROLYTES W MCC	Negative	Negative

CHAPTER 6

STATISTICAL ANALYSIS FOR 2011 DATASET

6.1 BASIC REGRESSION OUTCOMES FOR 2011 DATA

The multivariate regression analysis was performed on the first dependent variable (falls per discharge) against all 17 independent variables and seven interaction variables (total of 24 independent variables) presented in Table 20 below.

Table 20: All 24 Independent Variables and Interaction Effects of the Study

Independent Variable	Decsription of Variable
NTHS	Total Nursing Staff
RNTS	Fraction of nurses with RN qualifications
HTBO	Hospital Days Occupancy for All Beds
ALSH	Average Length of Stay for All Patients
ALSM	Average Length of Stay for Medicare Patients
PTFI	Propensity to Fall Index
NCSS	Star scoring for nurse communication
SRSS	Star scoring for staff responsiveness
Urban	Hospital location
Rural	Hospital location
HPPR	Hospital Type: proprietary
HPAO	Hospital Type: private nonprofit voluntary
HPRE	Hospital Type: other nonprofit voluntary
HPNP	Hospital Type: all voluntary nonprofit

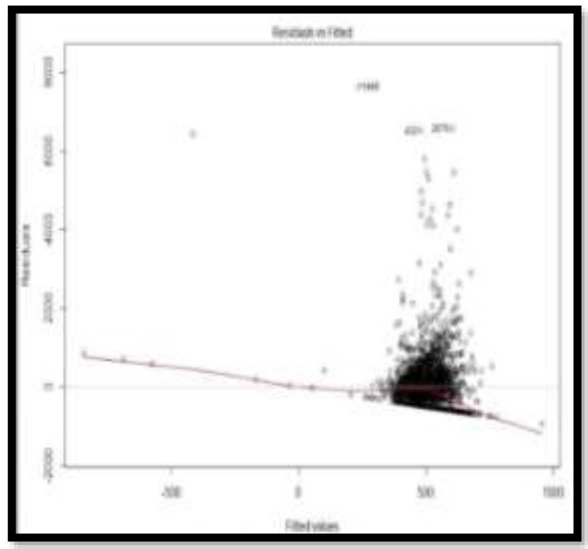
HSBD	Total number of hospital beds
HSMB	Total certified (Medicare) hospital beds
Magnet	Magnet Status
Interaction Effects	**Decsription of Interaction Effects**
NTHS, HTBO	Nursing staff levels and a high occupancy level
RNTS, ALSM	Experienced nursing staff and patients who present a higher severity of illness (measured by average length of stay among Medicare patients)
HTBO, ALSM	Occupancy level average length of stay and patients who present a higher severity of illness (measured by average length of stay among Medicare patients)
SRSS, PTFI	Staff responsiveness and patients who present to the hospital with demanding conditions
NCSS, PTFI	Nurse communication and patients who present to the hospital with demanding conditions
SRSS, ALSM	Staff responsiveness and patients who present a higher severity of illness (as measured by average length of stay among Medicare patients)
NCSS, ALSM	Nurse communication and patients who present a higher severity of illness (as measured by average length of stay among Medicare patients)

The analysis constituted a backwards weighted regression model, to allow for the significant variables to remain in the model while accounting for the weights (numbers of Medicare discharges per year) of each provider, and how this proportion affects the regression model. The use of weighted regression is an attempt to correct for the fact that the fall rate in small hospitals typically shows much greater variability than in large hospitals, which can skew the regression outcomes. For example, many small hospitals reported zero fall rates just by chance; when using unweighted regression, this would lead the regression model to interpret these data points as "better" than larger hospitals with small but non-zero fall rates. The weighted regression allows the model to interpret each fall rate in proportion to the number of discharges from that hospital, and so allowing for a more "equal representation" of the data.

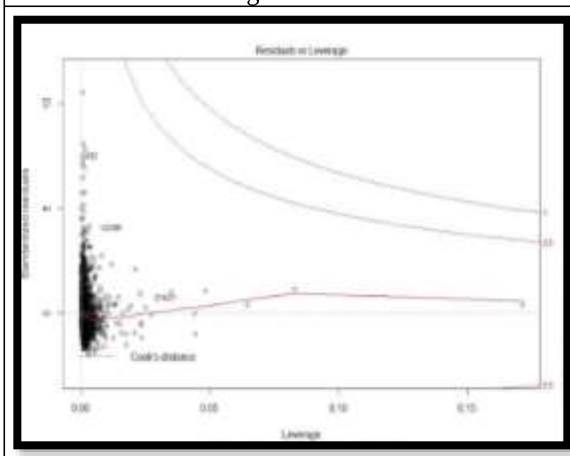
Figure 12 presents the backwards weighted regression for the falls per discharge. Notably, for all regressions in this study, the significance levels will be indicated as follows: *** < 0.0001, **= 0.01, * = 0.05, and ˙ = 0.1.

```
Call:
lm(formula = FallRate ~ PTFI + HSBD + HTBO + HTBOxALSM, data =
    weights = wts)

Weighted Residuals:
   Min     1Q Median     3Q    Max
-46682 -15365  -4571  10593 246566

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -959.38526  261.91326  -3.663 0.000253 ***
PTFI         257.40816   42.21992   6.097 1.21e-09 ***
HSBD          -0.07365    0.02556  -2.882 0.003979 **
HTBO          -3.54194    0.92485  -3.830 0.000131 ***
HTBOxALSM      0.33144    0.13387   2.476 0.013345 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 23430 on 3129 degrees of freedom
Multiple R-squared:  0.02514,   Adjusted R-squared:  0.02389
F-statistic: 20.17 on 4 and 3129 DF,  p-value: < 2.2e-16
```

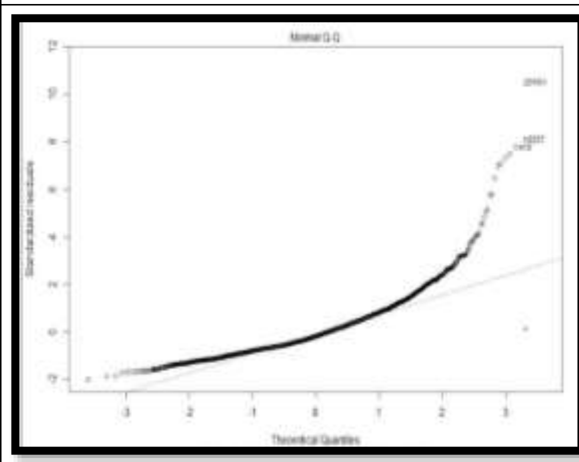
Regression Model



Residual vs Fitted Plot



Residual vs Leverage Plot



Normal Q-Q Plot

Figure 12: Regression Model and Residual Plots for Backward Weighted Regression on Falls per Discharge Using Multivariate Backward Weighted Regression for 2011

As shown, the Normal Q-Q plot in Figure 12 does not present a linear model, which will be addressed through transformation of the dependent variable.

6.2 ANALYSIS OF TRANSFORMED DEPENDENT VARIABLE FOR 2011 DATASET

To address the previous concerns of the nonlinear Q-Q plot, showing that the normality assumption of regression is not satisfied, a transformation is required. Generally, some of the most common forms of transformation are listed as*:* the *log, square root, polynomial transformation (power of 2, 3, 4, etc.)* and *the reciprocal of the dependent variable.* For this study, identifying which transformation to use will help in achieving a good fit for normality in the Q-Q plot of the observations as much as possible, without the threat of over fitting. Briefly, each form of transformation listed above will be explored to determine which best fits to the analysis:

1. Log and Reciprocal transformations: Although the Log and reciprocal transformations are common, applying them will not be possible because of the zero values present in the data set (i.e., hospitals with zero fall rates), where the Log of zero is infinite (negative) and the reciprocal of zero is also infinite, making the analysis outcome unattainable (Cox, 2007).

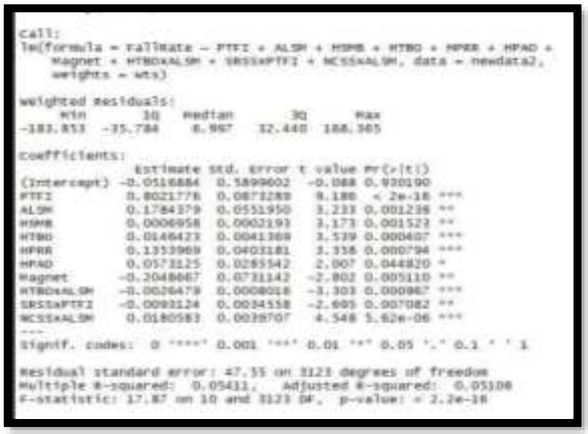
2. Log + constant and Reciprocal + constant Transformations: applying Log + constant and the reciprocal + constant, because the fall rates are physically meaningful rational numbers, and adding a constant to the fall rates will interfere with the meaning of the ratios (Cox, 2007),

but since almost 50 percent of the fall rates for this study are zero, adding a constant to them would allow the data to become more comparable (The Minitab Blog, 2013).

3. Square root transformations: can be applied to zero values and are also typically used to reduce heteroscedasticity (Prabhakaran, 2017) when the large values have the higher variance, leading to a more equally distributed variance (Cox, 2007).

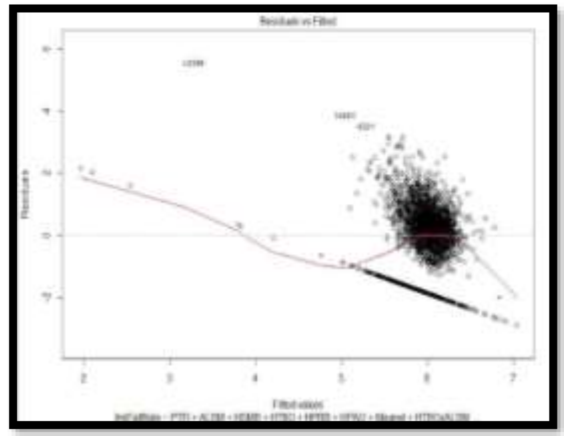
Based on these comparisons, it is determined that Log + a constant is appropriate for this study. The constant chosen is equal to 62, which is a common "small" fall rate in the dataset. This transformation will be applied to the fall rates to address the existence of the zero values upfront (Fundamentals of Statistics, 2012).

Figure 13 shows the weighted backward regression analysis for Log+62 falls per discharge against all 24 independent variables:

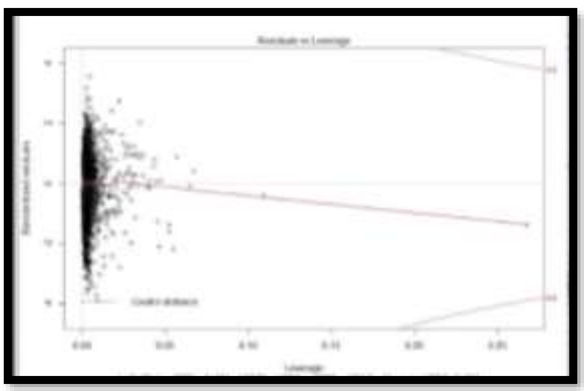


```
Call:
lm(formula = FallRate ~ PTFI + ALSM + HSMB + HTBO + HPRR + HPAD +
    Magnet + HTBOxALSM + SRSSxPTFI + NCSSxALSM, data = newdata2,
    weights = wts)

Weighted Residuals:
     Min       1Q   Median       3Q      Max
-183.853  -35.784    6.997   32.440  188.305

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.0516884  0.5899002  -0.088 0.930190
PTFI         0.8021776  0.0873289   9.186  < 2e-16 ***
ALSM         0.1784379  0.0551950   3.233 0.001238 **
HSMB         0.0006958  0.0002193   3.173 0.001523 **
HTBO         0.0146423  0.0041369   3.539 0.000407 ***
HPRR         0.1353969  0.0403181   3.358 0.000794 ***
HPAD         0.0573125  0.0285542   2.007 0.044820 *
Magnet      -0.2048067  0.0731142  -2.802 0.005110 **
HTBOxALSM   -0.0026479  0.0008016  -3.303 0.000967 ***
SRSSxPTFI   -0.0093124  0.0034558  -2.695 0.007082 **
NCSSxALSM    0.0180583  0.0039707   4.548 5.62e-06 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 47.55 on 3123 degrees of freedom
Multiple R-squared:  0.05411,    Adjusted R-squared:  0.05108
F-statistic: 17.87 on 10 and 3123 DF,  p-value: < 2.2e-16
```

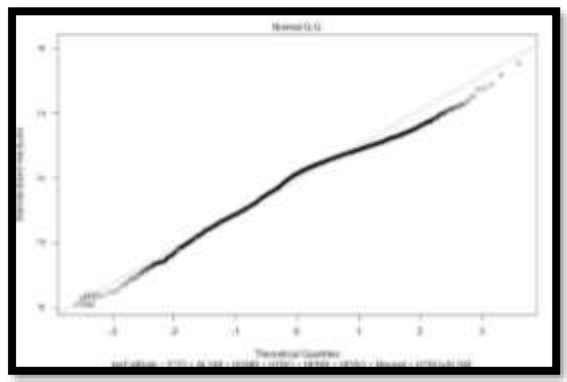
Transformed Regression Model



Transformed Residual vs Fitted Plot



Transformed Residual vs Leverage



Transformed Normal Q-Q Plots

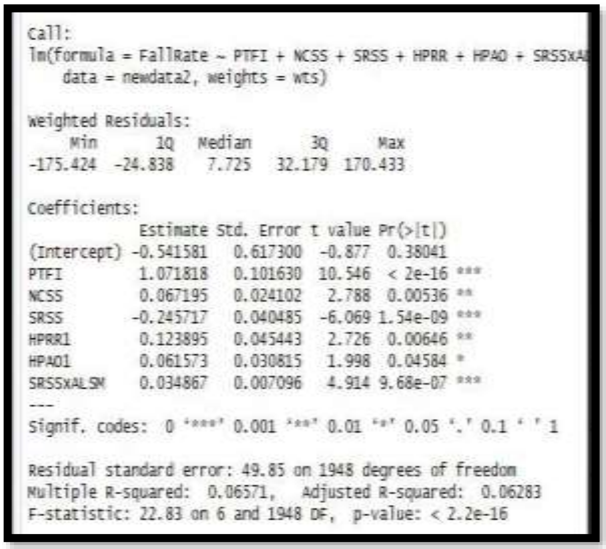
Figure 13: Transformed (Log+ 62) Falls per Discharge Regression and Residual Plots for All Providers Using Multivariate Backward Weighted Regression for 2011

Looking at the regression and plots post transformation, Figure 13, it is obvious that the previously observed nonlinear Normal Q-Q plot has improved, becoming more fitted to the line. Therefore, as a next step to assess the model, and how to measure it, there are multiple measures, two of which are available in the regression model; 1. Residual Standard Error (RSE) and 2. R-Squared (R^2). James et al. (2013) explained the RSE as “a measure of lack of fit of the model to the data at hand,” meaning that if the RSE value is near zero, then the model fits well with the data analyzed, while if there is a large RSE value, then that model does not fit the data well

(James et al., 2013). By contrast, the R^2 measures the fit of the model in a different manner. The R^2 takes on values between 0 and 1, independent of the units in which the dependent variable is measured, where generally a higher R^2 is better. When the R^2 is close to 1, this implies that the regression is explaining almost 100 percent of the variability in the data, but if the R^2 is close to zero then it is explaining almost none of the variability in the dependent variable. Importantly, it is not necessary that a low R^2 presents a bad model, nor does a high R^2 mean a good model; the R^2 can be low partly because a particular dependent variable may have more variability to explain (Frost, 2013). From Figure 13, the R^2 of the Log transformed model presents with an improved outcome of 0.05411, compared to 0.02514 of the post Log transformed R^2 from Figure 12.

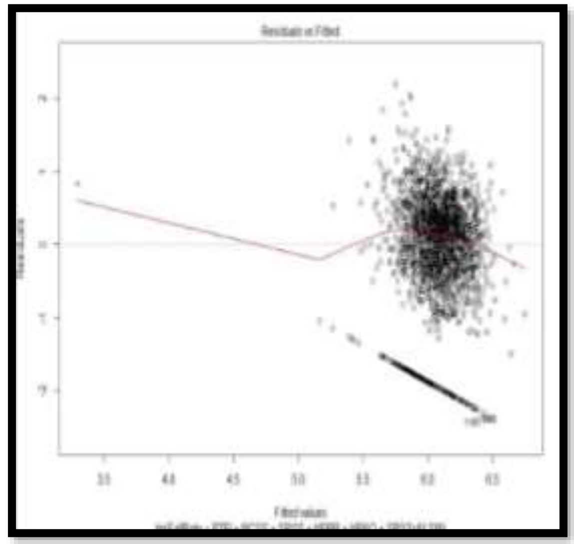
This study will now explore the outcome of removing the providers with Medicare discharges ranging between zero and 2,000. This is an attempt to remove all possible causes that can be skewing the data outcomes, over and above the correction provided by weighted regression. Additionally, the Appendix of this study will present additional regression analyses run by applying a different cutoff to the models (regressions with all providers included, and providers with more than 3,000 Medicare discharges), before and after the Log transformation, and also including analyses run for both falls per Medicare days and falls per discharge.

Figure 14 presents the regression and residual plots with ln+62 falls per discharge for those with 2,000 or more Medicare discharges (also known as large hospitals). It is important to note that although outliers were removed during the analyses (shown in the Appendix), the final results in Figure 14 present the regression with the outliers included. This is because the outliers did not go beyond the Cook's distance threshold; also, when the outliers were removed, this caused more outliers to appear causing the study more data loss. Therefore, although the R-squared of the regression with the outliers removed was *higher* than that with outliers included, and given that the significant coefficients with *and* without the outliers were similar (except for the Magnet award variable becoming significant with the outliers removed), it was decided to maintain the outliers in the analysis.

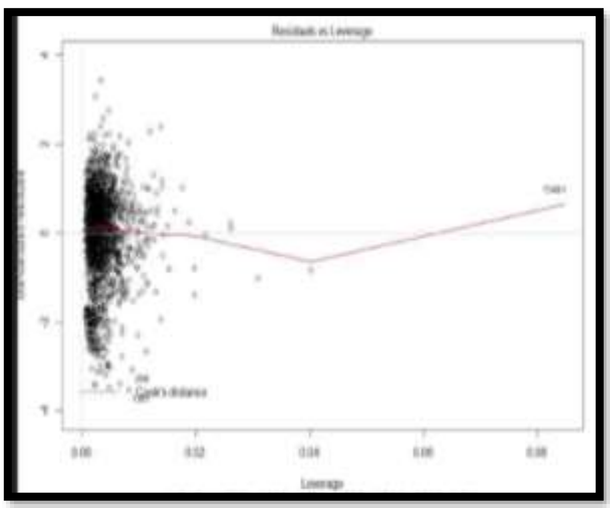


```
Call:
lm(formula = FallRate ~ PTFI + NCSS + SRSS + HPRR + HPAO + SRSSxAL
    data = newdata2, weights = wts)

Weighted Residuals:
     Min       1Q   Median       3Q      Max
-175.424  -24.838    7.725   32.179  170.433

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.541581   0.617300  -0.877  0.38041
PTFI         1.071818   0.101630  10.546  < 2e-16 ***
NCSS         0.067195   0.024102   2.788  0.00536 **
SRSS        -0.245717   0.040485  -6.069 1.54e-09 ***
HPRR1        0.123895   0.045443   2.726  0.00646 **
HPAO1        0.061573   0.030815   1.998  0.04584 *
SRSSxALSM    0.034867   0.007096   4.914 9.68e-07 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 49.85 on 1948 degrees of freedom
Multiple R-squared:  0.06571,    Adjusted R-squared:  0.06283
F-statistic: 22.83 on 6 and 1948 DF,  p-value: < 2.2e-16
```

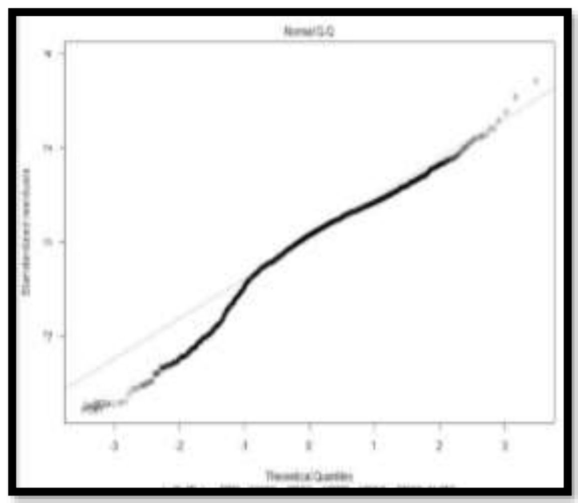
Transformed Regression Model for Large Hospitals



Transformed Residual vs Fitted Plot for Large Hospitals



Transformed Residual vs Leverage for Large Hozpitals



Transformed Normal Q-Q Plots for Large Hospitals

Figure 14: Transformed (Log+ 62) Falls per Discharge Regression and Residual Plots for Large Providers Using Multivariate Backward Weighted Regression for 2011

The improved linearity which was presented in the previous Normal Q-Q plot of Figure 13 has become distorted once the smaller hospitals were removed. Assessing the regression model, it seems more ideal to use the RSE to understand the 'better' model, since models with different datasets may have different amounts of variability for the model to "explain," and hence different R-Squared values. Therefore, the RSE can be used to compare the "goodness of fit" across the multiple models (Ross, 2019). Observing the outcome of the RSE between Figure 13 (47.55) and Figure 14 (49.85), a slight increase in the new model's RSE value is observed. The smaller RSE confirms that adopting the Log+62 of the dependent variable for *all* providers (Figure 13) can be considered a better model than the model with only the large providers (Figure 14), since the value in Figure 13 is slightly closer to zero than that of Figure 14, suggesting that it is a 'better fit' to the data analyzed.

6.3 CONCLUSION FOR ANALYSIS FOR 2011 DATASET

To understand the impact of each of the variables on falls per discharge, Table 21 below presents the coefficients of the final variables and their ranges. This table is formulated as follows:

- The data values of each variable (minimum, median, maximum, etc.) were multiplied by the coefficient for that variable, to represent the impact of each variable on the Log of the fall rate. Then, the 25th percentile of the impact was subtracted from the 75th percentile (with the exception of the Magnet and HPRR values, for which the 25th and 75th percentile were both zero); for those variables, the minimum value was subtracted from the maximum value. Finally, since the results apply to the Log of the fall rate, the exponential is taken, to convert the results back to raw fall rates, as presented in the orange row. For example, ALSM has a coefficient of 0.1784 in the regression analysis, a 25th percentile of 4.15 days, and a 75th percentile of 5.42 days. So, the impact on the Log of the fall rate is given by 0.1784 (5.42 – 4.15) = 0.23, and taking the exponential yields an impact of 1.26 on the actual fall rate.

- For convenience, independent variables with negative coefficients are shown in yellow.
- Note also that the columns in Table 21 are sorted from largest to smallest impact on Log fall rate (in absolute value), to make it easier to determine which variables have a large vs. small impact on fall rates.

To provide additional explanation of the final coefficients and their impact, each variable will be assessed, and evaluated against its original hypothesis.

Table 21: Coefficients of Final Variables and Their Ranges For 2011 Dataset

Variable	Ln(Fall Rate)	HTBOxALSM	ALSM	Magnet	PTFI	NCSSxALSM	HPRR	SRSSxPTFI	HPAO	HSMB
Minimum	0	9.36	1.15	0.00	1.07	0.00	0.00	0.00	0.00	0
1st Quartile	114	166.60	4.15	0.00	6.02	10.68	0.00	12.13	0.00	10
Median	406	255.75	4.78	0.00	6.13	14.80	0.00	18.14	0.00	28
Mean	511	263.83	4.84	0.01	6.12	13.94	0.21	16.40	0.34	44
3rd Quartile	669	344.79	5.42	0.00	6.23	18.23	0.00	24.06	1.00	61
Maximum	7874	1096.70	17.75	1.00	7.75	60.50	1.00	38.76	1.00	558
Coefficient		-0.0026	0.1784	-0.2049	0.8022	0.0181	0.1354	-0.0093	0.0573	0.0007
Impact on Ln(Fall Rate)										
Minimum		-0.02	0.21	0.00	0.86	0.00	0.00	0.00	0.00	0.000
1st Quartile		-0.44	0.74	0.00	4.83	0.19	0.00	-0.11	0.00	0.007
Median		-0.68	0.85	0.00	4.92	0.27	0.00	-0.17	0.00	0.019
Mean		-0.70	0.86	0.00	4.91	0.25	0.03	-0.15	0.02	0.030
3rd Quartile		-0.91	0.97	0.00	5.00	0.33	0.00	-0.22	0.06	0.042
Maximum		-2.90	3.17	-0.20	6.22	1.09	0.14	-0.36	0.06	0.388
75th-25th*		-0.47	0.23	-0.20	0.17	0.14	0.14	-0.11	0.06	0.04
Taking Exponential		0.62	1.26	0.81	1.18	1.15	1.14	0.89	1.06	1.04

Table 21 shows the average length of stay for the Medicare beds (ALSM) is presenting as hypothesized, where it indicates a possible increase in fall rates associated with the severity of stay. Moreover, from Table 21, ALSM is also the individual variable with the largest impact on fall rate. Even a small change in ALSM (from roughly four days to five and a half days) is associated with a 26 percent increase in fall rates (factor of 1.26 in the orange row of the table), consistent with the hypothesis about severity of illness. However, the effect of ALSM is modified by two interaction effects. In particular, good nursing communication increases the effect of ALSM on fall rates, contrary to the hypothesis. (In retrospect, this could perhaps be explained if good communication makes even severely ill patients more likely to get out of bed, thereby increasing the fall rates.) Also, surprisingly, the association of ALSM with high fall rates is reduced when occupancy (HTBO) is also high; it was hypothesized that high occupancy would exacerbate the difficulties of caring for severely ill patients. (Again, in retrospect, this could perhaps be explained if hospitals with both high occupancy and high average length of stay coped with this challenge by discouraging patients from getting out of bed.) Interestingly, the interaction effect involving high ALSM and high HTBO had such a large negative coefficient that it could not merely reduce, but actually counteract the effect of high ALSM. Thus, ALSM is best interpreted not as being associated with increased fall rates, but rather as being associated with increased fall rates when occupancy is low, and decreased fall rates when occupancy is high.

The variable with the next biggest impact on fall rates is Magnet hospitals. The Magnet designation is associated with a 1 – 0.81 = 19 percent decrease in fall rates, as hypothesized.

The propensity to fall variable also fit the original hypothesis; a change in the propensity-to-fall index from the 25^{th} to the 75^{th} percentile is associated with an 18 percent increase in fall rates. Again, the impact of propensity to fall was modified by an interaction effect with staff responsiveness, in the expected direction. In other words, good staff responsiveness reduced but did not eliminate the effect of propensity to fall, perhaps because patients with a high propensity to fall were more likely to be accompanied by a nurse when getting out of bed when staff responsiveness is high.

The impact of hospital ownership was in an unexpected direction. Proprietary and private voluntary nonprofit hospitals were associated with 14 percent and six percent increases in fall rates, respectively. The reasons for this effect are unclear.

Finally, hospital size (as measured by number of Medicare beds, HSMB) was associated with an increase in fall rates, again counter to the original hypothesis. In particular, an increase in size from 10 to roughly 60 Medicare beds was associated with a small (four percent) but statistically significant increase in fall rates. The original hypothesis was that hospitals with a large Medicare population would be more able to dedicate resources to fall prevention, but the effect seems to be in the opposite direction.

In conclusion, the 2011 analysis for the transformed (Log+ 62) falls per discharge for all providers will be replicated in the next chapter, Chapter 7, using the 2014 dataset, in order to determine the robustness of the results across both datasets.

CHAPTER 7

STATISTICAL ANALYSIS FOR 2014 DATASET

This chapter is the final step in the analysis process. From Chapter 6, the transformed (Log+ 62) falls per discharge is the dependent variable that produced the best outcome in terms of the improved linearity of the Normal Q-Q plots and also the R-Squared. This analysis is meant to compare the final outcomes of the 2014 dataset and those of 2011 using the same dependent variable, to determine whether the associations detected in the 2011 analysis are reliable. Therefore, the final 'best' outcome of the 2014 analysis will be compared to that of the final 'best' outcome from 2011.

Additionally, two PTFI indices will be applied, specifically for the dependent variable falls per Medicare discharge; where one of the indices uses the coefficients of the DRGs which were developed using the 2014 dataset (developed in Chapter 5), and the other uses the 2011 intercept and DRG coefficients and *applies* them to the 2014 data. To determine which PTFI to use, each of the PTFIs will be inserted into the 'full' regression and assessed based on the P-values of the variables in that regression, to find which regression would be more robust to use further in the 2014 analysis. Keeping in mind that the index developed from the 2014 data can present with the risk of over-fitting, if the index developed from the 2011 DRGs remains significant when applied to the 2014 data, then that would provide evidence that the 2011 index is capturing meaningful effects.

As a reminder, the PTFI assessed based on the 2014 DRGs applied the twelve DRGs determined as significant in this equation:

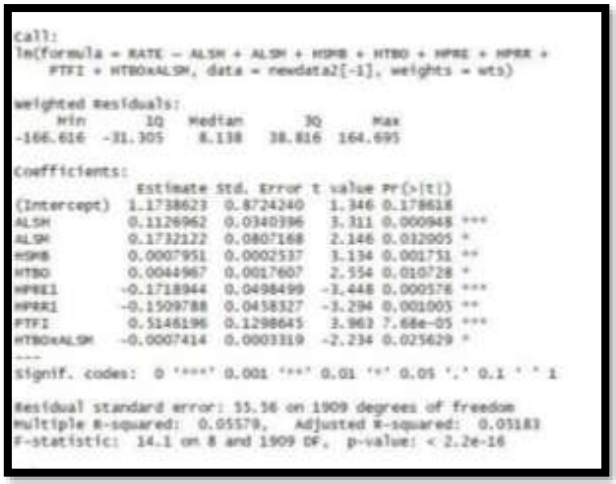
$$PTFI_{2014} = 5.7 + 16.8(DRG_{064}) - 59.7\ (DRG_{149}) - 17.9\ (DRG_{312}) + 49.5\ (DRG_{315}) + 36.1\ (DRG_{394}) + 20.7\ (DRG_{481}) - 39.5\ (DRG_{602}) - 19.8\ (DRG_{640}) - 39.8\ (DRG_{684}) + 27.8\ (DRG_{853}) - 6.4\ (DRG_{871}) + 44.2\ (DRG_{917})$$

Similarly, the PTFI based on the 2011 significant DRGs (applying the intercept, coefficients and DRGs of 2011 ***but*** with the discharge percentages of 2014 for those significant DRGs) is represented in this equation:

$$PTIF_{2011} = 5.87 + 24\ (DRG_{066}) - 13.39\ (DRG_{069}) - 22.97\ (DRG_{101}) + 7.61\ (DRG_{191}) + 15.86\ (DRG_{208}) + 27.1\ (DRG_{300}) - 21.2\ (DRG_{303}) - 20.71\ (DRG_{377}) + 14.14\ (DRG_{552}) - 12.9\ (DRG_{812}) - 4.77\ (DRG_{897}) + 25.8\ (DRG_{918})$$

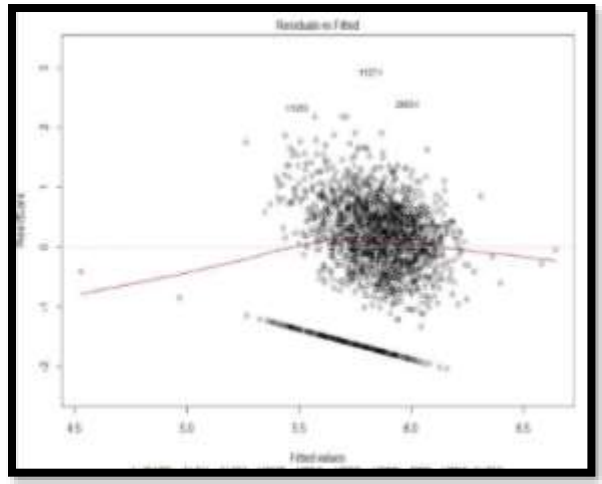
7.1 REGRESSION OUTCOMES FOR 2014 DATA FOR BOTH PTFI ANALYSES

Figure 15 presents the 2014 dataset with PTFI 2011 inserted into a multivariate backward weighted regression. The analysis constituted a backwards weighted regression model for large providers (2,000 Medicare discharges per year) to allow for the significant variables to remain in the model while accounting for the weights (numbers of Medicare discharges per year) of each provider, as was done in Chapter 6.

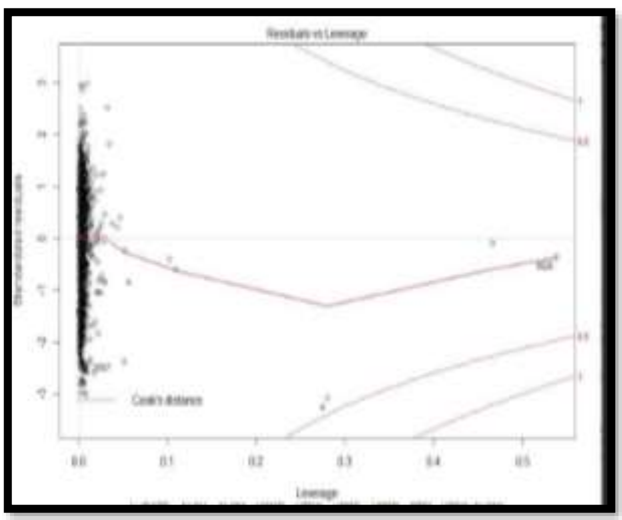


```
Call:
lm(formula = RATE ~ ALSH + ALSM + HSMB + HTBO + HPRE + HPRR +
    PTFI + HTBOxALSM, data = newdata2[-1], weights = wts)

Weighted Residuals:
     Min       1Q   Median       3Q      Max
-166.616  -31.305    8.138   38.816  164.695

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  1.1738623  0.8724240   1.346 0.178618
ALSH         0.1126962  0.0340396   3.311 0.000948 ***
ALSM         0.1732122  0.0807168   2.146 0.032005 *
HSMB         0.0007951  0.0002537   3.134 0.001751 **
HTBO         0.0044967  0.0017607   2.554 0.010728 *
HPRE1       -0.1718944  0.0498499  -3.448 0.000576 ***
HPRR1       -0.1509788  0.0458327  -3.294 0.001005 **
PTFI         0.5146196  0.1298645   3.963 7.68e-05 ***
HTBOxALSM   -0.0007414  0.0003319  -2.234 0.025629 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 55.56 on 1909 degrees of freedom
Multiple R-squared:  0.05579,    Adjusted R-squared:  0.05183
F-statistic:  14.1 on 8 and 1909 DF,  p-value: < 2.2e-16
```

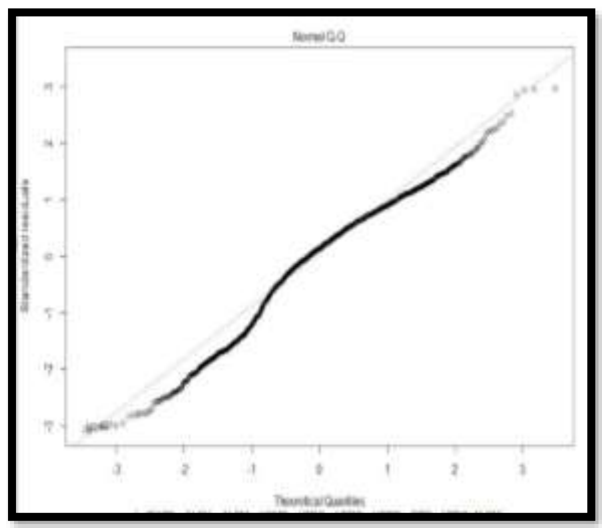
Transformed Regression Model for Large Hospitals



Transformed Residual vs Fitted Plot for Large Hospitals



Transformed Residual vs Leverage Plot for Large Hospitals



Transformed Normal Q-Q Plot for Large Hospitals

Figure 15: Transformed (Log+ 62) Falls per Discharge Regression and Residual Plots for Large Providers Using Multivariate Backward Weighted Regression for 2014 with PTFI 2011

Figure 15 presents eight significant variables for 2014 Data with 2011 PTFI (ALSM, ALSH, HSMB, HTBO, HPRE (-), HPRR (-) PTFI and HTBO x ALSM (-)). Notably, the analysis for the PTFI 2014 yield seven significant variables, where all seven variables are consistent with those of the PTFI 2011 in effect and signs, except for ALSH, which was lost in the PTFI 2014 analysis. Also, the values of the variable's impact on falls are comparable across both PTFI analyses. Table 22 presents a comparison between the coefficient outcomes of the 2014 dataset applied to both the 2011 PTFI and the 2014 PTFI, to show their similarities in outcomes and effects. The PTFI 2014 analysis presented with a higher R-squared (0.0821) compared to the PTFI 2011 analysis, but as mentioned previously, this could potentially be a result of over-fitting, since the 2014 PTFI was developed using the same falls data as used in the overall regression.

Realizing this risk of overfitting, and given that the two analyses produce similar outcomes, the study will continue to focus only on the PTFI 2011 analysis. Notably, the Appendix will include additional analyses using the 2011 PTFI.

Table 22: Comparison of Coefficients and Their Effects for PTFI 2011 and PTFI 2011 Using the 2014 Dataset

PTFI index used in the analysis	HTBO x ALSM	HTBO	ALSM	HPRE	HPRR	ALSH	PTFI	HSMB
PTFI 2011 Falls per Discharge Coefficients	-0.0007	0.005	0.17	-0.17	-0.15	0.11	0.52	0.0008
PTFI 2014 Falls per Discharge Coefficients	-0.0007	0.004	0.19	-.016	-0.11	N/A	0.86	0.0006

Comparing Figure 15 in Chapter 7 for PTFI 2011 (using the 2014 dataset) to Figure 13 from Chapter 6, the above analysis showed an R-squared value of 0.0558, whereas the analysis for the 2011 dataset had an R-squared value of 0.0542. These results indicate that the independent variables explain a slightly higher fraction of variance of the dependent variable (fall rate) in the 2014 dataset, compared to the 2011 dataset.

7.2 CONCLUSION FOR ANALYSIS FOR 2014 DATASET

The final eight independent variables with significance level of 0.05 or less in the analysis using the 2011 PTFI are: average length of stay for all hospital patients (ALSH); average length of stay for Medicare patients (ALSM); total Medicare hospital beds (HSMB); hospital occupancy (HTBO); other nonprofit voluntary hospitals (HPRE (-)); proprietary hospitals (HPRR (-)); propensity to fall index ($PTFI_{2011}$); and the interaction of ALSM with occupancy (HTBO x ALSM (-)). To further understand the final independent variables, as in Chapter 6, an impact table, Table 23 using PTFI 2011 for the 2014 dataset is created to understand the consequences of these variables on the transformed fall rate.

Table 23: Impact Table for Final Significant Variables for 2014 Dataset with PTFI 2011

PTFI 2011 Falls per Discharge for 2014 Dataset	Log (Fall Rate)	HTBO x ALSM	HTBO	ALSM	HPRE	HPRR	ALSH	PTFI	HSMB
Minimum	0	11.52	9.20	1.02	0	0	1.10	1.36	0
1st Quartile	0	558.04	134.34	4.03	0	0	3.69	6.00	9
Median	299	890.74	193.18	4.66	0	0	4.27	6.09	26
Mean	259	2045.49	302.68	6.74	0.5	0	6.30	6.00	184
3rd Quartile	551	1230.09	244.15	5.29	0	0	4.84	6.19	57
Maximum	8000	8478.85	1569.58	33.01	1	1	26.41	7.26	591
Coefficient		-0.0007	0.0045	0.1732	-0.172	-0.151	0.113	0.515	0.0008
Impact on Ln(Fall Rate)									
Minimum		-0.01	0.04	0.18	0.00	0.00	0.12	0.70	0.00
1st Quartile		-0.41	0.60	0.70	0.00	0.00	0.42	3.09	0.01
Median		-0.66	0.87	0.81	0.00	0.00	0.48	3.13	0.02
Mean		-1.52	1.36	1.17	-0.09	0.00	0.71	3.09	0.15
3rd Quartile		-0.91	1.10	0.92	0.00	0.00	0.55	3.19	0.05
Maximum		-6.29	7.06	5.72	-0.17	-0.15	2.98	3.74	0.47
75th-25th*		-0.50	0.49	0.22	-0.17	-0.15	0.13	0.10	0.04
Taking Exponential		0.61	1.64	1.24	0.84	0.86	1.14	1.10	1.04

From Table 23, the highest impact on the fall rates is shown by the interaction of ALSM with HTBO, while the individual variables HTBO and ALSM also had large impacts on fall rates (39 percent (1-0.61 = 39), 64 percent, and 24 percent respectively). The association of the individual variables HTBO and ALSM with an increased fall rate matches the hypothesis of a possible increase in fall rates due to a longer average length of stay and a high level of occupancy of patients and their possible demand on the hospital resources. The interaction HTBO x ALSM (-)) shows a surprising relation with *decreased* fall rates, which is opposite to the hypothesis of having a long ALSM with high occupancy rates leading to a possible increase in falls. The interaction effect has a bigger impact than HTBO or ALSM alone, so they are associated with an increased fall rate only when the other variable is small.

Next, the slightly smaller impact variables are HPRE (-) and HPRR (-). Both show an association with decreased fall rates, matching the hypothesis of these hospitals having the funds to provide fall prevention policies, being associated with 16 percent and 14 percent decrease in fall rates, respectively.

ALSH and PTFI both show as smaller impacts on fall rates. The relation of these variables with increased fall rates can be due to the possible demand on the hospital resources from patients with increased severity of illness. These variables are associated with 14 and 10 percent increases in fall rates, respectively.

Finally, the variable with the smallest impact on fall rates is HSMB, with a four percent increase in fall rates. This is a surprising association, opposite to the hypothesis that hospitals with large numbers of beds would have low fall rates due to the available funds allowing for improved fall prevention policies (but in the same direction as was found for the 2011 dataset in Chapter 6).

Looking more closely at the 2011 dataset impacts vs 2014 dataset (2011 and 2014 PTFI) impacts in Table 24, there are four variables that remain significant with the same direction of their effects (HTBO x ALSM (-), ALSM, PTFI and HSMB) (highlighted in blue). They remain good predictors for fall rates in 2014 (in both PTFI analyses), as they were in 2011.

Table 24: Impact Table for Final Significant Variables for 2014 Dataset with PTFI 2011

2011 Results (Transformed Falls per Discharge All Providers)	2014 Results of PTFI 2011 (Transformed Falls per Discharge All Providers)	2014 Results of PTFI 2014 (Transformed Falls per Discharge All Providers)
HTBO x ALSM (-), ALSM, PTFI, HSMB, Magnet (-), NCSS x ALSM, SRSS x PTFI (-), HPRR and HPAO	HTBO x ALSM (-), ALSM, PTFI, HSMB, HTBO, ALSH, HPRE (-) and HPRR (-)	HTBO x ALSM (-), ALSM, PTFI, HSMB, HTBO, HPRE (-) and HPRR (-)

The variables highlighted in blue represent the four variables overlapping across the 2011 dataset and the 2014 dataset. The PTFI variable continued with its expected sign to increase falls. Hospitals with large numbers of Medicare beds (HSMB) had an unexpected sign of increasing falls, opposite to the idea that large hospitals would have the financial resources to prevent falls. ALSM showed an expected sign of increasing the fall rates, where the original hypothesis of having Medicare patients with long average length of stay can increase the rate of falls. Finally, the interaction with average length of stay, HTBO x ALSM (-), is presenting with an unexpected sign, suggesting a decrease in falls.

In conclusion, from the seven interactions, and 12 variables, four were identified to have been consistently significant in both 2011 and 2014. One additional variable (HPRR) was consistent between 2011 and 2014 in its statistical significance, but not the direction of its effect. The fact that four variables remained consistent across both 2011 and 2014 datasets provides added confidence in the effect of those four specific variables, suggesting that they may therefore be worth further exploration. Also, the fact that the analysis of the 2014 dataset using the 2011 PTFI gives a comparable R-squared to that of the 2011 dataset analysis (0.0558 vs 0.0542) provides confidence to the idea that PTFI is a *meaningful and stable* concept.

CHAPTER 8

CONCLUSIONS, CHALLENGES AND RECOMMENDATIONS

8.1 CONTEXTUALIZING THE RESULTS OF THE STUDY

One of the initial reasons for this study is the importance of falls and how it affects the US economy and also the social impact on the US population, especially the elderly. Also, the level of data and information this study provides, available from CMS datasets, has been identified as an important factor of this study. Previously, most studies considered only one or two possible explanatory variables, using data from a limited number of hospitals, while this study is the first of its kind to delve into the entire dataset of CMS's 3,000+ hospitals *and* apply 17 different variables plus seven interaction effects to identify possible associations with fall rates. Also, using the injurious falls dataset allowed for a reduced risk of misclassification and selection bias due to differences in reporting thresholds.

There is no precedent to a study as large as this. Due to the limitations in the datasets, the analyses conducted were deemed from the idea's inception to be at the introductory and exploratory level, to create a basis for future research.

Notably, using large national databases allowed the outcomes to be representative of *most* large US hospitals in the United States. Although approximately 50 percent of the original 3,000+ hospitals were dropped due to their small size, nevertheless, over 1,500 large providers were assessed, with the realization that the small providers do possess unique characteristics. Moreover, using hospital-level data has also proven important to understand how multiple hospital-level factors, when analyzed together, can help draw a picture for researchers on which variables to focus on, keeping in mind ecological fallacies (Trochim, 2006). However, ecological fallacies can occur, since the final outcomes for the entire study may not apply to individual hospitals (Trochim, 2006).

Even though the R-squared in this study is relatively small (approximately five percent), small values are considered common for analyses of this nature. In particular, hospital-level data can capture only limited aspects of fall risk. Studies using patient data could be expected to have a higher R-squared.

In the end, four variables were consistently significant in the analysis of both the 2011 and 2014 datasets, providing reliability to the study. These variables are comprised of three main effects and one interaction effects: propensity to fall index (PTFI), average length of stay for Medicare patients (ALSM), numbers of hospital Medicare beds (HSMB), and the interaction of hospital bed occupancy with the average length of stay of Medicare patients (HTBO x ALSM (-)). Note, the negative sign indicates an association with reduced fall rates.

The propensity to fall index (PTFI) is a unique statistical product of this study, and a continuous predictor of increased fall rates throughout both the 2011 and 2014 datasets, presenting with an expected positive impact (consistent with the study's hypothesis that a large propensity to fall index can be associated with high fall rates) in every regression of the study. Notably, the current published literature on variables associated with falls only discussed medications; investigations into how fall rates relate to administrative categories such as DRGs have not been performed.

Even though the 2014 PTFI included different DRGs than the 2011 PTFI, it is noteworthy that the 2011 PTFI remained a good predictor of fall rates even in the 2014 analysis. It is important to note that while this suggests the theoretical construct of the PTFI is a meaningful tool, it will need to be reassessed to clarify which diagnoses are consistently associated with the highest fall risk.

The PTFI variable was developed from CMS's top 100 DRGs, and the specific DRGs chosen to be included in the PTFI were determined based on their P-value or significance level of their association with fall rates. The PTFIs were developed in relation to fall rates for the inpatient elderly to enable a better understanding of the relationship between diagnoses and fall rates. Multiple diagnoses were identified to be possibly related to the increase (or decrease) in fall rates during the admission of a patient. It is important to note that the DRGs of each year's PTFI were different, which leads to the necessity of additional exploration on why DRGs changed from one dataset to the other. Continuing the analysis of the PTFI variable can help guide hospital management regarding whether extra attention should be given to patients with certain diagnoses, and also to better understand possible causes leading to the risk of falls while walking to enable an efficient fall-free or low-risk process to implement in the medical facilities. Fisher et al. (2011) reported that acutely ill elderly inpatients spend only about four percent of their time walking in hospitals, which affects their general recovery process and physiological health, as low mobility can decrease the elderly's functions, allowing for a higher fall risk in future. This suggests that the concept of the PTFI can help hospitals risk-adjust their fall rates, and therefore determine whether their fall rates are excessive relative to their diagnosis mix.

The individual variable of ALSM showed an expected sign of increasing the fall rates. This is consistent with the original hypothesis that having Medicare patients with a long average length of stay can increase the rate of falls. This hypothesis is based on two concepts: first, that patients with a long average length of stay may be more severely ill, and therefore at greater fall risk; and second, that having inpatients remaining in the hospital for extended periods allows them to become deconditioned and more prone to falls once they start becoming mobile (King, 2016)

On the other hand, the consistent highest impact on the fall rates (in the 2011 dataset, and for both PTFIs in the 2014 dataset) was the interaction of ALSM with HTBO (HTBO x ALSM (-)), which shows a surprising relationship with *decreased* fall rates, opposite to the hypothesis that having a long ALSM with high occupancy rates would lead to a possible increase in falls. The interaction of HTBO x ALSM (-) presents with an unexpected sign while also having a bigger impact than HTBO or ALSM alone. This suggests that HTBO and ALSM are associated with an increased fall rate only when the other variable is small; i.e., if HTBO *or* ALSM is high, then the variable would be associated with an increased fall rate, but when *both* are high, the predicted fall rate is not any greater than when just one of them is high. One possible explanation for this might be if hospitals with both a severely ill Medicare population and a high occupancy rate were more likely to keep patients restricted in their beds, as a way of coping with the high occupancy.

Finally, the individual variable numbers of Medicare beds (HSMB) had an unexpected sign of increasing falls. This was opposite to the hypothesis that large hospitals would have the financial resources to prevent falls. A possible explanation for this might be that hospitals with large numbers of Medicare beds can be understaffed or overworked, and thus staff may be unable to devote adequate attention to falls prevention.

8.2 LIMITATIONS OF THE STUDY

A limitation for this study was assuring that all falls reported had a common definition. Currently, there is no specific or universal definition for falls or when a fall occurs; therefore, how and when falls are reported is difficult to identify. Given the study's focus on injurious falls, the plethora of definitions may be less problematic, since restricting the analyses to those falls associated with injury reduces the risk of misclassification. On the other hand, since our dataset reports *only* falls related to six specific kinds of injuries, this poses a difficulty if researchers are interested in studying *all* falls, injurious or not. This is because if there are numerous falls occurring, but these falls are not necessarily injurious, it will be challenging to know whether the fall prevention tools or policies in place are effective, because falls without trauma are not reported *at all*. In fact, AHRQ (2013) has recommended that falls should be tracked separately from falls with trauma.

The next limitation was locating open access datasets relevant to hospitals with variables related to the falls, so that multiple attributes can be analyzed against each other. Acquiring datasets with specific patient or incident related information proved to be a hardship, since these datasets must be purchased from CMS. Therefore, this study focused on hospital-specific data (HAC-POA reports, which are hospital/provider-specific).

These datasets were limited, making it impossible to analyze patient-level data. These limitations create the risk of confounding factors, such as patient demographics, pre-existing comorbidities affecting the status of the patient, high fall risk factors, patient medications (specifically drugs that can cause sleepiness and drowsiness), data on location and time of fall in the hospital, the description of the injury related to the fall, and number of falls recorded per unit. All these restrictions meant that multiple confounding factors may exist, causing potential weaknesses in the study.

Also, given that CMS data (which combine both Medicare and Medicaid patients) is used in this study, it is not possible to confirm that the population in the falls and trauma dataset is exclusively 65+ years old (since Medicaid allows individuals younger than 65 years to sign up based on specific conditions, as discussed earlier in Chapter 1). Therefore, assumptions were made that the majority of the falls reported are related to the elderly signed up for Medicare.

Another limitation that was realized early on was the discrepancy among the datasets, where missing (partial or full), duplicated or wrongfully entered information was identified. Eventually, as mentioned in Chapter 4, the numbers of data points that presented with errors were reported to account for any data discrepancy. Notably, the missing data was equal to 4.5 percent and 3.5 percent of the total 2011 and 2014 datasets, respectively. Also, having approximately 50 percent of both datasets comprised of small hospitals proved a burden on the analysis. In particular, fall rates at extremely small hospitals can be noisy and exhibit extremely high or low values just by chance, unrelated to fall prevention methods. Due to this, it was not possible to assume that the fall prevention methods of these hospitals (if such methods were in place) were the reason for either low or nonexistent fall rates or large fall rates (high variability).

A limitation when creating the PTFI was having a limited number of variables, which does not allow for a complete picture of how DRGs can impact fall rates, since looking at more DRGs across multiple datasets can help with understanding the trend (if any) of DRGs and fall rates. This specifically was obvious in the 2011 dataset, which provided only the top 100 DRGs, where better results could have been obtained with more DRGs. It was also challenging to find that none of the DRGs for the 2011 dataset overlapped with the 2014 dataset, with no current explanation. Due to these challenges, future research is required before the PTFI variable is used in future analyses or applications.

8.3 DIRECTIONS FOR FUTURE WORK AND RECOMMENDATIONS FROM THE STUDY

Suggestions for future work and recommendations for new research to be conducted are provided in this section. Given that the problem of falls is complex, more work remains to be done.

Although the causes are not yet identified, hospitals with a long average length of stay for Medicare patients (ALSM) and large hospitals (HSMB) appear to be at a greater risk of falls. ALSM and HSMB have 75th percentile values of approximately five days and 57 beds, respectively. Therefore, it is recommended that hospitals above the aforementioned cutoffs should look specifically at whether they need to improve fall prevention. In addition, the data of this study can be used to determine whether a hospital has an excessive fall rate compared to other hospitals with comparable attributes (e.g., small/large, similar DRGs), keeping in mind that small hospitals have more variability in fall rates (an issue that may need to be addressed in future analyses).

Another recommendation is that hospitals could be examining their own fall data, to determine which diagnoses are associated with high fall rates at a population level, to apply risk adjustment measures (once a more stable PTFI measure has been developed). Price (2015) compiled a list of multiple fall risk assessment tools, which help show the leading causes for both fatal and non-fatal injuries in the elderly; e.g., the Morse Fall Scale, Johns Hopkins Fall Risk Assessment Tool, STEADI (Stopping Elderly Accidents, Deaths and Injuries), etc. Although a general PTFI has not yet been developed and validated, the fact that some diagnoses are related to higher fall rates still provides a useful clue to hospitals looking at how to improve.

Also, discovering the effect of different diagnoses on the propensity to fall is a primary recommendation for future research. Given that this variable was created and first applied in this study, many questions remain to be answered until a more detailed picture of the illnesses requiring additional care for fall prevention in the analysis can be formulated. Moreover, the inconsistency in the PTFIs (e.g., different DRGS in the 2011 PTFI from those in the 2014 PTFI) leads to the recommendation of additional investigations to discover which diagnoses consistently pose a higher risk of falls.

Additionally, further investigation with hospital-level data can be recommended for a more extensive exploration of the best grouping of DRGs. For example, applying a reasonable conceptual model of how DRGs can contribute to fall rate (e.g., through separate effects on a patient's length of stay, walks s/he takes per day, and the risk per walk) could help create a better PTFI based on the grouped DRG's outcomes.

It could also be beneficial to research the characteristics of the hospitals that reported improved fall rates between 2011 and 2014 vs. those that did not. The availability of data for well over 1,000 hospitals across multiple years may make it possible to identify which facilities need to put greater focus on fall prevention efforts (and which are a lower priority for additional fall prevention).

An additional suggestion would be to apply patient-level data to explore whether for example particular DRGs are associated with high or low fall rates for individual patients, rather than for hospitals as a whole. With patient-level data, it would be possible to consider variables such as chronic conditions for each fallen patient, medications per patient, the age per patient, the impact of the fall on the patient, the geographic location of the patient, the language spoken per patient etc., and how each of these variables (individual or as interactions) can be associated with the fall rate. Even in the absence of patient-level data, it would be beneficial to explore the demographics of the patients served by particular regions; e.g., some regions (and some hospitals within a region) may serve populations at greater risk of falls for numerous reasons, whether it is more of an aging population (including fraction of the extreme elderly), poverty, high rate of non-native English speakers, low rate of education or literacy, high rate of drug addiction or alcoholism, etc. Correcting for these demographic factors may yield new insights into fall risk. That was considered for this study, but not actually done, due to the data challenges and scope of work.

In conclusion, a possible ideal study for future work would be to create an analysis merging hospital and patient-level datasets and explore the possibilities of what these datasets can produce. This analysis has barely scratched the surface of what's possible in understanding fall rates, so this should be a fruitful area for future research.

APPENDIX

APPENDIX TABLE OF CONTENTS

2014 ANALYSIS

Figure A-24: Multivariate Backward Regression and Plots Outcomes for Transformed (Log+ 62) Fall per Medicare Days for Large Providers (2,000 + Yearly Medicare Discharges) Post Removing Outliers - 2014

APPENDIX A.1: ADDITIONAL CONSTRUCTION OF 2011 PTFI VARIABLE FOR 2011 DATASET

An extended process was applied to develop the PTFI variable. As mentioned in Chapter 5, the Top 100 DRGs datasets for both 2011 and 2014 were fully analyzed across both dependent variables (falls per discharge and falls per Medicare days). Backwards weighted regressions for the DRGs were applied against all the hospitals, hospitals with 3,000 or more Medicare discharges a year and hospitals with 2,000 or more Medicare discharges a year. The P-values which were chosen to indicate significance were one, five and ten percent.

The study presented the PTFI outcomes of the transformed falls per discharge dependent variable at five percent significant level for hospitals with 2,000 or more Medicare discharges. Since it was realized from the 2011 analysis that the remaining regressions will continue with the large providers, none of the small providers (less than 2,000 Medicare discharges per year) were included in the PTFI analysis.

Therefore, in the Appendix, the outcomes of the backward weighted regressions for all providers of the falls per discharge variable against the top 100 DRGs and presented for year 2011.

Model 1: PTFI – 2011 DRGs for falls per discharge for all providers

Variable	Label	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Standardized Estimate	Variance Inflation
Intercept	Intercept	1	390.23204	24.51768	15.92	<.0001	0	0
DRG069	DRG069	1	4909.87673	2270.00569	2.16	0.0306	0.04456	1.41476
DRG101	DRG101	1	-7790.19134	3120.63395	-2.50	0.0126	-0.04721	1.19231
DRG191	DRG191	1	3246.47170	1134.44624	2.86	0.0042	0.06118	1.52373
DRG208	DRG208	1	5889.45453	2701.08173	2.18	0.0293	0.04236	1.25797
DRG313	DRG313	1	-2690.33713	1068.27818	-2.52	0.0118	-0.05077	1.35480
DRG377	DRG377	1	-13600	4120.40854	-3.30	0.0010	-0.06234	1.18921
DRG389	DRG389	1	-8177.87729	4062.79002	-2.01	0.0442	-0.04132	1.40480
DRG470	DRG470	1	1217.50741	183.07130	6.65	<.0001	0.12294	1.13915
DRG481	DRG481	1	7922.63010	2431.02154	3.26	0.0011	0.06731	1.42224
DRG536	DRG536	1	17022	5617.38759	3.03	0.0025	0.06532	1.54904
DRG641	DRG641	1	-2907.54713	1165.56901	-2.49	0.0127	-0.05441	1.58577
DRG918	DRG918	1	13304	4232.47647	3.14	0.0017	0.06294	1.33640

Figure A-1: 2011 PTFI DRG Outcome for Falls per Discharge Weighted Backward Regression for All Providers vs. Top 100 DRGs at Five Percent Significance level

Model 2: PTFI – 2011 DRGs for transformed falls per discharge (Log +62) for all providers

Variable	Label	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|	Standardized Estimate	Variance Inflation
Intercept	Intercept	1	5.89736	0.05507	107.10	<.0001	0	0
DRG069	DRG069	1	10.97119	5.11065	2.15	0.0319	0.04832	1.74017
DRG101	DRG101	1	-13.46460	6.69200	-2.01	0.0443	-0.03960	1.33053
DRG149	DRG149	1	-30.64095	11.89552	-2.58	0.0100	-0.06588	2.24702
DRG203	DRG203	1	-20.70115	9.43577	-2.19	0.0283	-0.04912	1.72187
DRG207	DRG207	1	-27.96483	10.14484	-2.76	0.0059	-0.05839	1.54094
DRG208	DRG208	1	21.23874	5.88263	3.61	0.0003	0.07413	1.44792
DRG280	DRG280	1	-11.62312	4.93193	-2.36	0.0185	-0.04696	1.36394
DRG286	DRG286	1	-38.72507	11.99707	-3.23	0.0013	-0.07947	2.08189
DRG287	DRG287	1	8.63000	2.54592	3.39	0.0007	0.07752	1.79642
DRG291	DRG291	1	6.04673	2.60510	2.32	0.0203	0.05145	1.68729
DRG300	DRG300	1	23.77339	10.44576	2.28	0.0229	0.04658	1.43876
DRG312	DRG312	1	9.63291	3.70155	2.60	0.0093	0.07158	2.59838
DRG313	DRG313	1	-8.29942	2.57242	-3.23	0.0013	-0.07601	1.90634
DRG377	DRG377	1	-26.94187	9.89416	-2.72	0.0065	-0.05994	1.66397
DRG378	DRG378	1	10.11821	4.38610	2.31	0.0211	0.05371	1.86195
DRG418	DRG418	1	-29.25460	13.07250	-2.24	0.0253	-0.05150	1.81903
DRG439	DRG439	1	-26.20757	13.26810	-1.98	0.0483	-0.04502	1.78423
DRG470	DRG470	1	0.83994	0.37431	2.24	0.0249	0.04116	1.15560
DRG481	DRG481	1	16.08221	5.31092	3.03	0.0025	0.06632	1.64720
DRG552	DRG552	1	14.13348	5.95964	2.37	0.0178	0.04934	1.48691
DRG641	DRG641	1	-5.92051	2.47749	-2.39	0.0169	-0.05377	1.73859
DRG897	DRG897	1	-3.90094	1.02730	-3.80	0.0001	-0.06550	1.02176
DRG918	DRG918	1	22.93831	8.95520	2.56	0.0105	0.05266	1.45180
DRG948	DRG948	1	13.59373	5.74973	2.36	0.0181	0.04945	1.50260

Figure A-2: 2011 PTFI DRG Outcome for Transformed (Log +62) Falls per Discharge Weighted Backward Regression for All Providers vs. Top 100 DRGs at Five Percent Significance level

APPENDIX A.2: ADDITIONAL REGRESSION RUNS FOR 2011 and 2014 DATA SETs

The two models presented for each dataset are as follows: first model applied the falls per Medicare discharge as the dependent variable and second applied the falls per Medicare days as the dependent variable. All regressions are run using backwards elimination process against the final 17 independent variables, and seven interaction effects (final 24 independent variables).

Model 1 is the Y= falls per discharge

Model 2 is the Y= Log (ln) (falls per discharge + 62)

Model 3 is the Y= falls per Medicare days

Model 4 is the Y= Log (ln) ((falls per discharge + 62)/Medicare days)

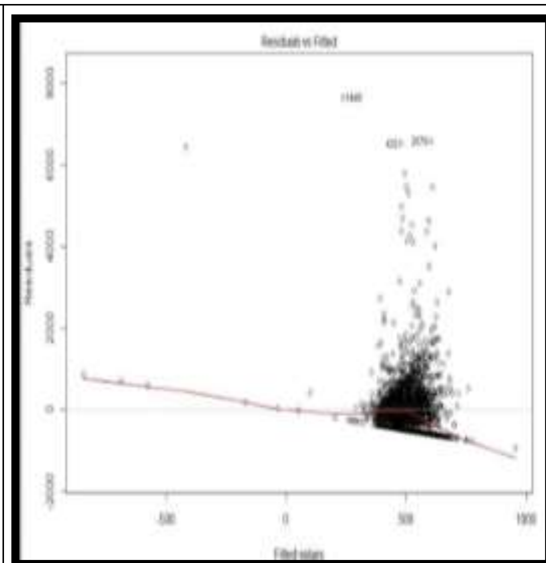
All logs were = Log (ln) (Y + 62) and all regressions are weighted by the Medicare discharges per year.

2011 ANALYSIS

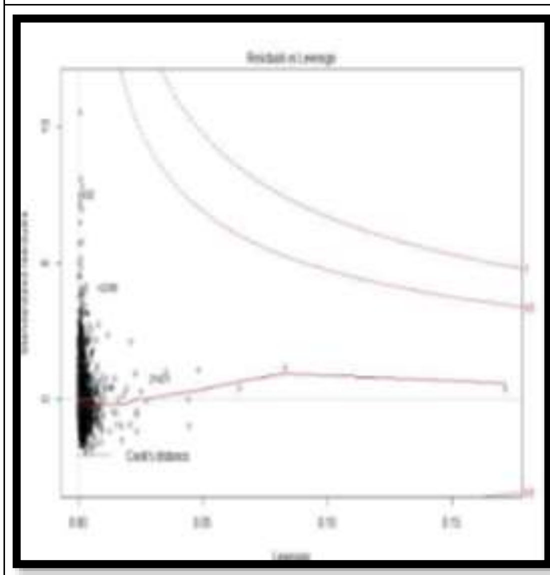
Model 1: Falls per discharge for all providers

```
Call:
lm(formula = FallRate ~ PTFI + HSBD + HTBO + HTBOxALSM, data =
    weights = wts)

Weighted Residuals:
   Min     1Q Median     3Q    Max
-46682 -15365  -4571  10593 246566

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -959.38526  261.91326  -3.663 0.000253 ***
PTFI         257.40816   42.21992   6.097 1.21e-09 ***
HSBD          -0.07365    0.02556  -2.882 0.003979 **
HTBO          -3.54194    0.92485  -3.830 0.000131 ***
HTBOxALSM      0.33144    0.13387   2.476 0.013345 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 23430 on 3129 degrees of freedom
Multiple R-squared:  0.02514,   Adjusted R-squared:  0.02389
F-statistic: 20.17 on 4 and 3129 DF,  p-value: < 2.2e-16
```

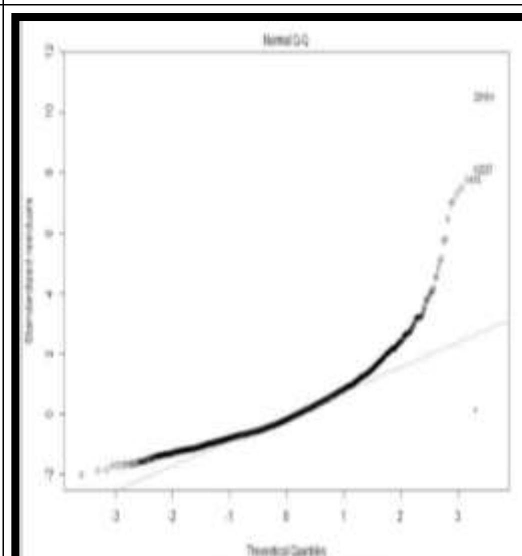
Regression for Fall per Discharge All Providers



Residual vs Fitted Plot for Fall per Discharge All Providers



Residual vs Leverage for Fall per Discharge All Providers



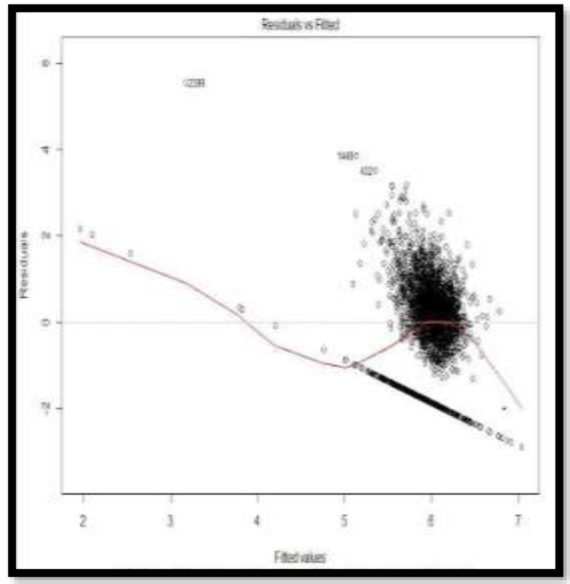
Normal Q-Q plot for Fall per Discharge All Providers

Figure A-3: Multivariate Backward Regression and Plots Outcomes for Fall per Discharge for All Providers - 2011

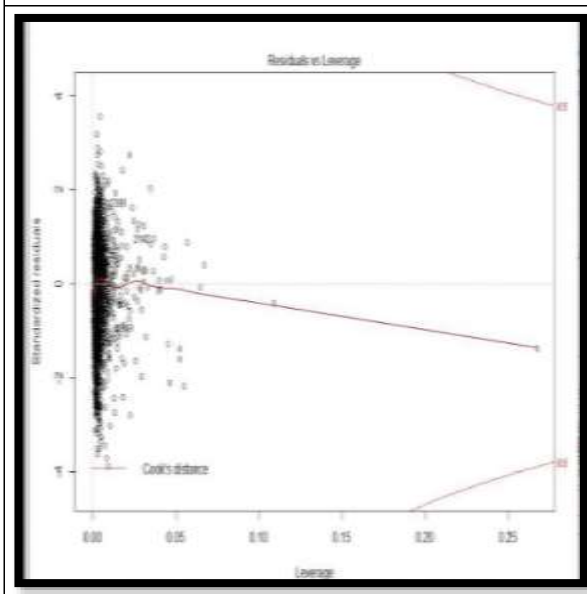
Model 2: Transformed falls per discharge (Log +62) for all providers

```
Call:
lm(formula = FallRate ~ PTFI + ALSM + HSMB + HTBO + HPRR + HPAO +
    Magnet + HTBOxALSM + SRSSxPTFI + NCSSxALSM, data = newdata2,
    weights = wts)

Weighted Residuals:
     Min       1Q   Median       3Q      Max
-183.853  -35.784    6.997   32.440  168.365

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.0516884  0.5899602  -0.088 0.930190
PTFI         0.8021776  0.0873289   9.186  < 2e-16 ***
ALSM         0.1784379  0.0551950   3.233 0.001238 **
HSMB         0.0006958  0.0002193   3.173 0.001523 **
HTBO         0.0146423  0.0041369   3.539 0.000407 ***
HPRR         0.1353969  0.0403181   3.358 0.000794 ***
HPAO         0.0573125  0.0285542   2.007 0.044820 *
Magnet      -0.2048667  0.0731142  -2.802 0.005110 **
HTBOxALSM   -0.0026479  0.0008016  -3.303 0.000967 ***
SRSSxPTFI   -0.0093124  0.0034558  -2.695 0.007082 **
NCSSxALSM    0.0180583  0.0039707   4.548 5.62e-06 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 47.55 on 3123 degrees of freedom
Multiple R-squared:  0.05411,   Adjusted R-squared:  0.05108
F-statistic: 17.87 on 10 and 3123 DF,  p-value: < 2.2e-16
```

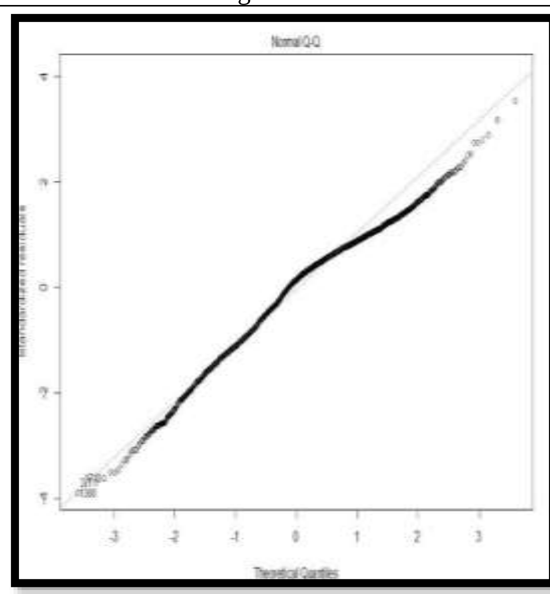
Regression for Transformed Falls per Discharge for All Providers



Residual vs Fitted Plot for Transformed Falls per Discharge for All Providers



Residual vs. Leverage Plot for Transformed Falls per Discharge for All Providers



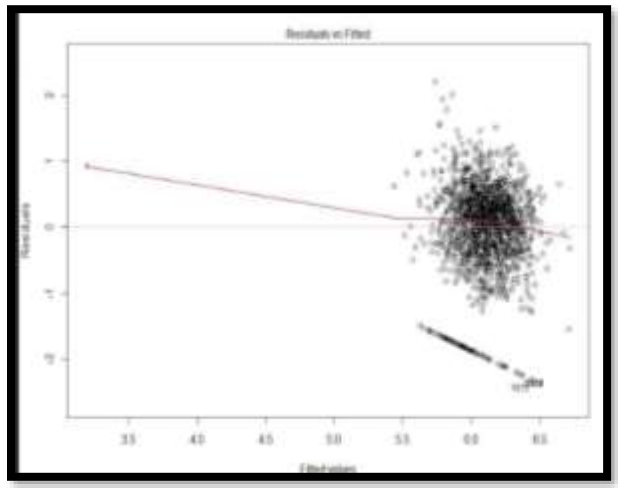
Normal Q-Q Plot for Transformed Falls per Discharge for All Providers

Figure A-4: Multivariate Backward Regression and Plots Outcomes for Transformed (Log+ 62) Fall per Discharge for All Providers - 2011

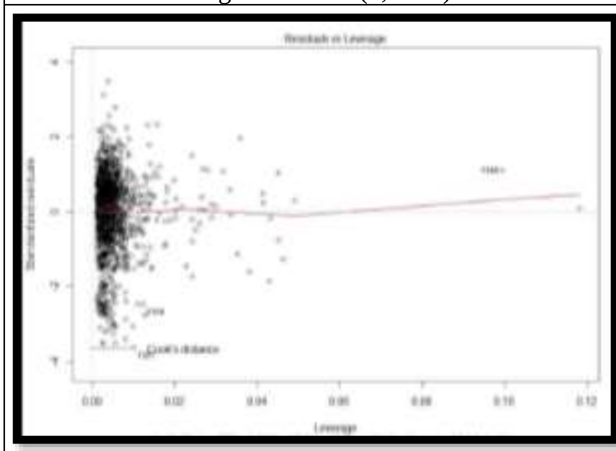
Model 2: Transformed falls per discharge (Log +62) for large providers (3,000 + Medicare discharges per year)

```
Call:
lm(formula = FallRate ~ PTFI + NCSS + SRSS + HPRR + HPAO + Magnet +
    SRSSxALSM, data = newdata2, weights = wts)

Weighted Residuals:
     Min       1Q   Median       3Q      Max
-177.974  -25.252    6.715   30.892  171.112

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.838703   0.660645  -1.270  0.20444
PTFI         1.127409   0.108703  10.371  < 2e-16 ***
NCSS         0.076348   0.025150   3.036  0.00244 **
SRSS        -0.259118   0.043880  -5.905 4.31e-09 ***
HPRR1        0.150764   0.047867   3.150  0.00167 **
HPAO1        0.084332   0.031549   2.673  0.00759 **
Magnet1     -0.152218   0.075002  -2.030  0.04257 *
SRSSxALSM    0.032668   0.007621   4.287 1.92e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 49.26 on 1570 degrees of freedom
Multiple R-squared:  0.08102,   Adjusted R-squared:  0.07692
F-statistic: 19.77 on 7 and 1570 DF,  p-value: < 2.2e-16
```

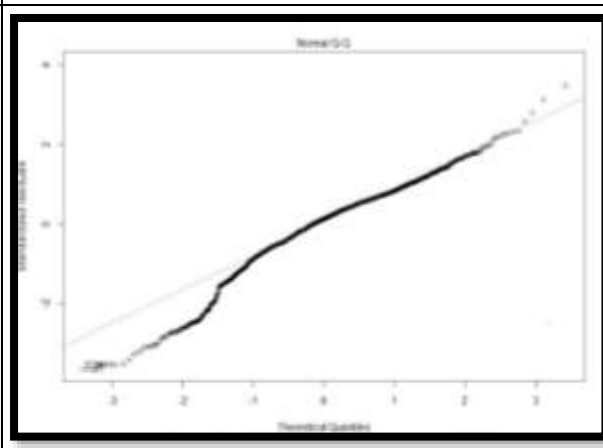
Regression for Transformed Falls per Discharge for Large Providers (3,000+)



Residual vs Fitted Plot for Transformed Falls per Discharge for Large Providers (3,000+)



Residual vs. Leverage Plot for Transformed Falls per Discharge for Large Providers (3,000+)

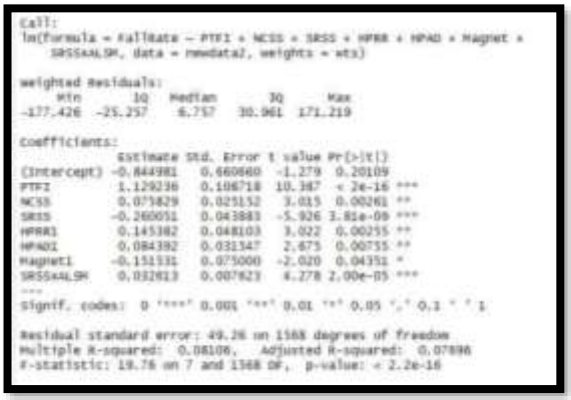


Normal Q-Q Plot for Transformed Falls per Discharge for Large Providers (3,000+)

PTFI	NCSS	SRSS	HPRR	HPAO	Magnet	SRSSxALSM
1.076750	2.276422	6.227386	1.233541	1.143166	1.032064	5.220638

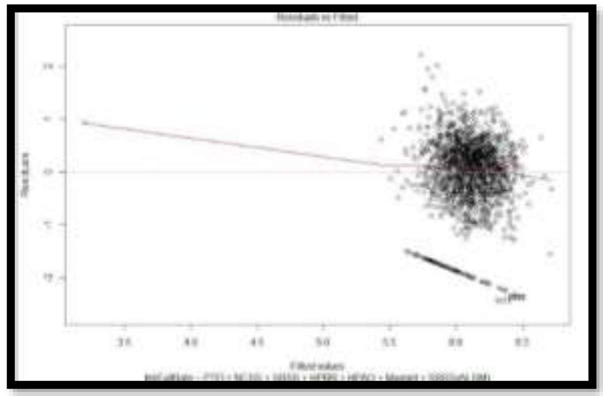
Figure A-5: Multivariate Backward Regression, Plots and VIF Outcomes for Transformed (Log+ 62) Fall per Discharge for Large Providers (3,000 + Yearly Medicare Discharges) – 2011

Model 2: Transformed falls per discharge (Log+62) for large providers (3,000 + Medicare discharges per year) post removing outliers

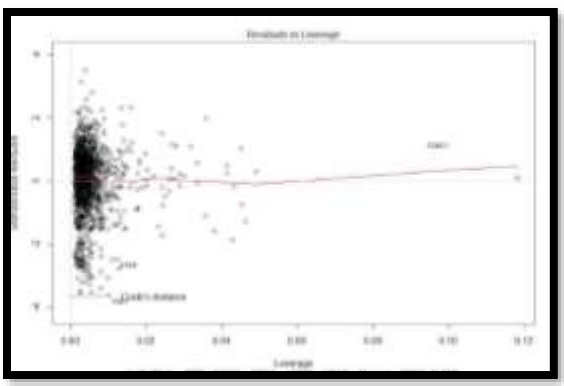


```
Call:
lm(formula = FallRate ~ PTFI + NCSS + SRSS + HPRR + HPAO + Magnet +
    SRSSxALSM, data = newdata2, weights = wts)

Weighted Residuals:
     Min       1Q   Median       3Q      Max
-177.426  -25.257    6.757   30.961  171.219

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.844981   0.660660  -1.279  0.20109
PTFI         1.129236   0.108718  10.387  < 2e-16 ***
NCSS         0.075829   0.025152   3.015  0.00261 **
SRSS        -0.260051   0.043883  -5.926 3.81e-09 ***
HPRR1        0.145382   0.048103   3.022  0.00255 **
HPAO1        0.084392   0.031547   2.675  0.00755 **
Magnet1     -0.151531   0.075000  -2.020  0.04351 *
SRSSxALSM    0.032613   0.007623   4.278 2.00e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 49.26 on 1368 degrees of freedom
Multiple R-squared:  0.08106,   Adjusted R-squared:  0.07896
F-statistic: 19.76 on 7 and 1368 DF,  p-value: < 2.2e-16
```

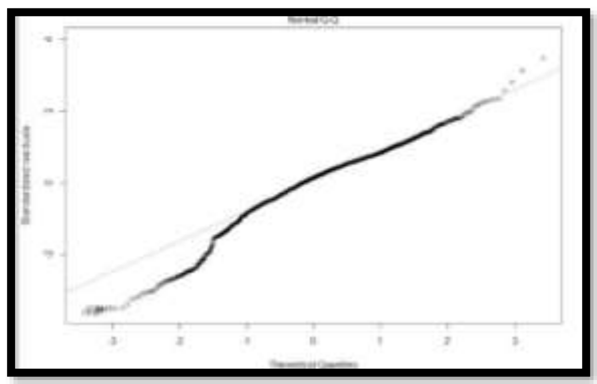
Regression for Transformed Falls per Discharge for Large Providers (3,000+) without Outliers



Residual vs Fitted Plot for Transformed Falls per Discharge for Large Providers (3,000+) without Outliers



Residual vs Fitted Plot for Transformed Falls per Discharge for Large Providers (3,000+) without Outliers



Normal Q-Q Plot for Transformed Falls per Discharge for Large Providers (3,000+) without Outliers

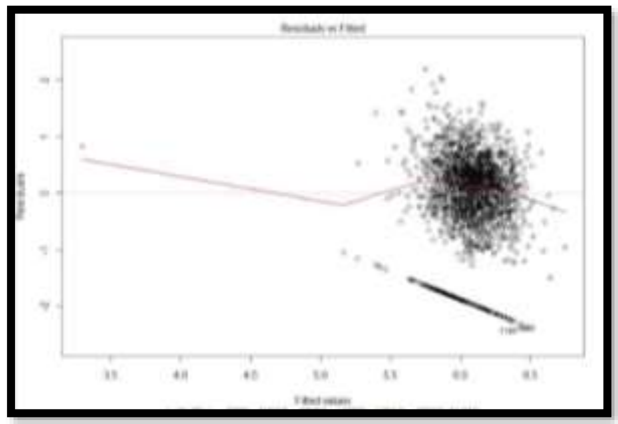
PTFI	NCSS	SRSS	HPRR	HPAO	Magnet	SRSSxALSM
1.077045	2.274251	6.205419	1.234858	1.141995	1.032111	5.203463

Figure A-6: Multivariate Backward Regression, Plots and VIF Outcomes for Transformed (Log+ 62) Fall per Discharge for Large Providers (3,000 + Yearly Medicare Discharges) Post Removing Outliers – 2011

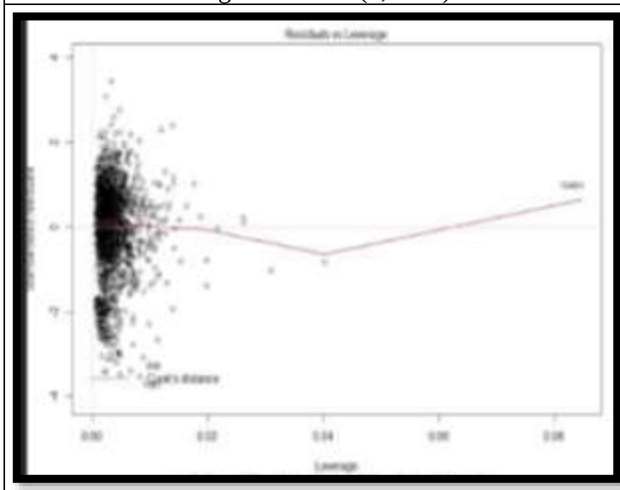
Model 2: Transformed falls per discharge (Log +62) for large providers (2,000 + Medicare discharges per year)

```
Call:
lm(formula = FallRate ~ PTFI + NCSS + SRSS + HPRR + HPAO + SRSSxA
    data = newdata2, weights = wts)

Weighted Residuals:
     Min       1Q   Median       3Q      Max
-175.424  -24.838    7.725   32.179  170.433

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.541581   0.617300  -0.877  0.38041
PTFI         1.071818   0.101630  10.546  < 2e-16 ***
NCSS         0.067195   0.024102   2.788  0.00536 **
SRSS        -0.245717   0.040485  -6.069 1.54e-09 ***
HPRR1        0.123895   0.045443   2.726  0.00646 **
HPAO1        0.061573   0.030815   1.998  0.04584 *
SRSSxALSM    0.034867   0.007096   4.914 9.68e-07 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 49.85 on 1948 degrees of freedom
Multiple R-squared:  0.06571,   Adjusted R-squared:  0.06283
F-statistic: 22.83 on 6 and 1948 DF,  p-value: < 2.2e-16
```

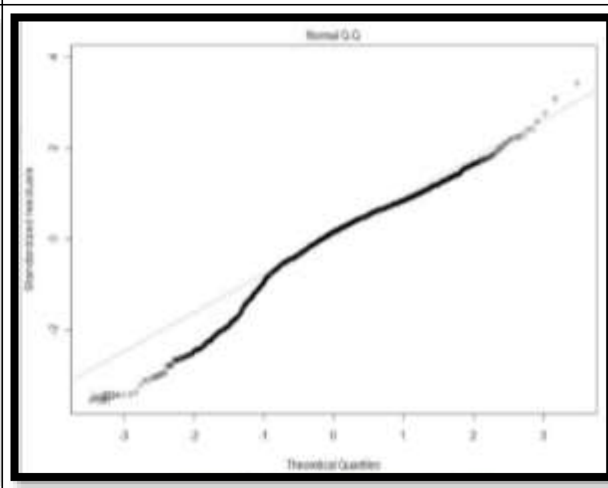
Regression for Transformed Falls per Discharge for Large Providers (2,000+)



Residual vs Fitted Plot for Transformed Falls per Discharge for Large Providers (2,000+)



Residual vs. Leverage Plot for Transformed Falls per Discharge (2,000+)



Normal Q-Q Plot for Transformed Falls per Discharge for Large Providers (2,000+)

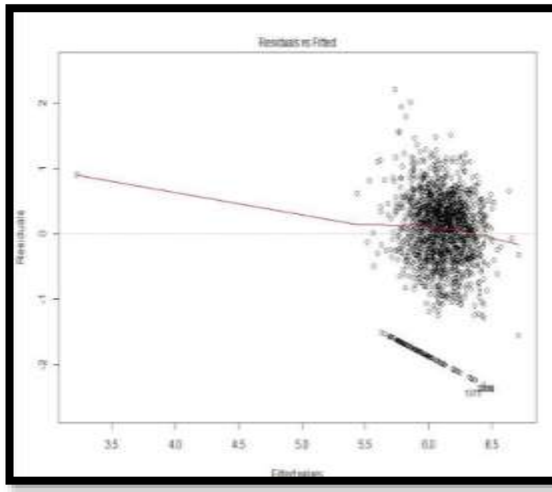
PTFI	NCSS	SRSS	HPRR	HPAO	SRSSxALSM
1.066703	2.301853	5.903335	1.236716	1.148737	4.894951

Figure A-7: Multivariate Backward Regression, Plots and VIF Outcomes for Transformed (Log+ 62) Fall per Discharge for Large Providers (2,000 + Yearly Medicare Discharges) - 2011

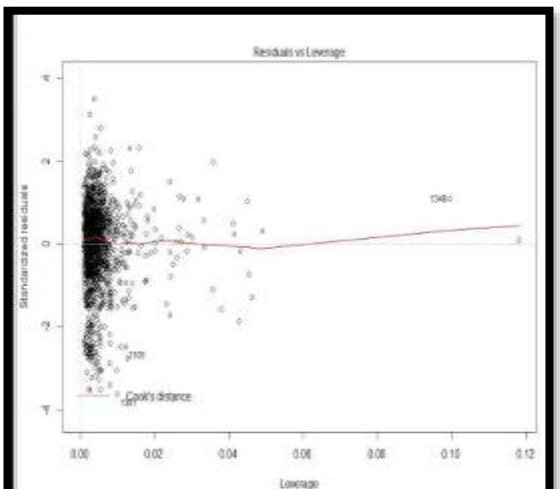
Model 2: Transformed falls per discharge (Log +62) for large providers (2,000 + Medicare discharges per year) post removing outliers

```
Call:
lm(formula = FallRate ~ PTFI + NCSS + SRSS + HPRR + HPAO + Magnet +
    SRSSxALSM, data = newdata2, weights = wts)

Weighted Residuals:
     Min       1Q   Median       3Q      Max
-177.599  -25.345    6.788   30.978  171.228

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.793951   0.661053  -1.201  0.22992
PTFI         1.121107   0.108775  10.307  < 2e-16 ***
NCSS         0.076214   0.025140   3.032  0.00247 **
SRSS        -0.258664   0.043868  -5.896 4.54e-09 ***
HPRR1        0.146543   0.048082   3.048  0.00234 **
HPAO1        0.085783   0.031542   2.720  0.00661 **
Magnet1     -0.150687   0.074962  -2.010  0.04458 *
SRSSxALSM    0.032056   0.007627   4.203 2.78e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 49.23 on 1567 degrees of freedom
Multiple R-squared:  0.08036,   Adjusted R-squared:  0.07626
F-statistic: 19.56 on 7 and 1567 DF,  p-value: < 2.2e-16
```

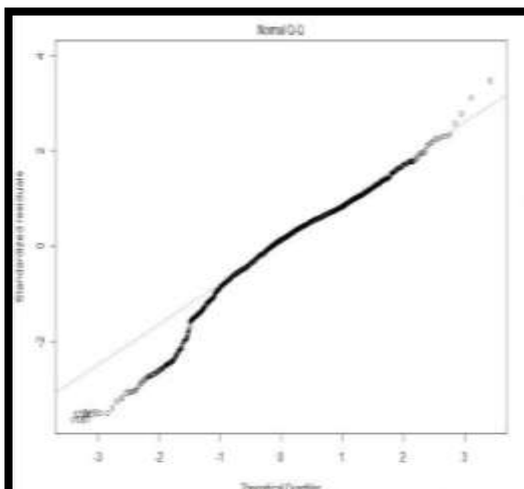
Regression for Transformed Falls per Discharge for Large Providers (2,000+) without Outliers



Residual vs Fitted Plot for Transformed Falls per Discharge for Large Providers (2,000+) without Outliers



Residual vs. Leverage Plot for Transformed Falls per Discharge for Large Providers (2,000+) without Outliers



Normal Q-Q Plot for Transformed Falls per Discharge for Large Providers (2,000+) without Outliers

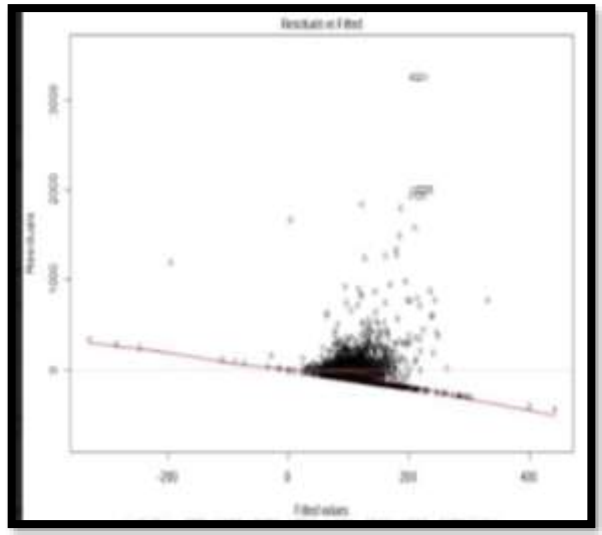
PTFI	NCSS	SRSS	HPRR	HPAO	Magnet	SRSSxALSM
1.077028	2.273141	6.197082	1.235014	1.142293	1.032133	5.199728

Figure A-8: Multivariate Backward Regression, Plots and VIF Outcomes for Transformed (Log+ 62) Fall per Discharge for Large Providers (2,000 + Yearly Medicare Discharges) Post Removing Outliers - 2011

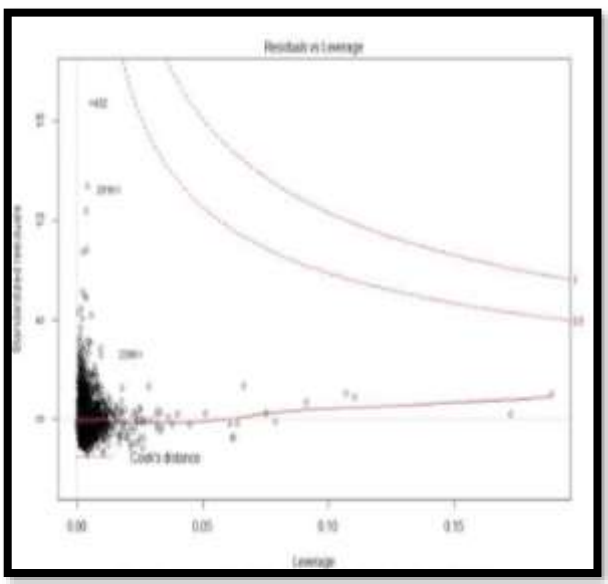
Model 3: Falls per Medicare days for all providers

```
Call:
lm(formula = FallRate ~ PTFI + HSBD + RNTS + HTBO + NCSS + SRSS +
    HPRR + RNTSxALSM + HTBOxALSM + NCSSxPTFI + SRSSxALSM, data = newdata3,
    weights = wts)

Weighted Residuals:
   Min     1Q Median     3Q    Max
-10115  -3293   -853   2167  87815

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -2.240e+02  7.298e+01  -3.069 0.002165 **
PTFI         7.817e+01  1.636e+01   4.779 1.85e-06 ***
HSBD        -1.157e-02  6.161e-03  -1.878 0.060533 .
RNTS         1.765e+02  4.727e+01   3.734 0.000192 ***
HTBO        -2.820e+00  5.037e-01  -5.598 2.36e-08 ***
NCSS         3.918e+01  2.324e+01   1.685 0.091997 .
SRSS         1.622e+01  8.240e+00   1.969 0.049077 *
HPRR1        7.014e+00  4.481e+00   1.565 0.117623
RNTSxALSM   -3.608e+01  8.910e+00  -4.049 5.26e-05 ***
HTBOxALSM    4.706e-01  9.642e-02   4.884 1.09e-06 ***
NCSSxPTFI   -8.127e+00  5.231e+00  -1.554 0.120345
SRSSxALSM   -3.564e+00  1.571e+00  -2.269 0.023363 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 5538 on 3122 degrees of freedom
Multiple R-squared:  0.0827,    Adjusted R-squared:  0.07947
F-statistic: 25.59 on 11 and 3122 DF,  p-value: < 2.2e-16
```

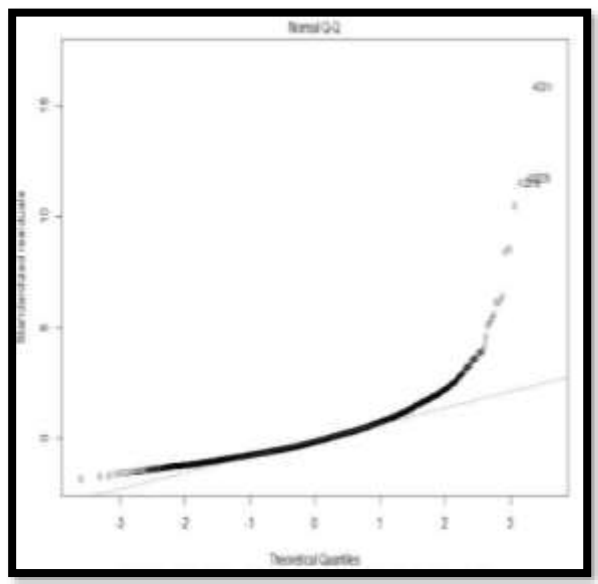
Regression for Fall per Medicare Days All Providers



Residual vs Fitted Plot for Fall per Medicare Days All Providers



Residual vs Leverage Plot for Fall per Medicare Days All Providers



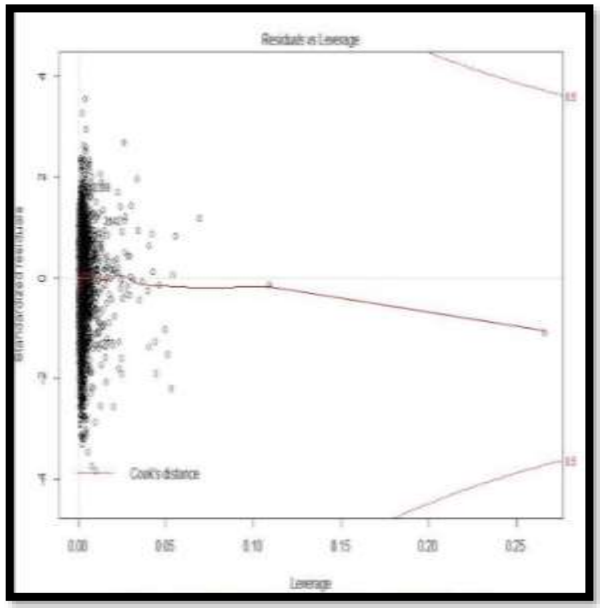
Normal Q-Q Plot for Fall per Medicare Days All Providers

Figure A-9: Multivariate Backward Regression and Plots Outcomes for Fall per Medicare Days for All Providers - 2011

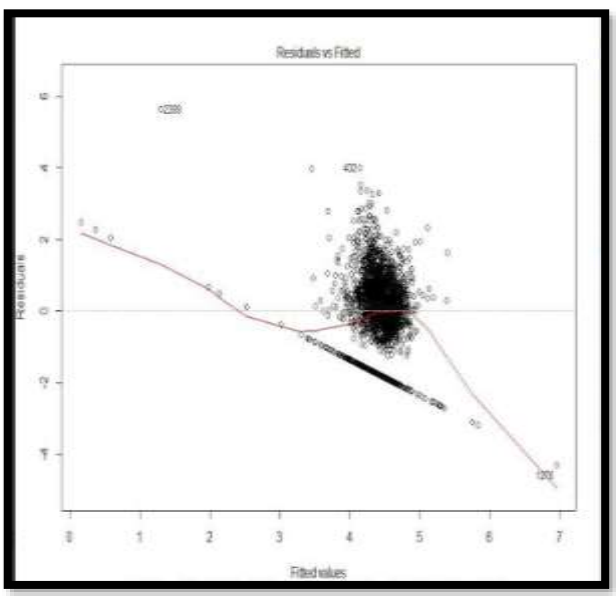
Model 4: Transformed falls per Medicare days (Log+ 62) for all providers

```
Call:
lm(formula = FallRate ~ PTFI + HSMB + HTBO + NCSS + HPRR + Magnet +
    HTBOxALSM + SRSSxPTFI + SRSSxALSM, data = newdata3, weights = wts)

Weighted Residuals:
     Min       1Q   Median       3Q      Max
-177.194  -35.224    6.286   32.332  164.212

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.6233043  0.3098091   2.012 0.044316 *
PTFI         0.8117407  0.0687876  11.801  < 2e-16 ***
HSMB         0.0006786  0.0002116   3.207 0.001353 **
HTBO         0.0095067  0.0024238   3.922 8.96e-05 ***
NCSS         0.0697534  0.0214517   3.252 0.001160 **
HPRR1        0.0970927  0.0375266   2.587 0.009718 **
Magnet1     -0.1983083  0.0713552  -2.779 0.005482 **
HTBOxALSM   -0.0016627  0.0004220  -3.940 8.34e-05 ***
SRSSxPTFI   -0.0421454  0.0110816  -3.803 0.000146 ***
SRSSxALSM    0.0274133  0.0093965   2.917 0.003555 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 46.44 on 3124 degrees of freedom
Multiple R-squared:  0.0666,    Adjusted R-squared:  0.06391
F-statistic: 24.77 on 9 and 3124 DF,  p-value: < 2.2e-16
```

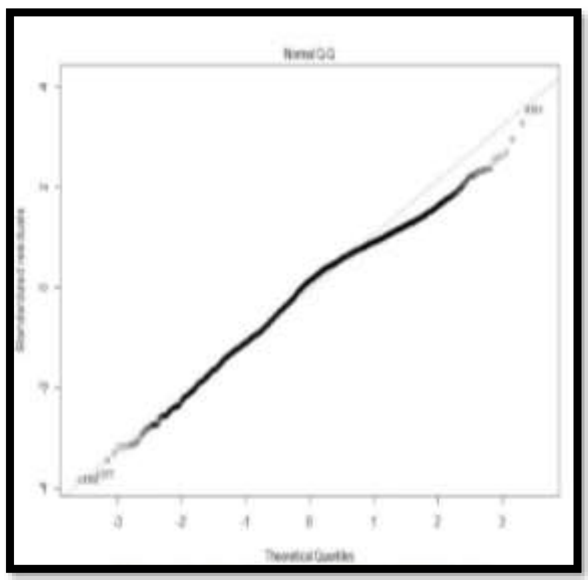
Regression for Transformed Falls per Medicare Days for All Providers



Residual vs Fitted Plot for Transformed Falls per Medicare Days for All Providers



Residual vs Leverage Plot for Transformed Falls per Medicare Days for All Providers



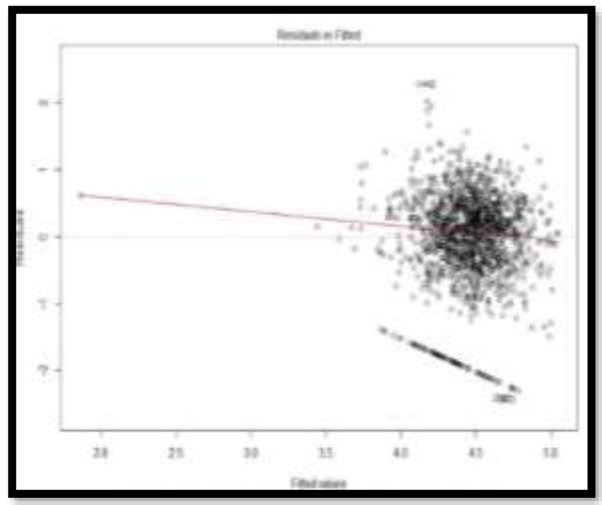
Normal Q-Q Plot for Transformed Falls per Medicare Days for All Providers

Figure A-10: Multivariate Backward Regression and Plots Outcomes for Transformed (Log+ 62) Fall per Medicare Days for All Providers - 2011

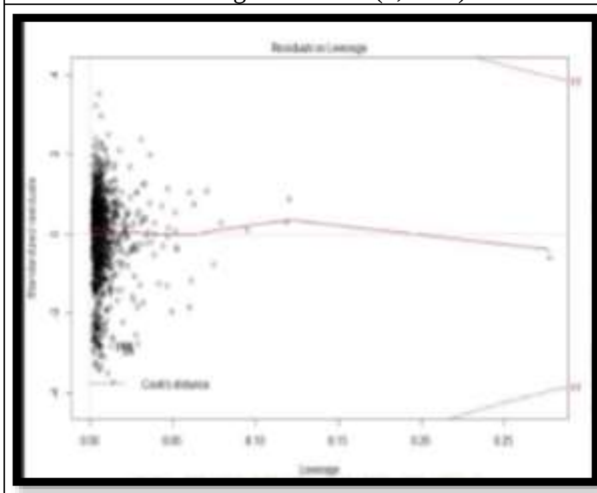
Model 4: Transformed falls per Medicare days (Log +62) for large providers (3,000 + Medicare discharges per year)

```
Call:
lm(formula = FallRate ~ PTFI + HSMB + RNTS + HTBO + NCSS + SRSS +
    HPRR + HPAO + Magnet + RNTSxALSM + SRSSxALSM, data = newdata3,
    weights = wts)

Weighted Residuals:
     Min       1Q   Median       3Q      Max
-182.738  -24.569    6.695   31.261  172.493

Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.701555   0.394193   1.780  0.07531 .
PTFI         0.886562   0.083018  10.679  < 2e-16 ***
HSMB         0.000457   0.000235   1.945  0.05198 .
RNTS         0.762849   0.344000   2.218  0.02673 *
HTBO        -0.002298   0.001243  -1.849  0.06467 .
NCSS         0.063267   0.025486   2.482  0.01313 *
SRSS        -0.342007   0.109803  -3.115  0.00187 **
HPRR1        0.133772   0.048413   2.763  0.00579 **
HPAO1        0.070758   0.031911   2.217  0.02674 *
Magnet1     -0.168063   0.076527  -2.196  0.02823 *
RNTSxALSM   -0.163888   0.061573  -2.662  0.00785 **
SRSSxALSM    0.048270   0.020522   2.352  0.01879 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 49.3 on 1586 degrees of freedom
Multiple R-squared:  0.115,     Adjusted R-squared:  0.1088
F-statistic:  18.5 on 11 and 1586 DF,  p-value: < 2.2e-16
```

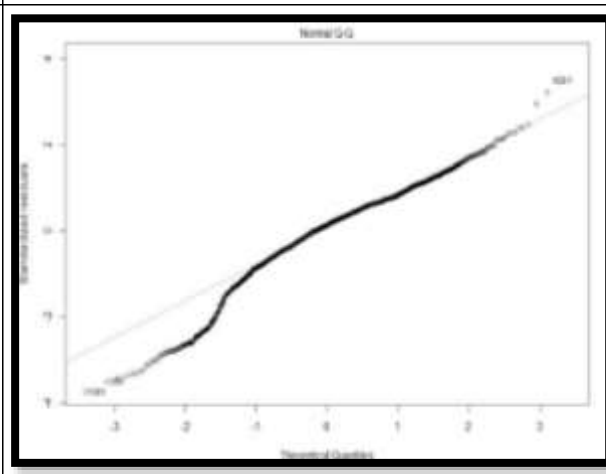
Regression for Transformed Falls per Medicare Days for Large Providers (3,000+)



Residual vs. Fitted Plot for Transformed Falls per Medicare Days for Large Providers (3,000+)



Residual vs. Leverage Plot for Transformed Falls per Medicare Days for Large Providers (3,000+)



Normal Q-Q Plot for Transformed Falls per Medicare Days for Large Providers (3,000+)

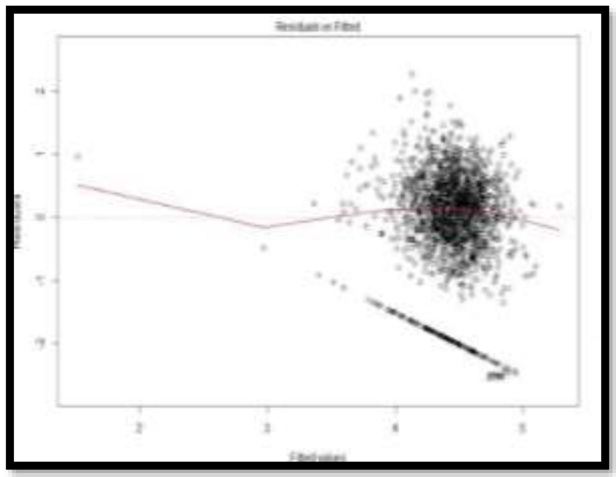
```
     PTFI      HSMB      RNTS      HTBO      NCSS      SRSS      HPRR      HPAO    Magnet
 1.311522  1.456264  9.680294  1.325384  2.334782 38.943598  1.260257  1.168046  1.073086
RNTSxALSM SRSSxALSM
18.214411 37.812285
```

Figure A-11: Multivariate Backward Regression, Plots and VIF Outcomes for Transformed (Log+ 62) Fall per Medicare Days for Large Providers (3,000 + Yearly Medicare Discharges) - 2011

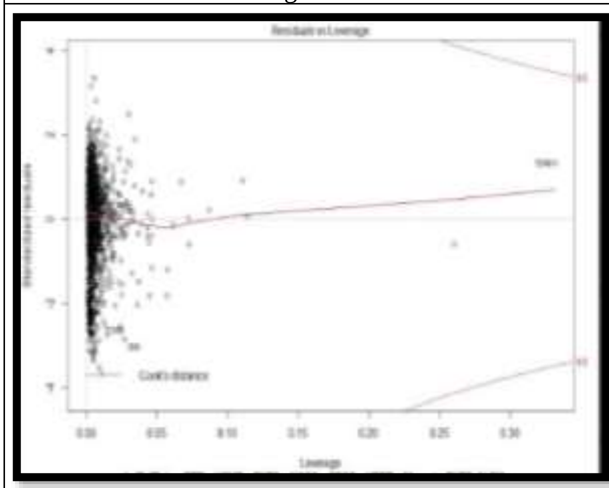
Model 4: Transformed falls per Medicare days (Log +62) for large providers (2,000 + Medicare discharges per year)

```
Call:
lm(formula = FallRate ~ PTFI + HSMB + RNTS + NCSS + SRSS + HPRR +
    Magnet + RNTSxALSM + SRSSxPTFI + NCSSxPTFI + SRSSxALSM, data = newdata1,
    weights = wts)

Weighted Residuals:
   Min     1Q Median     3Q    Max
-182.5  -23.8    7.8   32.0  167.0

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -0.0834804  0.8795885  -0.095  0.92440
PTFI         1.0299682  0.1992573   5.169 2.59e-07 ***
HSMB         0.0005347  0.0002241   2.386  0.01713 *
RNTS         0.7530335  0.3351972   2.247  0.02478 *
NCSS         1.2061318  0.5027611   2.399  0.01653 *
SRSS        -1.3858747  0.6188035  -2.240  0.02523 *
HPRR1        0.0928309  0.0435187   2.133  0.03304 *
Magnet1     -0.1757084  0.0773109  -2.273  0.02315 *
RNTSxALSM   -0.1668090  0.0602321  -2.769  0.00567 **
SRSSxPTFI    0.2424667  0.1306650   1.856  0.06366 .
NCSSxPTFI   -0.2594576  0.1131118  -2.294  0.02191 *
SRSSxALSM    0.0462442  0.0201215   2.298  0.02165 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 50.1 on 1943 degrees of freedom
Multiple R-squared:  0.09588,	Adjusted R-squared:  0.09076
F-statistic: 18.73 on 11 and 1943 DF,  p-value: < 2.2e-16
```

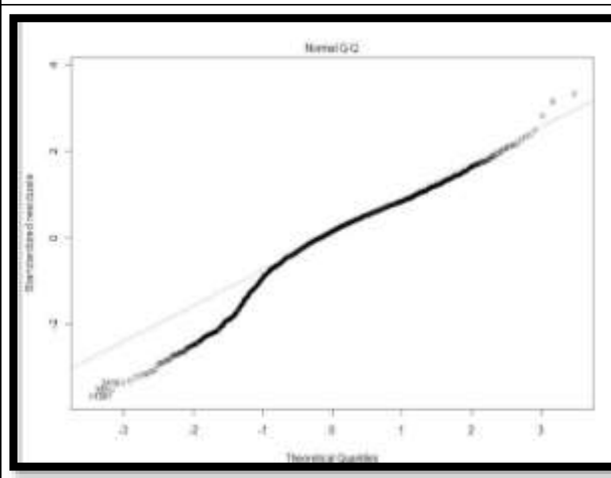
Regression for Transformed Falls per Medicare Days for Large Providers



Residual vs. Fitted Plot for Transformed Falls per Medicare Days for Large Providers (2,000+)



Residual vs. Leverage Plot for Transformed Falls per Medicare Days for Large Providers (2,000+)



Normal Q-Q Plot for Transformed Falls per Medicare Days for Large Providers (2,000+)

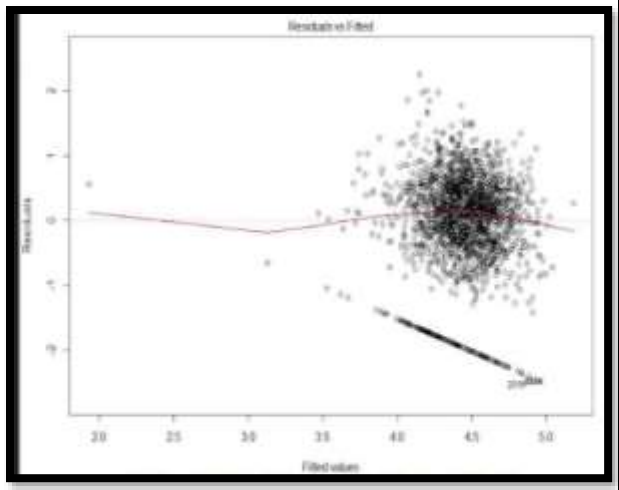
PTFI	HSMB	RNTS	NCSS	SRSS	HPRR	Magnet
8.428477	1.388108	9.645176	991.828873	1365.686846	1.123088	1.073006
RNTSxALSM	SRSSxPTFI	NCSSxPTFI	SRSSxALSM			
18.726113	1300.249822	1052.510328	38.977434			

Figure A-12: Multivariate Backward Regression, Plots and VIF Outcomes for Transformed (Log+ 62) Fall per Medicare Days for Large Providers (2,000 + Yearly Medicare Discharges) - 2011

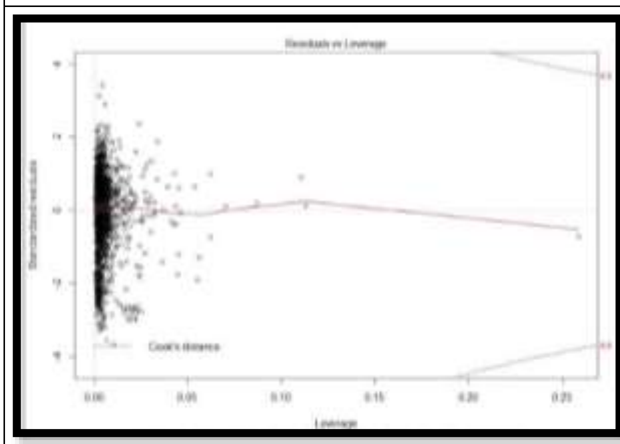
Model 4 Transformed falls per Medicare days (Log +62) for large providers (2,000 + Medicare discharges per year) post removing outliers

```
Call:
lm(formula = FallRate ~ PTFI + HSMB + RNTS + NCSS + SRSS + HPRR +
    Magnet + RNTSxALSM + SRSSxALSM, data = newdata3, weights = wts)

Weighted Residuals:
     Min       1Q   Median       3Q      Max
-184.053  -23.895    7.905   32.239  170.350

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  0.5971795  0.3610301   1.654  0.09827 .
PTFI         0.8722874  0.0778413  11.206  < 2e-16 ***
HSMB         0.0005943  0.0002232   2.663  0.00780 **
RNTS         0.7165132  0.3153967   2.272  0.02321 *
NCSS         0.0549674  0.0248008   2.216  0.02678 *
SRSS        -0.2946031  0.0989982  -2.976  0.00296 **
HPRR1        0.0977624  0.0435085   2.247  0.02475 *
Magnet1     -0.1751012  0.0774027  -2.262  0.02379 *
RNTSxALSM   -0.1593870  0.0565090  -2.821  0.00484 **
SRSSxALSM    0.0440845  0.0186614   2.362  0.01826 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 50.16 on 1942 degrees of freedom
Multiple R-squared:  0.09338,   Adjusted R-squared:  0.08918
F-statistic: 22.23 on 9 and 1942 DF,  p-value: < 2.2e-16
```

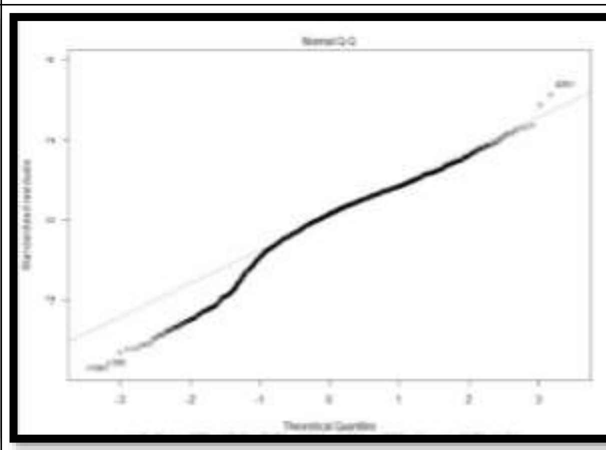
Regression for Transformed Falls per Discharge for Large Providers (2,000+) without Outliers



Residual vs Fitted Plot for Transformed Falls per Discharge for Large Providers (2,000+) without Outliers



Residual vs Leverage Plot for Transformed Falls per Discharge for Large Providers (2,000+) without Outliers



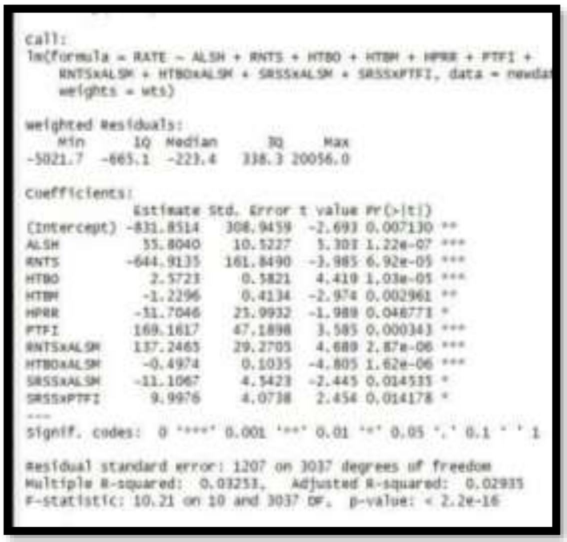
Normal Q-Q Plot for Transformed Falls per Discharge for Large Providers (2,000+) without Outliers

PTFI	HSMB	RNTS	NCSS	SRSS	HPRR	Magnet	RNTSxALSM	SRSSxALSM
1.281908	1.372369	8.514552	2.397958	34.791340	1.119345	1.072636	16.416278	33.370599

Figure A-13: Multivariate Backward Regression, Plots and VIF Outcomes for Transformed (Log+ 62) Fall per Medicare Days for Large Providers (2,000 + Yearly Medicare Discharges) Post Removing Outliers - 2011

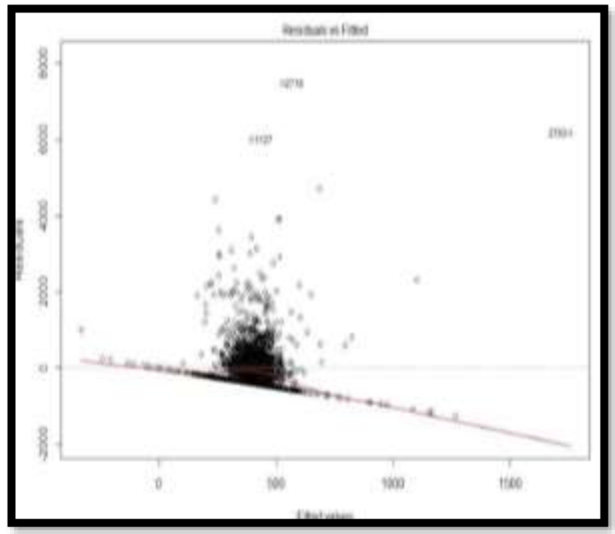
2014 ANALYSIS

Model 1: Falls per discharge for all providers

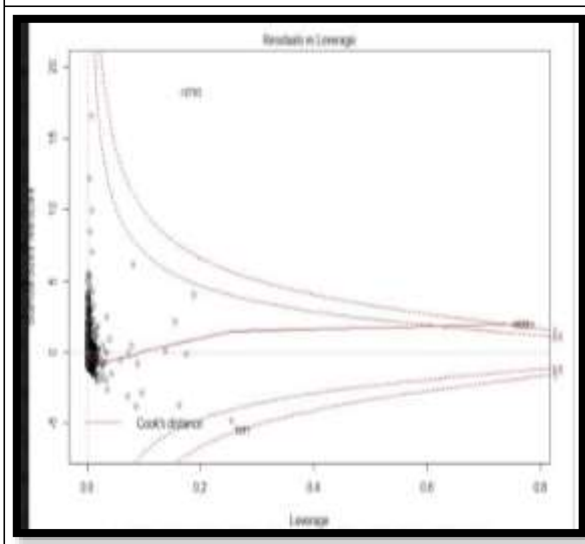


```
Call:
lm(formula = RATE ~ ALSH + RNTS + HTBO + HTBM + HPRR + PTFI +
    RNTSxALSM + HTBOxALSM + SRSSxALSM + SRSSxPTFI, data = newdat
    weights = wts)

Weighted Residuals:
    Min      1Q  Median      3Q     Max
-5021.7  -665.1  -223.4   338.3 20056.0

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -831.8514   308.9459  -2.693 0.007130 **
ALSH          55.8040    10.5227   5.303 1.22e-07 ***
RNTS        -644.9135   161.8490  -3.985 6.92e-05 ***
HTBO           2.5723     0.5821   4.419 1.03e-05 ***
HTBM          -1.2296     0.4134  -2.974 0.002961 **
HPRR         -51.7046    25.9932  -1.989 0.046773 *
PTFI         169.1617    47.1898   3.585 0.000343 ***
RNTSxALSM    137.2463    29.2705   4.689 2.87e-06 ***
HTBOxALSM     -0.4974     0.1035  -4.805 1.62e-06 ***
SRSSxALSM    -11.1067     4.5423  -2.445 0.014535 *
SRSSxPTFI      9.9976     4.0738   2.454 0.014178 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1207 on 3037 degrees of freedom
Multiple R-squared:  0.03253,	Adjusted R-squared:  0.02935
F-statistic: 10.21 on 10 and 3037 DF,  p-value: < 2.2e-16
```

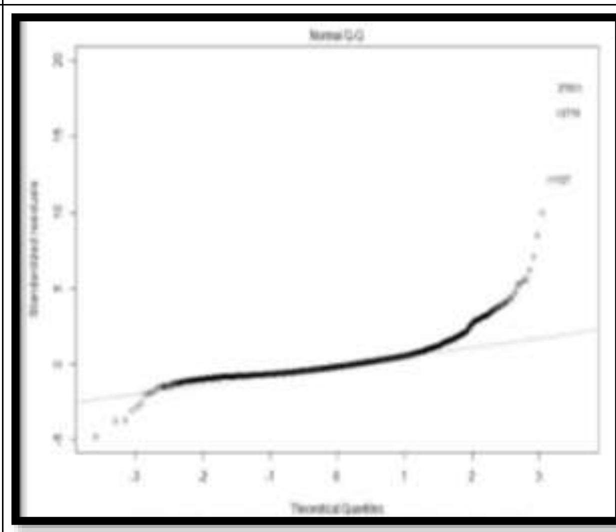
Regression for Fall per Discharge All Providers



Residual vs Fitted Plot for Fall per Discharge All Providers



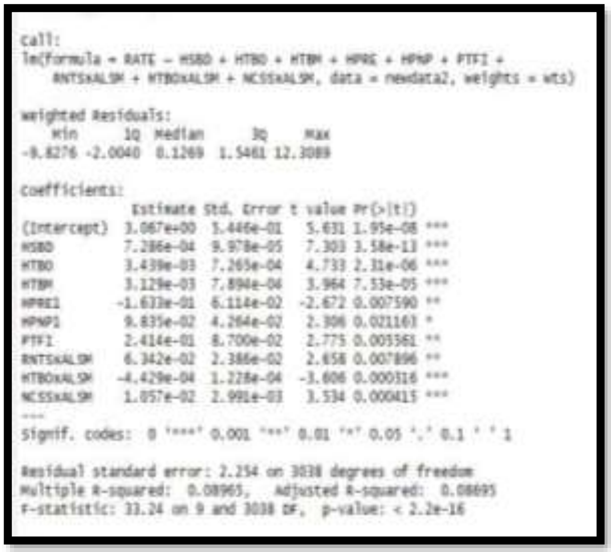
Residual vs Leverage for Fall per Discharge All Providers



Normal Q-Q plot for Fall per Discharge All Providers

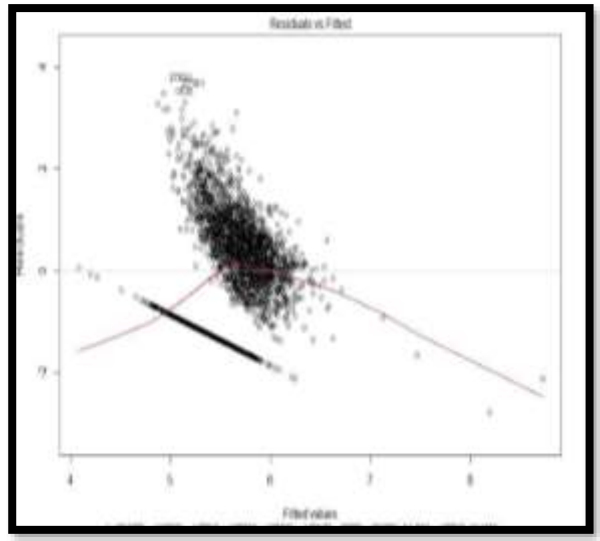
Figure A-14: Multivariate Backward Regression and Plots Outcomes for Fall per Discharge for All Providers - 2014

Model 2: Transformed falls per discharge (Log +62) for all providers

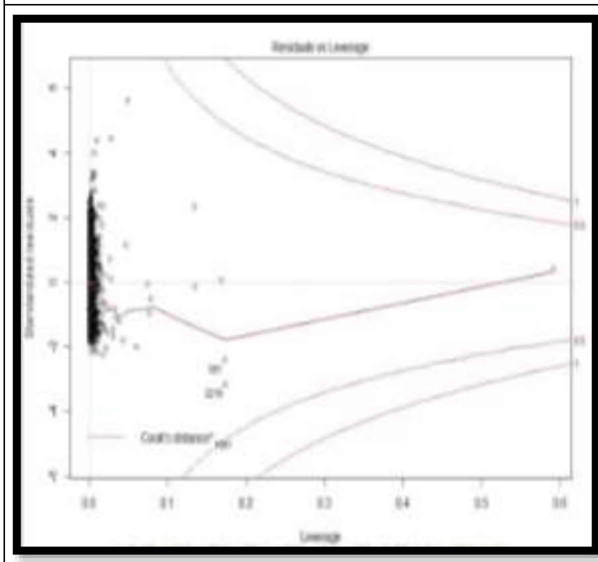


```
call:
lm(formula = RATE ~ HSBD + HTBO + HTBM + HPRE + HPNP + PTFI +
    RNTSxALSM + HTBOxALSM + NCSSxALSM, data = newdata2, weights = wts)

Weighted Residuals:
    Min      1Q  Median      3Q     Max
-9.8276 -2.0040  0.1269  1.5461 12.3089

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  3.067e+00  5.446e-01   5.631 1.95e-08 ***
HSBD         7.286e-04  9.978e-05   7.303 3.58e-13 ***
HTBO         3.439e-03  7.265e-04   4.733 2.31e-06 ***
HTBM         3.129e-03  7.894e-04   3.964 7.53e-05 ***
HPRE1       -1.633e-01  6.114e-02  -2.672 0.007590 **
HPNP1        9.835e-02  4.264e-02   2.306 0.021163 *
PTFI         2.414e-01  8.700e-02   2.775 0.005561 **
RNTSxALSM    6.342e-02  2.386e-02   2.658 0.007896 **
HTBOxALSM   -4.429e-04  1.228e-04  -3.606 0.000316 ***
NCSSxALSM    1.057e-02  2.991e-03   3.534 0.000415 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 2.254 on 3038 degrees of freedom
Multiple R-squared:  0.08965,   Adjusted R-squared:  0.08695
F-statistic: 33.24 on 9 and 3038 DF,  p-value: < 2.2e-16
```

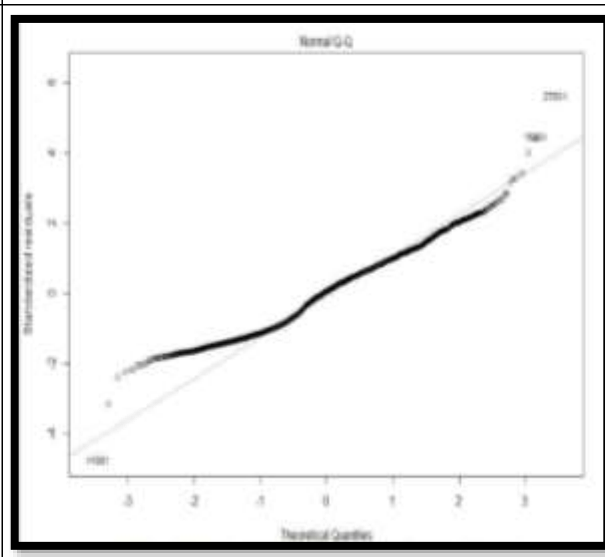
Regression for Transformed Falls per Discharge for All Providers



Residual vs Fitted Plot for Transformed Falls per Discharge for All Providers



Residual vs. Leverage Plot for Transformed Falls per Discharge for All Providers



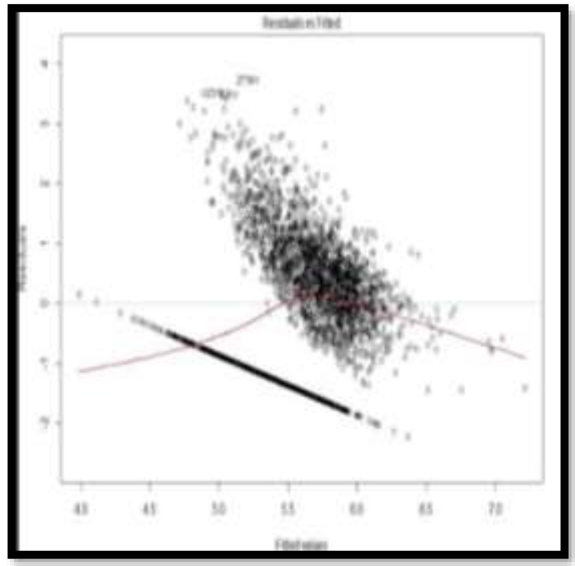
Normal Q-Q Plot for Transformed Falls per Discharge for All Providers

Figure A-15: Multivariate Backward Regression and Plots Outcomes for Transformed (Log+ 62) Fall per Discharge for All Providers - 2014

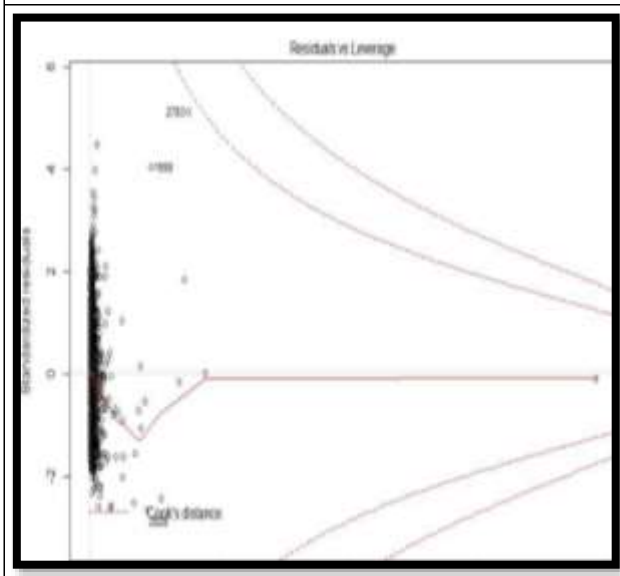
Model 2: Transformed falls per discharge (Log+62) for all providers post removing outliers

```
call:
lm(formula = RATE ~ ALSH + HSBD + HSMB + HTBO + HTBM + HPRE +
    PTFI + RNTSxALSM + HTBOxALSM + NCSSxALSM, data = newdata2,
    weights = wts)

weighted Residuals:
    Min      1Q  Median      3Q     Max
-5.7768 -1.8569  0.0948  1.5347 10.5216

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  2.5467556  0.5598830   4.549 5.61e-06 ***
ALSH         0.0526878  0.0194423   2.710  0.00677 **
HSBD         0.0016537  0.0003006   5.502 4.08e-08 ***
HSMB        -0.0040627  0.0012871  -3.156  0.00161 **
HTBO         0.0032874  0.0007511   4.377 1.24e-05 ***
HTBM         0.0063447  0.0011080   5.726 1.13e-08 ***
HPRE1       -0.1452710  0.0582844  -2.492  0.01274 *
PTFI         0.2611104  0.0869641   3.003  0.00270 **
RNTSxALSM    0.0672411  0.0240540   2.795  0.00522 **
HTBOxALSM   -0.0005269  0.0001271  -4.146 3.47e-05 ***
NCSSxALSM    0.0153677  0.0030692   5.007 5.84e-07 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 2.237 on 3034 degrees of freedom
Multiple R-squared:  0.102,     Adjusted R-squared:  0.09901
F-statistic: 34.45 on 10 and 3034 DF,  p-value: < 2.2e-16
```

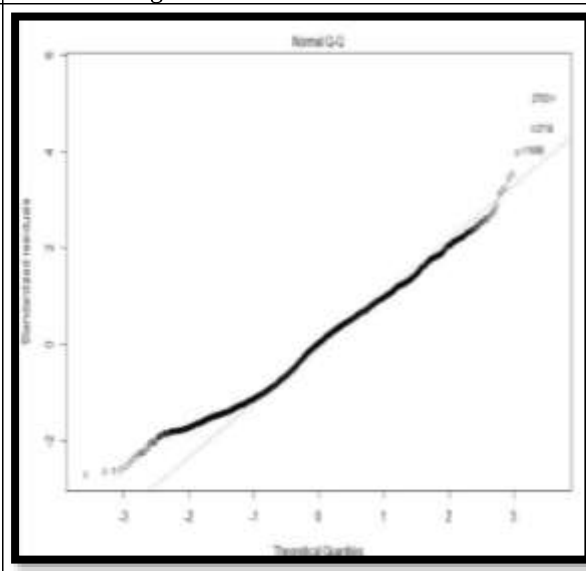
Regression for Transformed Falls per Discharge for All Providers without Outliers



Residual vs Fitted Plot for Transformed Falls per Discharge for All Providers without Outliers



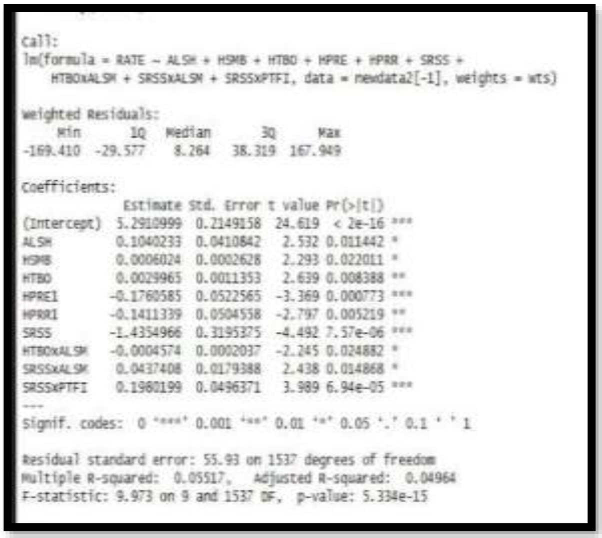
Residual vs Fitted Plot for Transformed Falls per Discharge for All Providers without Outliers



Normal Q-Q Plot for Transformed Falls per Discharge for All Providers without Outliers

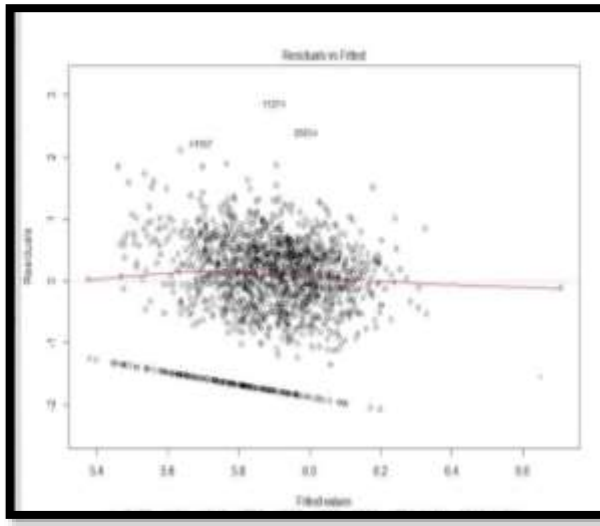
Figure A-16: Multivariate Backward Regression and Plots Outcomes for Transformed (Log+ 62) Fall per Discharge for All Providers Post Removing Outliers -2014

Model 2: Transformed falls per discharge (Log+62) for large providers (3,000 + Medicare discharges per year)

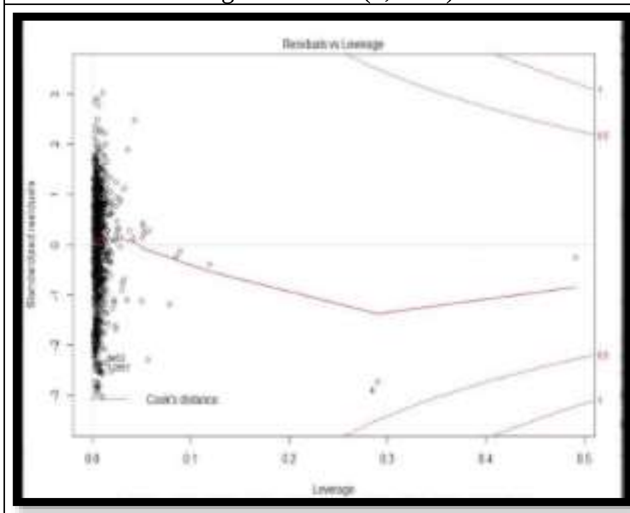


```
Call:
lm(formula = RATE ~ ALSH + HSMB + HTBO + HPRE + HPRR + SRSS +
    HTBOxALSM + SRSSxALSM + SRSSxPTFI, data = newdata2[-1], weights = wts)

Weighted Residuals:
     Min       1Q   Median       3Q      Max
-169.410  -29.577    8.264   38.319  167.949

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  5.2910999  0.2149158  24.619  < 2e-16 ***
ALSH         0.1040233  0.0410842   2.532 0.011442 *
HSMB         0.0006024  0.0002628   2.293 0.022011 *
HTBO         0.0029965  0.0011353   2.639 0.008388 **
HPRE1       -0.1760585  0.0522565  -3.369 0.000773 ***
HPRR1       -0.1411339  0.0504558  -2.797 0.005219 **
SRSS        -1.4354966  0.3195375  -4.492 7.57e-06 ***
HTBOxALSM   -0.0004574  0.0002037  -2.245 0.024882 *
SRSSxALSM    0.0437408  0.0179388   2.438 0.014868 *
SRSSxPTFI    0.1980199  0.0496371   3.989 6.94e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 55.93 on 1537 degrees of freedom
Multiple R-squared:  0.05517,   Adjusted R-squared:  0.04964
F-statistic: 9.973 on 9 and 1537 DF,  p-value: 5.334e-15
```

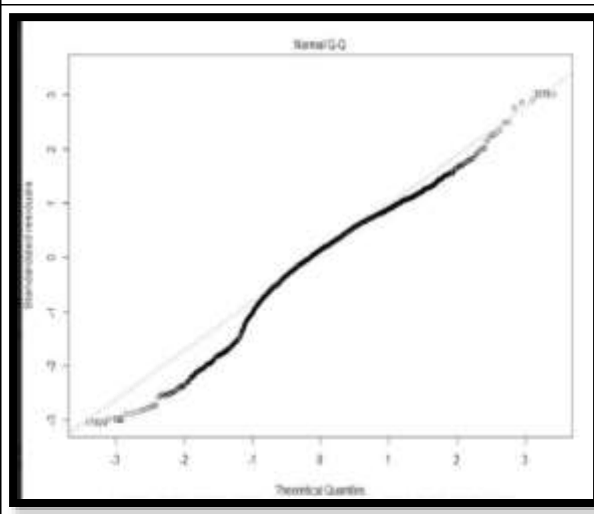
Regression for Transformed Falls per Discharge for Large Providers (3,000+)



Residual vs Fitted Plot for Transformed Falls per Discharge for Large Providers (3,000+)



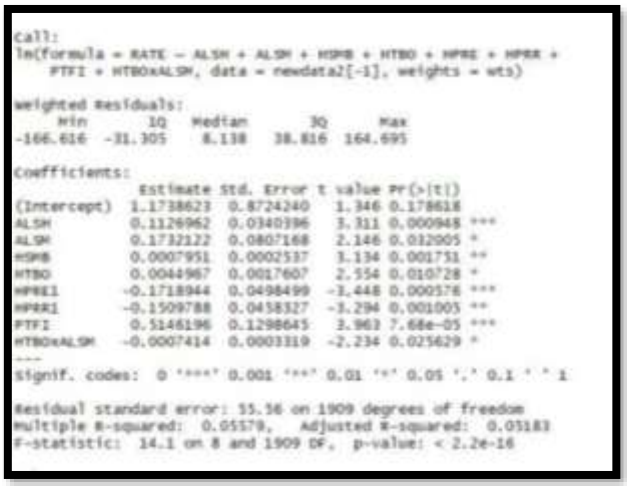
Residual vs Fitted Plot for Transformed Falls per Discharge for Large Providers (3,000+)



Normal Q-Q Plot for Transformed Falls per Discharge for Large Providers (3,000+)

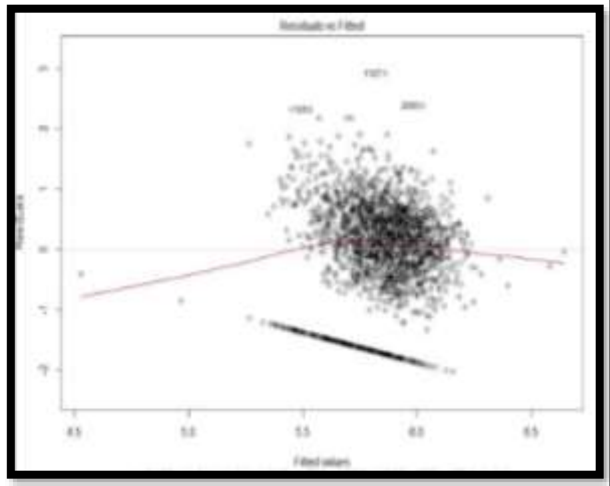
Figure A-17: Multivariate Backward Regression and Plots Outcomes for Transformed (Log+ 62) Fall per Discharge for Large Providers (3,000 + Yearly Medicare Discharges) - 2014

Model 2: Transformed falls per discharge (Log +62) for large providers (2,000 + Medicare discharges per year)

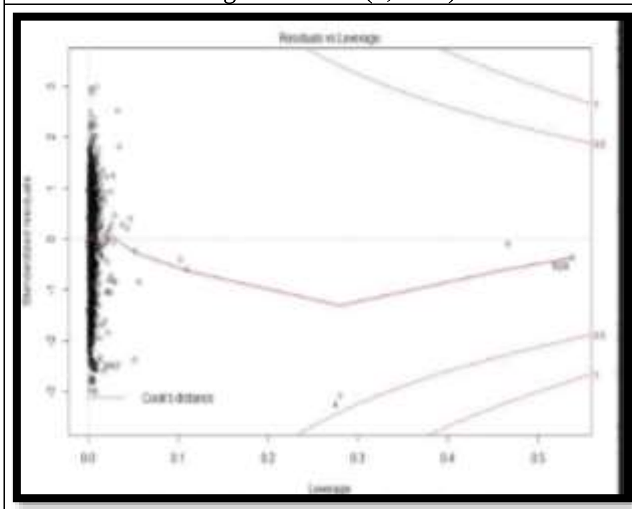


```
call:
lm(formula = RATE ~ ALSH + ALSM + HSPB + HTBO + HPRE + HPRR +
    PTFI + HTBOxALSM, data = newdata2[-1], weights = wts)

Weighted Residuals:
     Min       1Q   Median       3Q      Max
-166.616  -31.305    8.138   38.816  164.695

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  1.1738623  0.8724240   1.346 0.178618
ALSH         0.1126962  0.0340396   3.311 0.000948 ***
ALSM         0.1732122  0.0807168   2.146 0.032005 *
HSPB         0.0007951  0.0002537   3.134 0.001751 **
HTBO         0.0044967  0.0017607   2.554 0.010728 *
HPRE1       -0.1718944  0.0498499  -3.448 0.000578 ***
HPRR1       -0.1509788  0.0458327  -3.294 0.001005 **
PTFI         0.5146196  0.1298645   3.963 7.68e-05 ***
HTBOxALSM   -0.0007414  0.0003319  -2.234 0.025629 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 55.56 on 1909 degrees of freedom
Multiple R-squared:  0.05579,   Adjusted R-squared:  0.05183
F-statistic:  14.1 on 8 and 1909 DF,  p-value: < 2.2e-16
```

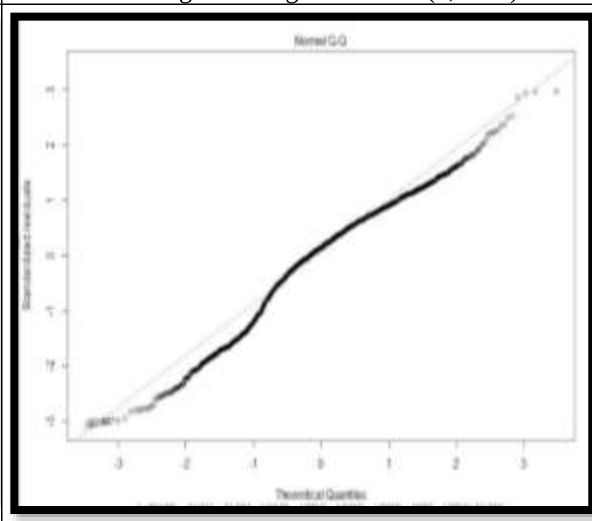
Regression for Transformed Falls per Discharge for Large Providers (2,000+)



Residual vs Fitted Plot for Transformed Falls per Discharge for Large Providers (2,000+)



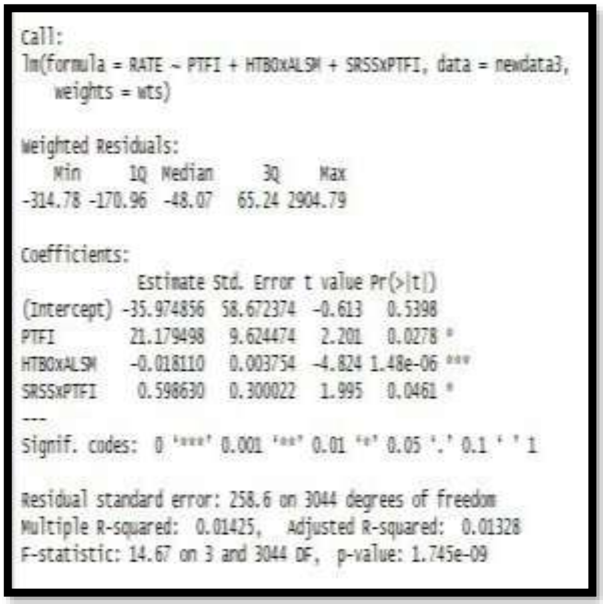
Residual vs. Leverage Plot for Transformed Falls per Discharge for Large Providers (2,000+)



Normal Q-Q Plot for Transformed Falls per Discharge for Large Providers (2,000+)

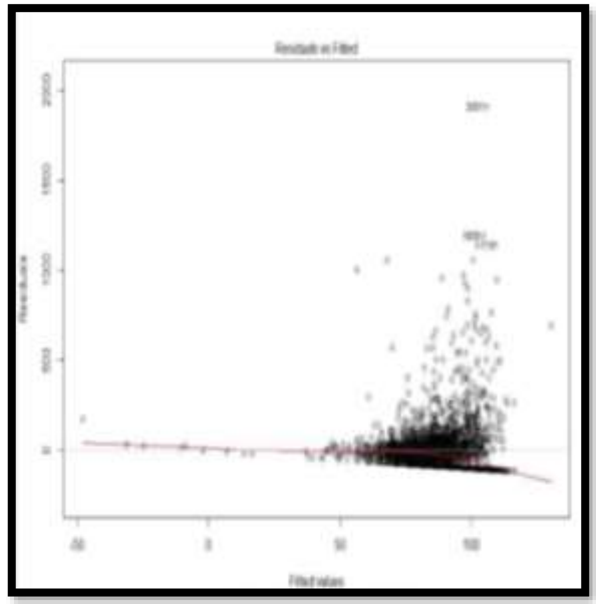
Figure A-18: Multivariate Backward Regression and Plots Outcomes for Transformed (Log+ 62) Fall per Discharge for Large Providers (2,000 + Yearly Medicare Discharges) - 2014

Model 3: Falls per Medicare days for all providers

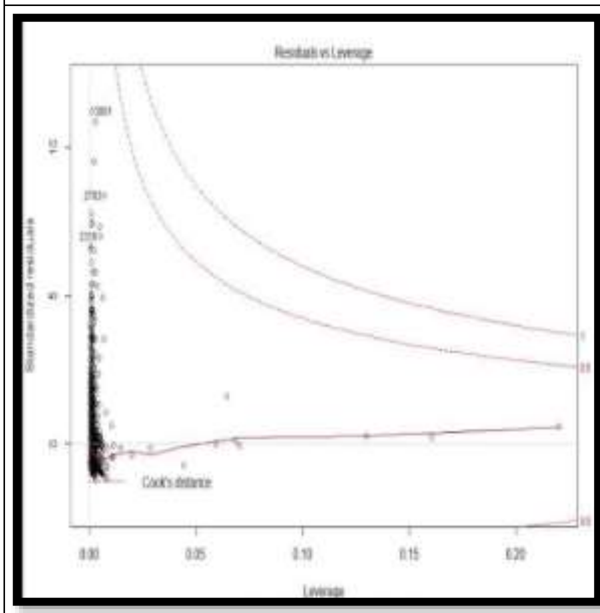


```
Call:
lm(formula = RATE ~ PTFI + HTBOXALSM + SRSSxPTFI, data = newdata3,
    weights = wts)

Weighted Residuals:
    Min      1Q  Median      3Q     Max
-314.78 -170.96  -48.07   65.24 2904.79

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept) -35.974856  58.672374  -0.613   0.5398
PTFI         21.179498   9.624474   2.201   0.0278 *
HTBOXALSM    -0.018110   0.003754  -4.824 1.48e-06 ***
SRSSxPTFI     0.598630   0.300022   1.995   0.0461 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 258.6 on 3044 degrees of freedom
Multiple R-squared:  0.01425,	Adjusted R-squared:  0.01328
F-statistic: 14.67 on 3 and 3044 DF,  p-value: 1.745e-09
```

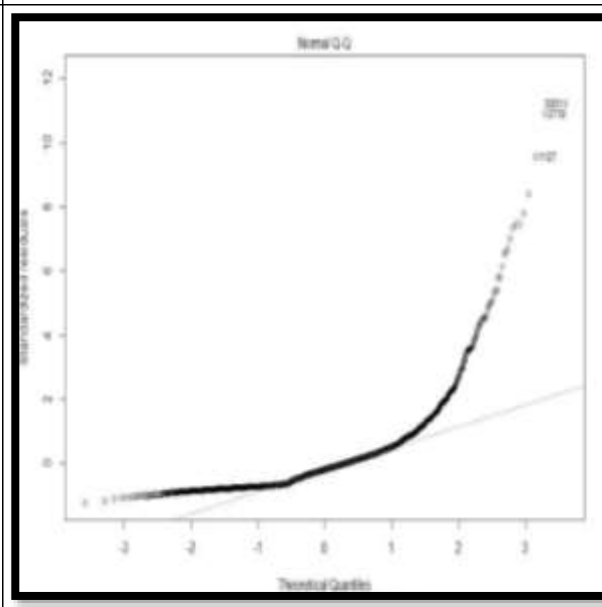
Regression for Fall per Medicare Days All Providers



Residual vs Fitted Plot for Fall per Medicare Days All Providers



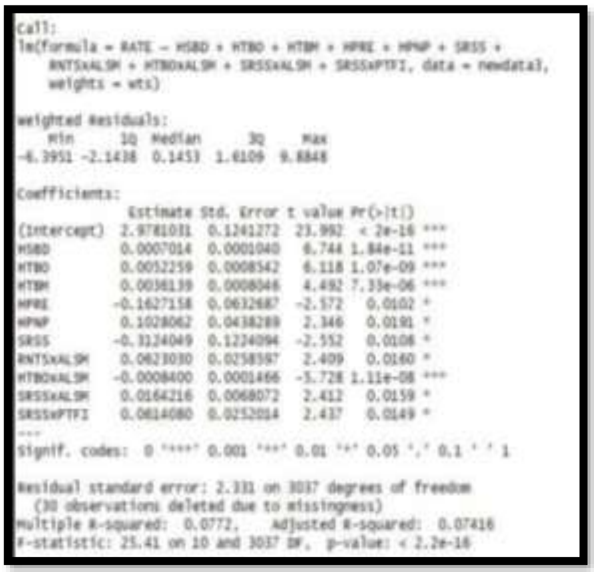
Residual vs Leverage Plot for Fall per Medicare Days All Providers



Normal Q-Q Plot for Fall per Medicare Days All Providers

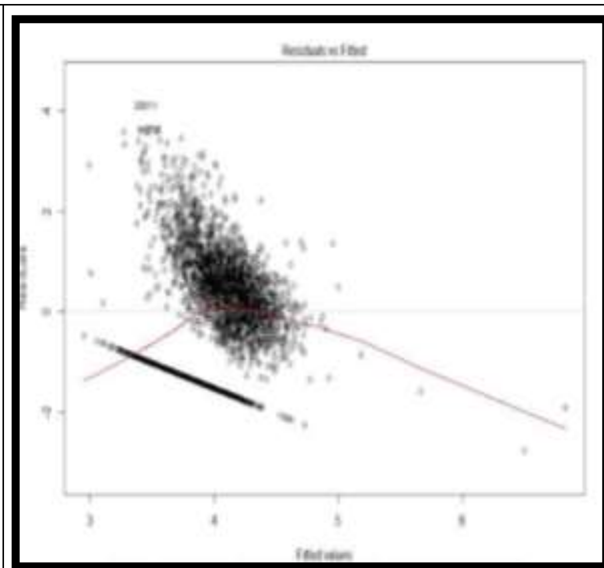
Figure A-19: Multivariate Backward Regression and Plots Outcomes for Fall per Medicare Days for All Providers - 2014

Model 4: Transformed falls per Medicare Days (Log+ 62) for all providers

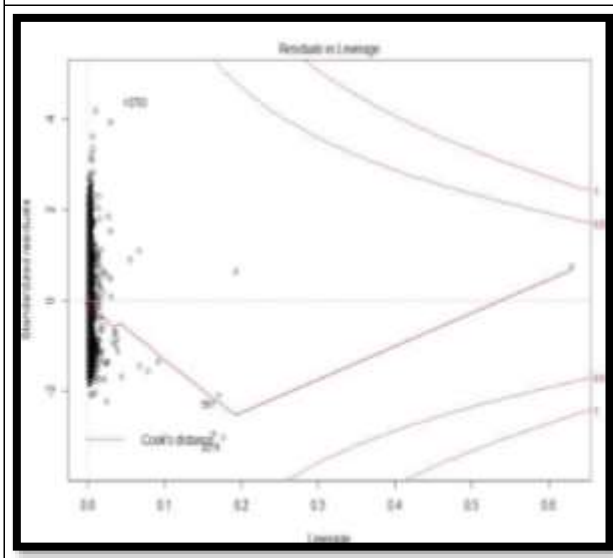


```
Call:
lm(formula = RATE ~ HSBD + HTBO + HTBM + HPRE + HPNP + SRSS +
    RNTSxALSM + HTBOxALSM + SRSSxALSM + SRSSxPTFI, data = newdata1,
    weights = wts)

Weighted Residuals:
    Min      1Q  Median      3Q     Max
-6.3951 -2.1438  0.1453  1.6109  9.8848

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  2.9781031  0.1241272  23.992  < 2e-16 ***
HSBD         0.0007014  0.0001040   6.744 1.84e-11 ***
HTBO         0.0052259  0.0008542   6.118 1.07e-09 ***
HTBM         0.0036139  0.0008046   4.492 7.33e-06 ***
HPRE        -0.1627158  0.0632687  -2.572   0.0102 *
HPNP         0.1028062  0.0438289   2.346   0.0191 *
SRSS        -0.3124049  0.1224094  -2.552   0.0108 *
RNTSxALSM    0.0623030  0.0258597   2.409   0.0160 *
HTBOxALSM   -0.0008400  0.0001466  -5.728 1.11e-08 ***
SRSSxALSM    0.0164216  0.0068072   2.412   0.0159 *
SRSSxPTFI    0.0614080  0.0252014   2.437   0.0149 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 2.331 on 3037 degrees of freedom
  (30 observations deleted due to missingness)
Multiple R-squared:  0.0772,    Adjusted R-squared:  0.07416
F-statistic: 25.41 on 10 and 3037 DF,  p-value: < 2.2e-16
```

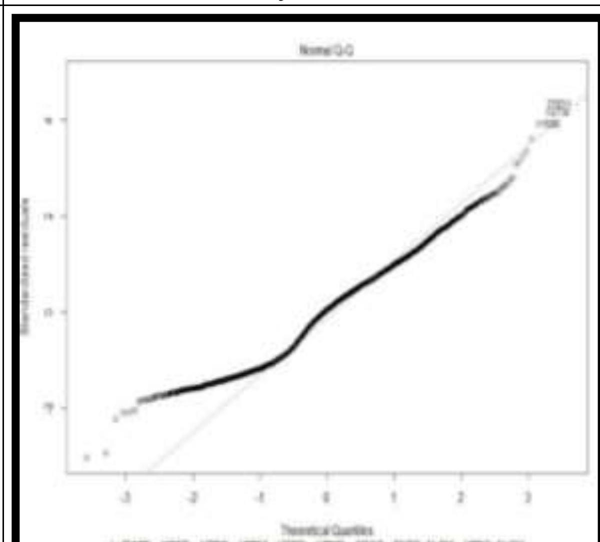
Regression for Transformed Falls per Medicare Days for All Providers



Residual vs Fitted Plot for Transformed Falls per Medicare Days for All Providers



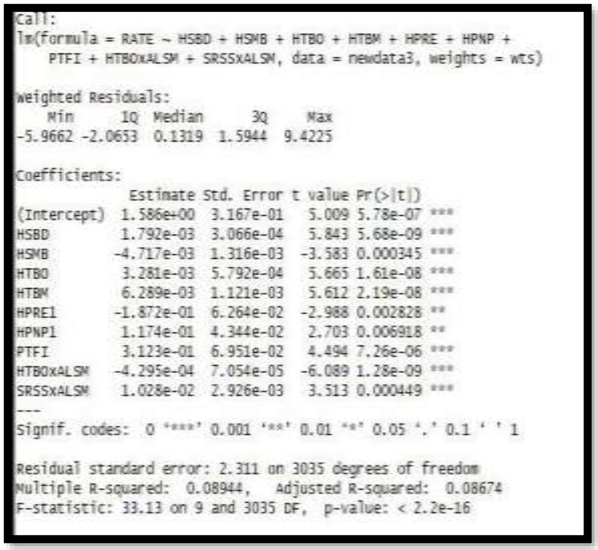
Residual vs Leverage Plot for Transformed Falls per Medicare Days for All Providers



Normal Q-Q Plot for Transformed Falls per Medicare Days for All Providers

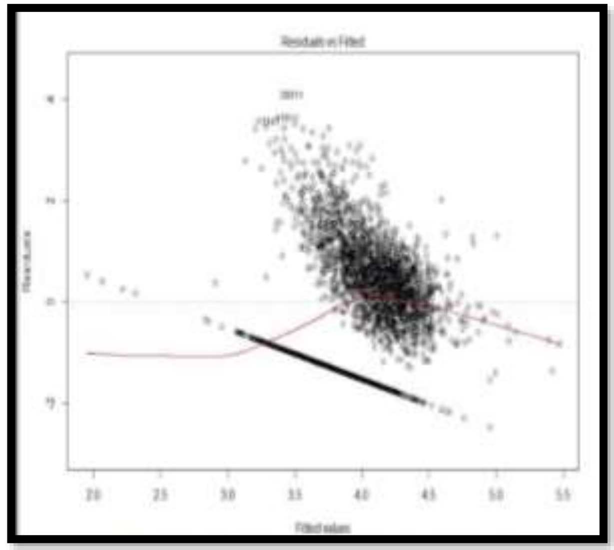
Figure A-20: Multivariate Backward Regression and Plots Outcomes for Transformed (Log+ 62) Fall per Medicare Days for All Providers - 2014

Model 4 Transformed falls per Medicare days (Log +62) for all providers post removing outliers

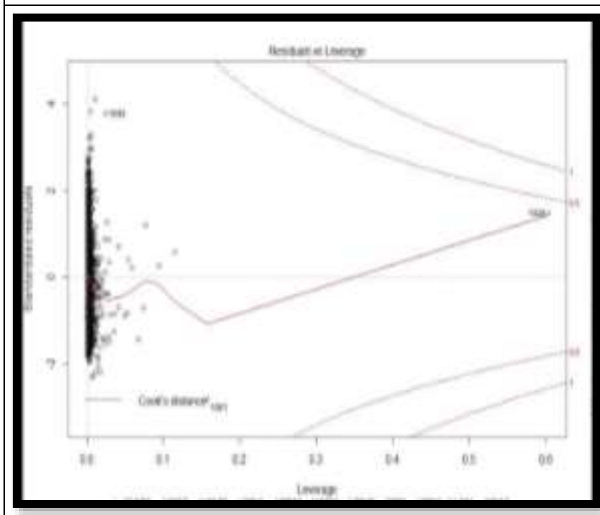


```
Call:
lm(formula = RATE ~ HSBD + HSMB + HTBO + HTBM + HPRE + HPNP +
    PTFI + HTBOxALSM + SRSSxALSM, data = newdata3, weights = wts)

Weighted Residuals:
    Min      1Q  Median      3Q     Max
-5.9662 -2.0653  0.1319  1.5944  9.4225

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  1.586e+00  3.167e-01   5.009 5.78e-07 ***
HSBD         1.792e-03  3.066e-04   5.843 5.68e-09 ***
HSMB        -4.717e-03  1.316e-03  -3.583 0.000345 ***
HTBO         3.281e-03  5.792e-04   5.665 1.61e-08 ***
HTBM         6.289e-03  1.121e-03   5.612 2.19e-08 ***
HPRE1       -1.872e-01  6.264e-02  -2.988 0.002828 **
HPNP1        1.174e-01  4.344e-02   2.703 0.006918 **
PTFI         3.123e-01  6.951e-02   4.494 7.26e-06 ***
HTBOxALSM   -4.295e-04  7.054e-05  -6.089 1.28e-09 ***
SRSSxALSM    1.028e-02  2.926e-03   3.513 0.000449 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 2.311 on 3035 degrees of freedom
Multiple R-squared:  0.08944,   Adjusted R-squared:  0.08674
F-statistic: 33.13 on 9 and 3035 DF,  p-value: < 2.2e-16
```

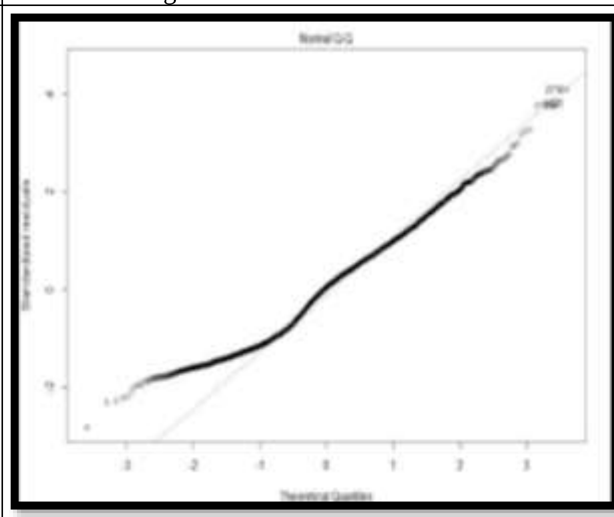
Regression for Transformed Falls per Discharge for All Providers without Outliers



Residual vs Fitted Plot for Transformed Falls per Discharge for All Providers without Outliers



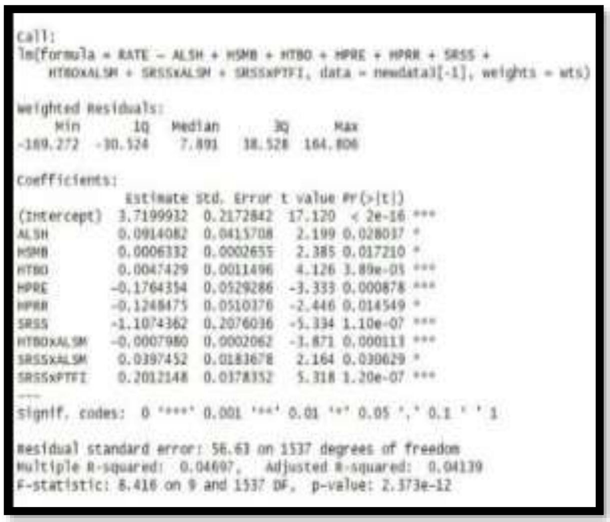
Residual vs Leverage Plot for Transformed Falls per Discharge for All Providers without Outliers



Normal Q-Q Plot for Transformed Falls per Discharge for All Providers without Outliers

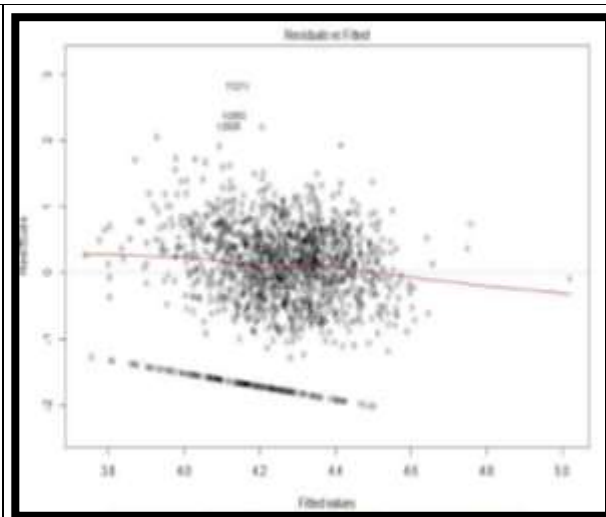
Figure A-21: Multivariate Backward Regression and Plots Outcomes for Transformed (Log+ 62) Fall per Medicare Days for All Providers Post Removing Outliers - 2014

Model 4: Transformed falls per Medicare days (Log +62) for large providers (3,000 + Medicare discharges per year)

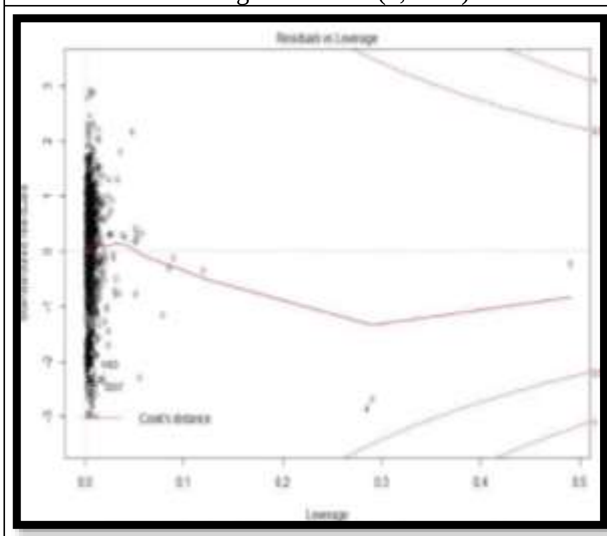


```
Call:
lm(formula = RATE ~ ALSH + HSMB + HTBO + HPRE + HPRR + SRSS +
    HTBOxALSM + SRSSxALSM + SRSSxPTFI, data = newdata3[-1], weights = wts)

Weighted Residuals:
     Min       1Q   Median       3Q      Max
-189.272  -30.524    7.891   38.528  164.806

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  3.7199932  0.2172842  17.120  < 2e-16 ***
ALSH         0.0914082  0.0415708   2.199 0.028037 *
HSMB         0.0006332  0.0002655   2.385 0.017210 *
HTBO         0.0047429  0.0011496   4.126 3.89e-05 ***
HPRE        -0.1764354  0.0529286  -3.333 0.000878 ***
HPRR        -0.1248475  0.0510376  -2.446 0.014549 *
SRSS        -1.1074362  0.2076036  -5.334 1.10e-07 ***
HTBOxALSM   -0.0007980  0.0002062  -3.871 0.000113 ***
SRSSxALSM    0.0397452  0.0183678   2.164 0.030629 *
SRSSxPTFI    0.2012148  0.0378352   5.318 1.20e-07 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 56.63 on 1537 degrees of freedom
Multiple R-squared:  0.04697,   Adjusted R-squared:  0.04139
F-statistic: 8.416 on 9 and 1537 DF,  p-value: 2.373e-12
```

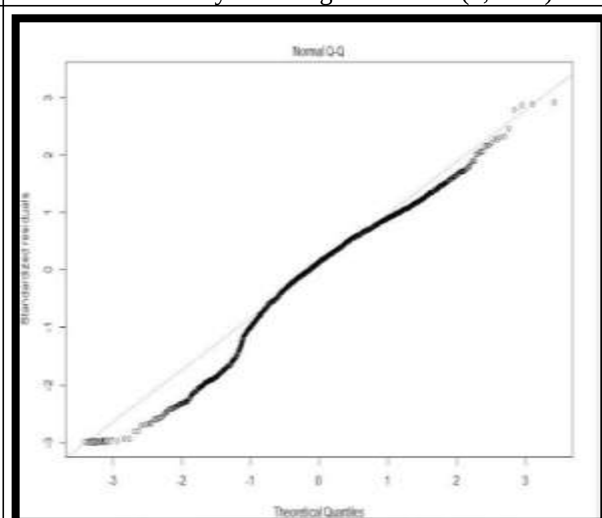
Regression for Transformed Falls per Medicare Days for Large Providers (3,000+)



Residual vs. Fitted Plot for Transformed Falls per Medicare Days for Large Providers (3,000+)



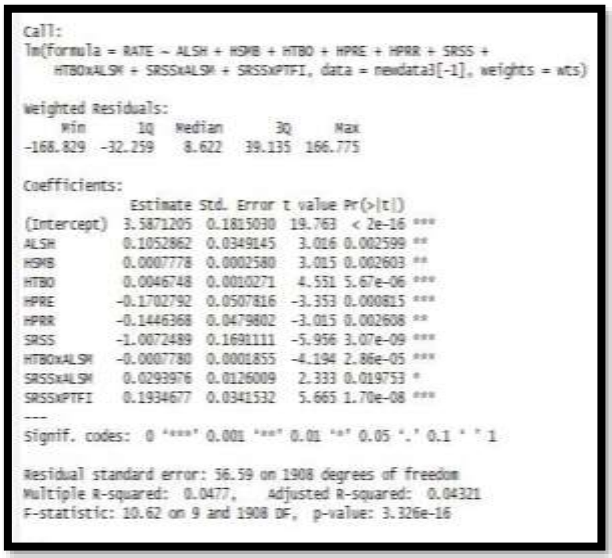
Residual vs. Leverage Plot for Transformed Falls per Medicare Days for Large Providers (3,000+)



Normal Q-Q Plot for Transformed Falls per Medicare Days for Large Providers (3,000+)

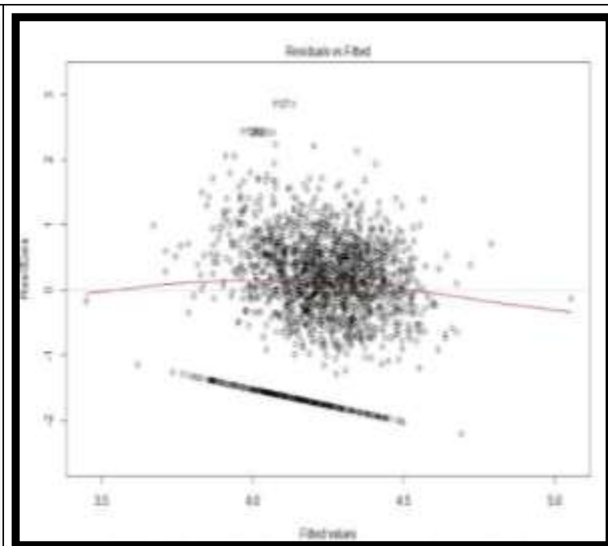
Figure A-22: Multivariate Backward Regression and Plots Outcomes for Transformed (Log+ 62) Fall per Medicare Days for Large Providers (3,000 + Yearly Medicare Discharges) - 2014

Model 4: Transformed falls per Medicare days (Log +62) for large providers (2,000 + Medicare discharges per year)

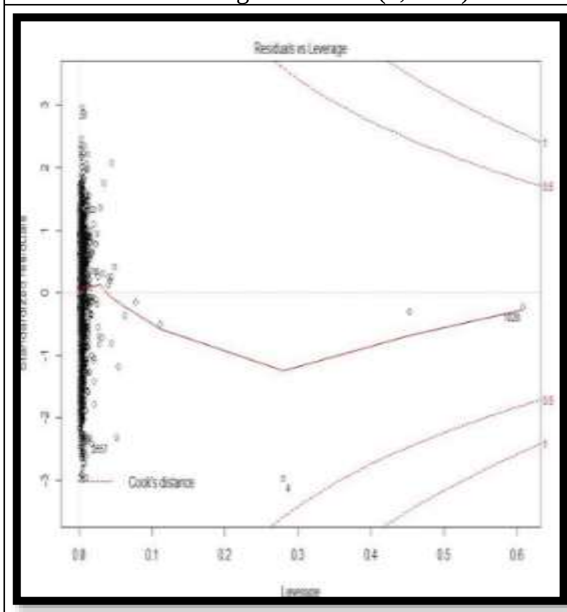


```
Call:
lm(formula = RATE ~ ALSH + HSMB + HTBO + HPRE + HPRR + SRSS +
    HTBOxALSM + SRSSxALSM + SRSSxPTFI, data = newdata3[-1], weights = wts)

Weighted Residuals:
     Min       1Q   Median       3Q      Max
-168.829  -32.259    8.622   39.135  166.775

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  3.5871205  0.1815030  19.763  < 2e-16 ***
ALSH         0.1052862  0.0349145   3.016 0.002599 **
HSMB         0.0007778  0.0002580   3.015 0.002603 **
HTBO         0.0046748  0.0010271   4.551 5.67e-06 ***
HPRE        -0.1702792  0.0507816  -3.353 0.000815 ***
HPRR        -0.1446368  0.0479802  -3.015 0.002608 **
SRSS        -1.0072489  0.1691111  -5.956 3.07e-09 ***
HTBOxALSM   -0.0007780  0.0001855  -4.194 2.86e-05 ***
SRSSxALSM    0.0293976  0.0126009   2.333 0.019753 *
SRSSxPTFI    0.1934677  0.0341532   5.665 1.70e-08 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 56.59 on 1908 degrees of freedom
Multiple R-squared:  0.0477,    Adjusted R-squared:  0.04321
F-statistic: 10.62 on 9 and 1908 DF,  p-value: 3.326e-16
```

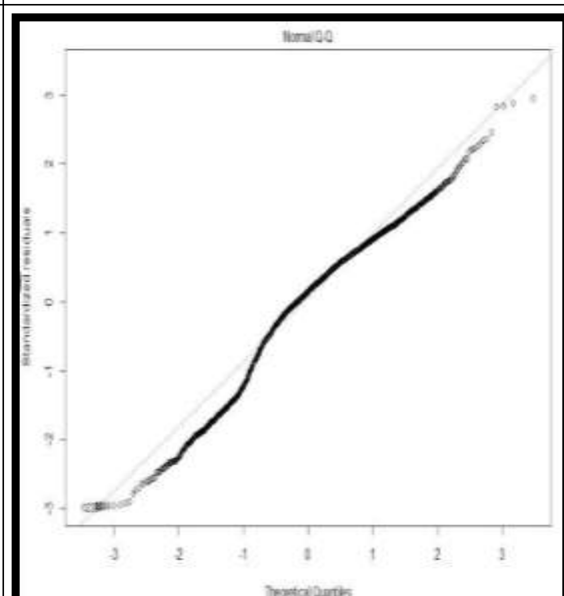
Regression for Transformed Falls per Medicare Days for Large Providers (2,000+)



Residual vs. Fitted Plot for Transformed Falls per Medicare Days for Large Providers (2,000+)



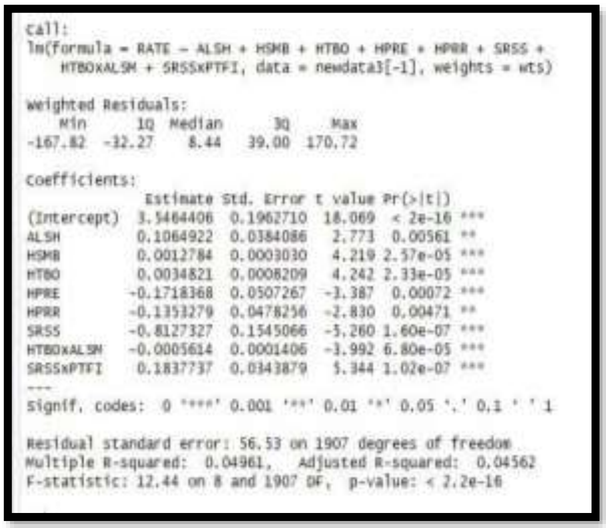
Residual vs. Leverage Plot for Transformed Falls per Medicare Days for Large Providers (2,000+)



Normal Q-Q Plot for Transformed Falls per Medicare Days for Large Providers (2,000+)

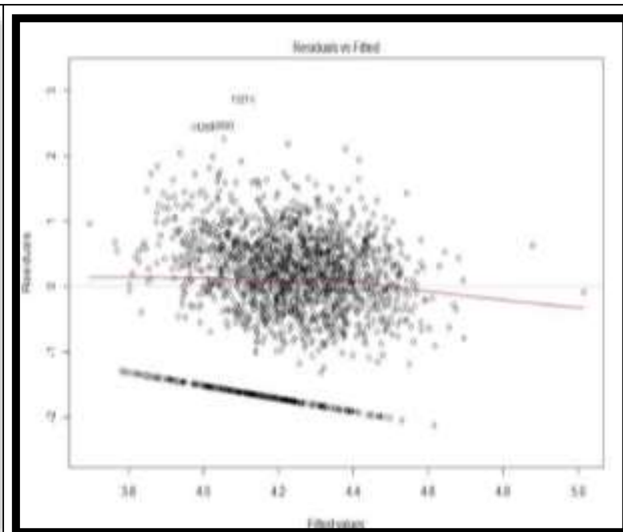
Figure A-23: Multivariate Backward Regression and Plots Outcomes for Transformed (Log+ 62) Fall per Medicare Days for Large Providers (2,000 + Yearly Medicare Discharges) - 2014

Model 4 Transformed falls per Medicare days (Log +62) for large providers (2,000 + Medicare discharges per year) post removing outliers

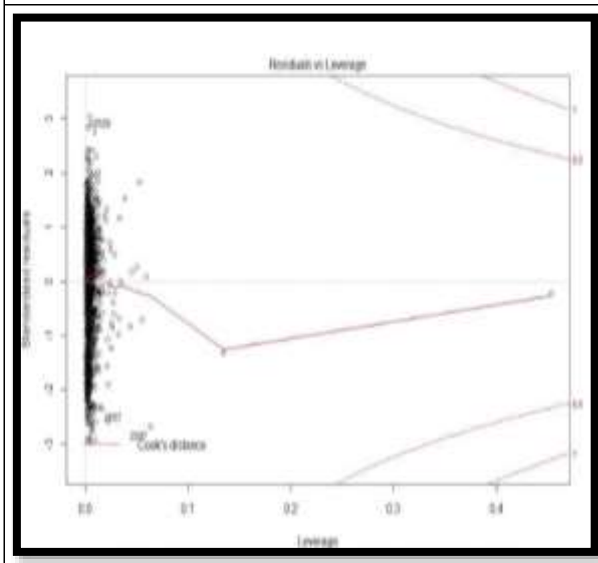


```
Call:
lm(formula = RATE ~ ALSH + HSMB + HTBO + HPRE + HPRR + SRSS +
    HTBOxALSM + SRSSxPTFI, data = newdata3[-1], weights = wts)

Weighted Residuals:
    Min      1Q  Median      3Q     Max
-167.82  -32.27    8.44   39.00  170.72

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  3.5464406  0.1962710  18.069  < 2e-16 ***
ALSH         0.1064922  0.0384086   2.773  0.00561 **
HSMB         0.0012784  0.0003030   4.219 2.57e-05 ***
HTBO         0.0034821  0.0008209   4.242 2.33e-05 ***
HPRE        -0.1718368  0.0507267  -3.387  0.00072 ***
HPRR        -0.1353279  0.0478256  -2.830  0.00471 **
SRSS        -0.8127327  0.1545066  -5.260 1.60e-07 ***
HTBOxALSM   -0.0005614  0.0001406  -3.992 6.80e-05 ***
SRSSxPTFI    0.1837737  0.0343879   5.344 1.02e-07 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 56.53 on 1907 degrees of freedom
Multiple R-squared:  0.04961,	Adjusted R-squared:  0.04562
F-statistic: 12.44 on 8 and 1907 DF,  p-value: < 2.2e-16
```

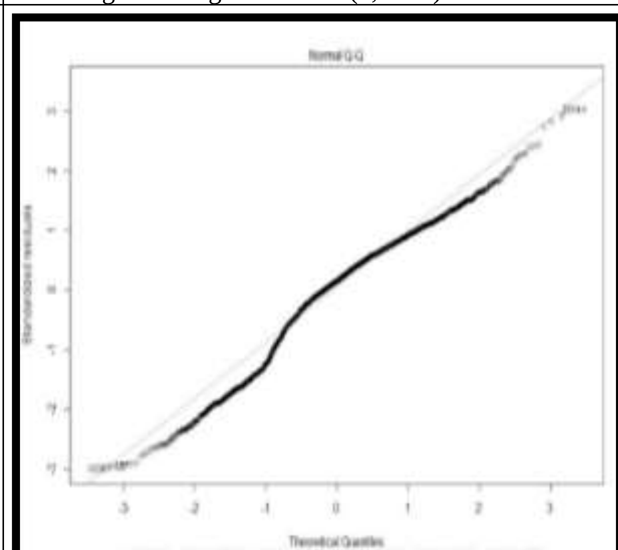
Regression for Transformed Falls per Discharge for Large Providers (2,000+) without Outliers



Residual vs Fitted Plot for Transformed Falls per Discharge for Large Providers (2,000+) without Outliers



Residual vs Leverage Plot for Transformed Falls per Discharge for Large Providers (2,000+) without Outliers



Normal Q-Q Plot for Transformed Falls per Discharge for Large Providers (2,000+) without Outliers

Figure A-24: Multivariate Backward Regression and Plots Outcomes for Transformed (Log+ 62) Fall per Medicare Days for Large Providers (2,000 + Yearly Medicare Discharges) Post Removing Outliers - 2014

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