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Medicare Readmission Rates After Hospitalization for Acute Myocardial Infarction Among Seven Connecticut Hospitals

Anthony Joseph Landino

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MEDICARE READMISSION RATES AFTER HOSPITALIZATION FOR ACUTE MYOCARDIAL INFARCTION AMONG SEVEN CONNECTICUT HOSPITALS

Anthony Joseph Landino

B.S., University of Connecticut, 1994

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MEDICARE READMISSION RATES AFTER HOSPITALIZATION FOR ACUTE MYOCARDIAL INFARCTION AMONG SEVEN CONNECTICUT HOSPITALS

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1998
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Abstract

**Objective:** To define the variation in readmission rates among Medicare beneficiaries discharged from seven different Connecticut acute-care hospitals with a diagnosis of acute myocardial infarction (AMI). Also, to identify patient- and hospital-level characteristics that might account for any observed variation in readmission rates. Lastly, to investigate the feasibility of abstracting and analyzing provider-specific Medicare claims data for future research in this area.

**Design:** The cohort study identified patients discharged with a primary diagnosis of AMI from May 1, 1997 through October 31, 1997. The cohort was identified retrospective to the time of the research. The outcomes of death and readmission were examined by linking patients to their medical claims.

**Setting and Participants:** Seven Connecticut hospitals with similar patient populations and organizational structures were selected. Medicare beneficiaries (n=1060) aged 65 years or older who were discharged alive from one of the seven hospitals over a six month period in 1997 were eligible. These patients were enrolled in traditional fee-for-service health plans.

**Data Sources:** Medicare Part A claims data and eligibility files were used to obtain patient- and provider-level variables. American Hospital Association data files were used to evaluate hospital characteristics.
**Outcome Variables:** 30-day readmission rates were calculated during the study period. The readmission rates were defined as the proportion of patients in the index population who required rehospitalization within 30 days of initial discharged.

**Explanatory Variables:** Both patient and hospital characteristics were used to predict the occurrence of a patient readmission. The primary patient variables were age, gender, race, severity of illness (Deyo index), length of stay (LOS), discharge disposition, and cardiac procedures (percutaneous transluminal coronary angioplasty, PTCA, and coronary artery bypass graft surgery, CABG) performed during the index admission. Hospital variables included total bed count, physician and nurse staffing ratios, and volume of confirmed AMIs.

**Statistical Analysis:** Patient-level data were analyzed from Medicare Part A administrative files with the statistical package, SAS (citation) Version 6.11. Multivariate regression was used to identify patient factors associated with readmission. Similar regression methods were used to compare hospital-specific readmission rates after adjusting for patient variables.

**Results:** Two patient-level variables (CABG and PTCA performed during the index admission) were significantly associated with the rate of readmission. One hospital-level variable (bed count) was significantly associated with the rate of readmission. All three variables demonstrated a decreased likelihood for readmission. Patients, who underwent a PTCA during their index admission, were 50% less likely to be readmitted to the hospital than those patients who did not undergo PTCA. Patients, who underwent a CABG during their index admission, were 54% less likely to be readmitted to the hospital
than those patients who did not undergo CABG. Patients discharged from hospitals with
greater than 617 beds were 48% less likely to be readmitted than those patients discharged
from hospitals with less than 617 beds. Unadjusted interhospital 30-day readmission rates
varied by hospital from a high of 21.88 (7/32) to a low of 8.99 (17/189). After adjusting
for patient characteristics (including comorbidity), three hospitals varied significantly from
the reference hospital (hospital with the lowest observed readmission rate).

Conclusion: None of the covariates significantly predicted an increased risk of
readmission. Instead, three covariates exhibited a protective effect against readmission;
thus decreasing one’s risk for rehospitalization. Wide variation in 30-day readmission
rates existed between the seven hospitals despite efforts to pre-select hospitals with
comparable populations and to adjust for patient- and hospital-level characteristics. Also,
it appears feasible to abstract State- and hospital-specific data from Medicare claims. The
utility of readmission rates, as an outcomes measure, appears promising; however, further
research is necessary to better explain the variation in these rates.
Introduction and Background

Introduction

The purpose of this research is threefold. First, the work provides a solid foundation to investigate interhospital variation in readmission rates. A historical perspective on the evolving field of health services research and an introduction to variation in health care resources, expenditures, and utilization is presented. To demonstrate the relevance and importance of this thesis topic, a discussion of the implications of readmissions after acute myocardial infarctions (AMI) to the Medicare program is described.

Secondly, this project defines the variation in readmission rates among Medicare beneficiaries in the State of Connecticut during a six-month period in 1997. We particularly focus on Medicare beneficiaries rehospitalized after being discharged with a primary diagnosis of AMI. Patient and hospital characteristics that may have attributed to this variation are investigated.

And thirdly, this research explores the feasibility of investigating interhospital variation in readmission rates using Medicare claims data provided by the Connecticut Peer Review Organization (CPR0). Seven hospitals that were similar in both patient population and organizational structure were selected as part of this study. After accounting for these characteristics, it was theorized that any interhospital variation might reflect process of care differences in the provision of care.
Health Services Research

The Early Years

Lewis (1) defined health services research (HSR) in several ways: as an iterative process whose purpose is to influence the health-care system; as a pragmatic, multidisciplinary effort without easily defined boundaries; and as an enterprise with several components, including the collection and diffusion of information, the development and evaluation of new health services systems and processes, research and training (of researchers), and policy analyses. Although these definitions were stated over 20 years ago, the federal government has only recently conceptualized HSR in this context, particularly the last definition.

The federal government recognized the need to evaluate the delivery of our health care system over thirty years ago. Although formal research directed at investigating the workings of health services is not a new inquiry, it has been slow to develop. In the late 1960s, shortly after the newly established Medicare and Medicaid programs were implemented, the federal government sought better methods to evaluate the quality of care being provided (2). Government agencies used the phrase, “health services research”, to describe the evaluative tool that would be utilized to achieve their objectives. These objectives were defined as the following: (i) to contain the cost of health care and (ii) to ensure the quality of care being provided.

One of the first federal agencies delegated by Congress to address the objectives of health services research was the National Center for Health Services Research (NCHSR). The National Center for Health Services Research was created in 1968, and as of 1977,
Lewis (1) cited that agency has spent approximately $370 million supporting studies ranging from the effects of different cost-containment mechanisms to methods for evaluating the quality of care. This is a pittance compared to the federal outlays for biomedical research that exceeded $700 billion in that same time interval (1). It appeared clear early on that the government’s priorities were with biomedical rather than health services research.

However, despite a relatively small financial commitment, NCHSR, after its establishment in 1968, developed a program called the Experimental Medical Care Review Organization (EMCRO). This program initially sought the assistance of volunteer physicians to develop methods of evaluating physician performance that would meet scientific and technical standards of objectivity and reliability (2). EMCROs developed process measures of quality of care, which compared actual care to relevant standards (2). These centers were short lived, and the 16 NCHSR-funded centers later became professional standards review organizations (PSROs).

PSROs, established by the Social Security Amendments of 1972, exemplified a federal initiative to reduce the costs and improve the quality of health care. By the early 1970s, Congress recognized the extent to which the Medicare and Medicaid programs were utilized. Congress, once again, addressed the objectives of health services research, cost containment and quality health care. The goal of the PSRO program was to slow the increase in utilization of services while ensuring high-quality health care for Medicare patients (3). PSROs performed individual case reviews of how providers delivered health care and revealed any inappropriate or undesirable practices. The case-by-case review
targeted extreme outliers who provided care ostensibly inconsistent with the scientific and technical standards. However, PSROs did not demonstrate substantial financial savings.

So, in 1975, the federal government enacted the Health Planning and Resource Development Act in an attempt to centralize regulation of the growth of health care facilities, limit the influx of new technologies, and bring “rationality” to the health care delivery system (3). Soon, this program failed.

In response to the unabated pressures to decrease health care costs and ensure quality, the PSRO program was replaced, in 1982, by the peer review organization (PRO) program of the Tax Equity and Fiscal Responsibility Act (TEFRA). The federal government contracted with PROs in each State to serve as quality assurance organizations. Once again, the PROs focused on extreme deviates (outliers) in health care provision by utilizing case-by-case medical chart review retrospective to the episode of care.

Initially, the PROs continued to develop the quality assurance systems begun by their predecessors; however, they soon encountered controversy. Theoretically, these quality assurance programs were to function both to control costs and ensure quality care (2). However, many believed that the PROs were too narrowly focused and could only have marginal effect on the way health care is provided. Opponents argued that PROs only restricted the outliers of practice styles and did not change practice norms. Salive et al. (2) noted that although the standards were developed carefully, thoroughly, and using scientifically sound methods, some of the criteria made little sense to the clinicians. Differences in physician practice by specialty, among patient populations, and among
regions also made it difficult for PROs to detect inappropriate care or devise a set of
generalizable criteria (2).

Berman (3) believed the PROs had been unable to address: the criteria for medical
treatment and the setting in which the services were delivered (outpatient versus inpatient)
were defined by the practice styles of the physician population rather than by
documentation of efficacy. Thus, as we entered the third decade of a federal commitment
to health services research, federal programs chartered for this purpose appeared
ineffective in the eyes of government and lacked credibility in the eyes of health care
providers.

*The Impetus for Change*

Through the early 1980s, HSR contributed relatively little to the delivery of care in
the U.S. Nevertheless, the 1980s brought significant changes both to the structure of the
U.S. health care delivery system as well as the federal approach to HSR. By the early
1990s, HSR adopted a new agenda that influenced health care policy more substantially.

Organizations that contracted for health care services, particularly large
corporations and the federal government, became alarmed by the precipitous growth in
health care cost (3). Corporations saw the spiraling costs of health care cutting into their
profit margins; and in the case of the government, federal officials projected that the
growth of health care was outpacing the U.S. Gross National Product. Many health care
policy experts credited the large corporations and the federal government as the impetus
for change in the U.S. health care delivery system. The large employers of this country
were credited with the explosion of health maintenance organizations (HMOs). In response to a corporate demand for lower health care costs, HMOs restructured the financial arrangements for health care in this country. Similarly, the federal government devised the prospective payment system (PPS), which reimbursed hospitals for episodes of care rather than fee-for-service. Subsequently, the growth in health care costs waned. Both HMOs and the PPS were products of a revolution in health care; and in the wake of this revolution, health services research was about to change as well.

Berman (3) stated that, in the fall of 1986, the Omnibus Budget Reconciliation Act (OMBRA) amended the Social Security Act authorizing the secretary of the Department of Health and Human Services (DHHS) to establish “a patient outcomes assessment research program of selected medical treatments and surgical procedures for the purpose of assessing their appropriateness, necessity, and effectiveness.” OMBRA signified a new federal approach to evaluating the workings of the nation’s health care delivery system. "HCFA effectiveness initiative proposed that effectiveness research was "to improve the general level of standard medical practice", and explicitly stated that is was not "to isolate low quality outliers or take punitive action” (3).

Another significant component of the effectiveness initiative was the utility of outcomes (measurements of patient’s health conditions subsequent to medical procedures) to serve as indicators of effective care. Under OMBRA, Congress established NCHSR’s Patient Outcome Assessment Research Program with funding from the Medicare Trust Fund. The government demonstrated its commitment to this new HSR approach by enabling the NCHSR to fund studies of the treatment of prostatic hypertrophy, heart
disease, hypertension, diabetes, and rheumatoid arthritis, coronary artery bypass surgery, and intensive care therapy (2).

There were many proponents to this paradigm shift in federal HSR policy. One seminal health services researcher, Dr. John Wennberg (4), argued the case for evaluative clinical sciences and the need to support a national program to assess the outcomes of medical care. “For too long, and at the peril to the welfare of patients and the public as well, we have neglected the essential part of medical science whose job it is to establish the validity of clinical theory and help patients and patients reach the right decisions in their choice of medical care” (4). Wennberg believed too little was known about the outcomes of any risky procedures. “Evaluative clinical sciences offer the promise of a scientific program that can greatly decrease uncertainly about the probabilities and the value to patients of the outcomes of care, and can improve the information base for clinical as well as policy decisions” (4).

Similarly, Berman (3) believed effectiveness of medical treatment in the future should be based strictly on outcomes, not on guidelines formulated by groups of experts, third-party payers, or government agencies. Both investigators recognized the necessity of outcomes research to provide physicians, patients, and federal policy-makers with some clinically proven body of knowledge.

With the focus of HSR redirected to emphasize outcomes of care measures rather than process of care, Congress sought to establish an agency to exemplify their commitment to effectiveness standards and outcomes measurements. In 1989, Congress passed OMBRA that provided for the establishment of an agency, the Agency for Health
Care Policy and Research (AHCPR). Berman (3) stated its purpose was to “enhance the quality, appropriateness, and effectiveness of health care services, and access to such services, through the establishment of a broad base of scientific research and through the promotion of improvements in clinical practice and in the organization, financing, and delivery of health care services.”

By September 1989, AHCPR funded four research endeavors, entitled the Patient Outcomes Research Teams (PORTs), to represent the next phase of medical effectiveness research. The PORTs were funded to study acute myocardial infarction, benign prostatic hyperplasia and locally invasive prostatic carcinoma, low back pain, and cataracts (2). As AHCPR expanded, more research programs were proposed and awarded funding.

The emphasis toward patient outcomes research was clear. Jencks and Wilensky (5) stated that the observations made by Dr. Arnold Relman in light of the remarkable changes in health care and health services research were described as three revolutions. Relman described these recent developments as three revolutions in medicine. First came the Era of Expansion, from World War II through the late 1960s; then the Era of Cost Containment; and, just beginning, the Era of Assessment and Accountability, whereby we refocus on the quality and effectiveness of health care. He describes the goal of the current era as “to achieve an equitable health care system, of satisfactory quality, at a price we can afford.” Health services researchers will be part of the leading edge of Relman’s third era, and must expand their role in performing and disseminating community-based and academic research on patient outcomes when controversy exists (5).

The Health Care Quality Improvement Initiative

As we approached the 1990s, the federal government’s commitment to quality improvement efforts was clear. The Health Care Financing Administration (HCFA) has
been the federal agency responsible for the financing and administration of health care. In August, Jencks and Wilensky (5) described how HCFA was reshaping its approach to improving care for Medicare beneficiaries by instituting the Health Care Quality Improvement Initiative (HCQII). They stated that three objectives spearheaded HCQII: (i) change how clinicians review quality of care, (ii) focus primarily on trends in care, and (iii) help clinicians identify and solve problems.

This initiative stressed analysis of more nationally uniform criteria to examine patterns of care across a group of providers instead of localized individual case review. Also, the initiative completely revolutionized the traditional approach to quality improvement. Previously, quality improvement organizations (PROs, PSROs, etc.) reviewed individual medical charts in search of health care practices well beyond professional standards. These case-by-case reviews occurred retrospective to the care provided and thus could add little improvement to future episodes of care. However, the new approach sought a more proactive role by evaluating patterns of care between the observed and achievable outcomes in place of isolated, unusual patterns of care.

HCFA hoped the initiative would be more successful than the traditional approach in changing providers' practices. Jencks and Wilensky (5) cited evidence of effective strategies. They observed that exhortation and publishing consensus documents appeared to achieve little, changing payment policy was quite effective, face-to-face contacts with professionals and opinion leaders appeared to occupy a middle ground. However, in every case, change was more easily accepted when substantiated with specific information on outcomes patterns. It was anticipated that by displaying how well a group of practitioners
performed relative to the national or local trends in health care, practitioners would positively respond to any deficiencies in their provision of care. In other words, these models focused on improving the processes of providing typical care rather than using inspection to correct unusual errors (5).

The approach was believed to be more proactive in nature and one that might alter physicians' practices sooner rather than later. Furthermore, HCQII differed from the traditional one in another significant fashion. Traditionally, the federal government used the feedback from PSROs and later PROs, to chastise a physician whose care was deemed inappropriate. Under HCQII, the federal government commissioned the PROs to act as liaisons and foster more collaborative efforts with the providers. “The HCQII has a much stronger educational and collaborative emphasis than tradition case review, but HCFA will still be responsible for imposing sanctions if education fails” (5).

Shortly after HCFA announced the HCQII, it unveiled the Health Care Quality Improvement Program (HCQIP). Based upon the HCQII, HCQIP projects were designed as partnerships between the PROs and hospitals, health plans, or physicians in which the partners (i) agreed on an aspect of care that may need improvement and developed or adopted quality indicators, (ii) collected data and used the indicators to confirm the need for improvements, (iii) devised and carried out steps to bring about change, generally through improving the system of care, and (iii) used the indicators to measure success (6).

One HCQIP project called the Medicare Hospital Information Project was piloted by PROs from Connecticut and Wisconsin. The Connecticut PRO (CPR0) pilot project specifically partnered the Connecticut PRO with the Interhospital Study Committee (7).
The Interhospital Study Committee incorporated physicians, nurses, health care administrators, health services researchers, and medical records personnel from a host of health care organizations. The project evaluated 1989 to 1991 mortality data issued by HCFA’s claims data base. The Interhospital Study Committee allowed a limited chart abstraction to be developed to investigate acute myocardial infarction (7). Meehan et al. (7) reported substantial variations in the process of care among six hospitals in Connecticut randomly sampled across terciles of risk-adjusted mortality rates. This and similar studies provided valuable evidence to the feasibility of conducting HCQIP projects in collaboration with providers. Lastly, these results further exemplified the utility of outcomes data as an effective evaluative tool.

**Medicare Claims Data and Outcomes Based Research**

Is it feasible? Michele L. Robinson (8) reported that HCFA was committed to fostering research in this area. They cited former HCFA Administrator, William Roper, MD, who emphasized that there has been little scientific research to substantiate the effectiveness of any current medical practices. Although it was not HCFA’s intent to rate physicians based upon outcomes measures, the agency hoped that cooperative efforts with providers could raise the level of effectiveness of medical procedures. In other words, federal officials looked to HSR to utilize vast claims data base capabilities to resolve some of the unanswered questions on differing outcomes and practice patterns (8).

Using the pilot experience of the Medicare Hospital Information Project in Connecticut, Meehan et al. (7) concluded that Medicare claims data could be used by
PROs to initiate cooperative projects, to assess processes and outcomes of care, and to identify areas in which quality improvements were possible. The Medicare Hospital Information Project and several subsequent projects utilized the Medicare claims payment system, or the Medicare claims data base. The Medicare claims data base has provided a particularly rich source of information for the evaluation of medical care (9).

Medicare fee-for-service claims data bases collect information on all services provided to Medicare beneficiaries. This information is primarily provided in two forms: (i) hospital (inpatient) services which is referred to as Part A and (ii) physician (outpatient) services or Part B. Medicare Part A is an insurance plan which covers inpatient hospital procedures such as open heart bypass surgery. This part of Medicare is subsidized predominantly through payroll taxes. Americans who previously contributed to this fund are entitled to its benefits upon reaching 65 years of age; however, other qualifications exist. Medicare Part B is called supplemental medical insurance and covers outpatient procedures including physicians visits. Part B is subsidized mainly from premiums that are charged to participants. In order to receive Medicare Part B insurance, a person must have Medicare Part A and submit a monthly premium payment. Both forms of insurance plans generate claims data that have served as the cornerstone of numerous HSR projects.

Medicare’s analysis data base is a transformation of a bill payment stream that is typical of those found in most insurance companies (9). Each Medicare beneficiary is assigned a unique identification number, or HIC, and each provider, i.e., physician, hospital, skilled nursing facility, etc., is assigned a unique provider number. This coding system allows an investigator to build an episode of care by linking patient care to the
physicians or hospitals that provided that care. Nevertheless, the usefulness of the Medicare claims data for epidemiological, clinical, or health services research depends on administrative regulations governing data collection and the accuracy of the data abstraction process (9).

Mitchell (9) reported three main methodological issues that needed to be addressed in constructing episodes of care from claims data: (i) how to identify the index cases or patient cohorts to be studied; (ii) how to identify the length of the episode itself; and (iii) how to measure the outcome. A typical example identifies the index patients with a given ICD-9-CM diagnosis code (i.e., 410 for acute myocardial infarction). Once the index population is identified, a researcher uses exclusionary criteria to limit the number of patients or cases to be investigated. This step often results in producing a more homogeneous cohort with similar patient characteristics (i.e., aged 65 years or older, discharged alive, etc.). To define an episode of care, researchers must consider the length of time for a particular event to occur. For example, when health services researchers study mortality rates, they often utilize an exact duration (i.e., 30 days, 60 days, three months, etc.). The last step requires the investigator to measure patient outcomes. These outcomes often serve as an indicator of care provided. Outcomes measurements include patient mortality, patient readmission, or discharge destination (i.e., home, nursing home, another hospital, etc.).

In 1994, Mitchell (9) believed cohort studies based on data from Medicare claims data systems occupied a promising niche between randomized clinical trials (RCT) and clinical case studies. While generally regarding as producing the most conclusive body of
evidence, RCT have been long, expensive, and narrowly focused. Alternatively, Medicare
claims data bases are large, population-based and relatively inexpensive. Moreover, they
are generated continuously and afford the investigator to develop long-term episodes of
care. Therefore, these data bases, especially as reporting consistency improves, offer great
opportunities for studying health outcomes (9).

Is it effective and is there support? Studies confirm HSR, in its pursuit of medical
effectiveness via outcomes research, is an efficacious evaluative tool. Jencks (6) noted
that experience to date showed that PROs could develop indicators and data showing an
opportunity to improve medical practice. He added that selling the researcher/provider
partnership or involving hospitals in quality improvement partnerships was a marketing
challenge. However, by the mid-1990s, there was evidence of a driving force for quality
improvement. Jencks (6) also cited that one of the most important lessons from studies of
quality improvement was that clinical quality improvement probably saved hospital money.
“Various organizations, such as the Joint Commission on Accreditation of Healthcare
Organizations, and purchasers, such as HMOs and corporations, are beginning to demand
that hospitals demonstrate that they are quality improving organization” (6).

Benchmarking was a second ramification of health services research.
Benchmarking reported how a particular hospital compared to what was achievable by its
most successful competitor (6). This form of HSR not only served as a quality
improvement mechanism but also a performance measure. Performance measures were
instrumental in recruiting hospitals and other providers to partner with quality
improvement organizations. “A growing number of hospitals have not only reconciled
themselves to the public disclosure of comparative clinical data, but have eagerly sought to involve themselves with research projects... it is critically important for hospitals to recognize that we have a responsibility for public accountability, and that we accept that responsibility voluntarily” (10).

Variation in Health Care Resources, Expenditures, and Utilization

In order to address the objectives of health services research, researchers have conducted studies to collect and diffuse information pertaining to the delivery of care. A major component of these studies has included the investigation of variation in health care resources, expenditures, and utilization. Many health care experts believe that a better understanding of variation may improve cost containment and quality of care efforts.

The government has been a major player in the research of health services variation. Health Care Financing Administration (HCFA) (11), for example, has published 1996 statistics onto its Web site. Information on health care resources, expenditures, and utilization can be found at the Web site. The government has even made these data, in the form of text files, available to the public for research purposes.

The escalation in health care costs has provoked societal and governmental interest in the apparent geographic variation in the frequency of performance of medical procedures and therapies (12). Variation lies at the core of several private and public research ventures. As a show of concern, federal officials established The Agency for Health Care Policy and Research (AHCPR) to provide a national focal point on health care variations research and the development of clinical guidelines aimed at reducing
variation (2). Furthermore, pressures from large corporations to lower the cost of health care has precipitated significant changes in the structure of our health care delivery system and of health services research.

As early as 1973, Wennberg and Gittelsohn (13) reported the presence of wide dispersion in the rate with which similar populations in the New England states received tonsillectomies. In the 1980s, others reported the same type of variation for certain orthopedic procedures (14). Investigators have tried to explain the causes of variation with little progress. However, Katz et al. (12) believed variation suggested different practice styles across the country and uncertainty among physicians, patients, and the population at large about the appropriate indications for the procedures.

Although variation research has been steadily conducted since the early 1970s, few explanations are known. Studies report significant differences in utilization; yet, the medical community grapples with how to interpret their results. Many health care experts believe that a better understanding of variation may improve cost containment and quality of care efforts. At this time, the importance of variation research appears evident, while its efficacy remains inconclusive.

**Dr. John Wennberg’s Early Work**

In 1973, Wennberg and Gittelsohn (13) examined the extent to which bed and manpower use, expenditures, and utilization varied among hospital service areas in Vermont. Wennberg and colleagues discovered small area variation in the health care delivery system within the State of Vermont. The investigators identified three major
types of variation: (i) variation in the use of resources, (ii) variation in expenditures, and (iii) variation in utilization.

First, he investigated variation in resource use when he discovered that the number of beds per 10,000 persons ranged from 34 to 59, and the number of hospital personnel per 10,000 persons from 68 to 128. The variation showed that the density of internists and general surgeons were more than twice in some hospital service areas what it was in others (13). Another discrepancy was realized when Dr. Wennberg estimated per capita expenditures for hospital services in some areas were more than twice those in other areas. Thirdly, hospital discharge rates for all causes, adjusted for age composition, varied from a low of 122 to a high of 197 per 1000. These rates varied tremendously over the 13 hospital service areas. Tonsillectomies, which varied from a low of 13 to a high of 151 cases per 10,000, were the most striking example.

Joseph Califano, former Secretary of Health, Education, and Welfare, penned America’s Health Care Revolution: Who Lives? Who Dies? Who Pays? (15). In his book, Califano estimated the financial implications of the variation discovered by Wennberg. “Typical variation uncovered between the lowest and highest surgical rates, if projected nationally in 1984, would have amounted to a cost difference of about $16 billion - almost 10% of the nation’s hospital bill. Califano continued that Wennberg estimated that adoption of more conservative surgical and medical practice styles by doctors could have easily produced a 40% reduction in money spent for hospitalization alone - a savings of more than $60 billion in 1984, almost 20% of all personal health care expenditures.
Wennberg collaborated with Gittelsohn again on another poignant study of small area variation (16). The researchers cited a city in Maine where hysterectomies were performed so frequently that if the rate persisted, 70% of the women would have had the operation by age 75. However, in a city less than 20 miles away, the hysterectomy rate was so much lower that if the rate persisted, only 20% of the women would have had the operation. The colleagues found no significant difference in the general health of the two communities. Furthermore, the two communities were similar in economic status. Despite apparently similar communities, a sizable disparity existed in the hysterectomy rate. Wennberg and Gittelsohn (16) believed the differences in the number of physicians, the supply of hospital beds and coverage by medical insurance plans could not explain the variation; but rather, the style of medical practice of the physicians in the two cities. Some were biased toward hysterectomies, while others were not.

In that same article, the investigators discovered the amount spent per capita on all treatments in hospitals was also inconsistent. Wennberg and Gittelsohn (16) stated that in 1975, $324 was spent per capita in Boston, $225 in Providence, and $153 in New Haven. Assuming that the services that hospitals provided in those areas were similar, they investigated potential explanations for the variation. The study showed that the residents of some areas received much more medical treatment than others received and spent more on that care.

Wennberg dismissed that health differences in the communities accounted for the variation. Instead the researcher asked the question, "What is it that takes effect after the patient sees a physician to increase the patient’s chances of being hospitalized or of having
surgery or a diagnostic procedure?” (16). He later found that demographic and health characteristics did not differ much between the areas. But, the number of hospital beds and physicians in proportion to the population did vary widely. So, he concluded that the crucial factor appeared to be the system of medical care in the community. “The total rate of surgery and the likelihood of being admitted to a hospital for treatment thus depends on the supply of physicians and hospital beds in the area” (16).

A later study compared hospital services in the cities of Boston and New Haven. Wennberg and colleagues (17) reported that the populations of New Haven and Boston were demographically similar and received most of their hospital care in university hospitals, but in 1982 their expenditures per head for inpatient care were $451 and $889, respectively. When Wennberg applied the rates of New Haven residents to those of Boston, he found that Bostonians incurred about $300 million more in hospital expenditures and used 739 more beds. “These findings indicate that academic standards are compatible with widely varying patterns of practice and ... they also emphasize the need for increased attention to the outcome and cost implications of differences in practice style” (17).

Califano (15) further noted that Wennberg believed the variances revealed physician uncertainly about whether to perform numerous common operations, and the “intellectual confusion and chaos that sit at the root of much medical practice.” Similar to Wennberg’s beliefs, Califano quoted Harvard School of Public Health professor Benjamin A. Barnes when he said, “differences exist that do not in any way reflect differences
among residents of the communities investigated. In other words, he added, the differences have no “rational explanation.”

Early on, Wennberg understood the importance of this research as well as its limitations. He recognized the opportunity to assign professional standards review organizations (PSROs) broad responsibility for establishing the medical necessity of current health care patterns within their particular regions. Also, PSROs were the appropriate agencies to come to grips with the meaning of variation in population-based utilization rates among different medical care markets. Wennberg and Gittelsohn (13) remarked:

However, rational inquiry into the meaning of variation in probability of surgical removal of organs, diagnostic procedures, hospital admission case mix, and so forth, will often require formal testing of an hypothesis concerning the relations between health care and outcomes. This is a long-range proposition and requires a high level of organization and technical attainment, which will not be easily developed.

Wennberg realized the difficulties involved with variation research and the need for sophisticated evaluative tools. He saw population-based health information systems, because they could provide information on the performance of health care systems and regulatory agencies, as an important step in the development of rational public policy for health. “Population-based indicators of resource input, utilization, and mortality are particularly useful in identifying communities whose health care experience deviates from regional averages” (13). Dr. Wennberg’s seminal work constructed a framework for variation research, warned of its limitations, and provided insight to potential explanations. His work was well ahead of its time.
Further Studies

Chassin et al. (14) documented large geographic variations in the rates of use of many different medical and surgical services by Medicare beneficiaries during 1981. These differences were found across most physician procedures and across physician specialties. Chassin and his colleagues suggested that the degree of variation observed for a particular procedure was linked directly to the degree of medical consensus concerning the indications for its use. He outlined three possible explanations:

For any given procedure, geographic differences may reflect substantial inappropriate overuse in the high-use areas with very little inappropriate use in the low-use areas. On the other hand, the variation may have occurred because physicians in the low-use area were not providing enough services to those who needed them, whereas those in the high-use areas were meeting legitimate medical needs in an appropriate manner. A third possibility is that the rates of use of procedures were appropriate in both high-use and low-use areas and that the differences in rates resulted from differences in the incidence of disease. Finally, some combination of the three possibilities may have been responsible for our findings (14).

Chassin called for a concerted medical community effort to grapple with the thorny issues of how to define appropriateness in both the presence and absence of clinical studies. In other words, consensus on the appropriateness for how to treat, when to treat, for how long, when to discharge, and how to discharge were all topics that physicians must address to help explain intrahospital variation (14).

Similar to Chassin’s consensus theory, Keller et al. (18) believed that the degree to which the use of the hospitals varies tended to be characteristic of the
medical condition or the operative procedure that was being reviewed, and was related to the number of options for treatment that were available to the physician. For example, Keller and colleagues cited the use of colectomy, the treatment of choice for colon cancer, varied little per capita. However, the use of hysterectomy, which was one of several alternatives for non-cancerous conditions of the uterus, varied extensively. “Thus, there are some conditions for which a specific treatment is almost universally accepted as offering the best outcome, and there are others for which no method has been universally accepted as best for which rates of treatment vary widely among physicians” (18).

Leape et al. (19) refuted that variation in utilization rates could be explained by differences in the appropriateness of use. “Although many explanations for these difference have been proposed, the evidence supporting them is inconclusive and conflicting” (19). The researchers believed that many of the proposed explanations were based upon the untested assumption that high utilization rates translated into inappropriate use.

An important prospective study performed by O’Conner et al. (20) investigated the use of mortality rates as an indicator of the quality of medical care. The overall crude inhospital mortality rate for isolated coronary artery bypass graft (CABG) surgery was 4.3%. Variation existed among hospitals ranged from 3.1% to 6.3% and among surgeons from 1.9% to 9.2%. However, the researchers were aware of the concerns raised that observed differences in mortality rates by institutions were the result of confounding characteristics of patient case mix.
Interestingly, after adjusting for the effects of potentially confounding variables, significant variability was still observed among medical centers (p=0.021) and among surgeons (p=0.025).

Lu-Yao et al. (21) examined temporal trends and geographic variation in the use of radical prostatectomy (RP) in the U.S. The collaborators focused on short-term mortality and morbidity of the procedures as the major outcomes. The rates per 100,000 male Medicare beneficiary ranged from a low of 20.4 in Rhode Island to a high of 428.5 in Alaska. Lu-Yao et al. (21) reported marked variation among geographic regions persisted even after adjusting for secular trends, age, and race; moreover, the differences in rate grew over time. Based on the data, the incidence rate of prostate cancer increased by 24% between 1984 and 1988, which was considerably smaller than the 245% increase in the rate of RP. Once again, the investigators pointed to differences in treatment patterns to account for the almost sixfold increase from 1984 to 1990.

Guadagnoli et al. (22) investigated variation in the use of cardiac procedures after acute myocardial infarction. They studied Medicare patients admitted in two states with different rates of use of cardiac procedures - New York and Texas. In order to assess differences in patient case mix, the study design adjusted for patient characteristics. Coronary angioplasty was performed more often in Texas than New York (45% versus 30%, p<0.001). And over a two year period, the adjusted likelihood of death was lower in New York than Texas (hazard ratio, 0.87, 95% confidence interval, 0.78 to 0.98).
Another interstate comparison study used admission characteristics to predict short-term mortality from myocardial infarction in elderly patients. Normand et al. (23) noted the odds of mortality, after controlling for clinical status at admission, of a patient admitted to a hospital in Connecticut were 0.59 (95% confidence interval, 0.51-0.68) relative to a patient with an index admission to a hospital in Alabama. However, at that time, the investigators believed that while comparisons of mortality rates across hospitals were theoretically possible, such comparative results should be interpreted with the realization that much of the variability in mortality rates cannot be explained by current risk-adjusted mortality models. Thus a major limitation was how much of the remaining variation was related to systematic differences in unmeasured patient characteristics, to quality of care, and to chance.

The Federal Government as a Major Stakeholder

After the Medicare and Medicaid programs were established, the federal government became a major contributor to the cost of health care. From 1967 to 1996, there has been a 95% increase in persons enrolled for Medicare coverage (19.5 million to 38.1 million) (11). The Health Care Financing Administration (HCFA), the agency responsible to manage federal health care programs, reported that nearly 62 million persons were projected to receive services paid by Medicare or Medicaid in fiscal year 1996 (11).
America spent 13.6% of its Gross Domestic Product (GDP), or almost one-seventh of all output of the United States, on health care in 1996 (24). That amount reached the unprecedented figure of $1.035 trillion. Of that $1.035 trillion, almost 88% go to purchase personal health care and supplies (24).

In 1996, the nation’s health care bill was financed accordingly: 32 cents by private insurance companies, 20 cents by Medicare, 17 cents by individuals (out-of-pocket), 14 cents by Medicaid, 13 cents by other government programs, and 4 cents by other private funds (See Appendix A). A recent trend showed that the federal government was financing an increasing amount of our health care costs. In 1990, public sources financed 40.7% of health care costs; in while 1996 that figure had risen to 46.7% (24). However, average annual growth in private-sector spending decelerated markedly between 1989 and 1996 to 5.8%, from the 12% average annual growth seen during 1975-1989 (24) Thus, the private sector has been more successful than the public in containing the grow of health care.

Of the roughly $900 billion spent on personal health care services and supplies in 1996, 35 cents on the dollar went to hospital care, 26 cents to other personal health care, 19 cents to physician services, 12 cents to other spending, and 8 cents on nursing home care (See Appendix B). Although the rate of growth has been waning, hospital care expenditures remained the single largest spending component, accounting for $358.5 billion.

The Medicare program is the largest public payer for health care, financing approximately $203.1 billion in 1996. A recent report (11) concluded that of the 62
million persons projected to utilize health care services in 1996, one out of five, or more than 11.7 million persons would have used inpatient hospital services covered by Medicare or Medicaid. Aggregate Medicare spending grew 4.9% faster than private health insurance spending in 1996 (8.1% compared with 3.2%).

Cardiovascular Disease

Cardiovascular disease has predominantly affected older segments of our population. The American Heart Association (25) cited that in 1995, 5,885,000 Americans were discharged from short-stay hospitals with a first listed diagnosis of cardiovascular disease. Of these, 65% were age 65 years and older. In other words, most of these individuals were Medicare beneficiaries.

The Morbidity and Mortality Weekly Report (MMWR) cited (26) ischemic heart disease (IHD) was the leading cause of death in the United States. Of all chronic diseases, IHD contributed most to our health care burden. MMWR (26) further reported that beginning in 1985, acute myocardial infarction (AMI) replaced chronic IHD as the most common primary diagnosis among persons hospitalized for IHD. The Agency for Health Care Policy and Research conducted a federal-state research partnership, called the Healthcare Cost and Utilization Project (HCUP-3), to assemble health care data for use in HSR (27). The project found that AMI was the fifth leading diagnosis at discharge behind such diagnoses as pneumonia and childbirth. Direct costs of cardiovascular disease in 1998 have been estimated at $119 billion (27).
Acute myocardial infarction is a leading cause of hospitalization in the United States. Hospitalizations account for more than one-third of the approximately $1 trillion spent on health care in 1996. Moreover, the federal government remains one of the major contributors to health care costs, financing nearly 50 cents of every health care dollar. Therefore, research investigating Medicare rehospitalizations following AMIs would appear to be of great interest to providers, payers, and policy-makers of health care. It is believed that a better understanding of variation in AMI readmissions may improve cost containment and quality of care efforts.

An extensive literature review revealed a number of prior studies (28, 29,30) have investigated the association between AMI (and related cardiac procedures) and mortality rates. Some (31,32,33) have investigated associations readmission rates and congestive heart failure (CHF); while, others studied the impact of early discharge after CABG surgery and hospital readmission. However, only a handful of studies appeared to investigate readmission rates and AMI (34). In fact, Maynard et al. (34) reported, “it is remarkable that the scientific literature contains such little information about rehospitalization of patients with AMI.”
Methods and Measures

Methods

Study Design

The study utilized Medicare claims data from a six-month period in 1997; and thus it was retrospective in the sense that data had been collected prior to the start of the research. Whereas the patient- and hospital-level characteristics (patient demographics, total bed count, etc.) were identified prior to the start of the 30-day study period, the occurrence of patient readmission was analyzed throughout the 30-day period. These study characteristics defined a retrospective cohort study.

Data Sources

Two main sources of data were used. First, all patient level data was abstracted from the Medicare claims data base. HCFA maintains this data base and periodically downloads these administrative files to the PROs. With technical assistance from CPRO personnel, six months of Part A Medicare claims data was downloaded. HCFA eligibility data was also utilized. These data bases provided the patient level information.

A second source of data was the 1996 American Hospital Association Annual Survey. This survey has been conducted since 1946 and is widely regarded as the most authoritative and comprehensive source of individual hospital data available (35). The AHA data was used to define the hospital characteristics.
Cohort Definition

The patient population was comprised of Medicare beneficiaries who had been discharged to one of the seven selected Connecticut hospitals. The patient characteristics were defined based upon three primary inclusion criteria.

First, the patient had to be at least 65 years or older. Second, all patients had to have a primary diagnosis upon discharge of AMI, ICD-9-CM 410.xx (See Appendix C). Third, each patient had to have been discharged within a six-month period ranging from May 1, 1997, to October 31, 1997. The format of the Medicare claims data base was such as to limit the claims information to fee-for-service claims; and thus it did not include any HMO or risk contract claims.

Two exclusion criteria further defined the patient cohort. First, to ensure that each patient was discharged alive, we excluded all subjects who died within their initial hospital admission. Secondly, we excluded all subjects who were discharged to other short-term hospitals or transferred during their index admission. Transfers were eliminated in an attempt to accurately link a patient to the hospital that provided the majority of their care. After all these criteria were applied, the resulting sample was referred to as the index cohort.

Hospitals were identified using the following characteristics: large, urban, and teaching. Seven acute care hospitals, where length of stays (LOS) were usually less than 90 days, operating within the State of Connecticut were chosen. To ensure that these
hospitals served comparable patient populations, we carefully selected hospitals based upon the following characteristics.

First, each hospital had to be a large facility capable of serving a sizable patient population (total bed count greater than 390 beds). A large patient population potentially included a diverse patient base. The second criterion was that the hospital served an urban population. These seven hospitals were all located in urban areas. This was done in an attempt to induce comparable populations with similar demographic characteristics. A third criterion required that each hospital participated in graduate medical education.

These institutions were usually similar in their organizational structure. All hospitals provided general medical and surgical services to the majority of their patients. In all cases, the type of authority responsible for establishing policy concerning overall hospital operation was not-for-profit. Additionally, we attempted to select hospitals with full invasive cardiovascular capabilities. Six of the seven hospitals provided the following cardiac care: cardiac catheterization, percutaneous transluminal coronary angioplasty (PTCA), and coronary artery bypass graft surgery (CABG).

Outcome Determination

Once the index cohort was defined, the readmission cohort could be created. To do this, we devised a computer program that identified all the patients within the index cohort by their Medicare identification code or HIC number. The Medicare claims data included the total number of admissions and discharges for each patient. In other words,
this data base captured the entire claims history for each patient’s hospitalization(s). This allowed us to devise a program which calculated the time or number of days between a patient’s discharge and a subsequent admission. We referred to the number of days between the date of discharge and the date of a later admission as the days prior to a readmission.

Our computer program then subtracted the subsequent admission date from the prior discharge date and created a variable that quantified this difference. We identified our readmission cohort to include all patients with a subsequent admission (referred to as readmission) within 30 days of their prior discharge. In other words, the readmission cohort included all patients where the newly created variable equaled less than 30. Since the computer program was designed to recognize a patient’s first readmission, multiple readmissions were not recorded. Also, our computer program identified patients’ deaths that occurred during the 30 days following an AMI discharge.

Measures

Outcome Variable

The outcome measure or dependent variable was readmission rates within 30 days of discharge after a primary diagnosis of AMI. It was important to note that all causes of readmission were considered and that rehospitalization could be to any acute-care hospital in the State of Connecticut.
Unadjusted or raw readmission rates were first calculated to identify the degree of variation. To do this, the number of patients from the readmission cohort was divided by the total number of patients at risk for readmission (index cohort). A rate was developed for each of the seven hospitals.

*Explanatory Variables*

Key explanatory or independent patient-level variables obtained from the Medicare claims and eligibility data bases were age, gender, race, length of stay, and discharge destination. Procedures employed during the index hospitalization were also obtained and included cardiac catheterization, PTCA, and CABG (See Appendix C). We used the Charlson comorbidity index (36) as modified by Deyo for use with ICD-9-CM codes (37) in order to control for comorbidities. Krumholz et al. (33) cited that comorbidity, which was summarized using the Deyo comorbidity index, has been shown to correlate with outcomes.

Independent hospital level variables obtained from the American Hospital Association Survey data were medical and nurse staffing ratios. The medical staffing ratio was calculated using the full time equivalents (FTEs) of physician, dentist, and resident provided by the AHA Survey data. The FTEs of physicians, dentists, and residents were summed and then divided by the total number of beds to obtain ratios for each hospital. Similarly, nurse staffing ratios were constructed by summing the total registered nurse (RN) and licensed practicing nurse (LPN) FTEs and dividing by total number of beds per
hospital. The total number of beds in each hospital was provided by CPRO. And lastly, the volume of confirmed AMIs for each of the seven hospitals was extrapolated from previous findings of the Cooperative Cardiovascular Project (38).

Statistical Analyses

We used descriptive statistics to display the patient and hospital characteristics and the 30-day readmission rates.

To investigate the association between patient and hospital characteristics and the outcome of interest, we developed multivariate regression models. These models utilized the Cox regression method. Standard logistic regression is particularly applicable when the dependent variable for the experimental subject contains information only on whether or not a response occurred (39). The Cox regression model utilizes a hazard function to explore the analysis of time to a particular response. In the case of this study, we were counting the number of days until a patient was readmitted to the hospital.

For a clearer understanding of how the Cox method works, let's image three different possibilities that affect the readmission rates. First, a situation where a patient is discharged and neither dies nor is readmitted within 30 days. In this example, the patient remains only a member of the index cohort and contributes to the denominator of the readmission rate. A second situation exists where a patient is readmitted, say for example, 15 days after being discharged. In this example, we observe the outcome of interest (readmission) and the patient becomes a member of the readmission cohort, contributing
to the numerator of the rate. A third situation, which exemplifies the reason for the Cox method, exists where a patient is discharged and dies at home say for example, on the 18th day. The conventional logistic model would have observed this patient as not being readmitted to the hospital and this patient would have contributed 30 days of risk for readmission to the denominator (index cohort). However, because the Cox method contains a time dimension, it would have observed that this patient contributed 18, not 30, days of risk for readmission prior to death. Therefore, the Cox method serves as a correction factor to ensure a more accurate readmission rate calculation.

Four Cox models were run. First, using the patient characteristics, the Cox model attempted to predict readmission from AMI in the Medicare population. Second, using hospital characteristics, the modeling attempted to predict readmission following an AMI. Third, similar to the first two models, using patient- and hospital-level characteristics, Cox modeling attempted to predict readmission after an AMI. The last model investigated the adjusted relative rates of readmission among the seven hospitals. To do this, the hospital with the lowest unadjusted readmission rate was defined as the reference hospital. The remaining six hospital readmission rates were then compared to the reference rate, after adjusting for patient-level characteristics.
Results

Patient Characteristics

Descriptive statistics were used to display the patient-level variables by hospital cohort (Table 1). These baseline characteristics were derived from the entire index cohort of the seven selected hospitals.

Mean age did not appear to vary considerably. Hospital C had the highest mean patient age of 78.47 and Hospital E had the lowest mean age of 75.29. The standard deviations of the means or the spread of the data were consistently around 7.0. This indicated that mean age was similar for all seven hospitals.

Table 1 displayed other demographic data including gender and race. Both patient characteristics appeared proportionately equivalent. The percentage of women in each of the patient populations was approximately 50%, Hospital B had a high of 53.69% and Hospital E had a low of 45.62%. Race also appeared similar among the seven hospitals as each institution was at least 90% white.

Comorbidity or illness severity was an important variable to consider. An adaptation of the Charlson score, specific for ICD-9-CM codes, called the Deyo index was utilized. The Deyo index assigned a score to each patient to account for previous hospitalizations and diagnoses. The scale ranged from 0 to 12. A score of 0 represented a relatively less severe case mix and a score of 12 the worst. A host of previous studies dichotomized the Deyo scores as greater or less than 1. With this said, the percentage of Deyo scores greater than 1 among the seven hospitals was consistent. Hospital G had a high of 38.17% and Hospital D had a low of 33.63.
Length of stay (LOS) was also calculated for patient discharged from each hospital. Mean LOS ranged from approximately 6 to 10 days. With the exception of one hospital, the values were tightly spread around the mean standard deviation, which were approximately 5.

Discharge destination was considered as a potential risk factor for readmission. Upon discharge, patients were usually sent to a nursing home, a skilled nursing facility, other health care facilities, or home with self-care. The percentage of patients sent home without health care services varied, ranging from 87.56% to 40.63%.

The patient-level characteristics of the study population appeared homogeneous, and should thus diminish variation in patient characteristics. Most importantly, the severity of illness indicator, Deyo index, suggested that the seven hospitals had a comparable case mix.

**Hospital Characteristics**

As with the patient characteristics, the seven hospitals were selected to be comparable. To ensure comparability, all selected hospitals were not-for-profit and performed medical and surgical services to a majority of their patients. The seven hospitals were affiliated with medical schools and deemed Medicare certified by HCFA. For reasons of confidentiality, some hospital characteristics have been omitted from discussion in this document.

The total bed counts ranged from a high of 819 to a low of 391. Whereas most hospital characteristics were gleaned from 1996 AHA Annual Survey data files, the total bed count were provided by CPRO.
Hospital staff was another variable of interest. To quantify a hospital’s personnel, full-time equivalents (FTEs) were utilized. FTEs were listed for physicians, dentists, registered nurses (RNs), licensed practicing nurses (LPNs), and residents. Medical staffing ratios were calculated by summing the physician, dentist, and resident FTEs and dividing by total bed count. Similarly, nurse-staffing ratios were calculated summing RN and LPN FTEs by total bed count. These ratios varied across the seven hospitals, ranging from 1.0 to 1.8.

30-Day Readmission Rates

We calculated unadjusted 30-day readmission rates for each hospital cohort (Table 2). We computed these crude rates by dividing the number of patients readmitted within 30 days by the total of number of patients at risk for readmission following a primary diagnosis of AMI. The total number of patients readmitted within 30 days for all seven hospitals was 150. The index population comprised of 1060 patients. Therefore, the average crude 30-day readmission rate was 14.15. The unadjusted readmission rates ranged from 8.99 to 21.88. Figure 1 displayed the variation in the 30-day readmission rates among the seven selected hospitals. In light of other research, a crude average 30-day readmission rate of 14.15 was reasonable.

Multivariate Analyses

Multivariate regression models allowed us to examine the effects of covariates and to identify those that may have contributed to the observed variation in readmission rates. Four models were constructed using Cox proportional hazards.
We constructed the first model to identify possible patient-level characteristics that might contribute to an increased risk for readmission (Table 3). Ten covariates were placed into the model. Age was categorized into three groups: 65-74, 75-84, and 85+. Sex was categorized into men or female; and race categorized into white and non-white.

Discharge destination, the Deyo index, and length of stay were entered into the models to account for comorbidity factors. Discharge destination was categorized into discharged to home without health care services or discharged to a facility other than home. The Deyo index covariate was dichotomized as greater or less than 1. For length of stay, the covariate was dichotomized as greater or less than 12 days.

While not significant, age, race, and discharge destination were associated with a decreased likelihood to be readmitted. Also, while not significant, sex, LOS, the Deyo index, and cardiac catheterization were associated with an increased risk for readmission. Two covariates, PTCA and CABG, were significant.

We found PTCA and CABG, performed during the index admission, significantly lowered the likelihood for subsequent readmission. AMI patients, who underwent a PTCA, were 50% less likely to be readmitted within 30 days of discharge. While, those who underwent CABG surgery were 54% less likely to be readmitted.

A second model was constructed to identify potential hospital-level characteristics that might contribute to the risk for readmission (Table 4). We placed four variables into the model: total bed count, volume of confirmed AMIs, and medical and nurse staffing ratios.

Total bed count was categorized into greater and less than 617 beds. The volume of confirmed AMIs was dichotomized as greater or less than 315. The medical staffing
ratio was categorized into greater or less than 0.34. While, the nurse staffing ratio was
dichotomized as greater or less than 1.35.

Results from Table 4 displayed that the volume of AMIs, while not significant,
decreased a patient’s risk for readmission. However, while also not significant, both the
medical and nurse staffing ratios were associated with an increased risk for readmission.
One hospital covariate did significantly predict readmission. The study found that
patients discharged from hospitals with total bed counts greater than 617 were 48% less
likely to be readmitted.

A third model combined the patient- and hospital-level variables into one model.
This model attempted to identify predictors of readmission after adjusting for all
variables simultaneously (Table 5). Similar to the two previous models, the same three
variables, PTCA, CABG, and total bed count significantly lowered a patient’s risk for
readmission. However, the risk ratios generated by this model were slightly higher than
those generated in models 1 and 2 for these three covariates. In other words, after
adjusting for patient- and hospital characteristics, three covariates were associated with a
decreased likelihood for readmission.

The last model placed six hospitals in comparison to a reference hospital after
adjusting for the patient-level variables (Table 6). The reference hospital had a crude 30-
day readmission rate of 8.99. This model calculated adjusted relative rates of
readmission. Or, after adjusting for patient variables, how the six other hospitals
compared to the hospital with the best crude readmission rate.

In our study, when readmission rates were examined at the hospital level,
substantial variation was found between the reference hospital and three other hospitals.
Figure 2 graphically displayed the variation that still remained after adjusting for patient cohort variables. We found that Medicare beneficiaries who were discharged from Hospital A for AMI had a 95% greater chance of being readmitted within 30-days than those discharged from Hospital F (reference). When compared to patients discharged from the reference hospital, patients discharged from Hospital G had a 91% greater chance of being readmitted for any reason within 30-days. Lastly, the greatest difference in relative risk for readmission between hospitals existed between hospital D and F. If a Medicare beneficiary was discharged from Hospital D with a primary diagnosis of AMI, they would be at a 140% greater risk for readmission than a beneficiary released from Hospital F.
### Table 1. Characteristics of the Sample Study

<table>
<thead>
<tr>
<th>Characteristics</th>
<th>A (SD)</th>
<th>B (SD)</th>
<th>C (SD)</th>
<th>D (SD)</th>
<th>E (SD)</th>
<th>F (SD)</th>
<th>G (SD)</th>
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<tbody>
<tr>
<td>Mean Age, years (SD)</td>
<td>76.99 (6.98)</td>
<td>76.21 (6.87)</td>
<td>76.47 (7.39)</td>
<td>76.91 (7.02)</td>
<td>75.29 (7.21)</td>
<td>76.34 (7.12)</td>
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<td>Sex, No. (%)</td>
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</tr>
<tr>
<td>Female</td>
<td>57 (47.90)</td>
<td>109 (53.69)</td>
<td>16 (50.00)</td>
<td>61 (53.51)</td>
<td>99 (45.62)</td>
<td>92 (48.68)</td>
<td>94 (50.54)</td>
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<td>Race, No. (%)</td>
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<tr>
<td>White</td>
<td>115 (96.64)</td>
<td>194 (95.57)</td>
<td>31 (96.88)</td>
<td>104 (91.23)</td>
<td>195 (90.28)</td>
<td>178 (93.62)</td>
<td>169 (90.86)</td>
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<td>&gt;1</td>
<td>45 (38.14)</td>
<td>73 (35.96)</td>
<td>11 (34.38)</td>
<td>38 (33.63)</td>
<td>77 (36.84)</td>
<td>69 (36.51)</td>
<td>71 (38.17)</td>
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<td>Mean LOS, days (SD)</td>
<td>10.07 (17.06)</td>
<td>8.54 (5.29)</td>
<td>6.38 (5.28)</td>
<td>6.07 (5.04)</td>
<td>7.63 (5.88)</td>
<td>7.63 (5.07)</td>
<td>7.68 (4.90)</td>
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<td>Discharge Destination, No. (%)</td>
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<tr>
<td>Home without health services</td>
<td>52 (43.70)</td>
<td>118 (58.13)</td>
<td>13 (40.63)</td>
<td>74 (64.19)</td>
<td>190 (87.56)</td>
<td>118 (62.43)</td>
<td>101 (54.30)</td>
</tr>
</tbody>
</table>

All data were retrieved from Medicare Part A claims data base in cooperation with CPRO

(SD) = Standard Deviation
<table>
<thead>
<tr>
<th>Hospital</th>
<th>Patients discharged with AMI</th>
<th>Those Readmitted</th>
<th>Those Not Readmitted</th>
<th>Readmission Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>119</td>
<td>20</td>
<td>99</td>
<td>16.81</td>
</tr>
<tr>
<td>B</td>
<td>203</td>
<td>27</td>
<td>176</td>
<td>13.3</td>
</tr>
<tr>
<td>C</td>
<td>32</td>
<td>7</td>
<td>25</td>
<td>21.88</td>
</tr>
<tr>
<td>D</td>
<td>114</td>
<td>23</td>
<td>91</td>
<td>20.18</td>
</tr>
<tr>
<td>E</td>
<td>217</td>
<td>23</td>
<td>194</td>
<td>10.6</td>
</tr>
<tr>
<td>F</td>
<td>189</td>
<td>17</td>
<td>172</td>
<td>8.99</td>
</tr>
<tr>
<td>G</td>
<td>186</td>
<td>33</td>
<td>153</td>
<td>17.74</td>
</tr>
<tr>
<td>Totals</td>
<td>1060</td>
<td>150</td>
<td>910</td>
<td>Ave. Rate 14.15</td>
</tr>
</tbody>
</table>
Table 3. Patient-level Predictors of Readmission within 30 Days of Discharge

<table>
<thead>
<tr>
<th>Variable</th>
<th>Risk Ratio</th>
<th>95% Confidence Interval (CI)</th>
<th>p value, (* significance at &lt; 0.05)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age, years</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>75-84</td>
<td>0.89</td>
<td>0.62 - 1.27</td>
<td>0.52</td>
</tr>
<tr>
<td>85+</td>
<td>0.84</td>
<td>0.51 - 1.41</td>
<td>0.51</td>
</tr>
<tr>
<td>Sex</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>1.19</td>
<td>0.86 - 1.66</td>
<td>0.30</td>
</tr>
<tr>
<td>Race</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>White</td>
<td>0.90</td>
<td>0.52 - 1.58</td>
<td>0.72</td>
</tr>
<tr>
<td>LOS, days</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>&gt;12</td>
<td>1.39</td>
<td>0.88 - 2.20</td>
<td>0.16</td>
</tr>
<tr>
<td>Discharge Destination</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Home</td>
<td>0.91</td>
<td>0.63 - 1.31</td>
<td>0.60</td>
</tr>
<tr>
<td>Deyo Index</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>&gt; 1</td>
<td>1.03</td>
<td>0.94 - 1.13</td>
<td>0.50</td>
</tr>
<tr>
<td>Cardiac Procedures</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CABG</td>
<td>0.54</td>
<td>0.33 - 0.91</td>
<td>* 0.02</td>
</tr>
<tr>
<td>PTCA</td>
<td>0.50</td>
<td>0.34 - 0.76</td>
<td>* &lt; 0.000</td>
</tr>
<tr>
<td>Catheterization</td>
<td>1.02</td>
<td>0.70 - 1.47</td>
<td>0.93</td>
</tr>
</tbody>
</table>
Table 4. Hospital-level Predictors of Readmission within 30 Days of Discharge

<table>
<thead>
<tr>
<th>Variable</th>
<th>Risk Ratio</th>
<th>95% Confidence Interval (CI)</th>
<th>p value, (* significance at &lt; 0.05)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Beds</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>&gt;617</td>
<td>0.48</td>
<td>0.29 - 0.81</td>
<td>* 0.006</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Volume of AMIs</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>&gt;315</td>
<td>0.89</td>
<td>0.57 - 1.38</td>
<td>0.59</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Medical Staffing Ratio</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>&gt;0.34</td>
<td>1.22</td>
<td>0.73 - 2.03</td>
<td>0.45</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Nurse Staffing Ratio</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>&gt;1.35</td>
<td>1.01</td>
<td>0.60 - 1.70</td>
<td>0.99</td>
</tr>
</tbody>
</table>
Table 6. Using and Patient- and Hospital-level Variables to Predict Readmission within 30 Days of AMI Discharge

<table>
<thead>
<tr>
<th>Variable</th>
<th>Risk Ratio</th>
<th>95% Confidence Interval (CI)</th>
<th>p value, (*significance at &lt; 0.05)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Patient-level</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age, years</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>75–84</td>
<td>0.88</td>
<td>0.82 - 1.26</td>
<td>0.49</td>
</tr>
<tr>
<td>85+</td>
<td>0.87</td>
<td>0.52 - 1.45</td>
<td>0.59</td>
</tr>
<tr>
<td>Sex</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>1.19</td>
<td>0.86 - 1.67</td>
<td>0.30</td>
</tr>
<tr>
<td>Race</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>White</td>
<td>0.85</td>
<td>0.48 - 1.50</td>
<td>0.57</td>
</tr>
<tr>
<td>LOS, days</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>&gt;12</td>
<td>1.40</td>
<td>0.88 - 2.21</td>
<td>0.16</td>
</tr>
<tr>
<td><strong>Discharge Destination</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Home</td>
<td>0.97</td>
<td>0.67 - 1.42</td>
<td>0.89</td>
</tr>
<tr>
<td><strong>Deyo Index</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>1.04</td>
<td>0.94 - 1.14</td>
<td>0.48</td>
</tr>
<tr>
<td><strong>Cardiac Procedures</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>CABG</td>
<td>0.58</td>
<td>0.34 - 0.98</td>
<td>* 0.04</td>
</tr>
<tr>
<td>PTCA</td>
<td>0.53</td>
<td>0.35 - 0.79</td>
<td>* 0.002</td>
</tr>
<tr>
<td>Catheterization</td>
<td>1.05</td>
<td>0.72 - 1.52</td>
<td>0.81</td>
</tr>
<tr>
<td><strong>Hospital-level</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total Beds</td>
<td>0.57</td>
<td>0.34 - 0.97</td>
<td>* 0.04</td>
</tr>
<tr>
<td>Volume of AMIs</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>&gt;515</td>
<td>0.96</td>
<td>0.62 - 1.51</td>
<td>0.87</td>
</tr>
<tr>
<td>Medical Staffing Ratio</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>&gt;0.34</td>
<td>1.2</td>
<td>0.73 - 1.99</td>
<td>0.48</td>
</tr>
<tr>
<td>Nurse Staffing Ratio</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>&gt;1.35</td>
<td>1.02</td>
<td>0.59 - 1.74</td>
<td>0.95</td>
</tr>
</tbody>
</table>
Table 6. Adjusted Relative Rate of Readmission after Index Admission, According to Hospital Cohort

<table>
<thead>
<tr>
<th>Hospital</th>
<th>Relative Rate</th>
<th>95% Confidence Interval (CI)</th>
<th>p value, ((^* \text{significance at &lt; 0.05}))</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>1.95</td>
<td>1.02 - 3.75</td>
<td>(^* 0.0445)</td>
</tr>
<tr>
<td>B</td>
<td>1.49</td>
<td>0.81 - 2.76</td>
<td>0.20</td>
</tr>
<tr>
<td>C</td>
<td>1.98</td>
<td>0.80 - 4.88</td>
<td>0.14</td>
</tr>
<tr>
<td>D</td>
<td>2.40</td>
<td>1.27 - 4.54</td>
<td>(^* 0.0073)</td>
</tr>
<tr>
<td>E</td>
<td>1.33</td>
<td>0.70 - 2.52</td>
<td>0.38</td>
</tr>
<tr>
<td>F</td>
<td>1.00</td>
<td>Reference</td>
<td></td>
</tr>
<tr>
<td>G</td>
<td>1.91</td>
<td>1.06 - 3.44</td>
<td>(^* 0.032)</td>
</tr>
</tbody>
</table>

\(^* \text{Analyses of relative readmission rates were adjusted by patient characteristics}\)
Figure 1. Unadjusted 30-Day Readmission Rates by Hospital

Readmission Rates

<table>
<thead>
<tr>
<th>Hospitals</th>
<th>Rates</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hospital A</td>
<td>16.84</td>
</tr>
<tr>
<td>Hospital B</td>
<td>12.90</td>
</tr>
<tr>
<td>Hospital C</td>
<td>24.66</td>
</tr>
<tr>
<td>Hospital D</td>
<td>20.42</td>
</tr>
<tr>
<td>Hospital E</td>
<td>10.80</td>
</tr>
<tr>
<td>Hospital F</td>
<td>2.00</td>
</tr>
<tr>
<td>Hospital G</td>
<td>17.74</td>
</tr>
</tbody>
</table>
Figure 2. Adjusted Relative Rates of Readmission, According to Hospital Cohort

<table>
<thead>
<tr>
<th>Hospital</th>
<th>Relative Rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hospital A</td>
<td>1.95</td>
</tr>
<tr>
<td>Hospital B</td>
<td>1.48</td>
</tr>
<tr>
<td>Hospital C</td>
<td>1.98</td>
</tr>
<tr>
<td>Hospital D</td>
<td>*2.16</td>
</tr>
<tr>
<td>Hospital E</td>
<td>1.92</td>
</tr>
<tr>
<td>Hospital F</td>
<td>1.66</td>
</tr>
<tr>
<td>Hospital G</td>
<td>*1.04</td>
</tr>
</tbody>
</table>

* denotes significance at p < 0.05
Conclusion

Previous research has shown evidence that evaluating outcomes of care (i.e., mortality and readmission rates) for AMI can be useful as a quality-of-care screening tool. A study, which investigated the process and outcome of care for AMI among Medicare beneficiaries in Connecticut, concluded it was feasible to link claims-based pattern analysis with medical record review in the assessment of quality of hospital care (40).

Our research identified patient- and hospital-level characteristics that were significantly associated with risk for readmission. After adjusting for patient-level characteristics, this study found significant interhospital variation in 30-day readmission rates between the seven Connecticut hospitals.

The study identified ten patient-level characteristics in an attempt to explore the cause(s) of the observed variation in readmission rates. These characteristics included age, sex, and race. Many studies (30, 32, 33, 34, 41) have identified these demographic variables as potential predictors of readmission. The Deyo index was utilized to account for potential case mix difference that may have existed between the index cohorts of the selected hospitals. The literature was replete with studies emphasizing the necessity to develop a severity of illness indicators. For example, Krumholz et al. (33) found that a Deyo score greater than 1 was associated with an increased risk for readmission.

Discharge destination was particular chosen because previous studies have found an association between where a patient was sent after discharge and their overall health outcome. Camberg et al. (42) cited that patients with dementia who were discharged to
nursing homes were less likely to be readmitted within 30 days of discharge than patients discharged to their homes.

Length of stay was investigated because previous research had implicated its potential association with patient readmission. Two studies spoke to the effect of LOS (32, 33) on readmission. Both studies found that longer postoperative LOS, in excess of 7 days, were associated with adverse outcomes.

Cardiac care was also implicated to have been associated with patient readmission. Maynard et al. (34) found that PTCA and CABG, performed during the index admission, were associated with a lower likelihood of rehospitalization.

Previous research has found patient readmission to be associated with demographic characteristics such as age, sex, and race. However, in this study, none of these variables were significantly associated with readmission. Although, in the past, comorbidity has been significantly associated with readmission, this study’s comorbidity indicators, the Deyo index, LOS, and discharge destination, was not significantly associated with readmission.

However, our findings did indicate a significant association between cardiac care and patient readmission. Our analyses were consistent with Maynard et al. (34). We found that PTCA and CABG, performed during the index admission, significantly lowered the risk for readmission.

Our study also identified four hospital-level characteristics in an attempt to explore the cause(s) of the observed variation in readmission rates. These characteristics included total bed count, volume of confirmed AMIs, and medical and nurse staffing ratios. Other
studies have looked to hospital volume variables to predict an outcome of interest (28). Piette and Moos (43) cited that in recent years, researchers have examined hospital characteristics such as size and academic affiliation.

This study found one of the hospital characteristics to be associated with risk for readmission. Total bed count correlated with a decreased risk for readmission. The three remaining characteristics did not significantly predicted patient readmission.

Other studies have also investigated interhospital variation in readmission rates. One study by Fisher et al. (31) attempted to define the differences in hospital readmission rates for cohorts of Medicare beneficiaries in Boston and New Haven. The researchers found that beneficiaries who were hospitalized in Boston had a 64% higher average readmission rate over a three year period than beneficiaries in New Haven for certain health conditions, including AMI.

Consistent with previous research, our study found interhospital variation in 30-day readmission rates between seven Connecticut hospitals. Six hospitals were compared to the hospital with the lowest unadjusted readmission rate (reference). After adjusting for patient-level characteristics, variation in readmission rates remained. Three of the hospitals were significantly associated with an increased risk for readmission. In other words, a patient discharged from one of those three hospitals was at an increased risk for readmission within 30 days. It can also be said that if that patient had been discharged from the reference hospital, then s/he would have significantly decreased their risk for readmission.
Despite finding few associations between patient- and hospital-level covariates and readmission, our study looked to further contribute to the body of knowledge in this area of research. First, this study utilized the Cox method for multivariate analyses. This type of regression was not executed in a majority of the previously cited research. The Cox method should be the model of choice whenever there is a time component associated with the dependent variable and where subjects may be lost during follow-up. Second, this research investigated the predictive value of new variables for risk of readmission, such as discharge destination, hospital volume of AMI, and medical and nurse staffing ratios. Thirdly, this research revealed variation in Medicare readmission rates among seven Connecticut hospitals. Thus, this study found that it was plausible to use Medicare claims data to compare interhospital variation in 30-day readmission rates.

Two major limitations of this study were encountered. Due to the relatively small sample size, the study may have lacked the power to observe significant associations, had they existed. Sample size analyses should be used in the future to ensure sufficient power. Secondly, the outcomes measure, readmission, has been shown to explain only a limited amount of variability. It appears that much of the observed variation in 30-day readmission rates remains unexplained. Krumholz et al. (33) used a similar model to predict readmission after hospitalization for congestive heart failure. They found that the model predicting readmission accounted for only about 3.3% of the observed variation. Krumholz and colleagues believed that the Medicare administrative data set has limited use in the analyses of risk-adjusted outcomes.

Although this study was consistent with sound research methods, there would be
means of improving its study design. First, our research identified patient readmissions based upon any health cause (i.e., chronic heart failure, fractured hip, pneumonia, etc.). An important next step to improve the focus of this thesis would be to differentiate between readmissions for cardiac and non-cardiac ailments. By taking this step, researchers could investigate a population, which reflect patients with complications arising from their primary diagnosis. In other words, analyses performed on this cohort may speak more accurately to the care delivered to the initial heart problem.

Second, research could investigate the services provided during the patients' index admissions. Our study examined three cardiac procedures, PTCA, CABG, and cardiac catheterization, performed during the index admission. Two of these three procedures significantly reduced a patient's risk for readmission. Research can also explore the type of services provided during the readmission. These two additional pieces of information could identify other procedures associated with readmission as well as to the procedures performed during the hospital stay of that readmission.

Third, a future study could increase the follow-up period to patient readmission. While our study investigated the rate of readmission over a 30 day period, perhaps a follow-up period of three months or one-year may prove to be beneficial. Potentially, a longer period of examination will result in detecting stronger associations between patient- and hospital-level characteristics and readmission.

A possible limitation of this study was the lack of power to detect a significant association. Although the study began with an index population of over 1000 patients, only 150 readmissions were identified. An important improvement to our research would
be to expand the breadth of the study. By including a broader population of hospitals, the index population would increase. Also, if we combine this approach with a longer follow-up period, then the number of readmissions would most likely increase as well. Together, these alterations in study design would surely increase the power to detect significant associations with patient readmission.

Researchers like Dr. John E. Wennberg have championed variations research for the last thirty years. Although these investigators have uncovered wide variation in health care resources, expenditures, and utilization, few explanations are known. The impetus of managed care has served to further focus attention to this area. Managed care demands the most efficient care, especially where providers have decided to assume financial risk. In order to assume risk successfully, physicians and other providers attempt to establish a system of care that does not under- or over-utilize health care resources. In a 1997 commentary, Mirvis and Chang (44) call for to the medical community to manage uncertainty. They argue that uncertainty in medical decision-making lies at the root of variation in health care, and thus makes it difficult to determine appropriate levels of care. While presently, some researchers question the utility of the Medicare claims data base for risk-adjusted analyses, no one appears to doubt the potential contained within this rich evaluative tool.


**Recommendations**

Currently, debate abounds on the means of conducting and explaining the findings of variations research. To address this, this section of the thesis will focus on discussing: the utility of the Medicare claims data base, the major problems facing health services research, and the political and financial implications of variations research.

*The Utility of Medicare Claims Data Bases*

The utility of Medicare claims data bases in variations research as well as other health services research has been held in high regard. However, despite its prospect as a rich evaluative tool, some researchers are quick to point out its limitations. The promise of Medicare claims data bases lies in their accessibility. These data bases represent a large repository of health services-related data, virtually at the public’s dispose. These repositories are continuously generated and contain information on over 38 million Medicare beneficiaries. This allows researchers access to inexpensive, population-based data, which is comprised of millions of potential study subjects. In other words, researchers can conduct retrospective and prospective cohort studies of varying follow-up periods at a fraction of the price of most cohort studies.

There are limitations to these data bases as well. First, the data is primarily administrative and thus lacks much of the clinical information found in patient medical records. For example, the Medicare claims data base contains information regarding the diagnosis related groups (DRGs); but not the physicians’ and nurses’ notes that are associated with those DRGs. The most apparent limitation has been researchers’ inability
to utilize sophisticated risk-adjustment or illness severity indicators with claims-based
data. As a result, some providers disregard variations research and reject comparisons
made between themselves and other providers.

At this point, there is some consensus among health services researchers on how
to best conduct research utilizing a claims database. First, studies should accurately
define a patient cohort. In our study, for example, to ensure that a cohort would include
all patients diagnosed with AMI, we designed a computer program to identify patients
with ICD-9-CM codes, ranging from 410.00 – 410.12. Second, the research should
define an episode or a length of time, in which to observe the outcome of interest. Third,
once the aforementioned criteria have been satisfied, the study should effectively measure
the outcome of interest (i.e., patient death or readmission). In our study, we employed
the use of a statistical software package to accurately measure the time from patient
discharge to readmission. And lastly, researchers should identify methods of
supplementing the results of administrative data analysis with patient medical records
information. These two forms of data may work in synergy to advance research in this
area.

Major Problems Facing Health Services Research

Early on, health services research, utilizing Medicare claims data, appeared
insufficient and lacking clinical validity. Recently, however, this type of research is
experiencing more common use by a host of quality improvement organizations,
especially the PROs. Federally, HCFA continues to contract with PROs; and the Public
Health Service still subsidizes AHCPR’s PORT projects. Furthermore, accrediting
agencies pressure health plans and other payers to perform similar quality improvement research. The result is a stronger show of support by the large provider associations (i.e., AMA, AHA); though, there is room for improvement.

Still, there are those who believe more is needed. Health care policy experts maintain their support of outcomes-based HSR; however, they cite the need for improved researcher/provider collaboration. Felch and Scanlon (45) described,

“The dream of medicine for the new millennium - that the care of patients will be evidence based, supported by carefully designed RCTs, and validated by focused outcomes studies - will only be fully realized when the major players in the health care arena find improved ways to work together.”

The authors referred to two players: one representing the research community comprised of academia, industry and government and the other representing the practicing community, mostly physician providers of medical care. Felch and Scanlon (45) cited a recent publication where investigators found an underuse of beta-blockers in elderly survivors of acute myocardial infarction. The study found that only 21% of eligible patients received beta-blockers. This medical care appeared inappropriate in light of evidence linking the administration of beta-blockers to decreased mortality and rehospitalization rates. Unfortunately, despite the advances made in outcomes-based research, some medical communities refuse to accept or are unaware of HSR.

Traditionally, HSR’s most significant limitation has been its inability to utilize sophisticated risk-adjustment or illness severity indicators. Without adjusting for patient risk for a particular outcome, researchers cannot accurately account for the case mix of a provider’s patient population. As a result, some providers disregard HSR and reject
comparisons made between themselves and other providers. Continuous health services research and funding is essential to develop reliable illness severity indicators.

In other cases, HSR has been unsuccessful in its attempt to change inappropriate physician practices. Evidence exists that physicians are complex creatures who gain information in a variety of ways, who must undergo a buying in process, applying reality testing to innovations, and comparing them with existing internal frameworks (45). “There is disappointing evidence that the mere promulgation of clinical practice guidelines does not necessarily invoke behavior change in physicians; they seem to need to go through the process of ‘buying in’ to the recommendation” (45).

Although HSR has made great strides over the past thirty years, the future poses two significant barriers: (i) development of accurate risk adjustment methods and (ii) creditability with providers. In order to overcome these hurdles, health services research must strive to develop not only more sophisticated methods of risk adjustment but also more persuasive means of conveying research into reality.

**Political and Financial Implications of Variations Research**

Evidence of variation in health care resources, expenditures, and utilization is plentiful; however, few explanations are available. Variation implies the absence of a standardized mechanism to invoke a consistent product. In the case of medical care, variation can perhaps, mean the absence of knowledge guiding providers to treat patients with standard protocols that result in favorable outcomes.

Idealistically, if all medical conditions developed and progressed in identical fashion, we could devise standard protocols that utilize the same level of
resources to treat every medical condition. In other words, we could standardize care. 

But, as we know, this situation does not exist and it probably never will.

Realistically, variation in resources, utilization, mortality and readmission rates, etc., probably reflects an underuse or overuse of services to treat conditions that vary extensively in their etiologies. Thus variation is at the root of why we continually grapple with defining the appropriate levels of utilization. Yet, for most health conditions, we have not reached a consensus for appropriate levels of care.

Utilization of health care services can be visualized along a continuum. At one end, there is underutilization; and at the other end, there is overutilization. Along that continuum, there lies an appropriate level of care for a particular health condition. However, in the absence of such appropriate measures of care, there is uncertainty.

Variations research can begin to define appropriate levels of care. If future variations research results in proven evidence-based medicine, then we can begin to eliminate some of the uncertainty found presently in health care utilization. This development would have profound implications on both the providers and payers of health care.

The Medicare program, for example, is the largest single payer of health care, financing approximately $203.1 billion (or 20% of all health care costs), in 1996. If health services research can define appropriate levels of care, then million of dollars could potentially be saved.

Let's image a situation, where research has provided us with appropriate standards of care for patients diagnosed with AMI. Since this patient population is
mostly Medicare eligible, the Medicare program could greatly benefit. Savings would be realized as the federal government and other payers lowered their costs by not financing the overutilization of health care services.

Another major stakeholder would be the providers of health care. Today, physicians and hospitals look for opportunities to assume more financial risk for their services, when they contract with payers (i.e., managed care organizations). If providers have evidence-based medicine at their disposal, then they, too, can better control the costs of their care. However, in the meantime, we should remain disciplined in how we interpret these studies into public policy or provider protocol.

For until definitive research enlightens us all, what we perceive as over- or under-use may actually be an appropriate level of care. Hypothetically, increased utilization rates of PTCA, for example, may lead to better quality of care. And in the long run, they may be more cost effective to the Medicare program. Therefore, the key is to proceed cautiously ahead with variation research and to incorporate changes into medical practice wherever sound science lends itself.
The Nation's Health Care Dollar: 1996

Where It Came From

- Private Health Insurance: 32%
- Medicare: 20%
- Out-Of-Pocket: 17%
- Medicaid: 14%
- Other Gov't Programs: 13%
- Other Private Funds: 4%
Appendix B
The Nation's Health Care Dollar: 1996

Where It Went

- Hospital Care: 35%
- Other Personal Heath Care: 26%
- Physician Services: 19%
- Other Spending: 12%
- Nursing Home Care: 8%
Appendix C
The International Classification of Diseases, 9\textsuperscript{th} Revision, Clinical Modification (ICD-9-CM)

ICD-9-CM Codes for Cardiac Procedures

**Acute Myocardial Infarction (AMI)**

410.00 – 410.12

**Coronary Artery Bypass Graft (CABG)**

36.10 – 36.14

**Percutaneous Transluminal Coronary Angioplasty (PTCA)**

39.50, 36.01, 36.03, 36.05, 36.09

**Cardiac Catheterization**

37.21 – 37.23, 38.93
References Cited – Appendices


