THE ECONOMICS OF MEDICAL TREATMENT INTENSITY

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ABSTRACT

Health care costs remain a critical policy concern. Most of the cost growth is the result of real increases in the technological intensity of medical care. Yet the determinants and consequences of medical treatment intensity decisions by physicians and hospitals are poorly understood. How does the use of more intensive treatments affect patient outcomes? Why does medical treatment intensity continue to increase, even in the presence of "high-powered" incentives such as fixed-price hospital payments under Medicare's Prospective Payment System? What causes the considerable variations in treatment intensity observed across medical providers and geographic areas for almost all health problems? The three essays that follow present new analytic approaches and empirical evidence on these questions.

Uncertainty about how treatment intensity affects patient outcomes is a central problem in economic studies of physician and hospital behavior, because unobserved differences between patients receiving different treatments complicate inferences about causal relationships using observational data. Chapter I develops an instrumental-variables framework using measures of differential access to alternative levels of treatment intensity to identify the "marginal" effects of these treatments. The framework uses no parametric assumptions, accounts for treatment heterogeneity, and permits a range of specification tests. The techniques are applied to an observational dataset including all elderly Americans hospitalized with a heart attack in 1987. For at least 40% of patients undergoing intensive surgical procedures after their heart attacks, the apparent effect of procedure use on outcomes is largely attributable to selection effects. Other dimensions of treatment intensity have significant consequences for acute mortality.

Chapter 2 turns to the question of why the use of such intensive treatments, and hence health care costs, continue to increase. In particular, trends in hospital costs under the Medicare Prospective Payment System (PPS) have been puzzling. PPS features "high-powered" fixed payments per admission, providing apparently strong incentives to minimize cost. In spite of these incentives, intensity per admission and intensity per beneficiary -- reflected in real costs and various measures of technology use -- continue to rise. Intensity growth has consequently been attributed to "exogenous" technological change in the hospital industry, and much more dramatic reforms have been proposed to control costs. In this chapter, I reexamine the incentives facing hospitals to use intensive technologies with exogenous prices for an admission. I develop a model of hospital production of medical treatment for a health problem with the following plausible features: (1) multiple treatment intensity levels are possible; (2) patients prefer higher-quality care, so that hospitals face demand that is upward-sloping in quality; (3) hospital and physician preferences for intensity choices may not coincide; (4) physicians retain residual control of the use of intensive hospital technologies; and (5) different intensity choices may lead to different hospital payments. After deriving equilibrium hospital investments in technologies in the model, I examine the effects of Medicare's current reimbursement rules and consider optimal pricing rules. Using this analytic framework, I reexamine aggregate evidence on the intensity and cost of hospital care under PPS. In
fact, the principal "puzzles" of PPS appear to be consistent with the price incentives and production constraints facing hospitals, and growth in hospital costs under PPS may be largely attributable to reimbursement rules rather than exogenous technological change.

While price incentives may be important determinants of the dynamics of medical treatment intensity, a massive research literature has also characterized large "area variations" in medical treatment intensity for almost all health problems. To characterize the effect of hospital characteristics on these variations, Chapter 3 analyzes the implications of the availability of intensive medical technologies at hospitals for intensity decisions in the treatment of heart attacks in the elderly. The probability of use of intensive procedures after AMI is much higher in patients initially admitted to hospitals that have the technologies, suggesting systematic differences in practice patterns. However, as in previous studies that have compared intensity choices across different kinds of providers, unobserved differences in patient mix may explain some or all of the differences in treatment. Instrumental variables methods that group patients on the basis of differential access to intensive providers for reasons independent of disease severity are introduced to address this problem. The results demonstrate that, while some patient selection does occur across hospital types, technology availability leads to fundamental differences in both treatment and diagnosis patterns at hospitals; patient demand factors are relatively unimportant. Differential initial admission rates to intensive hospitals after AMI entirely explains the lower catheterization rate in rural patients, but intensity differences in the treatment of black patients and female patients arise within hospitals. These results provide a foundation for future work on the dynamics of medical practice patterns.

The empirical work presented here concentrates on one common medical problem, heart attacks in the elderly. Directly or indirectly, heart attacks are primarily responsible for the mortality and other adverse health outcomes associated with heart disease. Thus, the results have direct implications for medical policies. In addition, the methods can be applied to many other health problems in which the determinants and consequences of treatment intensity decisions are uncertain.
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Health care costs are a critical policy concern. Over 13% of the Federal budget is committed to health care entitlements, primarily for elderly Medicare beneficiaries (Aaron, 1991), a share that has been projected to grow to 20% in five years (Congressional Budget Office, 1992). Private health expenditures, which totaled over $380 billion in 1990 and are mostly paid by employers (Levit et al., 1991), are projected to increase to almost $600 billion by 1995 (Sonnefeld et al., 1991). Not surprisingly, high cost is the principal reason cited by firms for limiting health insurance coverage or not offering it at all (A. Foster Higgins and Co., 1991); cost is a principal reason why the proportion of the U.S. population without health insurance has increased to over 15% in recent years (Congressional Budget Office, 1991).

Most of this cost growth results from real increases in the technological intensity of medical care (Weisbrod, 1991; Newhouse, 1992). Consequently, recent proposals to control the growth in health expenditures -- for example, through a combination of managed care programs, expenditure caps, and price controls in the Clinton Health Plan (Iglehart, 1993) -- center implicitly or explicitly on limiting the use of intensive technologies and otherwise controlling utilization. In spite of the core importance of medical treatment intensity in this policy dilemma, however, the determinants and consequences of treatment intensity decisions for health problems are very poorly understood. How does the use of more intensive treatments affect patient outcomes? Why does medical treatment intensity continue to increase, even in the presence of "high-powered" incentives such as fixed-price hospital payments under Medicare? Do
identifiable causes exist for the considerable geographic variations in treatment intensity observed for most diseases?

Many experts have argued that, at the margin, intensive medical treatments have minimal effects on health (e.g., Fuchs, 1986). But there is little empirical evidence on how health outcomes will be affected by reforms that influence treatment intensity decisions. The uncertainty exists despite the availability of increasingly comprehensive datasets documenting treatments and outcomes for large populations, especially Medicare beneficiaries (Jencks and Wilensky, 1992). The fundamental problem for biostatistical analysis is that the datasets are not experimental. Patients receiving alternative treatments are likely to differ in important unobserved health characteristics, so that differences in outcomes across groups receiving different treatments reflect both the effects of the treatments and the effects of the unobserved characteristics. Randomized clinical trials are the "gold standard" for estimating treatment effects because treatment assignment is uncorrelated with any unobserved patient characteristics. However, trials relevant to current practice are not feasible for many important treatment decisions. The design and execution of trials is expensive. More importantly, once clinician beliefs favor a particular treatment alternative, withholding that treatment is unethical (Royall, 1990). In addition, predicting the effects of policies that influence technology use and treatment patterns requires another major extrapolation from the controlled environments of clinical trials to the variety of real-world practice settings where the technologies will actually be used.

Chapter 1, "The Marginal Benefits of Medical Treatment Intensity: Acute Myocardial Infarction in the Elderly," develops and applies instrumental variables (IV)
estimation techniques to study the effects of alternative medical technologies. Though the basic techniques are well known in econometrics, they have rarely been applied in epidemiologic or biostatistical contexts. One cause may be justifiable suspicion among biostatisticians that the key assumption of instrument-error orthogonality is not satisfied, or that other functional form assumptions are driving estimated results. To address these concerns, the paper develops an econometric framework that makes no parametric assumptions, accounts explicitly for treatment heterogeneity, and permits a range of specification tests of the key identifying assumptions. These estimation methods are potentially applicable to many other treatment intensity problems of interest to biostatisticians and economists.

Chapter 2, "Why Do Medicare Costs Keep Rising? Hospital Reimbursement and the Dynamics of Medical Treatment Intensity," complements the analysis of the outcome consequences of intensive technologies with an analysis of hospital incentives to use the technologies. This chapter addresses some of the "puzzles" arising from the implementation of the Prospective Payment System (PPS) for hospital services. For example, even though hospitals are now paid on the basis of diagnosis-related groups (DRGs), which constitute essentially fixed prices for admissions in the DRG, average intensity per admission and per Medicare beneficiary continue to rise. Intensity growth has consequently been ascribed to "exogenous" technological change, and many analysts have proposed even more dramatic reforms in hospital reimbursement to control costs. The chapter develops a model that accounts for hospital incentives to provide alternative levels of treatment intensity for a health problem -- rather than for an admission -- and that builds on the analysis of hospital internal organization in Harris (1979) by examining
the distinct roles of physician and hospital preferences in determining treatment intensity. The model demonstrates that the Prospective Payment System supports certain types of intensity growth. Preliminary empirical evidence suggests that the model is consistent with observed patterns in hospital costs and reimbursement and may explain much of the dynamics of treatment intensity for Medicare beneficiaries since PPS was implemented.

The model in Chapter 2 assumes that physician beliefs about the net benefits of more intensive treatments are fixed. In fact, uncertainty about the consequences of policy reforms for treatment decisions and medical outcomes reflects a deeper uncertainty in medical practice. Following Wennberg and Gittelsohn (1973), a massive research literature has identified substantial variations across geographic areas in the use of many medical and surgical services that are unrelated to any plausible variations in health characteristics (e.g., Chassin et al., 1986). The variations seem to reflect important differences in provider beliefs about the costs and benefits of alternative treatments (Wennberg, 1984; McClellan and Brook, 1992), which in turn reflect the lack of evidence on the effectiveness of many treatment alternatives (Eddy and Billings, 1988; Phelps, 1992).

Chapter 3, "The Effect of Hospital Characteristics on Medical Treatment Intensity: Acute Myocardial Infarction in the Elderly," is an empirical analysis of how hospital decisions to adopt technologies influence medical practice patterns, presumably reflecting their influence on physician beliefs about treatment effectiveness. The analysis is part of a systematic effort to identify the causes of area variations in practice patterns explicitly. Many studies have documented differences in practice patterns between providers that are associated with the availability of intensive technologies. For example,
Hillman et al. (1990) documented differences in the use of radiologic services for apparently similar patients treated at physician offices with and without radiologic equipment. A critical issue in these studies, as in studies of the relationship of treatments and outcomes using observational data, is whether the differences in treatment patterns simply reflect unobserved differences in patient health characteristics. As in Chapter 1, instrumental-variables methods that group patients on the basis of differential access to the more intensive providers, independent of their disease severity, are used to address this problem. The methods permit variations in treatment intensity to be decomposed into between- and within-hospital components and also provide the foundation for future work on the dynamics of practice patterns.

The empirical analysis throughout uses comprehensive hospital utilization and outcome data for all elderly Americans hospitalized with an acute myocardial infarction (AMI, or heart attack) in 1987. AMI is one of the most common medical emergencies in the United States and, directly or indirectly, accounts for most of the morbidity and mortality associated with coronary heart disease, the leading cause of death in the United States. Thus, the empirical findings on outcomes, costs, and determinants of treatment intensity have important policy implications.

However, the methodologic approach has a further goal. A major theme of all of the chapters is that focusing on treatment intensity at the level of a health problem has many potential benefits for health economics research. In contrast to studies at the level of hospital admissions or other measures of utilization that have no direct relationship to what patients demand -- care for an illness -- studies at the level of health problems can provide much richer evidence than results at the level of procedure counts, admissions, or
aggregate mortality on the real consequences of alternative policies. Indeed, as the results suggest, focusing on measures such as DRGs may represent a theoretical misspecification with serious consequences for understanding the dynamics of health costs. The methods developed and applied here for analyzing the costs, benefits, and incentives to use alternative levels of treatment intensity are applicable to the analysis of any health problem which involves choices about intensive treatments that are not everywhere available and for which longitudinal observational data can be obtained.
REFERENCES


CHAPTER ONE

THE MARGINAL BENEFITS OF MEDICAL TREATMENT INTENSITY:
ACUTE MYOCARDIAL INFARCTION IN THE ELDERLY

with Joseph P. Newhouse

Increasing technological intensity is widely viewed as the principal cause of escalating health care costs, both in the United States and abroad (Weisbrod, 1991; Newhouse, 1992). In spite of these assessments, the economics literature generally treats the production of desirable health outcomes as a black-box process. Explicit specification of the relationship between health care inputs and outputs, not economists' comparative advantage, is immaterial if physicians made consistent cost-benefit tradeoffs on a production-possibility frontier. Production decisions would reflect an optimal tradeoff between costs, patient welfare, and other arguments in their objective functions.

But physicians do not make consistent treatment decisions. In fact, there is wide variation across geographic areas in how patients with similar health problems are treated (e.g., Glover, 1938; Wennberg and Gittelsohn, 1973; Wennberg et al., 1982). For example, patients are more than twice as likely to be hospitalized for several common medical conditions if they live in Boston rather than New Haven (Wennberg, Culp, and Freeman, 1987). The most compelling explanation for such variation is uncertainty about the effectiveness of medical technologies (Phelps, 1992). Assuming optimal production assumes away a fundamental problem in medical economics and health policy.

The "gold standard" for resolving uncertainty about technology effectiveness is a randomized clinical trial of alternative treatments. Randomization implies that treatment
assignment is independent of unobserved patient characteristics, so that these
characteristics are ignorable (Rubin, 1974), and treatment effects can be estimated by
comparing the groups receiving alternative treatments. For many reasons, however,
randomized clinical trials have not resolved fundamental uncertainties about the effects of
commonly-used technologies. Randomized clinical trials are (1) expensive, because of
patient enrollment and followup costs; (2) time-consuming, so that technological progress
or changes in standards of care often limit the relevance of their conclusions when they
are finally published; (3) sometimes difficult to generalize from the specific institutions
and specific kinds of patients involved in the trial; and (4) often problematic from an
ethical standpoint, if treatment is deliberately withheld from patients in whom a clinically
important benefit may be suspected.

These concerns have led many policymakers, medical ethicists, and biostatisticians
to advocate alternatives to randomized clinical trials (Roper et al., 1988; Royall, 1990).
But this strategy raises the usual problems of observational analysis: are differences in
outcomes between groups receiving different treatments due to the effects of treatment or
to unobserved differences between the groups?

We introduce a standard econometric strategy, instrumental-variables (IV)
techniques applied to observational data, to address this problem. Although IV techniques
are well known in economic studies of treatment effects, they have rarely been applied in
biostatistics and clinical epidemiology.¹ A major goal of the paper is to demonstrate
their applicability in these domains to questions of fundamental interest to economists and

¹Exceptions include Hearst et al. (1986) and Permutt and Hebel (1989). However, these
studies did not compare alternative medical technologies.
policymakers. In contrast to clinical trials, which seek to estimate an average treatment effect in a selected population or subpopulation of enrolled patients, the IV estimation techniques developed here estimate marginal effects of treatments in nonexperimental populations. Thus, these methods may provide more direct evidence than clinical trials on the outcome consequences of changes in policies affecting the use of medical technologies.

Our application of IV techniques for determining the marginal effects of medical technologies involves the treatment of heart attacks—acute myocardial infarctions (AMIs)—in the elderly, an important policy issue in its own right. Heart disease is the leading cause of death in the United States, and most of these deaths involve AMIs and related consequences of coronary-artery disease. The clinical management of a patient with AMI or at elevated risk for AMI involves many decisions with potentially important consequences for technology use, health care costs, and health outcomes. One major decision is whether to treat the patient with cardiac drugs and lifestyle modification or to use invasive surgical procedures. The principal surgical procedures -- cardiac catheterization, percutaneous transluminal coronary angioplasty, and coronary artery bypass surgery -- are commonly used and account for a substantial portion of the costs of treating patients with heart disease.

There is little decisive experimental evidence on the impact of these procedures on patient outcomes such as survival time.2 Uncertainty about the effectiveness of invasive

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2 Three randomized trials of bypass surgery were undertaken in the 1970's (European Coronary Surgery Study Group, 1982; Coronary Artery Surgery Study, 1983, 1984; Veterans Administration Coronary Artery Bypass Surgery Cooperative Study Group, 1984; Varnauskas et al., 1988; Rogers et al., 1990; Yusuf et al., 1990). These studies generally showed some benefits in quality of life and survival for certain subgroups of patients for at
cardiac procedures is a likely cause of the substantial variation across geographic areas in
their use (Wennberg et al., 1987). The effectiveness of many other technologies used to
treat AMI patients is also uncertain, and their use also varies significantly. For example,
AMI patients in rural or suburban areas with small community hospitals often have
reduced access to advanced emergency life support systems and other nonsurgical
treatments such as clot-dissolving drugs and specialized coronary care beds. Estimating
the consequences of these differences in treatment intensity would also be useful for
understanding how changes in medical treatment intensity would affect health outcomes.
But similar problems of unobserved "case mix" or severity differences confound
observational comparisons of treatments and outcomes across different types of hospitals.

To provide evidence on the marginal impact of these technologies on patient
outcomes, the study uses data on all elderly Americans who were admitted to a hospital
with a new AMI in 1987. Estimates of a patient's differential distances to alternative
types of hospitals are used as observable instruments that are plausibly uncorrelated with
patient disease severity and in effect randomizing patients to different probabilities of
treatment at alternative types of hospitals. Thus, consistent estimates can be obtained of
the average effect of these treatments in "marginal" patients, those whose treatment
decisions were influenced by differential distance.

Though the principal goal of the paper is to estimate the effectiveness of intensive
medical treatments, the research strategy also raises a number of important econometric

least five years after randomization. But they were limited to a small number of sites, they
enrolled less than a thousand nonelderly patients each (Gurwitz, Col, and Avorn, 1992), they
only studied particular subgroups of non-AMI bypass candidates (Fisher and Davis, 1985),
and they used surgical and medical techniques that are now outdated.
issues. The size of the dataset, the technical complexity of the decision problem, and the binary nature of the variables of interest provide an opportunity to apply some recent developments in generalized method of moment (GMM) IV estimation of statistical models that do not require specification of a parametric response function. In addition, the paper explicitly addresses the consequences of unobserved treatment heterogeneity in IV estimation; the framework developed here for modeling treatment heterogeneity is relevant to many other applied econometric studies.

Section I describes the medical treatment problem and the data in more detail. Section II develops an IV estimation framework that makes minimal assumptions about the processes generating the data and that explicitly accounts for treatment heterogeneity. Section III presents IV estimates of the effects of medical treatment intensity on outcomes as well as tests of the validity of the key assumptions underpinning the use of differential distances as instrumental variables. The results consistently show that the apparent differences in survival between patients who undergo intensive procedures after AMI (catheterization and revascularization) are largely attributable to patient selection effects, though other aspects of treatment intensity do affect acute survival. Section IV uses the estimates to simulate the effects of changes in policies for AMI treatment intensity in the elderly, and Section V concludes.

I. Background and Data

The occurrence of AMI is generally a sudden, major health shock associated with a high risk of death. For very severe attacks, death can be immediate. For patients who survive the attack itself, the acute risk of death remains high due to diminished cardiac
function and related complications. Acute management of AMI focuses on limiting the damage to the heart and on preventing acute complications. Technologies such as advanced cardiac life support in the ambulance and emergency room, thrombolytic (clot-dissolving) drugs and other pharmacologic agents, equipment to monitor cardiac rhythm and function, and many other intensive treatments available in dedicated coronary care unit beds may all contribute to acute survival and subsequent quality of life. In addition, a set of invasive procedures may be used.\(^3\) Invasive procedures include cardiac catheterization, a diagnostic procedure to image blood flow to cardiac muscle, and subsequent revascularization procedures to improve flow in compromised areas. There are two types of revascularization procedures: percutaneous transluminal coronary angioplasty (PTCA) and coronary artery bypass grafting (CABG). PTCA, also known as "balloon" angioplasty, involves inflating a balloon-tipped catheter at sites of significantly narrowed cardiac blood flow, as imaged in the catheterization procedure. CABG involves grafting an artery or vein into the cardiac arterial system during open-heart surgery to bypass areas of occlusion and thereby restore blood flow to the cardiac muscle. Decision paths for invasive or noninvasive management of AMI patients are summarized in Figure 1. While many nonsurgical decisions may also have important consequences for patient outcomes and resource use, decisions about catheterization and revascularization are thought to be particularly consequential (Braunwald et al., 1988).

The principal data source for our study of the marginal effects of these technologies is patient-level information on medical claims, demographic characteristics,  

\(^3\)Strictly speaking, there are many technologies used to treat AMIs that are "invasive." For purposes of this paper, "invasive" refers to major invasive procedures (catheterization and revascularization).
and death dates obtained from the Health Care Financing Administration for all elderly Medicare beneficiaries admitted to a hospital with a primary diagnosis of AMI in 1987, a preliminary sample of 218,427 patients. Claims included all hospital-based utilization of services through 1988. Death dates through 1991 were obtained from HCFA’s Health Insurance Skeletonized Writeoff File, based on death reports validated by the Social Security Administration.

Indicator variables for use of invasive procedures were created based on the occurrence of claims listing appropriate procedure codes for cardiac catheterization, PTCA, and CABG. Because procedure dates within an admission are not reliable, the admission date of the hospitalization during which the procedure occurred was used to date procedure use. Indicator variables for hospital characteristics at initial admission were defined in a two-step process. First, the number of admissions and procedures for elderly AMI patients were calculated for each hospital. Second, these counts were used to categorize hospitals based on their AMI volume and their invasive procedure capacity.

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4Udvarhelyi et al. (1992) describe the sample creation process in detail. The following patients were excluded: patients under age 65 (Medicare qualification due to disability), patients with end-stage renal disease, patients whose initial admission was not to an acute-care hospital or who were discharged alive after an initial length of stay counting transfers of less than five days (inconsistent with standards of care for an actual AMI), patients residing outside the United States, and patients not continuously enrolled in the Medicare program or enrolled in HMOs during the study period (unreliable claims data).

5Except for the immediate post-AMI phase, operative procedures will generally be performed on or near the date of admission. Particularly for CABG, procedures performed during the first AMI admission occur after the patient has been initially stabilized, so early (1-day and 7-day) procedure use indicators may be biased forward. Because physician claims were not included in the dataset, relevant procedures performed in ambulatory surgical centers might be missed. However, PTCA and CABG are not performed outside of hospitals, and evidence presented below suggests that approximately 95% of catheterizations after AMI were captured using these methods. Results were not sensitive to alternative assumptions about procedure dates.
so that a hospital type at initial admission could be assigned to all patients in the sample. Indicator variables for patient comorbid diseases were derived from secondary diagnoses listed at the time of initial discharge (not counting transfers) after AMI. 6 Indicator variables for survival time were based on the difference between the patient’s death date (if death occurred by 1991) and the date of the patient’s AMI.

Approximate distances to alternative types of hospitals were assigned to individual patients using a four-step process. First, an institutional dataset was created that grouped all facilities by invasive procedure capacity and AMI treatment volume for elderly AMI patients in 1987. For example, 1252 hospitals performed at least five catheterizations, and these hospitals comprised the “catheterization” universe of hospitals. Other institutional characteristics, such as “revascularization” (hospitals performing at least 10 revascularization procedures) and "high volume" (hospitals treating at least 75 patients), were defined similarly. Second, a commercial software package was used to assign approximate latitude and longitude coordinates to all patient residence zip codes and hospital zip codes in the United States. Third, distance to the closest hospital of each type for each residence zip code was estimated using an algorithm to determine the

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6Medicare discharge abstracts provide fields for one to four additional diagnoses besides the primary diagnosis. Because these diagnoses are coded at the time of discharge, some diagnoses representing acute medical problems may be a result of important treatment decisions and hence are not exogenous from the standpoint of patient management. For example, congestive heart failure, arrhythmias, and sepsis are possible complications of catheterization, PTCA, or CABG. On the other hand, conditions such as chronic obstructive pulmonary disease or cancer generally could not have developed acutely as a result of AMI treatment. With assistance from practicing cardiologists, secondary diagnoses were grouped according to whether they might plausibly represent complications of AMI treatment. The questionable diagnoses were dropped from subsequent analysis. (Including them did not change the results.)
minimum distance among nearby hospitals. The algorithm used the Pythagorean theorem to calculate distances between residence and alternative facility latitude and longitude coordinates, then chose the minimum.\textsuperscript{7} Fourth, minimum distances to alternative types of hospitals were linked to individual patients via their zip code of residence.

This method led to successful minimum-distance matches for 215,821 patients (98.6\% of the original cohort). Coordinates could not be obtained for the zip codes listed for the other 2,406 patients, who were dropped from further analysis. Patients in Alaska (N=93) were excluded because the distance estimates were unreliable at extreme northern latitudes. Patients who were initially admitted to hospitals more than 100 miles farther away than the nearest hospital (N=10,707) were also excluded, because these patients probably were traveling or had moved at the time of their AMI. As a result, the final analytic sample consisted of 205,021 patients (93.9\% of the original cohort).

Table 1 summarizes characteristics, treatments, and outcomes for patients in the sample.\textsuperscript{8} The first column, describing the entire sample, demonstrates that short-term

\textsuperscript{7}Bruce Bennett and Harold Luft provided useful assistance in the development of distance algorithms.

\textsuperscript{8}The comorbid disease information in Medicare discharge records has two important limitations. First, comorbid diseases tend to be undercoded in patients who die shortly after their AMI, so that the diseases appear to be associated with improved short-term survival. This anomaly has been noted previously (Jencks et al., 1990; Lezzone et al., 1992). Likely explanations are that (1) the brief stays ending in death precluded a full evaluation of all the patient’s medical problems, and (2) hospital reimbursement for AMI patients dying during their initial admission is independent of the comorbid conditions coded. Among 7-day survivors, most comorbidities have the expected effect of increasing mortality. Second, because no more than four comorbid diseases can be coded in Medicare discharge records, “milder” diseases such as high blood pressure are only recorded for patients who do not have more “severe” diseases such as cancer. Consequently, reliable interpretation of comorbidity effects is problematic, particularly for analyzing acute mortality. The comorbidity information is used in only a limited and largely qualitative way in the analysis that follows.
and long-term mortality risks associated with AMI in the elderly are considerably greater than those reported in smaller studies of mainly nonelderly patients (e.g., Goldberg et al., 1989): the overall 30-day mortality rate is 26%, the 2-year mortality rate is 48%, and the 4-year mortality rate is 58%. Approximately 23% of all patients were catheterized within 90 days of their AMI, with a higher proportion, 27%, occurring in patients who survive the acute phase. Approximately 87% of catheterizations within the 90-day post-AMI episode of care occur during the first 30 days post-AMI, most during admissions that begin at or shortly after the time of the AMI. Because 95% of all catheterizations in the cohort have been performed by 90 days, and because catheterizations after this interval are likely to reflect treatment for different clinical problems, the analysis concentrates on management decisions during the 90 days following the initial admission.

The third and fourth columns of Table 1 compare outcomes for patients who underwent catheterization to those who did not. Conditional on catheterization, 51% of patients underwent one or both revascularization procedures.\(^9\) Mortality is much lower for the catheterized group; for example, two-year mortality rates (0.21 vs. 0.55) and four-year mortality rates (0.30 vs. 0.67) are less than half as great among catheterized patients. However, patients who are catheterized tend to be younger and have a lower incidence of secondary diseases, and a substantial difference in mortality is apparent by the first day after AMI, before most revascularization procedures would have been performed. Thus, at least some of the difference in outcomes appears to result from the selection of

\(^9\)Approximately 1.5% of the patients in the non-catheterization group underwent revascularization procedures. Because catheterization is always performed prior to revascularization, this reflects the small proportion of catheterizations not captured in inpatient utilization records. The results were not sensitive to the assignment of these patients to the relevant catheterization group.
healthier or more stable patients to undergo major procedures, as might be expected. Catheterization use also appears correlated with other potentially effective treatments: catheterized patients are more likely to have been treated at hospitals performing invasive procedures and at high-volume hospitals.

Table 2 explores differences in intensity of AMI treatment that are associated with hospital characteristics. While half the hospitals in the U.S. treat a low volume of elderly AMIs (fewer than 25 per year), most AMI patients (88%) are admitted to higher-volume hospitals. Higher volume is not only associated with more beds and with greater experience and opportunities for specialization of medical personnel, but also with greater availability of many technologies, such as coronary care units, the ability to perform catheterization and revascularization procedures, pharmacologic sophistication with thrombolytic (clot-busting) agents and other cardiac drugs, advanced monitoring systems, and other "noninvasive" new technologies. Low-volume hospitals are more likely to be rural hospitals, where specialized emergency response systems able to perform advanced cardiac life support to stabilize patients shortly after AMI are less likely to exist. Thus, while patients admitted to the more sophisticated hospitals are more likely to undergo catheterization, they are also more likely to receive intensive AMI management in many other dimensions.

Because AMI generally requires prompt treatment, patients tend to be admitted to the nearest hospital. If practice patterns differ systematically across hospital types, differential proximity to technologies such as catheterization may influence treatment for reasons unrelated to health status. This propensity for treatment intensity is reflected in the concept of differential distance, defined as the distance to the nearest hospital of a
specific type minus the distance to the nearest hospital treating at least ten AMI patients in
the year.\textsuperscript{10} Figure 2 illustrates. Hospital 1 is a catheterization hospital; hospital 2 is a
noncatheterization hospital. Patient A has a differential distance to catheterization of
zero, since the nearest hospital (at distance $d_0$) is a catheterization hospital. Patient B has
a differential distance to catheterization of $(d_2 - d_1)$, since $B$ is distance $d_1$ from the nearest
hospital and distance $d_2$ from the nearest catheterization hospital.

This example illustrates a simple model of facility choice. Independent of disease
severity, proximity and treatment intensity influence facility choice. A patient prefers a
closer hospital, but may choose a hospital where more intensive technologies are available
if the hospital is not "too much" farther away.

The first two columns of Table 3 begin to explore the consequences of differences
in treatment intensity that may be unrelated to patient health status by comparing
treatments and outcomes for patients differentially near and far from catheterization
hospitals. The sample is divided based on whether the patient’s differential distance to
catheterization was less than or greater than two miles. The group differentially far from
catheterization has a slightly lower proportion of females and of blacks. In contrast to the
differences between catheterized and noncatheterized patients apparent in Table 1,
correlates of health status such as age and incidences of comorbid diseases in the two look
very similar.\textsuperscript{11}

\textsuperscript{10}A cutoff of 10 AMIs was used because the very small hospitals treating fewer than 10 AMIs
did not enter the facility choice considerations of nearby patients consistently. Approximately
98\% of patients were admitted to hospitals above this cutoff.

\textsuperscript{11}Stable angina, a comorbidity not included in Table 3, is the only disease that shows a
significantly greater prevalence in the near group and among catheterized patients generally.
A companion paper (McClellan, 1992) on the effects of technology availability on patterns
In spite of only slight differences in observable characteristics, Table 3 shows that the two populations differ substantially in treatment choice. Patients in the group near to a catheterization hospital are 32% more likely to undergo cardiac catheterization within 90 days of AMI; the differences in acute catheterization rates are even larger. Patients in the near group are also 32% more likely to undergo a revascularization procedure; the probability of revascularization conditional on catheterization does not differ. Although acute mortality rates are somewhat lower in the near group, one- through four-year mortality rates differ by less than one percentage point. Assuming that these populations do not in fact differ in unobserved health status and that catheterization is the only medical intervention that differentially affects survival, an unbiased estimate of the impact of catheterization is given by \( \Delta(\text{mortality rate})/\Delta(\text{catheterization rate}) \) between these groups. Using this approach, an estimate of the average effect of catheterization within 90 days after AMI on 2-year mortality is \((.4713-.4793)/(.2598-.1962) = -0.125 \) (standard error of .035), and on 4-year mortality is \((.5799-.5858)/(.2598-.1962) = -0.093 \) (standard error of .035). These are significant survival effects, but they are considerably smaller than the estimates of treatment effects in Table 1, -.340 and -.368 respectively, obtained by direct comparison of outcomes in catheterized and noncatheterized patients.

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of diagnosis and treatment presents strong evidence that this is a "coding" effect and not a true difference in health status. That is, a patient at a catheterization hospital is significantly more likely to be diagnosed with angina, a condition for which catheterization is an appropriate treatment, than he would be at a noncatheterization hospital.

12In general, "catheterization" refers to the invasive procedure AMI treatment path (including possible subsequent use of PTCA and CABG), as opposed to the noninvasive treatment path.
But the statistics in Table 3 also suggest that these estimates may be too high, because the groups near and far from catheterization hospitals differ in other treatments in addition to catheterization. In particular, the population differentially far from catheterization is much more likely to be rural,\(^{13}\) suggesting reduced access to other intensive treatments at least immediately after AMI. Patients far from catheterization are not only less likely to be treated initially at hospitals performing catheterization; they are also much more likely to be admitted to smaller hospitals. As Table 2 indicated, small hospitals tend to use fewer intensive technologies that may contribute to AMI survival. The last two columns of Table 3 provide some evidence on the cumulative impact of noninvasive technologies on survival by dividing the sample based on differential distance to a hospital treating at least 75 elderly AMI patients, since volume is correlated with use of such nonsurgical aspects of treatment intensity. Again, the patient groups are quite similar in terms of most demographic and comorbidity characteristics. But differences in average outcomes are slightly larger than in the previous two columns, in spite of much smaller differences in use of catheterization and revascularization procedures. Assuming that treatment at a high-volume hospital is the only "technology" influencing survival, an unbiased estimate of this treatment effect on two-year mortality is given by \((.4707-.4810)/(.7829-.1910) = -.0174\) (standard error of .0037), and on four-year mortality is \((.5797-.5867)/(.7829-.1910) = -.0118\) (standard error .0037).

Subsequent sections refine the two-group IV comparisons in Table 3, but the fundamental results of the IV methods are evident here. First, methods that account for selection bias in treatment decisions lead to much smaller estimates of the impact of

\(^{13}\)Rural residence is defined as residence in a zip code outside a metropolitan statistical area.
treatment intensity on survival than those that do not. Second, health care "production" is a complex process with many inputs. More than one technology affects AMI survival, so that IV methods must account for the correlations between different aspects of treatment intensity in trying to isolate the effects of each.

II. Instrumental Variables Estimation with Treatment Heterogeneity

This section presents a model of how treatment effectiveness and patient selection both contribute to observed differences in outcomes, while accounting for the correlated aspects of treatment intensity apparent in Tables 1 through 3. The model follows a framework originally introduced by Rubin (1974) and developed by Imbens and Angrist (1991). For an individual i, the effect of any treatment is the difference in outcomes that would occur if the individual changed from a nontreated to a treated state. For mortality within a given time interval after AMI, define this difference in outcomes as $m_i(1) - m_i(0)$, where $m_i(1)$ and $m_i(0)$ respectively indicate whether death occurs in the time interval with and without a treatment such as catheterization. A model describing these two possibilities is
\[ m_i(0) = \mu + h_i \]
\[ m_i(1) = m_i(0) + \eta_i' \]

where \( \mu \) is a population mean mortality rate without procedure use,\(^{14}\) \( h_i \) has mean zero and summarizes the impact of patient \( i \)'s health status on mortality, and \( \eta_i' \) is the impact of procedure use on patient \( i \)'s outcome. Neither \( h_i \) nor \( \eta_i' \) are observed by the analyst, and obviously only \( m_i(1) \) or \( m_i(0) \) can be observed for any individual.

In nonexperimental settings, generally \( \text{E}[m_i(1)|r=1] \neq \text{E}[m_i(1)|r=0] \), where \( r \) is an indicator variable denoting catheterization. Treatment choice is an active, nonrandom decision made after taking into account the patient's disease status, preferences, and other features of the case that are also associated with variations in \( h_i \). For example, a frail 75-year-old patient is less likely to be catheterized than a vigorous patient of the same age, and a patient with inoperable metastatic cancer is probably less likely to be catheterized than one with a benign tumor. In a large sample, the observed difference in outcomes between treated and nontreated groups,

\[ \text{E}[m(1)|r=1] - \text{E}[m(0)|r=0] = \text{E}[\eta'|r=1] + \{ \text{E}[h|r=1] - \text{E}[h|r=0] \}, \]

includes both an average treatment effect and an average selection effect. The problem of selection bias in estimating treatment effects in observational clinical studies is the same as in other nonexperimental program evaluations (see, e.g., Lalonde, 1986, or Heckman and Hotz, 1990).

\(^{14}\)Some patient characteristics that are correlated with health status (age, sex, comorbid conditions) are observed in observational data. In the models estimated below, outcomes for each demographic group are estimated separately, so that \( \mu \) is a conditional mean for the patient population with a given set of observable characteristics.
A critical question in IV estimation of such models is whether the average effect of treatment among patients whose treatment status is affected by the value of the instrument is identified. Imbens and Angrist (1991) describe sufficient conditions for identifying a meaningful local average treatment effect. Let $\mathbf{d}$ represent a K-dimensional vector of indicator variables that groups individual observations based on the value of the instrument. One well-known condition for instrument validity is that the hypothesized instrument vector $\mathbf{d}$ is uncorrelated with the unobserved individual characteristics $\mathbf{h}_i$ and $\eta_i$, but is significantly correlated with the treatment decision $r_i$: $E[r_i|\mathbf{d}]$ is a nontrivial function of $\mathbf{d}$, $E[m(0)|\mathbf{d}] = E[m(0)]$, and $E[m(1)|\mathbf{d}] = E[m(1)]$. This condition alone is not sufficient for identification. If changes in the value of the instrument have heterogeneous effects on treatment decisions, such as causing some patients to shift from a nontreated to treated state and others to do the opposite, and if the treatment effect is also heterogeneous, then it is possible that no meaningful average effect can be estimated using the instrument. A regularity condition sufficient to avoid this problem of instrument heterogeneity is that the probability of treatment conditional on the value of the instrument is monotonic for any individual.

A related but seldom-examined problem is heterogeneity in the nature of the treatment itself. In many natural experiments and even some formal social experiments, a treatment of interest in actuality represents a composite of many institutional details and is rarely completely homogeneous. For example, young men with low draft lottery numbers were more likely to enlist voluntarily for placement in desirable military services, so their military "treatment" may have differed from individuals with high lottery numbers who served, even though using lottery number as an instrument for military service plausibly
satisfies the two conditions for valid IV estimation described previously. In the
biomedical context, multiple dimensions of treatment intensity may be correlated, so that
differences in outcomes associated with exogenous variation in treatment intensity reflect
the impact of all technologies whose use is correlated with that variation. Because many
aspects of treatment intensity are not directly observable, IV methods may only identify
composite effects of these treatments.

For individual i, the model of treatment effectiveness described in (1) generalizes to

\[ m_i(0) = \mu + h_i \]  
\[ m_i(s_i) = m_i(0) + \eta_i(s_i) \]  

(2)

where \( s_i \) is a vector describing the use of all technologies that contribute to intensity of
treatment, many of which are imperfectly observed, and \( \eta_i(s_i) \) is the effect of the
combination of technologies \( s_i \) on patient i’s outcome. The vector \( s_i \) can be decomposed
into \( [r_i, q_i]’ \), where \( r_i \) is the specific treatment of interest (i.e., invasive procedure use)
and \( q_i \) represents use of other technologies. Note that some elements of \( q_i \) may represent
interaction effects among several technologies. The remainder of this section develops
three extensions of IV estimation theory that permit a systematic analysis of treatment
effects in the presence of unobserved treatment heterogeneity: estimation of bounds on
specific treatment effects, joint estimation of simultaneous treatment effects, and the
incorporation of prior information to tighten estimated bounds. Just as the relationship of
individual heterogeneity to the instruments must follow certain regularity conditions to
estimate meaningful effects, so must the relationship of treatment heterogeneity to the
instruments. If these conditions are empirically reasonable, then treatment heterogeneity may not represent a significant IV identification problem.

Equation (2) suggests that the problem of treatment heterogeneity in IV analysis is analogous to the problem of omitted variables in standard regression analysis. If some components of \( s \) are not observed, influence outcomes, and are affected by the value of the instrument for \( r \), then a consistent estimate of the average effect of \( r \) alone cannot be obtained even when an instrument for \( r \) exists that satisfies the two usual conditions for instrument validity. To illustrate, suppose that a single unmeasured dimension of treatment \( q \) exists. For each individual we can imagine four possible outcomes \( m(r,q) \), only one of which is actually observed (the individual subscript \( i \) is suppressed):

\[
\begin{align*}
m(0,0) & \quad \text{outcome in the absence of intensive treatments} \\
m(1,0) & \quad \text{outcome with use of } r \text{ only} \\
m(0,1) & \quad \text{outcome with use of } q \text{ only} \\
m(1,1) & \quad \text{outcome with use of } r \text{ and } q
\end{align*}
\]

Similarly, let \( r_d \) and \( q_d \) represent the use of technologies \( r \) and \( q \) given the instrument \( d \), which is assumed to satisfy the Imbens-Angrist conditions for identifying a local average treatment effect described previously. A patient’s observed outcome given \( d \), \( m_d \), is then

\[
m_d = m(0,0) + [m(1,0) - m(0,0)] \cdot r_d \\
+ \{[m(0,1) - m(0,0)] \cdot q_d \\
+ [m(1,1) - (m(1,0) + m(0,1) - m(0,0))] \cdot r_d \cdot q_d \}
\]

(3)

where \( r_d \) and \( q_d \) are indicators for treatment use given \( d \). Since only \( r \) is observed, the unobserved contributions of \( q \) represent omitted treatment effects.

Without loss of generality suppose individuals with instrument vector \( d = d_j \) are more likely to be treated with \( r \) than those with \( d = d_k \). Then the IV estimate of the
"marginal" effect of r, its effect on patients whose treatment status is \( r = 0 \) if \( \mathbf{d} = \mathbf{d}_k \) but \( r = 1 \) if \( \mathbf{d} = \mathbf{d}_j \), is \( \hat{\eta}' = \frac{\bar{m}_j - \bar{m}_k}{\bar{r}_j - \bar{r}_k} \), where the bars denote variable means for the instrument-based groups. The relationship of this estimate to the true effect \( E[\eta' | r_j \neq r_k] \) clearly depends on the correlation between \( r_a \) and the unobserved treatment \( q_a \), and the effect of \( q \) on outcomes. If, in addition to the standard IV conditions, use of \( q \) is positively correlated with use of the observed technology, and if \( q \) is nonharmful on average for individuals treated differently as a result of differences in the value of \( d \), then the IV estimate represents an upper bound on the average effect of \( r \) among patients whose treatment was influenced by the value of the instrument.\(^{15}\) The Appendix formalizes this conclusion with an arbitrary number of unobserved aspects of treatment intensity. Thus, even in the presence of treatment heterogeneity, useful bounds can be placed on the expectation of the treatment effect \( \eta' \) if the general form of the heterogeneity is known. The unmeasured aspects of intensity will not lead to an underestimate of the effect of an observed aspect of intensity.

Any two of the mean residual estimates for differential distance groups can be used to estimate a consistent bound on the average effect of treatment among patients whose treatment differs between the two instrument-based groups. GMM techniques (Chamberlain, 1987)\(^{16}\) can be used to combine estimates from independent pairs into an

\(^{15}\)Some treatments may be used inappropriately or harmfully. The assumption only implies that the average probability of receiving inappropriate or harmful unobserved technologies does not increase as observed treatment intensity increases.

\(^{16}\)For technology \( r \), define \( \rho_{k l} = \rho_{k l}(\mathbf{d}_k, \bar{r}_{k l}, \eta') \) as the mortality outcome residual for the \( k \)th instrument cell of observations \((k=1, \ldots, K)\) in demographic group \( l \) \((l=1, \ldots, L)\), where \( \eta' \) is the average treatment effect to be estimated. The instrument vector \( \mathbf{d} \) satisfies the conditional moment restriction \( E[\rho_{k l} | \mathbf{d}_l] = 0 \), which identifies the model. The large-sample analog is that, subject to the conditional-moment restrictions, \( \eta' \) minimizes
efficiently-weighted average treatment effect bound across all instrument groups.

Following Angrist (1991), GMM estimation can be implemented with two-stage least squares (2SLS) estimation of the equation

\[ m_i = \mu + \eta_i' r_i + \{ h_i + [\eta_i(s) \cdot s_i - \eta_i' r_i] \} \]

(4)

\[ = \mu + \eta_i' r + \{ h_i + \epsilon_i \} \]

using the vector d of instrumental variable groups as instruments for the treatment effect r within each demographic group l. An equivalent estimation strategy, which more clearly illustrates the "randomization" of patients to different likelihoods of receiving alternative treatments, is generalized least squares (GLS) estimation of the grouped equation

\[ m_k = \mu + \eta_k' r_k' + \{ h_k + \epsilon_k \} \]

(5)

where the bars denote averages within instrument-demographic group cells kl, and \( \eta \) and \( \bar{\epsilon} \) are average effects among individuals receiving treatments. The preceding discussion provides a framework for interpreting the components of the bracketed unobserved terms in these regressions. The unobserved factors include patient health status h -- which by the standard IV assumptions will not lead to biased IV estimation, since its expectation given d is zero -- and treatment heterogeneity factors \( \epsilon \) -- the IV omitted variables problem in estimating \( \eta' \).

\[
\sum_{k=0}^{K} \sum_{l=0}^{L} \frac{\rho_{kl}^2}{\hat{\nu}_{kl}}
\]

where \( \hat{\nu}_{kl} \) is the estimated conditional variance of the cell. The GMM IV estimator is thus an optimally-weighted minimum-distance estimator (e.g., Newey, 1990).
Heteroskedasticity can arise in these models for many reasons (differences in group sizes, heterogeneity in the treatment effects, and heteroskedasticity in the binary model itself), so that both approaches require heteroskedasticity-consistent estimation techniques such as White (1982). Seemingly-unrelated regression techniques can also be used to exploit covariance of in the regression error structure across different outcome periods. Since each paired estimate includes the impact of unobserved correlated technologies on survival in addition to the effect of \( r \), the estimated bounds on average marginal treatment effects will vary if the correlation of these unobserved technologies with the observed technology varies across values of the instrument. Thus the hypothesized constant bound on the average treatment effect imposed by this estimation structure would be more likely to be rejected in a general specification test of the GMM model (Newey, 1985), even if all the identifying assumptions held.

If additional endogenous dimensions of treatment intensity are observed, simultaneous estimation of the effects of multiple components of treatment intensity may be possible. The models are the same as in (3)-(5), but in this case both correlated treatments \( r \) and \( q \) are observed. If independent instruments for each treatment are observed, some instrument-based groups exist whose likelihood of receiving each treatment varies independently. For example, any three independent instrument-based groups (denoted \( j,k,l \)) can estimate two average treatment effects \( \tilde{\eta}^i \) and \( \tilde{\eta}^q \):

\[
\tilde{m}_j \cdot \tilde{m}_k = \tilde{\eta}_{jk} \cdot (\tilde{r}_j \cdot \tilde{r}_k) + \tilde{\eta}^q_{jk} \cdot (\tilde{q}_j \cdot \tilde{q}_k)
\]
\[
\tilde{m}_k \cdot \tilde{m}_l = \tilde{\eta}^i_{kl} \cdot (\tilde{r}_k \cdot \tilde{r}_l) + \tilde{\eta}^q_{kl} \cdot (\tilde{q}_k \cdot \tilde{q}_l)
\]
Interaction effects between treatments can be viewed as an additional average treatment effects to be estimated; in the present example, the interaction of r and q could be estimated if independent instruments for the use of both treatments existed.\textsuperscript{17}

The minimum-distance GMM estimator for multiple treatments has dimension equal to the number of simultaneous treatment effects being estimated. Analogous to the estimation of a single treatment effect, the IV estimate of simultaneous treatment effects is a weighted average of outcome differences over all such minimum identifying sets in the sample. The weights used to estimate the average effect of a particular treatment are proportional to the number of patients whose use of that treatment changes and inversely related to the number of patients whose use of the other treatments changes. If the use of two treatments is perfectly correlated, estimates of the average effect of each cannot be obtained. Since weights are proportional to instrument-based changes in the use of a particular treatment given the use of other treatments, estimation of average marginal effects from another sample in which changes in use of the treatment occurred at different levels of use of other treatments may also lead to different estimated effects. The Newey overidentification test provides a test for a constant average effect of each treatment, in addition to testing for the other specification failures noted above. Further, the simultaneous IV models provide a specification test for the assumption of correlated technologies. If the assumption is correct, estimating both average marginal effects simultaneously should result in smaller effects than estimating either alone.

Finally, for absorbing outcome measures such as mortality, it may be possible to integrate \textit{a priori} knowledge about the timing of estimated effects to distinguish the

\textsuperscript{17}Here and in the remainder of the section, such interaction effects are omitted for clarity.
impact of a particular treatment from unobserved correlated technologies. Extending the
model in (3), the effect of a treatment on an absorbing outcome in a given time period
can be viewed as the cumulative effect of treatment during the time increments (in this
case 1 and 2, denoted by superscripts) that constitute the time period:

\[
m_d = \{ m^1(0,0) + [m^1(1,0) - m^1(0,0)] \cdot r_d \\
+ [m^1(0,1) - m^1(0,0)] \cdot q_d \} \\
+ \{ m^2(0,0) + [m^2(1,0) - m^2(0,0)] \cdot r_d \\
+ [m^2(0,1) - m^2(0,0)] \cdot q_d \}
\]  
(6)

If, for example, \( \eta^* = m^1(1,0) - m^1(0,0) \) is known to be no greater than \( \alpha^* \), then an IV
estimate of this effect \( \hat{\eta}^* = [\tilde{m} - \tilde{m}^1_k] / [\tilde{r} - \tilde{r}_k] < \alpha^* \) is biased by at least \( b^1 = \hat{\eta}^* - \alpha^* \) if
the effect of \( q \) persists into period 2. Such information can potentially be used to tighten
the estimated upper bound on the treatment effect of interest from \( \hat{\eta}^* \) to \( \hat{\eta}^* - b^1 \). However,
this assumption is perhaps too strong. If use of \( q \) only affects period 1 survival, then the
estimated effect \( \hat{\eta}^* \) will in fact equal the true effect of \( r \). Inferring effects of specific
treatments based on prior knowledge of time patterns of outcomes thus requires some
empirical judgment about effect persistence.

In the estimation results that follow, all three of these methods are applied to
improve the precision of the estimated bounds on specific aspects of medical treatment
intensity.
III. Estimation of Average Marginal Effects of Medical Treatment Intensity

Patient selection bias is again evident in Table 4, which presents least-squares estimates of the average effect of catheterization on mortality.\(^\text{18}\) Conditioning only on state of residence (row 1), catheterization is associated with a moderate reduction of -.08 in one-day mortality and progressively greater reductions at longer time intervals. By two years, for example, mortality rates differ by -.35 between catheterized and noncatheterized patients. But Table 1 demonstrated that treated and nontreated patients differ significantly in many observed characteristics. Adjusting for observed demographic differences (age, sex, and race) between treated and nontreated patients (row 2) reduces the estimated effect by 15 to 25 percent for the longer outcome intervals. For example, the two-year mortality rate difference falls to -.29. Including differences in the incidence of comorbid diseases (row 3) leads to an additional reduction of 5 to 10 percent. But even with these adjustments, the differences in outcomes are substantial.\(^\text{19}\)

\(^{18}\)The estimated effect sizes using nonlinear models (e.g., probit and logit) are identical to the grouped-data estimates. For survival intervals of less than 90 days, the impact of catheterization during that time interval is estimated; for intervals of 90 days or more, the effect of catheterization during the 90-day episode of care after AMI is estimated. Here and in Table 5, treatment effects were estimated using full interactions of the following patient cells: female, black, age 65-69, age 70-74, age 75-79, age 80-84, age 85-89, age 90 and over, and urban/rural residence. Average effects of state of residence are also included in the models (omitting state effects did not substantially affect the estimates but reduced the explanatory power of the model). The resulting cells were generally quite large; for example, there were 6,501 rural nonblack females age 75-79 with AMI. The smallest cell, rural black males age 90 and over, consisted of 189 patients. For brevity, Tables 4 and 5 report a weighted-average rural effect over all patients.

\(^{19}\)For example, for an average 65-year old patient, catheterization is predicted to decrease 30-day mortality from .194 to .013 (a mortality effect of -.181) and in two-year mortality from .389 to .113 (an effect of -.276).
Patients treated initially at high-volume hospitals (row 4) have significantly lower mortality rates at all time periods (e.g., over 10% lower at 30 days after AMI, an effect that largely persists to four years). Rural residence is also associated with significantly poorer outcomes (row 5) with the adverse effect occurring within the first few days after AMI, suggesting that reduced access to emergency response technologies leads to higher mortality rates. But some of this effect is also likely to be attributable to the lower intensity of rural hospital treatment, evident in Tables 1 through 3. Sorting out these treatment effects requires the IV methods outlined in Section II that account for both the endogeneity of treatment decisions and correlations between various aspects of treatment intensity.

The IV estimation strategy assumes patients prefer higher-intensity hospitals to lower and closer hospitals to those further away, and that some "marginal" patients are treated differently based on the technological capabilities of the admitting hospital. These testable behavioral assumptions permit identification of treatment effect bounds with the further assumption that a patient's differential distances to alternative hospital types are uncorrelated with health status. Hospitals performing catheterization tend to use more intensive technologies in other dimensions that are difficult to measure, introducing treatment heterogeneity. Thus the models to be estimated are of the form in (4) and (5), with the effect of treatment at a high-volume hospital included in some specifications as a summary measure of the effects of noninvasive technologies.\textsuperscript{20} The differential-distance

\textsuperscript{20}Interaction effects of catheterization and high-volume treatments, instrumented using differential distance to hospitals with both these technologies, were insignificant and are not included in the results reported below.
instruments essentially randomize patients to different likelihoods of receiving the alternative levels of treatment intensity.²¹

Whether this identification strategy is plausible can be addressed using the framework of Section II. Since important aspects of health status are unobserved, the basic identification condition of instrument-error orthogonality could be violated, leading to underestimation of the true effect of treatment. First, patients differentially farther from intensive hospitals may have significantly poorer absolute access to any hospital, so that those with more severe AMIs at large distances would be more likely to die before admission to a hospital than those living nearby. Second, patients with more severe medical problems may choose to live nearer to major medical facilities, and thus nearer to intensive hospitals. These potential orthogonality violations involve hypothesized correlations between unobserved health status and absolute, not differential, distances. Still, to the extent that absolute and differential distances are correlated, a potential identification failure exists.

AMI is an acute health shock, so little opportunity exists for choosing residence based on health status. Immediate death from AMI tends to be literally immediate, and in any case few patients live very far from any hospital. Additionally, some correlates of health status are observable. The distribution of age and observable comorbid conditions in the AMI population suggest that populations at alternative differential distances are

²¹ A companion paper (McClellan, 1992) analyzes the relationship between the availability of catheterization and revascularization technologies and diagnosis and treatment patterns at hospitals in detail. That study finds a fundamental difference in practice patterns across hospital types: patients initially admitted to catheterization hospitals are more than twice as likely to undergo invasive procedures as those initially admitted to noncatheterization hospitals. These findings provide further evidence of the validity of the IV model.
quite similar (Table 3). Since unobserved health characteristics are likely to be correlated with these observed health characteristics, heterogeneous effects of observed patient characteristics such as age and race on outcomes across differential-distance groups would be expected to lead to significant rejections of Chow tests for stability of these average effects. Specification tests based on these hypotheses are presented below.

Differential distance intuitively satisfies the regularity condition of monotonicity: as a given patient moves relatively nearer to an intensive hospital, his probability of treatment by that hospital is not likely to decrease. Figure 3 extends the two-group treatment comparison in Table 3 to a plot of mean residual catheterization probabilities for 15 groups based on differential distance intervals. A strong monotonic relationship is evident: patients in the nearest differential distance group are more than 1.6 times as likely to undergo catheterization within 90 days after AMI as those in the farthest group. The empirical relationship suggests (though it cannot prove) that the monotonicity condition for treatment intensity and differential distance is satisfied.

Figure 4A plots the mean residual probability of admission to a high-volume hospital against the same intervals of differential distance to a catheterization hospital, in

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22 The absence of significant differences in age and comorbid diseases across differential distance groups holds for other intervals besides the two presented in Table 3.

23 The intervals for the 15 right-closed differential distance groups were (in miles): 0, 0-1, 1-2, 2-4, 4-6, 6-8, 8-10, 10-12, 12-15, 15-18, 18-21, 21-25, 25-30, 30-40, and over 40. Results were not sensitive to alternative interval specifications. Figure 3 plots the mean residual for each group at the median distance for patients in the interval. Circle areas are proportional to group size.

24 Procedure use differences for shorter time intervals are even more dramatic. For example, patients in the nearest group are more than twice as likely to undergo catheterization within 7 days as those in the farthest group.
addition to the mean residual probability of catheterization. The figure suggests that the assumption of a significant positive correlation between different aspects of treatment intensity is plausible. Patients with small differential distances to catheterization are not only more likely to be catheterized after AMI; they are also much more likely to be treated at a high-volume hospital. As was discussed in the context of Table 2, these hospitals have greater access to many aspects of nonsurgical intensity of AMI treatment which may also improve outcomes.

Figure 4B extends the two-group comparison of the final two columns of Table 3 by plotting likelihood of admission to a high-volume hospital and likelihood of catheterization for high-volume differential distance groups. The relationship of high-volume admission to this instrument set is much stronger than in Figure 4A: the treatments are correlated but not collinear. Estimation with both instruments permits comparisons across patient groups that differ in their likelihood of receiving each of these observable aspects of treatment intensity, thus accounting for some of the effects of the unmeasured treatments. In contrast, Figure 4C plots the residual probability of catheterization against the residual probability of undergoing a revascularization procedure (CABG or PTCA). Average use of these technologies is collinear, so independent estimates of the effect of catheterization, PTCA, and CABG are not possible. For this reason, the remaining empirical results focus on the entire catheterization treatment path; estimates of the consequences of changes in practice patterns for the revascularization procedures are identical.

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25Plots of residual catheterization probabilities versus CABG rates or PTCA rates are also linear, with a slightly higher slope for the latter.
Figures 5A and 5B illustrate the basis for IV estimation of average treatment effects for catheterization and treatment by a high-volume hospital. The figures plot two-year mean residual mortality rates as a function of catheterization and hospital volume, for all IV subgroups of all demographic cells. In Figure 5A, IV estimation using differential distance to a catheterization hospital shows an association of catheterization with survival, though the effect is much smaller than that estimated by OLS techniques in Table 4. In Figure 5B, IV estimation using differential distance to a high-volume hospital also shows an association with survival. (Similar relationships exist for other survival intervals, with the strongest relationships in the initial 30-day interval after AMI.) The slopes of the minimum-distance fitted average treatment effects indicate more intensive treatment leads to better outcomes for marginal patients.

Estimated average marginal treatment effects using these GMM IV methods are presented in Table 5. For survival intervals of less than 90 days, the impact of catheterization during that time interval is estimated; for intervals of 90 days or more, the effect of catheterization during the 90-day episode of care after AMI is estimated. The first three panels present IV estimates for catheterization effectiveness alone. For survival intervals beyond 7 days, the estimates are much smaller than the corresponding estimates in Table 4. Panel (1) estimates a bound on the catheterization effect using only a set of indicator variables for differential distance to a catheterization hospital; panel (2) uses this set of instruments plus a set based on differential distance to an aggressive revascularization hospital, which is another strong independent predictor of catheterization use. The estimated effects are quite similar using the more efficient multiple-instrument specification (e.g., a formal Hausman (1978) test does not reject the model).
The third panel estimates a separate average effect for patient residence in a nonmetropolitan area. Rural patients are less likely to undergo catheterization; if this difference is correlated with other aspects of treatment intensity such as the quality of emergency acute care, then the apparent catheterization effect in panels (1) and (2) in part results from increased access to emergency technologies for urban residents. The coefficient estimates indicate that rural residence is associated with significantly poorer acute survival, independent of hospital treatment intensity, with virtually all of the difference arising within the first day. This first-day difference strongly suggests that differences in the quality of emergency treatment are responsible for the poorer rural outcomes. By one year, this survival benefit from emergency services for urban residents disappears.

Panels (4) and (5) of Table 5 begin to address the correlation of catheterization use with the use of other nonsurgical hospital technologies. These panels present GMM estimates of the impact of admission to a high-volume hospital, using differential distance intervals to a high-volume hospital as instruments. As Figure 5B indicated, admission to a high-volume hospital is associated with significantly lower mortality. The treatment effect peaks at 30 days and is smaller but still significant at four years. Accounting for the acute mortality differences of rural patients, who are less likely to be treated at high-volume hospitals, reduces the estimated effect on short-term mortality by approximately .007 (panel 5). Compared to the OLS estimate of the effect of admission to a high-volume hospital, there is a noticeable difference in the time pattern of the volume effect. In Table 4, the OLS estimate is smallest acutely and becomes larger for long-term outcomes. Thus IV estimation demonstrates a selection effect across hospitals even for
emergent admissions such as AMI: patients who are treated at high-volume hospitals have had somewhat more severe attacks (worse acute mortality) but otherwise have better underlying health status (better long-term mortality). The magnitude of this selection effect is considerably less dramatic than for catheterization, a less emergent decision than hospital choice.

The final two panels estimate the treatment effects jointly, using all three sets of instruments. Panel (6) corresponds to panel (2) with the addition of an endogenous volume effect. The correlated effects of these technologies are evident, as the impact of each is considerably smaller than in models where their effects are estimated separately. Panel (7) is a full model that also includes rural residence effects; as in panels (3) and (5), poorer acute outcomes for rural patients account for some of the association of both technologies with improved survival. In panel (7), the estimated effect of treatment at a high-volume hospital is slightly smaller in the acute phase compared to the model without a catheterization effect included (−.015 versus −.018 at 30 days), with much of this effect persisting at longer time intervals. The estimated effect of catheterization in the acute phase falls substantially in the multiple-technology model (for example, −.048 in panel 7 versus −.093 in panel 3 at 30 days; −.053 versus −.092 at four years). These estimated bounds on the effect of catheterization on outcomes are very small compared to the OLS estimates of Table 4. The catheterization effect is significantly different from zero only in the acute phase. At one year, the IV-estimated effect is less than one-seventh of the OLS estimate; at two through four years, it is approximately one-sixth of the OLS estimate.
Much of the IV-estimated catheterization effect appears to occur within the first day after AMI. This time pattern is not consistent with evidence from recent clinical trials on the impact of acute procedure use on short-term survival. The formal trials showed no benefit from catheterization and PTCA within the first 48 hours after AMI.\textsuperscript{26} One possible explanatory unobserved technology is thrombolytic (clot-busting) drug use, which appears to have been more widespread in hospitals with catheterization facilities during this time period.

This clinical trial evidence indicates that using a hospital volume effect to control for unobserved correlated technologies does not capture all of their effects. If the improved one-day survival associated with greater use of catheterization is in fact bias due to correlated technologies, an even smaller bound can be placed on the effect of catheterization. Table 6 reports IV estimates of the effect of "intention to treat" during the 90-day episode after AMI on mortality in specific time increments, as opposed to the effects of predicted treatment during the interval for survival intervals of less than 90 days. It differs from panel (7) of Table 5 in that the instrumented catheterization effect is catheterization within 90 days in all columns (including mortality less than 90 days) and

\textsuperscript{26}Clinical trials of acute effects include Erbel et al., 1986; Topol et al., 1987; Simmoons et al., 1988; TIMI Study Group, 1989; Rogers et al., 1990; and Califf et al., 1991. These studies did not randomize treatments received after the first weeks post-AMI and only evaluated outcomes during the initial hospitalization. In most of the trials, reinfarction and mortality rates were slightly higher in the groups treated with early PTCA, though individual sample sizes were too small to document statistically worse outcomes. From a clinical standpoint, potential long-term effectiveness is the major motivation for nonemergent revascularization procedures, which include most of the use of PTCA and almost all use of CABG in AMI patients. As noted in Section I, though Table 1 suggests that a relatively high proportion of CABG and PTCA use occurs within one day of AMI, this is partly an artifact of the use of the patient’s admission date to date the procedures occurring during the hospitalization.
the dependent variable is whether or not the AMI patient died during the time increment (0-1 day, 2-7 days, etc.).\textsuperscript{27} For this reason, the estimates of the effects of treatment at a high-volume hospital and rural residence are approximately equal to the differences between successive average effect estimates in panel (7) of Table 5. However, because differential distance induces a smaller gradient on 90-day catheterization than catheterization in more acute time intervals, the estimated effect of intention to catheterize on death within one day of AMI (\(-.071\) with a standard error of \(.019\)) is considerably larger and less precise than the estimated one-day catheterization effect in Table 5 (\(-.041\), standard error \(.011\)).

Similarly, in Table 5 the estimated effect of 30-day catheterization on 30-day survival is only slightly smaller than the estimated 7-day catheterization effect. But Table 6 shows that the declining catheterization gradient actually masks a more substantial association of likelihood of catheterization with higher mortality after the first week. Specifically, patients likely to undergo catheterization thus lose half of their initial benefits between 8 and 90 days (\(+.046\)). The period between 8 and 90 days coincides with the time in which most of the operative mortality associated with CABG and the other surgical procedures would occur.\textsuperscript{28} In contrast to this positive incremental effect of catheterization on mortality, patients likely to be treated at high-volume hospitals continue

\textsuperscript{27}We thank Jonathan Skinner for suggesting this presentation of when mortality effects arise. Estimation of a full hazard model is an alternative approach, but the interval approach is adequate for making the point about the timing of average treatment effects.

\textsuperscript{28}Some operative procedures and hence operative mortality might occur later in the first week following AMI. In fact, the coefficient estimate for the effect of catheterization in the 2-7 day interval (\(-.019\)) can be decomposed into a moderate protective effect on days 2-3 (\(-.031\)) followed by increased mortality risk in days 4-7 (\(+.012\)).
to gain survival benefits between 8 and 30 days and lose an insignificant amount of benefits between 31 and 90 days. Not until after one year -- when the longer-term benefits of catheterization and revascularization might be expected to appear -- do the patients likely to undergo catheterization again have any incremental survival benefits (-.010). The estimated survival effect increases slightly between two and four years, but the total long-term survival benefit is approximately two percentage points.

If the survival gradient generated at one day is attributed to unobserved technologies correlated with catheterization, then the estimated long-term survival benefit of catheterization is very close to zero for the marginal AMI patients. In any event, catheterization does not lead to substantial incremental improvements in long-term outcomes over the range of variation in use observed in these patients; the IV treatment effects estimated in Table 5 may be considerably larger than the true marginal effects of catheterization.

The GMM estimates of average treatment effects in Table 5 include a variety of general specification tests. Newey (1985) overidentification tests of the IV models using the distance-based instrument groups are reported for regressions in panels (3), (5), and (7) of Table 5 (overidentification tests in the other panels yielded similar results). In all models, GMM overidentification tests either fail to reject the identifying moment

\footnote{IV estimates of the marginal effect of intention to treat with catheterization (and standard errors) corrected for the bias generated by the one-day survival gradient are: -.020 (.021) for 7 days, .011 (.027) for 30 days, .035 (.033) for one year, .023 (.034) for two years, .022 (.035) for three years, and .014 (.035) for four years. Thus the point estimates are positive, and the 95% confidence interval for the average marginal effect bound on long-term survival is around -.05. As noted in Section II, however, this assumption may be too strong: though the pattern is consistent with operative mortality, the total decrements in survival benefits associated with catheterization between 8 days and one year (+.058) could result from the effect of unobserved technologies on immediate survival "wearing off."}
conditions or reject only mildly. Given the very large sample size, this is a particularly strong finding; for example, if only 100,000 observations were included in the dataset, none of the tests would reject at the conventional 5% level. The rejections are strongest for acute-phase outcomes, diminish, then become somewhat stronger by 4 years. These findings suggest that heterogeneity in the use and effects of unobserved aspects of treatment intensity may be greatest during the acute treatment period, become less consequential, then increase again as the impact of AMI and its treatment on outcomes diminishes.

A variety of other specification tests provide further evidence on the validity of these treatment effect estimates. Models estimated using parametric assumptions about the effects of observable covariates and errors (probit and linear probability specifications) yielded identical estimates of treatment effects. Additionally, tests for equality of least-squares and IV estimates of the effects of observable demographic covariates such as age, sex, and race rejected strongly. For example, the least-squares estimate of the effect of age on one-year mortality was one-third larger in magnitude than the IV estimate. These findings are consistent with the importance of patient selection effects. If patients likely to survive with or without procedure use are those selected for catheterization, then differences in health status which are correlated with observable characteristics will be captured in the least-squares estimates of catheterization effects. Thus, the effects of observable patient mortality risk factors appear substantially smaller than their "true" average risk.

The correlation between observed and unobserved differences in health status yields additional specification tests of the potential correlation between instruments and
individual heterogeneity in the IV models. If sicker patients are substantially more likely to be close to major medical facilities that include catheterization labs, then interactions of patient covariates with absolute access measures should be highly significant and substantially affect the estimated effects of covariates on mortality. IV estimates of catheterization effects should also increase in absolute value, since the access-demographic interaction terms will capture at least some of the relatively better outcomes of distant patients. Each patient’s absolute distance to a catheterization hospital was used to construct indicator variables of "low" or "high" absolute access to intensive treatment that formed the basis for these tests.\textsuperscript{30} Chow tests of the correlation of average demographic effects with access to catheterization rejected parameter stability significantly, not surprising given the sample size. Most of the interacted estimates of demographic effects were small and negatively associated with access, so that the magnitudes of the estimated catheterization effects in these models were slightly smaller than in the models without interactions. For example, the rejection was strongest in the model for one-day survival, in which the estimated catheterization effect fell insignificantly from -.04 to -.03.\textsuperscript{31} In other specifications in which absolute distance

\textsuperscript{30}While absolute distance to catheterization is correlated with differential distance to catheterization, the two measures differ substantially for many patients. For example, 40\% of AMI patients live more than 10 miles away from a catheterization hospital.

\textsuperscript{31}In all cases, the explanatory power of the interacted covariates was small. For example, F tests with (15, 205K) degrees of freedom (based on interacting age, sex, and race with an indicator variable equal to one for absolute distance to catheterization less than 10 miles) yielded the following results (F test for the significance of the noninteracted base model in parentheses): 6.8 (36.2) at one day, 6.4 (113.7) at 30 days, and 5.7 (254.6) at two years. Similarly, models using only urban patients and only patients less than 10 miles in absolute distance from catheterization hospitals yielded slightly smaller estimated catheterization effects.
measures were included as covariates, the estimated treatment effects were similarly insignificantly smaller. If health status in AMI patients is significantly correlated with distance, then -- in contrast to the selection effect for catheterization -- it has no substantive correlation with any of the observed patient characteristics that influence mortality.\(^{32}\)

### IV. Policy Implications

Conservative estimates of the consequences for outcomes of using surgical technologies less frequently in AMI management are outlined in Table 7, based on the estimated effects in Tables 4 and 5. Here, policy changes are modeled as changes in patient distance to catheterization facilities. Patient distance is to some extent a policy option; for example, some states such as New York regulate the adoption of catheterization facilities through certification of need programs, and various authors have proposed regionalization of catheterization facilities (Maerki, Luft, and Hunt, 1986; Luft et al., 1990). Alternatively, publication of new information on procedure effectiveness may lead clinicians to revise their estimates of the net benefits of surgical procedures, shifting practice patterns for marginal patients without regulatory changes. Table 7 simulates the consequences of a substantial change in technology use -- the treatment of

\(^{32}\)Another set of specification tests used information on patient comorbid diseases as additional correlates of health status to examine the relationship of differential distance and patient health. As was noted previously, the incidence of comorbid diseases generally did not appear to be significantly correlated with distance. Including these disease covariates led to estimates of catheterization effects that were slightly smaller in magnitude than those reported in Table 5, and volume effects that were virtually identical.
AMI patients with differential distances to catheterization of less than 30 miles using practice patterns observed for patients at that distance -- that is within the range of variation observed in the data. Catheterization rates would fall by 23% (.228 to .176) but one-year mortality would only increase by at most 0.5% (.402 to .404; upper confidence limit .407) and four-year mortality would increase by at most 0.5% (.583 to .586). In contrast, the corresponding OLS estimates for mortality effects are 3.2% at one year (.402 to .415) and 2.6% at four years (.583 to .598).

The estimates do not consider important non-mortality outcomes such as freedom from pain or activity level. But quality of life considerations must be weighed against the apparent increased probability of death during the perioperative period (7 to 90 days after AMI) and the small incremental survival benefits after the first day in patients likely to receive catheterization. Indeed, if some of the survival benefits appearing at one day are attributed to unmeasured technologies that reduce immediate mortality, as Table 7 suggested, then the predicted consequences of more limited use of surgical technologies would be even smaller.

The final row of Table 7 presents preliminary estimates of the change in hospital costs for treating elderly AMI patients that would be associated with this change in treatment intensity.\textsuperscript{33} This estimate, which is probably quite conservative, suggests that

\textsuperscript{33}Cost estimates are based on actual Medicare payments to hospitals for AMI treatment in the elderly. In 1987, these costs exceeded $2 billion and averaged $15,407 for a catheterized patient, twice as high as for noncatheterized patients. The estimates do not reflect the better health status of catheterized patients and do not include differences in physician and outpatient costs of health care. For example, in 1987, average total physician fees for catheterization were around $1600, for PTCA were an additional $1500, and for CABG were over $5000 (Mitchell et al., 1989). Thus, the estimated effect of changes in treatment intensity on costs is likely to be quite conservative. A comprehensive analysis of the financial and resource costs of alternative strategies for AMI management, including
the marginal effect of catheterization and revascularization technologies on one-year survival is over $180,000 per year of life saved (95% lower confidence limit around $80,000), in contrast to the OLS estimate of around $40,000.\textsuperscript{34}

Though these simulations suggest that the adoption of less intensive treatment patterns would have minimal consequences for AMI outcomes in the elderly, catheterization and revascularization use have increased substantially since 1987. This study predicts that the trends toward greater intensity will lead to considerably higher costs without much effect on mortality, a hypothesis that is testable using data on AMI treatment and outcomes from more recent years.

The estimation results also demonstrated that other aspects of treatment intensity after AMI have consequences for patient survival. Patients treated at less intensive hospitals face a higher risk of death, especially in the acute post-AMI setting. Rural patients face a higher average risk, both as a result of a higher probability of admission to such hospitals, and as a result of poorer access to advanced emergency response technologies. Together, these treatment differences could account for as much as a 20% difference (.036) in 7-day mortality and a 15% difference (.034, at 30 days relative to patients admitted to high-volume, high-intensity urban hospitals, though the effects by one year (.016, 4%) are smaller.\textsuperscript{35} A redirection of resources for AMI treatment from longer-term cost consequences, is left for future work.

\textsuperscript{34}The range in the IV estimates of cost-benefit ratios is primarily due to the closeness of the estimated effect size to zero rather than its imprecision. Attributing some of the estimated survival effect to unobserved acute technologies would lead to a higher ratio.

\textsuperscript{35}For example, consider a "marginal" rural patient who would be admitted to a low-volume noncatheterization hospital. Providing that patient with the same emergency treatment as an average urban patient could reduce expected 30-day mortality by .007;
invasive procedures to greater availability of nonsurgical technologies, such as thrombolytic drugs or CCUs, and better emergency response systems could lead to improved AMI survival without increasing Medicare program costs.

V. Conclusions

This paper presents evidence on a critical problem in health economics: uncertainty about the consequences of medical treatment intensity for patient outcomes. The IV estimation framework features a very general model of treatment effects, accounts for the presence of unobserved aspects of treatment intensity, and permits a range of specification tests of key identifying assumptions. We apply this framework to analyze the impact of treatment intensity on short- and long-term mortality for all elderly patients hospitalized with new AMIs in the United States in 1987. For these patients, at least some components of treatment intensity affected mortality. The nature and magnitude of these estimated effects, however, are quite different when methods are used that account for substantial unobserved differences in patient health status compared to those that do not. Patients who underwent intensive surgical procedures did much better than those who did not, but this differential mortality is largely attributable to better health status in patients receiving these intensive procedures. Differences in nonsurgical treatment intensity between urban and rural patients and across hospital types have consequences for providing the technologies available at high-volume hospitals would reduce it on average by .015; providing the technologies available at catheterization/revascularization hospitals that affect acute survival would reduce it on average by .012. Together, this amounts to a 30-day mortality reduction of over 13%.
AMI survival, but the relative importance of these effects for long-term survival is limited by high baseline mortality rates in the elderly population. Conclusions about optimal tradeoffs between volume, technology availability, ease of access, and other considerations awaits more detailed analyses of variations in costs and access to treatment across hospital types.

This IV estimation strategy provides an important complement to randomized clinical trial evidence on the impact of medical technologies. In contrast to clinical trials, which attempt to estimate average effects over all patients (or subgroups of patients), IV methods estimate "local average" effects of treatments -- average effects among patients who are "marginal" in the sense that their treatment intensity was influenced by the instrumental variable. But these marginal effects in actual populations may be most relevant to predict the impact of policies affecting medical technology use. Inferences about the effect of changes in medical treatment patterns outside the controlled setting of a clinical trial are often speculative. Moreover, clinical trials that are relevant to current practice, have large enough sample sizes, and last long enough to reach meaningful conclusions cannot be conducted for many technologies that contribute significantly to growth in medical treatment intensity. Provided good instruments such as differential distance can be identified, IV methods are especially useful in these settings. On the other hand, IV methods applied to large observational datasets have limitations in disentangling the effects of multiple technologies whose use may be correlated, which may be important in understanding acute outcome processes (i.e., within several days of the event of interest). But these are cases where clinical trials tend to work well. Such
complementarity was evident in analyzing the consequences of treatment intensity in this study.

Consequently, the IV framework applied here may be widely applicable to problems in health economics and biostatistics where the effects of technology are uncertain and the more intensive treatment alternatives are not everywhere available. Given the importance of technology in determining health costs, the variations in treatment intensity, and the uncertainty about technology effects that exist in almost all medical practices, those applications may include much of medical care.
The Appendix presents formal conditions for identification of the simultaneous
treatment effect models presented in the text. From equation (2), the model to be estimated is

\[ m_i(0) = \mu + h_i \]

\[ m_i(s_i) = m_i(0) + \eta_i(s_i) \]  \hspace{1cm} (A1)

where \( m_i(*) \) is an indicator for patient i's mortality given treatment intensity choice, \( s \) is a
vector describing the use of technologies that contribute to intensity of AMI management,
many of which are imperfectly observed, and \( \eta_i(s_i) \) is a corresponding vector of the effect of
the technologies on patient i's outcome. The vector \( s_i \) can be decomposed into \([r_i, q_i]'\), where
\( r_i \) is the observable treatment of interest (e.g., invasive procedure use) and \( q_i \) represents use of
all other unmeasured technologies (including potential interaction effects).

To identify a treatment effect bound, the hypothesized instrument vector \( d \) must
satisfy four conditions; the reasonableness of these conditions in the context of estimating the
effects of medical technologies is discussed in the text. Imbens and Angrist (1991) describe
identification conditions for a single binary treatment \( r \) (individual subscripts \( i \) are suppressed
for notational simplicity):

**Condition 1.** For potential instruments \( d \), \( E[r|d] \) is a nontrivial function of \( d \), \( E[m(0)|d] = E[m(0)], \) and \( E[m(1)|d] = E[m(1)]. \)

A further regularity assumption, so that changes in the value of the instrument have a
unidirectional effect on treatment, is required to identify a meaningful treatment effect.\textsuperscript{\ref{footnote:monotonicity}} Let \( P_r \) denote the probability of receiving treatment \( r \) given a specific value of the instrument set \( d=d_r \).

\textbf{Condition 2 (Monotonicity).} For all \( d_r, d_w \) such that \( P_r \neq P_w \), \( (P_r - P_w) \cdot (r_r - r_w) \geq 0 \) and \( P_r = P_w \Rightarrow r_r = r_w \). Equivalently, \( \Pr(r_r - r_w \geq 0) = 1 \) or \( \Pr(r_r - r_w \geq 0) = 0 \).

Two additional conditions are required to generalize this model to estimation of treatment effects with heterogeneous correlated treatments. The conditions imply that changes in the value of the instrument do not lead to changes in overall intensity that offset the effect of the technology of interest. The first new condition is a multidimensional monotonicity assumption: an individual more likely to receive the observable technology \( r \) is not less likely to receive other treatments that improve outcomes. In other words, unobserved dimensions of intensity of treatment are correlated with observed dimensions. Let \( P_{d} \) represent a vector whose \( j \)th element is \( \Pr(s_j=1 \mid d) \), the probability that the \( j \)th technology is used if the instrument has value \( d \).

\textbf{Condition 3 (Generalized Monotonicity).} For all \( d_r, d_w, (P_r - P_w) \geq 0 \) and \( (s_r - s_w) \geq 0 \), or \( (P_r - P_w) \leq 0 \) and \( (s_r - s_w) \leq 0 \).

Second, in theory some interventions might increase the probability of adverse outcomes, so that their average effect on mortality is positive. In practice, though many interventions may

\textsuperscript{\footnote{As Imbens and Angrist note, monotonicity is actually a stronger condition than is required for identifying meaningful treatment effects.}}

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have negligible effects in some patients, and interventions may have adverse effects in some cases, treatments are unlikely to be harmful on average. Condition 4 formalizes this lower bound on the average effectiveness of correlated technologies \( q \) for individuals whose treatment is affected by changes in the value of the instrument.\(^{37}\)

**Condition 4 (Nonharmfulness).** \( \mathbb{E}[\eta(s_x) - \eta(s_w) \mid s_x > s_w] \leq 0, \) or equivalently
\[
\mathbb{E}[\eta(s_x) - \eta(s_w) \mid s_x < s_w] \geq 0.
\]

If these conditions hold, then the following Theorem states that a bound on the effect of the technology of interest \( \eta' \) can be estimated using IV techniques.

**Theorem 1:** Given Conditions 1–4, then a bound \( \alpha_{rw} \) on the average effect of treatment \( r \) is identified as
\[
\alpha_{rw} = \mathbb{E}[ m_x - m_w \mid s_x \neq s_w] / \mathbb{E}[r_x - r_w]
\]
for all \( d_x, d_w \) such that \( P_r^r \neq P_r^w \), and
\[
\alpha_{rw} \leq \mathbb{E}[ \eta(r) \mid r_x \neq r_w ] / \mathbb{E}[r_x - r_w].
\]

**Proof of Theorem 1**

The conditional probabilities \( \bar{m}_d = \mathbb{E}[ m \mid d ] \) and \( \bar{r}_d = \mathbb{E}[ r \mid d ] \) are identified for all \( d \). Assume the instrument values are ordered so that \( P_r^r > P_r^w \), which implies that each patient with instrument \( d = d_x \) receives at least as intensive treatment in unobserved dimensions

\(^{37}\)An equivalent interpretation is that if some treatments are harmful on average among patients receiving them, these treatments are not more likely to be used as observed intensity increases.
for \( d = d_z \) as for \( d = d_w \), that some patients receive \( r \) if \( d = d_z \) but not if \( d = d_w \), and that the instrument is ordered so that \( r_z > r_w \). First,

\[
\bar{m}_z - \bar{m}_w = \mathbb{E}[ m \mid d = d_z ] - \mathbb{E}[ m \mid d = d_w ]
\]

\[
= \mathbb{E}[ m(0) + \eta(s_z) ] - \mathbb{E}[ m(0) + \eta(s_w) ]
\]

using Condition 1,

\[
= \mathbb{E}[ \eta(s_z) - \eta(s_w) ]
\]

\[
= \Pr( r_z - r_w = 1 ) \cdot \mathbb{E}[ \eta(s_z) - \eta(s_w) \mid r_z - r_w = 1 ]
\]

\[
+ \Pr(s_z - s_w > 0 \text{ and } r_z - r_w = 1) \cdot \mathbb{E}[ \eta(s_z) - \eta(s_w) \mid s_z - s_w > 0 \text{ and } r_z - r_w = 0]
\]

By assumptions 2 and 3, there are no additional terms because \( \Pr(r_z - r_w < 0) = 0 \) and \( \Pr(s_z - s_w < 0) = 0 \). Note that the observed instrument-based difference in outcomes is equal to the effect of \( r \) among the individuals who receive \( r \) if \( d = d_z \) but not if \( d = d_w \), the effect of any other technologies these individuals receive if \( d = d_z \) but not \( d = d_w \), and the effect of any additional technologies received by individuals whose use of \( r \) does not change between \( d_z \) and \( d_w \). By assumption 4, the average effect on mortality of the additional technologies among individuals who receive them if \( d = d_z \) but not if \( d = d_w \) is less than or equal to 0, so that

\[
\bar{m}_z - \bar{m}_w \leq \Pr( r_z - r_w = 1 ) \cdot \mathbb{E}[ \eta' \mid r_z - r_w = 1 ]
\]

Since \( r_z - r_w > 0 \), \((\bar{m}_z - \bar{m}_w)/(\bar{r}_z - \bar{r}_w)\) bounds the average effect of technology \( r \) on patients who are treated with \( r \) if \( d = d_z \) but are not treated with \( r \) if \( d = d_w \) (note that \( \alpha_{z,w} \) will generally be negative in this case, unless the "marginal" patients treated with \( r \) do worse). For \( \bar{r}_z < \bar{r}_w \), by conditions 2 and 3 \( r_z \leq r_w \) and \( q_z \leq q_w \), and the same result follows. QED.

In general, the variance of the estimate of the bound is also an upper bound on the variance of the treatment effect. Since \( m_z \) and \( m_w \) are derived from independent samples,

\[
\text{var} \ (\alpha_{z,w}) = \left[ 1/(r_z - r_w) \right]^2 \cdot \left[ \text{var}(m_z) + \text{var}(m_w) \right]
\]

and
\[ \text{var}(m_a) = \text{var} [ h + \eta(s_a) ] . \]

Thus if all other treatment effects are constant, \( \text{var}(m_a) = \text{var}(m'_a) \). If other treatment effects are not constant, \( \text{var}(m_a) \) will generally be greater than \( \text{var}(m'_a) \) unless the covariance of treatments \( r \) and \( q \) is sufficiently negative among patients for whom both technologies are used (i.e., if other treatments are less helpful to those for whom technology \( r \) is more helpful). By Condition 3, \( E[\eta(s) \mid q_r \neq q_w] \leq 0 \), and in general \( E[\eta' \mid r_r \neq r_s] \leq 0 \), so that only in bizarre cases would such a substantial negative correlation occur.
FIGURE 1
INVASIVE PROCEDURE DECISION PATHS FOR HEART ATTACK PATIENTS

Heart Attack (AMI)

No Cath \[\rightarrow\] "Medical" Management (Anatomy Unknown)

Cath \[\rightarrow\] "Medical" Management (Anatomy Known)

\[\rightarrow\] PTCA Revascularization
\[\rightarrow\] CABG Revascularization

FIGURE 2
DIFFERENTIAL DISTANCE CALCULATION

\[\begin{array}{c}
\text{HOSPITAL 1} \\
\text{CATH} \\
\hline
A \\
\hline
B \\
\hline
\text{HOSPITAL 2} \\
\text{NO CATH} \\
\hline
\end{array}\]

\[d_0\]

\[d_1\]

\[d_2\]
FIGURE 3

[Graph showing a scatter plot with the x-axis labeled "Diff. Dist. to Cath. Hosp." and the y-axis labeled "Resid. Prob. (90-Day Cath.")]
<table>
<thead>
<tr>
<th>PATIENT CHARACTERISTICS</th>
<th>FULL COHORT (N=205,021)</th>
<th>7-DAY SURVIVORS (N=168,744)</th>
<th>FULL COHORT TREATMENT INTENSITY WITHIN 90 DAYS</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>NO CATH (N=158,261)</td>
<td>CATH (N=46,760)</td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>50.36</td>
<td>49.49</td>
<td>53.50</td>
</tr>
<tr>
<td>White</td>
<td>90.65</td>
<td>90.31</td>
<td>90.40</td>
</tr>
<tr>
<td>Black</td>
<td>5.65</td>
<td>5.91</td>
<td>6.04</td>
</tr>
<tr>
<td>Age in Years (Standard Deviation)</td>
<td>76.11 (7.26)</td>
<td>76.06 (7.13)</td>
<td>77.40 (7.29)</td>
</tr>
<tr>
<td>Urban</td>
<td>70.55</td>
<td>71.20</td>
<td>69.60</td>
</tr>
<tr>
<td>Cancer</td>
<td>1.89</td>
<td>1.80</td>
<td>2.20</td>
</tr>
<tr>
<td>Pulmonary Disease, Uncomplicated</td>
<td>10.70</td>
<td>11.24</td>
<td>11.11</td>
</tr>
<tr>
<td>Dementia</td>
<td>0.97</td>
<td>0.97</td>
<td>1.22</td>
</tr>
<tr>
<td>Diabetes</td>
<td>18.01</td>
<td>18.52</td>
<td>18.29</td>
</tr>
<tr>
<td>Renal Disease, Uncomplicated</td>
<td>1.92</td>
<td>1.73</td>
<td>2.27</td>
</tr>
<tr>
<td>Cerebrovascular Disease</td>
<td>4.80</td>
<td>4.77</td>
<td>5.39</td>
</tr>
</tbody>
</table>

68
<table>
<thead>
<tr>
<th>Rate (%)</th>
<th>Full Cohort (N=205,021)</th>
<th>7-Day Survivors (N=168,744)</th>
<th>Full Cohort Treatment Intensity Within 90 Days</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>No Cath (N=158,261)</td>
<td>Cath (N=46,760)</td>
<td></td>
</tr>
<tr>
<td><strong>Patient Treatments and Outcomes</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Admit to Cath. Hospital</td>
<td>45.89</td>
<td>46.63</td>
<td>40.86</td>
</tr>
<tr>
<td>Admit to Revasc. Hospital</td>
<td>26.19</td>
<td>26.72</td>
<td>21.63</td>
</tr>
<tr>
<td>Admit to High-Vol. Hospital</td>
<td>51.81</td>
<td>52.70</td>
<td>49.97</td>
</tr>
<tr>
<td>7-Day Catheterization</td>
<td>15.85</td>
<td>18.36</td>
<td>0</td>
</tr>
<tr>
<td>30-Day Catheterization</td>
<td>19.85</td>
<td>23.21</td>
<td>0</td>
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<td>90-Day Catheterization</td>
<td>22.81</td>
<td>26.81</td>
<td>0</td>
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<td>7-Day CABG</td>
<td>3.70</td>
<td>4.30</td>
<td>0.41</td>
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<tr>
<td>90-Day CABG</td>
<td>7.74</td>
<td>9.21</td>
<td>0.94</td>
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<tr>
<td>7-Day PTCA</td>
<td>3.87</td>
<td>4.40</td>
<td>0.46</td>
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<td>90-Day PTCA</td>
<td>5.30</td>
<td>6.14</td>
<td>0.59</td>
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<tr>
<td>1-Day Mortality</td>
<td>8.19</td>
<td>0</td>
<td>10.34</td>
</tr>
<tr>
<td>7-Day Mortality</td>
<td>17.69</td>
<td>0</td>
<td>21.96</td>
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<tr>
<td>30-Day Mortality</td>
<td>25.60</td>
<td>9.61</td>
<td>26.60</td>
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<td>1-Year Mortality</td>
<td>40.17</td>
<td>27.31</td>
<td>47.11</td>
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<td>2-Year Mortality</td>
<td>47.54</td>
<td>36.27</td>
<td>55.29</td>
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<td>3-Year Mortality</td>
<td>53.36</td>
<td>43.34</td>
<td>61.58</td>
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<td>4-Year Mortality</td>
<td>58.29</td>
<td>49.32</td>
<td>66.67</td>
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</table>
**TABLE 2: HOSPITAL CHARACTERISTICS FOR AMI TREATMENT**
(WEIGHTED BY NUMBER OF INITIAL AMI ADMISSIONS)

<table>
<thead>
<tr>
<th>HOSPITAL VOLUME</th>
<th>NO. HOSPS</th>
<th>PATIENT SHARE</th>
<th>&lt;100</th>
<th>100-300</th>
<th>300-500</th>
<th>500+</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt;25 AMI ADMISSIONS</td>
<td>2,909 (49.8)</td>
<td>25,050 (12.2)</td>
<td>75.9</td>
<td>21.4</td>
<td>1.9</td>
<td>0.8</td>
</tr>
<tr>
<td>25-74 AMI ADMISSIONS</td>
<td>1,889 (32.3)</td>
<td>73,747 (36.0)</td>
<td>20.8</td>
<td>61.3</td>
<td>13.5</td>
<td>4.4</td>
</tr>
<tr>
<td>75-149 AMI ADMISSIONS</td>
<td>824 (14.1)</td>
<td>70,109 (34.2)</td>
<td>1.0</td>
<td>39.5</td>
<td>42.5</td>
<td>17.0</td>
</tr>
<tr>
<td>&gt;150 AMI ADMISSIONS</td>
<td>222 (3.8)</td>
<td>36,115 (17.6)</td>
<td>0</td>
<td>9.6</td>
<td>41.2</td>
<td>49.2</td>
</tr>
<tr>
<td>TOTAL</td>
<td>5,844 (100.0)</td>
<td>205,021 (100.0)</td>
<td>35,082 (17.1)</td>
<td>81,717 (39.9)</td>
<td>55,157 (26.9)</td>
<td>33,065 (16.1)</td>
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<tr>
<td>HOSPITAL VOLUME</td>
<td>CCU</td>
<td>NONE</td>
<td>CATH</td>
<td>CATH/REVASC</td>
<td>90-DAY CATH</td>
<td>RURAL ADMITS</td>
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<tr>
<td>-----------------</td>
<td>-----</td>
<td>------</td>
<td>------</td>
<td>-------------</td>
<td>-------------</td>
<td>--------------</td>
</tr>
<tr>
<td>&lt;25 AMI ADMISSIONS</td>
<td>57.2</td>
<td>96.2</td>
<td>3.3</td>
<td>0.5</td>
<td>17.0</td>
<td>64.0</td>
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<tr>
<td>25-74 AMI ADMISSIONS</td>
<td>81.5</td>
<td>69.8</td>
<td>18.9</td>
<td>11.3</td>
<td>20.8</td>
<td>38.6</td>
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<tr>
<td>75-149 AMI ADMISSIONS</td>
<td>93.7</td>
<td>39.7</td>
<td>26.3</td>
<td>33.9</td>
<td>24.6</td>
<td>18.8</td>
</tr>
<tr>
<td>&gt;150 AMI ADMISSIONS</td>
<td>97.3</td>
<td>20.8</td>
<td>19.8</td>
<td>59.4</td>
<td>27.4</td>
<td>7.4</td>
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<td>TOTAL</td>
<td>175,188</td>
<td>110,933</td>
<td>40,382</td>
<td>53,706</td>
<td>46,760</td>
<td>60,380</td>
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<tr>
<td></td>
<td>(85.4)</td>
<td>(54.1)</td>
<td>(19.7)</td>
<td>(26.2)</td>
<td>(22.8)</td>
<td>(29.5)</td>
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<td>PATIENT CHARACTERISTICS</td>
<td>DIFFERENTIAL DISTANCE TO CATHETERIZATION HOSPITAL</td>
<td>DIFFERENTIAL DISTANCE TO HIGH-VOLUME HOSPITAL</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>-------------------------</td>
<td>--------------------------------------------------</td>
<td>--------------------------------------------</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>≤2 mi (N=102,744)</td>
<td>&gt;2 mi (N=102,277)</td>
<td>≤2 mi (N=113,312)</td>
<td>&gt;2 mi (N=91,709)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>51.18</td>
<td>49.52</td>
<td>51.24</td>
<td>49.27</td>
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</tr>
<tr>
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<td>92.38</td>
<td>89.97</td>
<td>91.49</td>
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</tr>
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<td>Black</td>
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<td>4.21</td>
<td>6.34</td>
<td>4.79</td>
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<tr>
<td>Age in Years (Standard Deviation)</td>
<td>76.11 (7.30)</td>
<td>76.11 (7.22)</td>
<td>76.11 (7.27)</td>
<td>76.11 (7.26)</td>
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<td></td>
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<td>48.25</td>
<td>89.09</td>
<td>47.64</td>
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<td></td>
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<td>1.85</td>
<td>1.93</td>
<td>1.84</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pulmonary Disease, Uncomplicated</td>
<td>10.43</td>
<td>10.96</td>
<td>10.64</td>
<td>10.77</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Dementia</td>
<td>0.99</td>
<td>0.94</td>
<td>0.97</td>
<td>0.96</td>
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</tr>
<tr>
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<td>18.00</td>
<td>18.38</td>
<td>17.57</td>
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<tr>
<td>Renal Disease, Uncomplicated</td>
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<td>1.85</td>
<td>1.97</td>
<td>1.85</td>
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<td></td>
</tr>
<tr>
<td>Cerebrovascular Disease</td>
<td>4.78</td>
<td>4.82</td>
<td>4.77</td>
<td>4.85</td>
<td></td>
<td></td>
</tr>
<tr>
<td>RATE (%)</td>
<td>DIFFERENTIAL DISTANCE TO CATHETERIZATION HOSPITAL</td>
<td>DIFFERENTIAL DISTANCE TO HIGH-VOLUME HOSPITAL</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>---------</td>
<td>-----------------------------------------------</td>
<td>--------------------------------------------</td>
<td></td>
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<tr>
<td></td>
<td>≤2 mi (N=102,744)</td>
<td>&gt;2 mi (N=102,277)</td>
<td>≤2 mi (N=113,312)</td>
<td>&gt;2 mi (N=91,709)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Admit to Cath. Hospital</td>
<td>75.20</td>
<td>16.45</td>
<td>59.09</td>
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<tr>
<td>Admit to Revasc. Hospital</td>
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<td>11.07</td>
<td>33.72</td>
<td>16.90</td>
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<td></td>
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<tr>
<td>Admit to High-Vol. Hospital</td>
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<td>37.38</td>
<td>78.29</td>
<td>19.10</td>
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<tr>
<td>7-Day Catheterization</td>
<td>20.53</td>
<td>11.14</td>
<td>16.93</td>
<td>14.52</td>
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<tr>
<td>30-Day Catheterization</td>
<td>23.51</td>
<td>16.17</td>
<td>20.51</td>
<td>19.02</td>
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<tr>
<td>90-Day Catheterization</td>
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<td>19.62</td>
<td>23.28</td>
<td>22.23</td>
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<tr>
<td>7-Day CABG</td>
<td>4.50</td>
<td>2.90</td>
<td>3.87</td>
<td>3.49</td>
<td></td>
<td></td>
</tr>
<tr>
<td>90-Day CABG</td>
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<td>6.94</td>
<td>7.90</td>
<td>7.55</td>
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<tr>
<td>7-Day PTCA</td>
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<td>3.76</td>
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<td>4.30</td>
<td>5.33</td>
<td>5.26</td>
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<tr>
<td>1-Day Mortality</td>
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<td>8.84</td>
<td>7.46</td>
<td>9.10</td>
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<td>18.56</td>
<td>16.65</td>
<td>18.99</td>
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</tr>
<tr>
<td>30-Day Mortality</td>
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<td>26.36</td>
<td>24.59</td>
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<td></td>
</tr>
<tr>
<td>1-Year Mortality</td>
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<td>40.60</td>
<td>39.55</td>
<td>40.93</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2-Year Mortality</td>
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<td>47.09</td>
<td>48.11</td>
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</tr>
<tr>
<td>3-Year Mortality</td>
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<td>53.67</td>
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<td>53.86</td>
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<td></td>
</tr>
<tr>
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<td>58.58</td>
<td>57.97</td>
<td>58.67</td>
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<td></td>
</tr>
</tbody>
</table>
TABLE 4: LEAST-SQUARES ESTIMATES OF TREATMENT EFFECTS

<table>
<thead>
<tr>
<th>TREATMENT EFFECT AND COVARIATES</th>
<th>(1) 1-DAY MORTALITY</th>
<th>(2) 7-DAY MORTALITY</th>
<th>(3) 30-DAY MORTALITY</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) CATHETERIZATION EFFECT, STATE CONTROLS ONLY</td>
<td>-.0778 (.0018)</td>
<td>-.1608 (.0023)</td>
<td>-.2190 (.0024)</td>
</tr>
<tr>
<td>(2) CATHETERIZATION EFFECT, STATE AND DEMOGRAPHIC CONTROLS</td>
<td>-.0667 (.0019)</td>
<td>-.1366 (.0024)</td>
<td>-.1865 (.0025)</td>
</tr>
<tr>
<td>(3) CATHETERIZATION EFFECT, STATE, DEMOGRAPHIC, COMORBIDITY CONTROLS</td>
<td>-.0678 (.0019)</td>
<td>-.1347 (.0024)</td>
<td>-.1785 (.0025)</td>
</tr>
<tr>
<td>(4) HIGH-VOLUME HOSP. EFFECT, STATE AND DEMOGRAPHIC CONTROLS</td>
<td>-.0163 (.0013)</td>
<td>-.0201 (.0018)</td>
<td>-.0233 (.0020)</td>
</tr>
<tr>
<td>(5) RURAL RESIDENCE EFFECT, STATE AND DEMOGRAPHIC CONTROLS</td>
<td>.0139 (.0015)</td>
<td>.0157 (.0021)</td>
<td>.0143 (.0023)</td>
</tr>
</tbody>
</table>

1 Each cell in the Table presents the least-squares regression estimate of a treatment effect, with standard errors in parentheses. Dependent variables for the regressions in each cell, mortality during a time interval after AMI, are listed in column heads (1) to (7). The treatment effect estimated in each row is listed in the first column, along with state, demographic, and comorbid disease controls if present in the model. State effects are indicator variables for state of residence (including DC). Demographic controls include fully-interacted effects of the following patient demographic characteristics: age 65-69, age 70-74, age 75-79, age 80-84, age 85-89, age 90 and over, sex, and black or nonblack race. Rural residence effects include interactions of rural residence with all of the demographic cells; a weighted-average rural effect is reported for clarity. Comorbidity controls include indicator variables for patient comorbid diseases noted at the time of discharge that were clinically unlikely to have arisen as complications of AMI treatment. See text for discussion.
### TABLE 4, CONT.: LEAST-SQUARES ESTIMATES OF TREATMENT EFFECTS\(^1\)

<table>
<thead>
<tr>
<th>TREATMENT EFFECT AND COVARIATES</th>
<th>(4) 1-YEAR MORTALITY</th>
<th>(5) 2-YEAR MORTALITY</th>
<th>(6) 3-YEAR MORTALITY</th>
<th>(7) 4-YEAR MORTALITY</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) CATH. EFFECT, STATE CONTROLS ONLY</td>
<td>-.3100 (.0025)</td>
<td>-.3450 (.0025)</td>
<td>-.3650 (.0025)</td>
<td>-.3721 (.0025)</td>
</tr>
<tr>
<td>(2) CATH. EFFECT, STATE AND DEMOGRAPHIC CONTROLS</td>
<td>-.2595 (.0026)</td>
<td>-.2870 (.0026)</td>
<td>-.3009 (.0026)</td>
<td>-.3039 (.0026)</td>
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<tr>
<td>(3) CATH. EFFECT, STATE, DEMOGRAPHIC, COMORBIDITY CONTROLS</td>
<td>-.2411 (.0026)</td>
<td>-.2655 (.0026)</td>
<td>-.2780 (.0026)</td>
<td>-.2808 (.0026)</td>
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<tr>
<td>(4) HIGH-VOLUME HOSP. EFFECT, STATE AND DEMOGRAPHIC CONTROLS</td>
<td>-.0216 (.0022)</td>
<td>-.0224 (.0023)</td>
<td>-.0219 (.0023)</td>
<td>-.0210 (.0022)</td>
</tr>
<tr>
<td>(5) RURAL EFFECT, STATE AND DEMOGRAPHIC CONTROLS</td>
<td>.0048 (.0026)</td>
<td>.0059 (.0026)</td>
<td>.0053 (.0026)</td>
<td>.0068 (.0026)</td>
</tr>
</tbody>
</table>

\(^1\) Each cell in the Table presents the least-squares regression estimate of a treatment effect, with standard errors in parentheses. Dependent variables for the regressions in each cell, mortality during a time interval after AMI, are listed in column heads (1) to (7). The treatment effect estimated in each row is listed in the first column, along with state, demographic, and comorbidity disease controls if present in the model. State effects are indicator variables for state of residence (including DC). Demographic controls include fully-interacted effects of the following patient demographic characteristics: age 65-69, age 70-74, age 75-79, age 80-84, age 85-89, age 90 and over, sex, and black or nonblack race. Rural residence effects include interactions of rural residence with all of the demographic cells; a weighted-average rural effect is reported for clarity. Comorbidity controls include indicator variables for patient comorbid diseases noted at the time of discharge that were clinically unlikely to have arisen as complications of AMI treatment. See text for discussion.
<table>
<thead>
<tr>
<th>Table 5: Generalized Method of Moments Estimates of Treatment Effects</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Treatment Effect(s)</strong></td>
</tr>
<tr>
<td>--------------------------</td>
</tr>
<tr>
<td>(1) CATHETERIZATION</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>(2) CATHETERIZATION</td>
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<tr>
<td></td>
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<tr>
<td>(3) CATHETERIZATION</td>
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<td></td>
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<td></td>
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<tr>
<td></td>
</tr>
<tr>
<td>(4) ADMIT TO HIGH-VOLUME HOSP</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>(5) ADMIT TO HIGH-VOLUME HOSP</td>
</tr>
<tr>
<td></td>
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<tr>
<td></td>
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<tr>
<td>(6) ADMIT TO HIGH-VOLUME HOSP</td>
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<tr>
<td></td>
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<tr>
<td>(7) ADMIT TO HIGH-VOLUME HOSP</td>
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<td></td>
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<tr>
<td>TREATMENT EFFECT(S)</td>
</tr>
<tr>
<td>---------------------</td>
</tr>
<tr>
<td>(1) CATHETERIZATION</td>
</tr>
<tr>
<td>(2) CATHETERIZATION</td>
</tr>
<tr>
<td>(3) CATHETERIZATION</td>
</tr>
<tr>
<td>RURAL RESIDENCE</td>
</tr>
<tr>
<td>GMM TEST STATISTIC (27)</td>
</tr>
<tr>
<td>(4) ADMIT TO HIGH-VOLUME HOSP</td>
</tr>
<tr>
<td>(5) ADMIT TO HIGH-VOLUME HOSP</td>
</tr>
<tr>
<td>RURAL RESIDENCE</td>
</tr>
<tr>
<td>GMM TEST STATISTIC (13)</td>
</tr>
<tr>
<td>(6) ADMIT TO HIGH-VOLUME HOSP</td>
</tr>
<tr>
<td>CATHETERIZATION</td>
</tr>
<tr>
<td>(7) ADMIT TO HIGH-VOLUME HOSP</td>
</tr>
<tr>
<td>CATHETERIZATION</td>
</tr>
<tr>
<td>RURAL RESIDENCE</td>
</tr>
<tr>
<td>GMM TEST STATISTIC (40)</td>
</tr>
</tbody>
</table>
Panels (1) to (7) in the Table present GMM IV estimates of treatment effects, with standard errors in parentheses. For time intervals of less than 90 days after AMI, the estimated catheterization effect is the effect of catheterization during the time interval; for intervals of more than 90 days, the estimated effect is that of catheterization during the 90-day interval after AMI. The first column lists the treatment effect(s) estimated for the model in that panel. The second column lists the set of differential-distance instrumental variables used. The instrumental variables are patient differential-distance indicators for the following distance intervals (in miles): 0, 0-1, 1-2, 2-4, 4-6, 6-8, 8-10, 10-12, 12-15, 15-18, 18-21, 21-25, 25-30, 30-40, and over 40. Dependent variables for the regressions, mortality during a time interval after AMI, are listed in column heads (1) to (7). Each model includes fully-interacted demographic cell effects and state effects as in Table 4; for specifications including rural effects, a single weighted-average rural effect is reported for clarity. For panels (3), (5), and (7) Chi-squared GMM overidentification tests of the model are reported (degrees of freedom in parentheses). See text for further discussion.
<table>
<thead>
<tr>
<th>Treatment Effect</th>
<th>0 Days-1 Day</th>
<th>2 Days-7 Days</th>
<th>8 Days-30 Days</th>
<th>31 Days-1 Year</th>
<th>1 Year-2 Years</th>
<th>2 Years-3 Years</th>
<th>3 Years-4 Years</th>
</tr>
</thead>
<tbody>
<tr>
<td>Admit to high-volume hospital</td>
<td>-.0083 (.0025)</td>
<td>-.0036 (.0027)</td>
<td>-.0034 (.0025)</td>
<td>.0023 (.0033)</td>
<td>.0016 (.0024)</td>
<td>-.0006 (.0022)</td>
<td>.0031 (.0020)</td>
</tr>
<tr>
<td>Catheterization in 90 days</td>
<td>-.071 (.020)</td>
<td>-.019 (.021)</td>
<td>.033 (.019)</td>
<td>.025 (.025)</td>
<td>-.010 (.019)</td>
<td>-.001 (.017)</td>
<td>-.008 (.016)</td>
</tr>
<tr>
<td>Rural residence</td>
<td>.0070 (.0019)</td>
<td>.0004 (.0021)</td>
<td>-.0006 (.0019)</td>
<td>-.0073 (.0025)</td>
<td>-.0010 (.0018)</td>
<td>-.0008 (.0017)</td>
<td>.0020 (.0015)</td>
</tr>
</tbody>
</table>

1 Model specification is the same as frame (7) of Table 5, except the dependent variable (listed in each column head) is death during the time increment after AMI, rather than death during a cumulative time interval. Standard errors in parentheses.
### TABLE 7:
ESTIMATED EFFECTS ON MORTALITY
OF PROCEDURE USE REDUCTION EQUIVALENT TO
INCREASING ALL DIFFERENTIAL DISTANCES TO 30 MILES

<table>
<thead>
<tr>
<th>Treatment/Outcome</th>
<th>Mean in 1987</th>
<th>OLS</th>
<th>IV(^1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Δ 7-Day Cath</td>
<td>.124</td>
<td>-.074</td>
<td></td>
</tr>
<tr>
<td>Δ 7-Day Mortality</td>
<td>.177</td>
<td>.0100</td>
<td>.0048</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(.0075)</td>
</tr>
<tr>
<td>Δ 30-Day Cath</td>
<td>.199</td>
<td>-.058</td>
<td></td>
</tr>
<tr>
<td>Δ 30-Day Mortality</td>
<td>.256</td>
<td>.0106</td>
<td>.0030</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(.0059)</td>
</tr>
<tr>
<td>Δ 90-Day Cath</td>
<td>.228</td>
<td>-.052</td>
<td></td>
</tr>
<tr>
<td>Δ 1-Year Mortality</td>
<td>.402</td>
<td>.0130</td>
<td>.0020</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(.0050)</td>
</tr>
<tr>
<td>Δ 2-Year Mortality</td>
<td>.475</td>
<td>.0143</td>
<td>.0026</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(.0061)</td>
</tr>
<tr>
<td>Δ 3-Year Mortality</td>
<td>.534</td>
<td>.0150</td>
<td>.0027</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(.0061)</td>
</tr>
<tr>
<td>Δ 4-Year Mortality</td>
<td>.583</td>
<td>.0152</td>
<td>.0030</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(.0065)</td>
</tr>
<tr>
<td>Δ 1-Year Hospital Costs</td>
<td></td>
<td></td>
<td>- $87.5 million</td>
</tr>
</tbody>
</table>

\(^1\)The 95% upper confidence limit for the IV-estimated effect bound is in parentheses.
REFERENCES


Wald, Abraham, 1940, The fitting of straight lines if both variables are subject to error, *Annals of Mathematical Statistics* 11: 284-300.


CHAPTER TWO

WHY DO MEDICARE COSTS KEEP RISING?

HOSPITAL REIMBURSEMENT

AND THE DYNAMICS OF MEDICAL TREATMENT INTENSITY

In 1984, the Health Care Financing Administration implemented the Prospective Payment System (PPS) to reimburse hospitals for treating Medicare patients. PPS features payment on the basis of the diagnosis-related group (DRG), which in essence is a fixed payments for the entire bundle of medical services provided during a hospital admission. DRG outlier payments provide some insurance to hospitals for treating patients with extraordinarily high costs or long stays within the DRG, and higher DRG payments for patients with versus without "complicating conditions" provide limited opportunities for hospitals to increase reimbursement by upcoding patients. But to a first approximation, DRGs are thought to provide strong incentives for efficient production of hospital admissions since the marginal change in reimbursement for a marginal change in input use is approximately zero.

The adoption of PPS reflected the application of principles of the economic analysis of regulatory mechanisms. Prior to PPS implementation, rapid increases in hospital treatment intensity -- reflected in the use of more intensive technologies more often in patient care -- and hence in hospital costs were attributed to low coinsurance rates for inpatient care on the demand side and "cost-based" reimbursement on the supply side. Intensity growth was also attributed to exogenous technological change, but the hope was that the stronger incentives to limit use of more intensive treatments would reduce the rate

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of growth of technological intensity and costs of hospital production (e.g., Weisbrod, 1991).

In some important respects, the actual experience of hospital costs under PPS has not worked out as expected. Consider the following "puzzles":

(1) Why did PPS lead to a decline in hospital admissions? Since DRG payments are fixed per admission, hospitals can increase profits by selecting healthier, lower-cost patients within DRGs, by "unbundling" services previously provided in a single admission, or by transferring or "dumping" unwanted patients. All of these responses suggest more hospital admissions, not fewer. In fact, PPS did lead to reductions in lengths of stay per admission, as expected, but it also led to a dramatic fall followed by a stabilization in Medicare admission rates. Only recently have admission rates began to increase again, and the rates remain well below their pre-PPS peak.

(2) Why is average intensity per discharge increasing? Hospitals can also increase profits by reducing intensity of treatment per admission directly. But considerable evidence suggests that admissions have become considerably more complex, not less. While some of the observed increase in case complexity is attributable to "DRG creep" and reimbursement policy changes, a careful comparison of discharge summaries to medical records by Carter, Newhouse, and Relles (1990) demonstrated that two-thirds of the increase in intensity per admission was attributable to real increases in case complexity. Between 1984 and 1990, the Prospective Payment Assessment Commission (1991) estimated that the case mix index per discharge increased by almost 20%, after adjusting for price updates and other policy changes.
Why do real per capita hospital costs keep increasing? Given puzzle (2), continuing real increases in hospital costs for the elderly are not surprising: a 1% increase in the case-mix index translates into an additional $750 million in Medicare payments. With almost a decade of hindsight, the general view is that the adoption of PPS led a one-time downward shift in trends in health care costs. This shift was marked by the reduction in average length of stay and in the number of hospital admissions in 1985 and 1986 noted above, but since that time real per-capita increases in hospital costs have approached pre-PPS growth rates, paralleling the increase in intensity per admission. As the Prospective Payment Assessment Commission (1991) has noted, "The most important influence on the overall level of PPS payments is the increase in the case mix index… In many instances, the effect of case-mix index change has negated or at least diminished the intended effects of PPS policy decisions."

These "puzzles" could be explained by appealing to the occurrence of exogenous technological changes valued enough to be adopted by hospitals in spite of fixed payments, or by appealing to the "special" nature of production in the medical industry. But it is disappointing that such high-powered incentives had such limited dynamic consequences. As Ellis and McGuire (1992) have noted, adoption of supply-side incentives has been "surprisingly easy," perhaps because their effects on hospital cost growth have been so limited. Consequently, many policymakers have concluded that even more fundamental reforms than decoupling supplier price from costs are required to control hospital costs.

In this paper, I will argue that a few basic economic implications of the nature of DRG payments, coupled with some understanding of the internal organization of hospital
production, can explain the "puzzles" in the context of a standard analysis of production incentives with price regulation. The analysis begins with the following question:

(4) Why aren't diagnosis-related groups more related to diagnoses? For example, in 1988 there were 477 DRGs. While the majority of DRGs were defined by particular diagnoses -- such as DRG 10 (nervous system neoplasms without complicating conditions) and DRG 404 (lymphoma and non-acute leukemia without complicating conditions)\(^1\) -- 206 of the DRGs (over 40% of the groups) are related to treatments rather than diagnoses -- such as DRG 8 (peripheral/cranial nerve procedures without complications) and DRG 400 (lymphoma and leukemia with major operating room procedure). These treatment-based DRGs primarily involve surgical procedures, though they are not exclusively "surgical." For example, some DRGs relate to endoscopy, catheterization, radiotherapy, chemotherapy, and other nonoperative procedures.

In the next section, I summarize some features of a hospital's production of care for a health problem which have implications for the incentive effects of treatment-based DRGs. These implications appear to have been largely overlooked in previous analyses of PPS effects. Intuitively, the replacement of administered prices based on costs for treatments with treatment-based DRGs implies little change in hospital incentives to perform the intensive treatments involved. Treatment-based DRGs may nonetheless be

\(^1\)"Complicating conditions" are an explicitly defined set of additional diagnoses that are associated with more severely ill patients who have higher costs. The existence of DRGs with complications reduces the net cost to the hospital of treating sicker patients. This paper does not address DRG creep (see Carter, Newhouse, and Relles, 1990, and Altman, 1990) or the incentive effects of "outlier" payments for the highest 3% of cost and day outliers (see Keeler, Carter, and Trude, 1988), implications of which are well understood.
optimal, if the fixed-price incentives would lead to too little investment by hospitals in the intensive technologies.

But why do treatment-based DRGs exist for some intensive technologies but not others? Section II develops a simple model of the internal organization of hospital production with the goal of formalizing the relative importance of the preferences of patients, physicians, and hospital managers in determining equilibrium hospital production decisions. The key features of the model are that treatment intensity for a health problem can vary, and that the elasticity of demand, the price-cost margins for alternative treatments, and the nature of the technologies involved are critical to determining equilibrium treatment intensity levels when prices are set exogenously. Section III uses this framework to analyze the static and dynamic effects of regulatory pricing strategies. I summarize some fundamental problems with the current payment system and then describe a theoretical foundation for some practical payment reforms that will improve incentives. Section IV presents some empirical evidence on the cost of treating a particular health problem and on time trends in patterns of hospital care for all common health problems in the elderly that is consistent with the model developed here. The evidence suggests that hospital intensity choices under PPS are entirely consistent with predicted behavior in the model. Section V concludes with a discussion of the implications of the analysis for improving hospital price regulation in the Medicare program.

I. Institutional Characteristics of Hospital Production
This section addresses two related topics: (1) the appropriate definition of the "good" produced for patients demanding hospital care, with an emphasis on the importance of decisions about use of intensive technologies, and (2) the implications of the internal organization of hospitals for treatment intensity choices in production. These features of hospital production motivate the formal model of hospital production decisions that follows.

Patients do not demand hospital treatments per se; they demand treatment for their particular health problems. "Production" of health care involves both diagnostic and therapeutic treatments, the most intensive of which are administered to patients who have been admitted to a hospital. For most health problems, many technological choices exist, and hence many alternative treatment intensities are possible. As a result, a hospital admission per se does not constitute a well-defined product. The following examples, drawn from some of the most common and costly diseases in the elderly, illustrate that: (1) hospitalizations may or may not be required for treatment, (2) when a patient is hospitalized, multiple treatment courses involving quite different medical technologies are possible, and (3) these treatment courses often result in different classifications for reimbursement purposes. The brief clinical summaries are not intended to imply that all patients with each of the health problems are equally appropriate candidates for all treatment alternatives. However, the net benefits of more intensive treatment may be modest or uncertain for a considerable fraction of patients with a health problem, providing considerable opportunities for physician discretion in treatment choices (Park et al., 1986; McClellan and Brook, 1992).
Coronary Heart Disease: Coronary heart disease is the leading cause of death in the United States. In most cases, death is directly or indirectly related to a heart attack, or acute myocardial infarction (AMI). Patients with symptoms of a heart attack such as crushing chest pain will be treated at a hospital to "rule out" AMI or manage its complications. The diagnostic and therapeutic management of all heart disease patients may include several intensive procedures: cardiac catheterization, percutaneous transluminal coronary angioplasty (PTCA), and coronary artery bypass graft (CABG) surgery. These technologies are substantially more costly than the less intensive alternatives, which involve noninvasive diagnostic studies, drug treatments, and lifestyle counseling.

Cancer: Treatment modalities for most types of cancer involve some combination of surgery, radiation therapy, and chemotherapy. For example, for breast cancer, treatment may involve total or partial mastectomy, followed by radiation or chemotherapy. Various cancer treatment regimens have different requirements for the intensity of these treatments and for the frequency of inpatient hospital stays.

Hip Fracture: Patients with hip fracture will be admitted to the hospital. Depending on the nature of the fracture, the treatment for setting the fracture may involve open reduction (a surgical procedure) or closed reduction (a nonsurgical procedure).

Gall Bladder Disease: Patients with chronic cholecystitis (gall bladder disease) can be managed "medically" (with drugs and dietary modification) or "surgically" (with removal of the gall bladder). For patients managed surgically, several types of cholecystectomy procedures are possible. Cholecystectomy may include intraoperative radiographic imaging of the biliary ducts with contrast dye enhancement to identify any
remaining gallstones. An alternative cholecystectomy technique for uncomplicated cases, laparoscopic cholecystectomy, involves a more limited surgical incision and (in the absence of complications) a shorter postoperative recovery.

**Benign Prostatic Hypertrophy:** Enlargement of the prostate gland, leading to urinary retention, frequency, and hesitancy, is extremely common in elderly males. One treatment is prostatectomy (primarily transurethral prostatectomy) to remove gland tissue. Alternatively, especially in milder cases, patients can simply endure symptoms (e.g., having to get up to urinate in the middle of the night). Patients who choose not to have surgery require hospitalization only for severe complications.

**Back Pain:** Back pain is an extremely common chronic health problem. Surgical treatments to reduce symptoms include spinal decompression (for pain, tingling, or numbness arising from nerve compression), intervertebral discectomy and spinal fusion, and laminectomy. Patients who are managed without these surgical procedures (through drugs, musculoskeletal therapies, and other regimens) may only require hospital treatments such as traction for severe complications.

**Arthritis:** Rheumatoid arthritis and osteoarthritis are leading causes of functional limitations in the elderly, especially elderly females. Many drug regimens of increasing strength (and side effects), as well as other nonsurgical treatments such as heat baths, are available to reduce pain and limit deterioration in affected joints. These treatments generally do not require hospitalization. For leg joints (knee and hip), surgical joint replacement procedures can be performed in the hospital.
The preceding illustrations, representing a spectrum of common diseases, demonstrate that an analysis of the incentive effects of hospital financing reforms should focus on incentives for treatment of a health problem rather than for producing a specific hospital episode of care. Not only are different levels of treatment intensity possible, but virtually all of the alternative treatments described involve distinct DRGs -- usually with very different reimbursement levels, reflecting the cost differences of the alternative treatments. In contrast to most previous studies of PPS effects, the model that follows recognizes that many important hospital production decisions involve technological intensity choices not confined to a single DRG. The implications for hospital treatment decisions, inpatient costs, and patient welfare are fundamentally different from previous models of hospital production.

The internal organization of hospital production has important implications for these intensity choices. Theoretical papers on the optimal regulation of hospitals have mostly assumed that the incentives facing hospitals match the incentives of the physicians practicing in them, at least up to the (costly) implementation of appropriate internal incentives.\(^2\) Thus, for example, a hospital could provide incentives to its physicians to encourage admissions in DRGs in which it can provide treatment at lower cost, or to

\(^2\)An exception is Ellis and McGuire (1986), who model hospital production as a reflection of treatment decisions by physicians. However, the physician’s marginal rate of substitution between patient and hospital objectives (that is, the relative weight placed on maximizing hospital profits versus maximizing patient welfare) is treated as exogenous in the model, there is no role for hospital investment decisions in influencing physician decisions, and hospital payment is modeled as fixed regardless of treatment choice. In contrast, the model developed here makes the tradeoffs between patient and hospital objectives endogenous and models the consequences of differences in payment for alternative treatments. Custer et al. (1990) model potentially noncooperative behavior between physicians and hospitals, but they do not account for the effects of patient demand, hospital technologies, or alternative reimbursement schedules.
admit less costly patients. But the preceding description of alternative treatments for health problems makes clear that technology use and even the need for hospitalization for many patients involves substantial physician discretion. The traditional institutional organization of the American health care system limits the ability of hospital managers to influence these decisions.

Harris (1979) analyzes some of these issues in the internal organization of hospitals. He informally describes hospital production as a noncooperative game between physicians engaged in specific relationships with patients on the one hand and hospital managers making investment decisions involving capacity, equipment, and staff hiring on the other. Physicians generally are not employees of the hospital, but rather are participants in highly incomplete contracts with both the hospital and their patients. When a patient seeks care for a health problem, the patient contracts for "appropriate" medical treatment, whatever the health problem turns out to be. Because these treatment contingencies are too numerous to describe ex ante or to verify ex post, patients and physicians cannot sign a complete contract that specifies how the physician will treat every possible medical contingency that may arise in the course of the treatment episode. Just as contingent production decisions are not specified in the contract between a medical expert and a patient, they are not specified in the physician's contractual arrangement with the hospital. Hospital contracts for admitting privileges specify few explicit restrictions on the use of hospital capital that is within the purview of the physician's specialty.

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3The physicians that tend to be contractual employees--radiologists, anesthesiologists, and pathologists--prove the rule, since these physicians specialize in technical aspects of hospital production rather than making decisions as agents for particular patients.
Harris emphasizes the transaction costs of all these treatment intensity decisions and the importance of physician preferences (as opposed to those of hospital managers) in resource allocation decisions for individual patients. But the problem is even more fundamental than transaction costs. A physician treating a specific patient develops detailed knowledge of the idiosyncrasies of the patient’s case. In theory, physicians or hospital managers could hold up patients for the value of these specific investments at critical junctures in the course of treatment, when the patient’s life may literally be at stake. Thus, due to very high transaction costs and major specific investments, the characteristics of hospital production suggest that markets or explicit contracts represent costly approaches to fostering efficient production.

In this view, the traditional organizational structure of the hospital may represent not so much a reflection of physicians’ desire for autonomy in treating patients (Starr, 1984) as an institutional mechanism to limit the power of incentives in the physician’s other role, as an agent for the hospital. Physicians do not control investment decisions for the hospital or own hospital capital, but they largely retain the rights of control for utilization of hospital capital equipment and other resources.\textsuperscript{4} Altering these residual rights of control over treatment decisions, for example through a direct employment

\textsuperscript{4}Some other capital-intensive professions in which the appropriateness of specific production decisions is difficult for managers to observe have similar arrangements. In many research laboratories, for example, the capital equipment may belong to the academic institution, but the researchers who use it may be paid largely through grants obtained independently rather than through employee relationships.
relationships between physicians and hospitals, would probably alter these residual rights of control and hence treatment decisions for hospitalized patients.\textsuperscript{5}

Thus, under current institutional arrangements, if a hospital finds that treating patients in the DRG for congestive heart failure (CHF) is unprofitable, it cannot order its admitting physicians not to treat patients with CHF. Physicians control specific admission decisions. Even if such a prohibition were technically possible, it might impose considerable externalities on hospital production. Many patients with CHF initially arrive at the emergency department with shortness of breath, water weight gain, feelings of weakness and lightheadedness, or even vaguer symptoms. Only after some evaluation of the specific case can the diagnosis of CHF be made and treatment initiated. By this time, physicians practicing at the hospital have invested in a relationship with the patient that involves some specific knowledge of the idiosyncrasies of the case. Similarly, CHF is a problem that frequently accompanies other common diseases -- such as a recent heart attack, diabetes, or hypertension -- which also may require hospitalization (possibly at the same time) and which may represent relatively profitable DRGs for the hospital. Prohibiting or restricting admissions for the diagnosis would limit gains from relationship-specific investments between the patient and physicians that permit the delivery of more effective care for other diagnoses.

However, hospital managers can substantially influence the environment in which physicians make these specific treatment decisions. For diseases such as CHF that involve "nonspecific" technologies, hospital choices about capacity investments in hospital

\textsuperscript{5}The consequences of the nature of the employment relationship for production choices and efficiency are examined in detail in Grossman and Hart (1986), which provides some of the foundation for this discussion.
beds, laboratory equipment, and support staffing levels may indirectly affect physician decisions on treatment intensity, but only by affecting treatment decisions for many other health problems as well. In contrast, for diagnoses and procedures requiring investments in specific capacity, the choices of hospital managers can significantly affect use of the treatments and admissions at the DRG level. For example, if a hospital finds cardiac catheterization unprofitable, it need not prohibit its physicians from catheterizing specific patients. It need only close its catheterization laboratory. By deciding its investment level in the technologies needed to produce catheterization, the hospital can effectively specialize or not in catheterization DRGs. Similarly, by determining whether to provide the specialized equipment and personnel required for cancer treatments or particular kinds of surgical procedures, hospital managers can significantly influence admissions in these DRGs.

Regardless of the nature of medical technologies, noncontractible hospital production decisions can hurt the patient if the physician makes decisions as a hospital agent, and can hurt the hospital if the physician makes decisions as a patient agent. The physician faces inherent agency conflicts when patient and hospital interests do not coincide. They will not coincide if intensive treatments are costly and if hospitals are not fully insured against costs of care. Vesting the residual rights of production decisions in the physician and separating physician reimbursement from hospital reimbursements clearly reduces the strength of the physician-hospital agency relationship. To the extent that physicians are reimbursed at cost for the services they provide, so that the tradeoffs they face between patient welfare and their own net profits (including effort costs) are
minimized, physician agency for patients may be much stronger than physician agency for
the hospital at the margin.

Whether this allocation of noncontractible rights of control is optimal depends on
hospital and patient incentives and on the nature of the alternative technologies that may
be involved in patient care. At the present time, it is easy to consider other allocations of
residual control. For purposes of this paper, I will assume that patients are fully insured,
which is a close approximation to actual Medicare coverage for most inpatient services.
If patients were fully informed and controlled marginal treatment decisions, they would
consequently demand all services with positive net benefits. I will also assume the
traditional limited integration between physician and hospital employment relationships
and production incentives. The implication for the model is that residual control by
physicians -- supported by loose contractual relationships with hospitals and a cost-based
physician payment system -- strengthens patient agency, leading physicians to prefer more
intensive treatment patterns than hospital managers prefer under fixed-price
reimbursement. 6

Together, these institutional characteristics imply that a model of the internal
organization of hospital production decisions must incorporate the following features:

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6 Another advantage of explicitly modeling the internal organization of hospital production
is that the consequences of other employment arrangements can be considered explicitly.
Strong residual control by physicians has other costs besides limiting the power of hospital
managers to influence use of some hospital technologies. For example, the costs of
coordinating treatment for an illness beyond the level of an admission may be higher than it
would be if the hospital (or HMO) employed all physicians involved in treating the illness.
The costs and benefits of the various possibilities for vertical and horizontal integration in
the production of treatment for an illness have not been explored much by economists. In
this paper, I consider only "traditional" arrangements, which currently describe the
production of care for most Medicare beneficiaries.
(1) Physicians -- who have the most knowledge about the benefits of alternative medical technologies for specific patients -- are dual agents, for patients in the production of medical treatments and for hospitals in the use of hospital capital. The incomplete contractual arrangements that form the basis for specific production relationships between physicians and patients, and between physicians and hospitals, leave the residual rights of control for decisions to fulfill these production relationships primarily to the physician.

(2) These open-ended contractual arrangements, coupled with generous demand-side insurance and a physician payment system that is largely independent of hospital payments, suggest that physicians involved in specific agency relationships with patients weigh patient welfare more than hospital profits, and in any case more than hospital managers weigh patient versus hospital objectives.

(3) The nature of the medical technologies used to treat particular illnesses affects how hospital payment incentives affect equilibrium production decisions. For treatments dependent on specific hospital investments, hospital managers have more control over production levels; for treatments involving nonspecific technologies that are difficult to ration, physicians have more control.

II. The Production of Medical Treatment Intensity

This section formalizes the noncooperative game of hospital production described in Section I. There are four parties: fully-insured patients with a health problem who decide which hospital to visit for treatment; physicians who learn the patient's expected benefits from alternative treatments and make treatment intensity decisions; hospitals that
provide medical technologies for treatment; and a regulator who sets the price schedule for hospitals. The structure of the game is as follows:

1. The regulator chooses the level of price aggregation (explained below) and sets prices.

2. The hospital invests in medical technologies that constitute the environment for medical treatment.

3. Physicians observe hospital investment choices, contract with hospitals to provide medical services, and define their equilibrium treatment intensity choices.

4. Patients observe some measure of hospital quality related to its investment decisions and, possibly with guidance from physicians, choose a hospital for treatment.

5. The physician observes the patient's expected benefit from alternative treatments and chooses treatment intensity. There are two treatment intensity choices, \( r = 0 \) (less intensive) and \( r = 1 \) (more intensive). The performance of \( r = 0 \) or \( r = 1 \) is observable and verifiable, and hence can be used as the basis for a reimbursement contract.

6. Patients receive treatment and hospitals are reimbursed for services.

The role of patients, physicians, and hospitals in determining equilibrium hospital treatment intensity given prices is described below for different types of medical technologies. The regulator's role is described in the next section.

(1) **Patients:** Patients with the health problem are identical except for a propensity for receiving the intensive treatment indexed by \( \theta \in [\underline{\theta}, \bar{\theta}] \), which is distributed in the patient population with p.d.f. \( f(\theta) \) and c.d.f. \( F(\theta) \). For purposes of this paper, the parameter \( \theta \) represents the expected net benefit of the more intensive treatment. That is, the expected
value of the patient's outcome is $\mu(\theta)$ if $r = 0$ and $\mu(\theta) + \theta$ if $r = 1$. Though $\theta$ is observed by the physician, it is not known to the patient and is not observable by the hospital or regulator. Patients are fully insured, so a fully-informed patient who could control the treatment decision would choose $r = 1$ if $\theta > 0$.

Although patients do not know $\theta$, they do observe some measure -- however noisy -- of a hospital's treatment intensity that influences their demand for the services provided by the hospital. For example, public information on hospital quality or physician advice about the "best" hospital for treatment may influence choices. As will be described in more detail momentarily, hospital intensity in this model can be parameterized by $\theta$, the level of $\theta$ above which patients receive the intensive treatment. Patients value intensity, so that patient demand for the hospital's care $q(\theta)$ is a function of intensity of treatment, $q'(\theta) \leq 0$, since intensity of treatment for the health problem is decreasing in $\theta$. I also assume $q''(\theta) < 0$ as a regularity condition, but I impose no further restrictions on the nature of the demand function. This permits the model to incorporate a full range of possibilities for the elasticity of demand with respect to hospital quality.\footnote{Nonetheless, the structure of patient demand described here may seem restrictive. For example, the level of demand may influence the distribution of $\theta$, or specifically $F_q(\theta) \neq 0$ (e.g., at higher levels of demand, healthier patients may be disproportionately represented). Such a modification complicates the analysis but does not change the nature of the results that follow; the basic point is simply that demand is not completely inelastic with respect to hospital quality.} I abstract from modeling the details of how patients choose hospitals to focus on the impact of the hospital's internal organization on production decisions. A large literature on hospital competition describes how factors such as information asymmetries, search costs, collusion, or entry barriers give hospitals market power.
(2) **Physician**: The model is developed using a single physician, but the "physician" can be viewed as the composite physician staff of the hospital involved in patient care. The physician observes \( \theta \) and controls the decision \( r \) for patient treatment intensity \((r=0\) or \(r=1)\). Lower-intensity treatment \((r=0)\) is always worthwhile. Physicians' net objective functions \( U(\theta,r;I) \) for performing the more intensive treatment are assumed to be separable, increasing in patient welfare, and decreasing in effort:

\[
U(\theta, r; I) = \theta \cdot r - \Delta(\theta; I)
\]

where \( \Delta(\theta; I) \) is the additional effort cost to the physician of performing \( r=1 \) rather than \( r=0 \) for patient \( \theta \) given the hospital's investment choice \( I \).\(^8\) The relationship between \( I \) and \( \Delta \) is described in more detail below. The physician's objective function is maximized using the decision rule

\[
\{r=1 \text{ if } \theta \cdot \Delta(\theta; I) > 0, \ r=0 \text{ otherwise}\}.
\]

This rule defines a medical practice pattern \( \theta(I) \) in which patients with \( \theta > \theta^* = \Delta \) receive \( r=1 \) and patients with \( \theta \leq \theta^* \) receive \( r=0 \). Physicians observe hospital investment before contracting, and so can anticipate patient demand.

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\(^8\)The physician's pecuniary reimbursement for providing treatment is assumed to be determined outside the model and hence is incorporated in \( U(\theta,r;I) \). This simplification is made to focus attention on hospital reimbursement issues and is not restrictive. For example, if physicians also face an (exogenous) administered price schedule for the services they provide, and if nonpecuniary physician effort also differs for the treatment alternatives, then define

\[
\Delta(\theta; I) = [v^1(\theta; I) - v^0(\theta; I)] - [p^1 - p^0],
\]

where \([p^1 - p^0]\) is the net physician price difference between \( r=1 \) and \( r=0 \) and \([v^1(\theta; I) - v^0(\theta; I)]\) is the (money-metric) nonpecuniary effort cost difference. To simplify models below, I assume that net physician effort costs are small relative to the intensity cost differentials to the hospital; alternatively (if physicians must receive a reservation expected utility level), they can be incorporated in marginal hospital production costs.
The extent of physician ability to choose among hospitals influences the elasticity of demand \( q(\theta) \) observed by a hospital. At one extreme, if physicians can freely choose among many hospitals for admitting privileges and completely control patient choice of hospitals, then demand for hospital care will maximize physician objectives subject to a hospital breakeven constraint (Pauly and Redisch, 1973; Pauly, 1980). At the opposite extreme, if physicians have no choice among hospitals and no control over patient choices of hospitals, then physician choice of hospitals does not affect demand. Between these extremes, hospital demand remains a function of hospital treatment intensity, \( q(\theta) \).

In the following analysis, it is generally assumed that physicians prefer a treatment intensity at least as high as that preferred by hospitals. This will be the case, for example, if physicians are reimbursed separately at cost for their services and if physicians have ethical concerns for patient welfare.

(3) **Hospital:** The hospital (hospital managers) makes ex ante investments \( I \) in resources (capital equipment, staff, material) to support the production of \( r = 1 \). The hospital knows \( F(\theta) \) and \( \Delta(\theta; I) \) but does not observe \( \theta \) of individual patients and does not control individual treatment decisions \( r \). The hospital faces exogenously-set prices \( \bar{p}^0 \) and \( \bar{p}^1 \) and incurs marginal production costs \( c^0(I) \) and \( c^1(I) \) for patients treated with \( r = 0 \) and \( r = 1 \), respectively. The hospital can produce any quantity of treatment \( r = 0 \) at its marginal cost (i.e., it does not choose a capacity constraint for \( r = 0 \)). For now assume that hospital investments last one period.⁹

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⁹This assumption is reasonable for inputs like nonphysician staff and materials but represents a simplification for long-lasting investments such as CT scanners or catheterization labs. This simplification does not change the main results.
The hospital chooses \( I \) to maximize its objective function. In a perfectly competitive hospital market, this means maximizing patient welfare subject to a zero-profit constraint. If the hospital faces demand that increases in quality of treatment, hospitals can earn rents by reducing intensity \((\hat{\theta}(I) \text{ by reducing } I)\), at the expense of losing patients. Rents may also translate into higher costs, due to managerial slack or other costly objectives besides patient welfare (Newhouse, 1970; Pope, 1989). Thus, regardless of the source of market power, a hospital trades off benefits to patients from more intensive treatments against these other arguments. To simplify the model, I assume in this section that hospitals maximize profits, but the nature of the results is not changed as long as hospitals have arguments other than patient welfare in their objective function.

Thus the hospital's objective function is

\[
\Pi(I) = \{F[\hat{\theta}(I) \cdot \bar{p}^0 - c^0(I)] + [1 - F[\hat{\theta}(I)] \cdot \bar{p}^1 - c^1(I)] \} \cdot q[\hat{\theta}(I)] - c^I \cdot I \tag{2}
\]

where \( c^0(I) \) and \( c^1(I) \) are the marginal costs to the hospital of producing \( r=0 \) and \( r=1 \), \( c^I \) is the price of investment \( I \), and \( \hat{\theta}(I) \) is as described previously.

The remainder of the section sketches the optimal hospital choices for four types of investments (given hospital prices) and the resulting treatment intensity levels, in the spirit of the description of medical technologies in Section 1. The first type is an investment in a specific technological capacity such as bypass surgery. This type of investment is analogous to specific production capacity investments in other industries. Thus investment \( I^1 \) in the capacity to produce \( r=1 \) includes such dedicated investments as building the required operating suite, purchasing specialized monitoring equipment, and hiring specialized cardiac operating room nurses and technicians. Investments in specific capacity directly affect hospital production. If \( l^1 = 0 \), then physicians cannot choose \( r=1 \).
More generally the level of $l^i$ acts as a capacity constraint on the use of $r=1$ by physicians, as long as the optimal level of investment for hospitals is less than that for physicians.

The second type investment in technological capacity is not specific to the treatment of a particular health problem (e.g., opening a hospital bed, purchasing a CT scanner, or providing a chemical analyzer for laboratory tests). For example $i=1$ is an inpatient admission, while $r=0$ is treatment in the hospital outpatient department. While each of these investments is associated with a more or less binding capacity constraint, they contribute to the intensity of treatment for a broad range of health problems. Because the hospital cannot direct their use to specific DRGs, it can only choose an optimal aggregate intensity level for all the health problems. It does so considering how physicians will allocate marginal units of capacity among patients with the various health problems, and the implications of these decisions for profits.

Finally, some specific and nonspecific investments by hospitals may represent "line of business" decisions rather than capacity choices. For example, a hospital can decide whether to stock specific drugs such as thrombolytic agents (for heart attacks) or less specific drugs such as antihypertensive and pain-reducing drugs (for many types of patients), but it cannot easily choose a capacity for these treatments. Hospitals can make binary choices about whether to adopt these technologies, knowing that physicians will choose the treatment pattern $\theta^p$ that they prefer.

(1) Hospital Investment in Specific Capacity
To simplify the derivations below, assume marginal costs $c^0$ and $c^1$, and costs per unit of capacity $b$ for the specific technology $I^1$, are constant. A strict capacity constraint $I^1$ implies $\Delta(I^1) = a$ for $\theta > \theta^b$ and $\Delta(I^1) = \infty$ for $\theta \leq \theta^b$, where the hospital's preferred treatment pattern $\theta^b$ is defined by $[1-F(\theta^b)] \cdot q(\theta^b) = I^1$. The physician chooses treatment intensity for specific patients subject to this constraint. Physicians would prefer a treatment pattern $\theta^p$ defined by $\theta^p = a$. But as long as $[1-F(\theta^p)] \cdot q > I^1$, the hospital's investment choice $I^1$ defines $\theta = \theta^p > \theta^b$. The first-best (socially optimal) rule for using $r=1$ is $\{r=1 \text{ if } \theta > \theta^*, \theta^* = (c^1 + b) - c^0\}$. This intensity level is associated with the socially-optimal level of investment $I^1*$ and a fraction $1-F(\theta^*)$ of patients treated with $r=1$.

The hospital will choose $I^1$ to

$$\max_{I^1} \Pi(I^1) = \{F[\hat{\theta}(I^1)] \cdot [\bar{\theta}^0 - c^0] + [1 - F[\hat{\theta}(I^1)] \cdot [\bar{\theta}^1 - c^1]] \cdot q[\hat{\theta}(I^1)] - b \cdot I^1 \} \tag{3}$$

subject to $[1-F(\hat{\theta}(I^1))] \cdot q[\hat{\theta}(I^1)] \leq I^1$.

Building capacity to provide intensive treatment beyond the optimal level is costly, so the constraint $[1-F(\theta)] \cdot q(\theta) = I^1$ is binding, and the first-order condition with respect to $I^1$ is

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10 The equalities in the equilibrium practice pattern relationships hold only if demand can be forecasted perfectly and there are no stochastic variations in the number or severity mix of patients arriving for treatment at a given time. While this may be a reasonable assumption for common health problems treated at large hospitals, especially at smaller hospitals optimal average utilization given capacity should be less than 100% to allow for stochastic shocks (i.e., equilibrium treatment intensity should be somewhat lower than the certainty case). However, the qualitative relationship between demand and capacity is unchanged. Joskow (1980) develops such a stochastic model of hospital demand, with the hospital's choice of expected waiting time itself constituting a measure of quality. While stochastic demand is not incorporated here, this model is less restrictive in the sense that it recognizes a physician response in intensity choices to hospital capacity choices.
\[
\begin{align*}
\{F[\hat{\theta}(I^1)] \cdot [p^0 - c^0] + [1 - F[\hat{\theta}(I^1)] \cdot [p^1 - (c^1 + b)]] \cdot q'(\hat{\theta}(I^1)) \cdot \hat{\theta}'(I^1) \\
+ \{f[\hat{\theta}(I^1)] \cdot \hat{\theta}'(I^1) \cdot [(p^0 - c^0) - (p^1 - (c^1 + b))] \} \cdot q(\hat{\theta}(I^1))
\} = 0
\end{align*}
\]

That is, at the optimal choice of \( l^1 \), a marginal increase in investment leads to an increase in profits from greater demand (first line) that just offsets the decrease in profits resulting from more intensive treatment of the "marginal" patients (second line). Rearranging terms yields

\[
\frac{1}{\eta_{0\theta}} \cdot [p^0 - c^0] + \frac{1}{\eta_{1\theta}} \cdot [p^1 - (c^1 + b)] = \frac{1}{\eta_{q\theta}} \cdot [(p^0 - c^0) - (p^1 - (c^1 + b))]
\]

(5)

where

\[
\eta_{0\theta} = (\partial F/\partial \theta) \cdot (\theta/F) \text{ is the elasticity of treatment with } r=0 \text{ with respect to } \hat{\theta},
\]

\[
\eta_{1\theta} = - (\partial(1-F)/\partial \theta) \cdot (\theta/(1-F)) \text{ is the elasticity of treatment with } r=1 \text{ with respect to } \hat{\theta}, \text{ and}
\]

\[
\eta_{q\theta} = -q' \cdot \hat{\theta}/q \text{ is the elasticity of demand with respect to } \hat{\theta}.
\]

All of these "quality elasticities" are defined to be positive. To illustrate the meaning of equation (5), assume that elasticity of demand is constant. Note that \( 1/\eta_{0\theta} + 1/\eta_{1\theta} = 1/\theta \) (\( f \) is a scale factor to weight the difference in price-cost margins by the number of patients shifting treatment, and \( \theta \) is a normalization for the elasticities). Thus, the left side of (5) is a weighted average of the two price-cost margins. If the Monotone Likelihood Ratio Property holds for \( F(\theta) \), then as \( l^1 \) increases and \( \hat{\theta}(l^1) \) decreases, the weight on \( p^0 - c^0 \)
decreases monotonically and the weight on \([\bar{p}^1-(c^1+b)]\) increases monotonically.\(^{11}\) Provided \([\bar{p}^1-(c^1+b)]<[\bar{p}^0-c^0]\) and demand is not too inelastic near \(\theta:=\bar{\theta}\), an internal solution will exist.\(^{12}\)

Equation (5) shows that equilibrium quality increases as the elasticity of demand with respect to quality increases; in the limit of perfect competition, the zero-profit constraint holds and intensity is maximized subject to the price constraints. For a given \(\bar{p}^0\), equilibrium quality also increases as \(\bar{p}^1\) increases and the difference in margins \([\bar{p}^0-c^0]-[\bar{p}^1-(c^1+b)]\) decreases (if \(\bar{p}^0\) is set high enough for production to occur).

Under pure prospective payment, hospital care for patients with a specific diagnosis is reimbursed using a single set price, so that \(\bar{p}^0=\bar{p}^1=\bar{p}\), whether or not \(r=1\).

Equation (4) simplifies to

\[
\frac{1}{\theta} \cdot \left\{ \bar{p} - \left[ F \cdot c^0 + (1-F) \cdot (c^1+b) \right] \right\} = \frac{(c^1+b)-c^0}{\eta_{q\theta}}
\]

(6)

From equation (6), some basic results with respect to the optimality of a fixed-price contract for providing treatment are evident.

\(^{11}\)The left side of equation (4) can be rewritten as

\[
\frac{1}{\theta} \cdot \left\{ F \cdot (\bar{p}^0-c^0) + (1-F) \cdot (\bar{p}^1-(c^1+b)) \right\}
\]

That is, \(F/f\theta+(1-F)/f\theta=1/f\theta\) is definitionally equivalent to \(1/\eta_{q\theta}+1/\eta_{q\mu}=1/f\theta\). Patients who stop getting \(r=1\) as \(\theta\) increases start getting \(r=0\) instead. Since \(1/\theta\) normalizes both weights \(F/f\) and \((1-F)/f\), if the Monotone Likelihood Ratio Property holds for \(F\) then the weight on \([\bar{p}^0-c^0]\) decreases as \(\theta\) falls and more patients receive \(r=1\).

\(^{12}\)Constant elasticity of demand with respect to quality is also not necessary for a unique equilibrium; all that is necessary is that elasticity of demand not increase too rapidly (relative to the changes in treatment elasticities) as \(I^1\) increases (and \(\theta\) falls).
First, there is no necessary relationship between valuation $\bar{\theta}$ for the "marginal" patient who receives $r=1$ in equilibrium and the socially optimal margin $\theta^*$. The socially optimal margin is equal to the numerator of the right side of (6). The equilibrium $\theta$ may be less than, greater than, or equal to $\theta^*$, depending on the nature of demand and the price level. For example, if hospitals are perfectly competitive, then $\theta$ solves $\bar{p} = F(\theta) \cdot c^0 + (1-F(\theta)) \cdot (c^1 + b)$, and average cost will equal $\bar{p}$ for any price level between $c^0$ and $(c^1 + b)$. If hospitals face downward-sloping demands, the exact relationship of $\theta$ and $\bar{p}$ depends on the structure of demand, but only by coincidence will $\theta = \theta^*$.\textsuperscript{13} The dynamic implications of the PPS pricing rule will be explored in the next section, but this conclusion in the static case is very different from the result by Schleifer (1985) on the ability of "yardstick" competition to achieve first-best production decisions. As Schleifer notes, the result depends on the product being well-defined: quality is fully observable and contractible, so that no opportunities for underproviding (or overproviding) quality

\textsuperscript{13}As an example, consider a specific set of simple functional form assumptions. Let $\theta$ be uniformly distributed on $[0,1]$, let the capacity constraint equal 1, let demand equal $1-\theta$ (with the number of patients normalized to 1), let the cost of $r=0$ equal $c^0$ and the cost of $r=1$ (inclusive of investment costs) equal $c^1$. In this case the socially-optimal intensity margin is $\theta^* = c^1 - c^0$ and the socially-optimal average cost is $c^* = (c^1 - c^0) \cdot c^0 + [1-(c^1 - c^0)] \cdot c^1$. The market equilibrium intensity is

$$\hat{\theta} = 1 - \frac{1}{2} \cdot \frac{\bar{p} - c^0}{c^1 - c^0}$$

and equilibrium average cost is

$$\hat{c} = \left[ 1 - \frac{1}{2} \cdot \frac{\bar{p} - c^0}{c^1 - c^0} \right] c^0 + \left[ \frac{1}{2} \cdot \frac{\bar{p} - c^0}{c^1 - c^0} \right] c^1$$

which depend on the initial price $\bar{p}$ and are clearly not equal to $c^*$ and $p^*$ in general. As will be demonstrated in the next section, updating $\bar{p}$ using the observed $\hat{c}$ of other "identical" hospitals also does not lead to convergence to $\theta^*$ and $c^*$. (For this demand function, the policy eventually converges to an equilibrium at $l^1=0$, $\hat{\theta} = \theta$, and $\hat{c} = c^0$.)

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exist. In that case, the regulator's only problem is to achieve production at minimum cost, which fixed-price reimbursement permits. As Joskow (1983) noted, for products like hospital services where quality may vary, "minimum cost" is not well defined. The result here is analogous to theoretical results for airlines facing price regulation and demand curves that are upward-sloping in quality (Douglas and Miller, 1974; Schmalensee, 1977).

Second, to the extent that demand functions differ among hospitals and diseases, uniform pricing encourages differences in medical practice patterns and hence costs among hospitals. For example, hospitals facing more elastic demand will tend to produce higher levels of quality, leading to higher costs. Hospitals may have lower costs and higher profits because they are in less competitive markets, not because prospective payment forces them to be more "efficient." Diseases for which demand is more elastic (for example, chronic diseases like cancer, where patients may "shop around" before undergoing treatment, versus acute diseases like pneumonia and heart attacks) may also tend to be treated more intensively.

Third, in contrast to previous studies that emphasize the role of physicians in trading off hospital profits against patient welfare in hospital production decisions, this model demonstrates that the quality and cost of hospital production need not depend on physician preferences in any direct way. Hospital managers, knowing that they have more interest in maximizing the hospital's objective function than physicians do, can render physicians' control of specific treatment decisions irrelevant for aggregate costs through the ex ante investment decisions that are under their control. However, specific
investments in capacity are an extreme case; for other technologies, physician objectives are more relevant to equilibrium intensity choices.

(2) **Hospital Investment in Nonspecific Capacity**

For nonspecific capacity investments such as hospital beds or radiologic equipment, hospitals maximize an objective function similar to (3) for all health problems \( j=1,\ldots,J \) in which the investments can be used. Thus the hospital chooses \( I^1 \) to

\[
\max_{I^1} \Pi(I^1) = \sum_{j=1}^{J} \left\{ F_j[\hat{\theta}(I^1)] \cdot [\bar{p}_j^0 - c_j^0] + [1 - F_j[\hat{\theta}(I^1)]] \cdot [\bar{p}_j^1 - c_j^1] \right\} \cdot q_j[\hat{\theta}(I^1)]
\]

\[ - b \cdot I^1 \]

\[ s.t. \sum_{j=1}^{J} [1 - F_j(\hat{\theta}(I^1))] \cdot q_j[\hat{\theta}(I^1)] \leq I^1 \]

where the \( j \) subscripts denote variables for each of the health problems. Physicians maximize their utility by choosing \( \hat{\theta} \) to be equal across all \( j \), given the nonspecific capacity constraint, so that the hospital cannot choose its optimal \( \hat{\theta}^b \) for each disease \( j \). Once again, there is no definite relationship between the equilibrium \( \hat{\theta} \) and the social optimum, though physician allocation decisions are efficient given the capacity constraint.

If prices and marginal costs differ across diseases, then in equilibrium costs may be lower than price for some diseases and higher than cost for others, whether or not hospitals have market power (but over all \( j \), margins will be positive if hospitals have market power and zero if they do not). In addition, hospitals have less control over which patients actually receive the more intensive treatment. For example, while hospital
choices of bed capacity will obviously influence physician decisions on allocating inpatient
days among patients, hospitals cannot choose directly which patients physicians will admit
or how long they will stay.

The inability of hospital managers to direct resources to specific DRGs contrasts
with the model of Dranove (1987), which predicts that hospitals will specialize in DRGs
in which hospital-specific efficiencies lead to greater profits.\textsuperscript{14} For nonspecific
investments, the ability of hospitals to specialize in profitable DRGs depends not only on
the elasticity of demand for quality among patients with a diagnosis but also the
correlation of hospital costs between relevant DRGs. Correlations of less than one lead to
aggregate price-cost margins that are smaller than if hospitals faced no agency problems.
Technology nonspecificity coupled with physician optimization behavior thus dampens
hospital responses to price signals across DRGs.

(3) \textbf{Hospital Investments in "Line of Business" Technologies}

The technologies described in (1) and (2) have the feature that physician effort
cost for using the technologies is constant below the constraint and infinite above it.
Alternatively, both specific and nonspecific technologies may be "line of business"
investments. For example, consider a technology with fixed adoption cost $b^t$, constant
marginal effort cost to physicians $\Delta^t$, and a constant marginal cost $c^t$ to the hospital. The
socially optimal intensity choice is $\theta^* = c^t - c^0$, assuming that the resulting surplus is greater

\textsuperscript{14}Dranove's model also differs from the model presented here in that it does not account
for the possibility of variations in intensity or competition for patients and physicians.
However, his approach can be readily extended to the present framework by allowing
variations in intensity cost, so that efficient hospitals can produce the same level of intensity
as inefficient hospitals at lower cost.
than \( b^1 \). If adopted, the physician’s decision rule for use of the treatment for patient \( \theta \) is \( \{ r=1 \) if \( \theta > \Delta^1, r=0 \) otherwise \}, which defines the marginal valuation level \( \theta = \theta^p \) above which patients will be treated with \( r=1 \). Provision of \( r=1 \) is reimbursed at a fixed price \( \bar{p}^1 \). In deciding whether to adopt this technology, the hospital compares two alternative profit levels \( \pi(1^1) \) as a function of its adoption decision:

Do not adopt \( \rightarrow \) \( \pi(0) = (\bar{p}^0 - c^0) \cdot q(\theta) \)

Adopt \( \rightarrow \) \( \pi(1) = \{ F(\theta^p) \cdot (p^0 - c^0) + [1 - F(\theta^p)] \cdot (\bar{p}^1 - c^1) \} \cdot q(\theta^p) - b^1 \)

In particular, the hospital cannot choose its profit-maximizing treatment intensity level \( \theta^h \) (and \( \theta^h > \theta^p \) if net effort costs for physicians are small).

If hospital investments precede physician choices of practice patterns, the hospital will choose \( l^1 = 1 \) if \( \pi(1) - \pi(0) > 0 \) or

\[
[F(\hat{\theta}^p) \cdot q(\hat{\theta}^p) - q(\overline{\theta})] \cdot (p^0 - c^0) + [1 - F(\hat{\theta}^p)] \cdot q(\hat{\theta}^p) \cdot (\bar{p}^1 - c^1) > b^1
\]  \( (8) \)

The first term on the left side is the change in revenue from patients treated with \( r=0 \) associated with the adoption of \( r=1 \), and the second term is the change in revenue associated with the use of \( r=1 \) on a share of patients given by the physician decision rule. With a fixed price \( \bar{p} \) for treatment of the disease, the margin for the more intensive treatment is again smaller (it is negative unless \( \bar{p} > c^1 \)).

If \( \theta^p \) is less than \( \theta^h \), and if hospitals choose \( r=1 \), physician control leads to greater equilibrium treatment intensity. But once again, there is no necessary relationship between the hospital’s actual \( l^1 \) and the socially optimal intensity level \( \theta^* \). Figure 1, which shows that adoption will occur for hospital profits corresponding to a range of values of \( \theta^p \) truncated by profit level \( \pi(0) \), illustrates further anomalous results. Hospitals with the most inelastic demand (least competitive markets) are least likely to adopt, since
π(0) will be highest. Analogous to results on the demand for insurance (Pauly, 1968), technology adoption may not occur even if socially optimal (benefits exceed total costs at θ*) and the hospital market is perfectly competitive if the level of use preferred by physicians leads to π(1) < π(0) (as illustrated by physician intensity preference θp' versus an alternative physician preference θp''). Alternatively, if physicians and hospitals engage in Nash bargaining over intensity choices for "line of business" technologies (e.g., the appropriate level of use of laboratory tests or drugs), then the only Nash equilibrium is θ = θp if θp > θl and θp = θl if θp < θl, where θl is the intensity level such that π(1, θl) = π(0).

For these technologies, physician preferences are quite important in determining the hospital production equilibrium.15

(4) Hospital Investments in "Intermediate" Technologies

Most medical technologies involve physician effort costs between the extremes of investments in fixed capacity and in a line of business. For example, effort costs for any particular θ may be decreasing in ι (congestion). Hospitals must trade off higher unit production costs associated with congestion against the effects of congestion on limiting resource use; the model is qualitatively similar to the capacity-constraint case. Hospitals may also make costly investments in technologies that influence physician use of other technologies. For example, hospitals may invest in monitoring systems that require physicians to justify particular admissions or long stays, in computer technologies that

15The result is analogous to studies of bureaucracy in which the objectives of the bureaucrat may differ from those of the legislature or other social planner. For example, in Romer and Rosenthal (1979), lower reversionary levels of public spending (analogous to unconstrained technologies here) give bureaucrats more budgetary power to pursue their own objectives at the expense of the principal.
make it easier to order certain tests or drugs but harder to order others, and other
"utilization management" investments that are not only costly to the hospital but also to
the physician. In the context of this model, such investments represent a signal that
hospital and physician incentives are in conflict. They are most likely to be observed in
hospitals for technologies that do not involve specific constraints and that are used in
treatments where physician and hospital incentives differ.

This model of the joint determination of hospital treatment intensity as a function
of the objectives of patients, physicians, and hospitals, the nature of medical technologies,
and the incentives provided in regulated prices has implications for empirical work. The
model predicts differential responses to hospital price incentives as a function of the
extent of hospital versus physician control of intensity choices for a health problem.
Important dimensions of treatment intensity choices and hospital technology investments
are increasingly observable in large datasets and can be categorized, on a priori clinical or
empirical grounds, in the framework developed here. Some preliminary empirical
evidence in the context of the Medicare PPS is presented in Section IV. First, in the next
section, I consider the implications of the model for PPS reimbursement and describe
welfare-improving modifications to the payment system. To the extent that hospital
profits or any other objective besides maximizing patient welfare (treatment intensity)
matters more to the hospital than physicians practicing in it, fixed-price reimbursement is
more likely to lead to suboptimal intensity equilibria for treatments where hospitals can
choose specific capacity levels. For other types of intensive treatments, hospital control
and hence responses to payment incentives may be much more limited. In these cases,
physician preferences for more intensive treatments have consequences for maximizing
treatment intensity subject to a budget constraint similar to increasing the elasticity of
demand for intensity.

III. Price Regulation of Medical Treatment Intensity

Using the model of hospital production developed in Section II, this section
presents a framework for understanding various forms of price regulation in health care,
demonstrates some major limitations of Medicare's current system of hospital price
regulation, describes the optimal payment system, and sketches practical reforms in the
Medicare hospital payment mechanism that are likely to reduce the use of intensive
technologies in marginal cases and hence reduce growth in hospital costs.

A benevolent regulator would set hospital prices to maximize the net social
benefits of hospital production. This is not the same as encouraging efficient production
of particular medical treatments. Indeed, any administered price system will lead to
efficient production of the individual services for which prices are set exogenously: the
fixed price makes the producer the residual claimant for all savings resulting from cost
minimization in production of the service. Administered price systems for medical care,
as for other industries, are not new. The so-called "cost-based" hospital reimbursement
system that Medicare PPS replaced was such a disaggregated administered price system.
Hospitals could not charge any desired price for services billed to Medicare; instead,
hospital regulators reviewed reported hospital costs for their "reasonableness" in relation
to the services provided. Most large private insurers rely on such disaggregated
administered price systems today for hospital services; they are also widely used for reimbursement of physician services.

At the opposite extreme of individual administered prices for all specific services provided by hospitals is a single fixed-price contract for producing all medical care. This is a pure HMO contract: the provider receives a single price for all services for an individual, fully independent of the services actually provided. A system of per capita payments for all hospital services is used in many other countries (Schieber, Poullier, and Greenwald, 1991). As Figure 2 illustrates, Medicare PPS is between these extremes. The system provides a single payment per hospitalization, which is a more aggregated level of administered prices than the cost-based reimbursement system that it replaced. However, some particular treatments or types of treatments -- primarily intensive surgical procedures -- still define administered-price groups. In contrast to the current DRG system, one can imagine a more-aggregated DRG system at the level of diagnoses only.\(^\text{16}\)

As Section II demonstrated, if hospitals have market power and can effectively control treatment intensity, increasing the aggregation of the pricing system reduces the costs of producing care for a health problem through intensity reductions. A single price for two intensity choices means that the difference in margins for the treatments equals the difference in their marginal costs, in contrast to the milder differences possible in a price system that reimburses each treatment separately. Both systems provide incentives

\(^{16}\)Diagnoses themselves may also be more or less aggregated. DRGs for most major diagnostic categories include a number of specific diagnoses (e.g., acute myocardial infarction, deep vein thrombophlebitis), some less specific diagnoses (e.g., chest pain), and catch-all residual categories (other circulatory system diagnoses). Here I focus on the effects of allowing DRG classification to depend on treatment intensity decisions.
to produce each treatment at minimum cost, but they have different implications for the returns to a marginal increase in intensity. At the extreme, when the pricing rule sets $\bar{p}^0 = c^0$ and $\bar{p}^1 = c^1 + b^1$, the relationship given in equation (5) for equilibrium intensity choice breaks down: regardless of its intensity choice, hospital profits are zero, so that the hospital may as well choose intensity levels that reflect physician and patient preferences. There is no conflict between physician agency for patients and for hospitals with respect to the intensity choices that are each reimbursed at cost. Thus, the framework developed in Section II predicts that using treatment-based surgical DRGs priced at cost will tend to encourage the use of these treatments to the point that marginal benefits are close to zero.

On the other hand, aggregated prices may provide too strong incentives to minimize the cost of treating a health problem. The equilibrium intensity choice of the hospital facing a fixed price, given by equation (6), may result in lower social welfare than the overconsumption result associated with disaggregated pricing. This result requires that (1) hospitals have market power and that (2) physician preferences for more intensity are not relevant at the margin due to technological capacity constraints chosen by the hospital. If the market for hospital services is competitive or if physicians as near-perfect agents control marginal intensity decisions, then hospitals will produce near the maximum intensity level that the administered price will support.

It also requires that (3) the regulator is restricted to setting an administered price equal to cost. If the regulator knows the demand function and the distribution of net benefit levels from more intensive treatment, he can use equation (5) to solve for the $(\bar{p}^0, \bar{p}^1)$ combination that implements any desired intensity level between $\hat{\theta}^1$ and $\hat{\theta}^2$. Since
treatment intensity is increasing in \((\vec{p}^1 - \vec{p}^0)\), this procedure involves setting a price for \(r = 0\) greater than \(c^0\) and a price increment for \(r = 1\) less than the cost difference \([c^1 + b - c^0]\). While such a "first-best" rule seems to have strong informational requirements, welfare-improving changes in the Medicare price structure are possible with much more limited information. Before considering such rules, I illustrate the implications of the current reimbursement system for the dynamics of health costs and treatment intensity. I assume no exogenous changes in technology occur over time to illustrate dynamic implications of the Medicare price rule.

The dynamic implications can be illustrated qualitatively with phase diagrams. Consider a true diagnosis-related DRG; that is, reimbursement is a fixed price for the diagnosis regardless of the treatment intensity level chosen. Figure 3 illustrates the current Medicare pricing rule for a DRG of setting \(\vec{p}_{t+1} = \hat{c}_t\), where \(\hat{c}_t\) is average cost in the DRG in period \(t\).\(^{17}\) If there are a large number of identical hospitals (the best case for yardstick competition), the impact of intensity choices by a particular hospital will have no effect on price in the next period, so hospitals will not behave strategically and all will choose the same equilibrium intensity and cost for a given price. At \(X\), \(P_t(X)\) is lower than \(C_t(X)\), so \(P_{t+1}(X)\) increases to offset the difference. At \(Y\), \(P_t(Y)\) is higher than \(C_t(Y)\), so \(P_{t+1}(Y)\) fails to offset the difference. At \(Z\), \(P_t(Z)\) equals \(C_t(Z)\), so \(P_{t+1}(Z)\) is unchanged. Assuming for now that regulators can measure hospital costs accurately, it is

\(^{17}\)The actual Medicare pricing rule is to set price equal to a conversion factor times the relative weight of a particular DRG, where the weight is determined by the ratio of charges in the DRG to average charges for all Medicare patients. The conversion factor is set to achieve a particular total expenditure target. Thus the price update rule is exact only if the conversion factor updates hospital output prices by the rate of increase in hospital input prices; below, I explore the consequences of deviations from this model.
evident that a diagonal line with slope 1 through the origin traces out the set of \((P_t, C_t)\) combinations for which \(P_{t++}\) will be unchanged; this is the \(dP/dt=P=0\) equilibrium line. To the northwest, \(\dot{P}>0\); to the southeast, \(\dot{P}<0\).

Figure 4 illustrates a complementary relationship for the dynamics of equilibrium cost. If cost happened to be very low in a period when a very high price was offered, cost will increase (the higher price increases the returns to attracting more demand). Thus, in the southeast corner of Figure 4, for example at point \(Y\), \(C_{t++}(Y) > C_t(Y)\). In contrast, if equilibrium cost happened to be very high and a low price was introduced, cost will fall. Thus, in the northeast corner, for example at point \(X\), \(C_{t++}(X) < C_t(X)\). At point \(Z\), cost and price are such that no equilibrium adjustment is necessary, so \(\dot{C} = 0\). A sample \(\dot{C} = 0\) line is traced out in the figure; the line reflects an equilibrium cost function that becomes less sensitive to price at higher price levels. Different demand functions, intensity costs, distributions of net benefits \(\theta\), and degrees of physician control over intensity choices will generate different forms for \(\dot{C} = 0\). Intensity is increasing in costs (\(\dot{\theta}\) falling as cost increases), so the \(\dot{C} = 0\) mapping also implies an equilibrium intensity level \(\theta\) as a function of price.

Combining the \(\dot{C} = 0\) and \(\dot{P} = 0\) relationships, as in Figure 5, illustrates how the prospective payment system might influence the dynamics of equilibrium cost and intensity levels in the DRG. In this example, two points comprise equilibrium price-cost relationships, \(A\) and \(B\). \(A\) is an unstable equilibrium, since any perturbation away from \(A\) will tend to move further from \(A\). \(B\) is a stable equilibrium, since local perturbations tend to return to \(B\). A key feature is that at \(B\) the slope of the \(\dot{P} = 0\) function is greater than that of the \(\dot{C} = 0\) function. The phase diagram does not depict time to convergence,
but the time course of a sample intensity path from point W to point B is illustrated in Figure 6. Cost and intensity first fall then rise to converge on B (that is, \( \hat{b} \) first rises then falls).

Note that, if costs are measured accurately, the \( \hat{P}=0 \) line also comprises the zero-profit line for hospital production. One feature of Figure 5, that \( \hat{C}=0 \) equilibria could occur in a range where \( P>C \), may seem implausible. However, it is possible if subsidies exist across health problems (e.g., hospital investments are nonspecific), if hospital costs are subsidized from other sources (e.g., separate reimbursement of capital costs, as described below, or subsidies from non-Medicare patients), if hospital reported cost estimates are biased upward, or if other arguments in the hospital objective function besides patient welfare can be disguised as necessary costs of care. I return to these possibilities momentarily.

If none of these possibilities exist, Figure 7 represents a more realistic path in the case where hospitals have market power. Point A represents a stable equilibrium, occurring at the minimal intensity level. The reason is demonstrated by the Figure. At any given price, a hospital with market power can earn positive price-cost margins on average by decreasing quality slightly below the level that maximizes consumer welfare (and earns zero profits). Consequently, average cost is less than price. Thus the \( \hat{C}=0 \) line will generally have a flatter slope and be located to the right of the \( \hat{P}=0 \) line over the range of prices in which hospitals can choose intensity levels above the minimum. The updated price (equal to observed cost in the previous period) will be lower, leading to a lower optimal intensity level, and this downward spiral continues until the minimum intensity level is reached. However, higher equilibrium intensity levels (or at least a
slower rate of decline) are possible if the technologies used at equilibrium are such that physicians acting as patient agents control intensity or if hospitals face perfect competition.

In fact, whenever hospital demand is perfectly elastic or hospitals maximize patient welfare for other reasons, any point along the $\hat{p}=0$ line is a stable equilibrium. Intensity is maximized subject to the zero-profit constraint, so price equals cost for any price at least as high as the minimum intensity level for production (and lower than the maximum intensity level, which may be very high). Thus, as shown in Figure 8, an infinite number of stable equilibria are possible; the particular equilibrium that exists depends only on the initial price level.

Perfect competition or physician choices leading to intensity maximization for a given price result in stable equilibria. In contrast, Figure 9 presents a more worrisome situation, in which the price rule encourages dynamic increases in intensity. The equilibrium $\hat{c}=0$ curve is above the equilibrium $\hat{p}=0$ curve in the relevant range of prices and costs. Equilibrium A is unstable: from any initial condition with cost or price beyond A, cost and price will continue to increase over time as long as the $\hat{c}=0$ line is above the $\hat{p}=0$ line. This instability is a general characteristic of pricing rules that increase the steepness of the $\hat{c}=0$ line. Three scenarios that tend to lead to such relationships are considered below: separate cost-based reimbursement of specific dimensions of intensity, non-profit hospital objectives, and overestimation of hospital marginal production costs in the reimbursement formulas.

In some respects the Medicare pricing rule is less high-powered than suggested by the fixed-price rules described in the preceding Figures. Consider the extreme case of
disaggregated pricing at average cost for each treatment, preserving the incentive to produce the treatment efficiently but making hospital profits zero regardless of intensity choice. Then every point on the $C=0$ line is a dynamic equilibrium. (In fact, any intensity level in which price equals cost is sustainable.) Medicare actually reimburses only certain dimensions of treatment intensity separately, but this can still encourage broader intensity and cost increases in the treatment of a disease. In general, as equation (5) indicated, increasing the price differential between alternative intensity levels increases the steepness of the market equilibrium ($C=0$) curve, increasing the probability of unstable cost growth.\(^{18}\)

Another possible cause of unstable intensity growth even if measured costs are correct is the existence of non-profit objectives in hospital objective functions. Only a small fraction of hospitals are for-profit, so that most hospitals should not be expected to show much total accounting profits. Instead, not-for-profit hospitals maximize an objective function -- which may include profits -- subject to a budget constraint (Newhouse, 1970; Hansmann, 1980). Dranove (1988) noted that if not-for-profit hospitals value quantity or quality, they will respond less to price incentives than profit-maximizing hospitals; Hoerger (1990) proposed a test for the existence of hospital objectives other than profit on the basis of such dampened responses. To the extent that such non-profit objectives translate into higher observed costs of treating Medicare

\(^{18}\)Of course, reimbursing some dimensions of treatment intensity at higher levels also affects the form of the $P=0$ curves for treatment of the health problem in ways that cannot easily be captured in a two-dimensional phase diagram. In general, however, smaller intensity price differentials lead to higher equilibrium intensity levels; if these cost increases result in further price increases, the likelihood of further increases in intensity over time is higher.
patients, they will tend to push hospital $\hat{C}=0$ curves towards -- if not above -- the $\hat{P}=0$
curve, increasing the probability of dynamic cost and intensity increases in the absence of
 technological change.

Finally, incremental hospital production costs are probably not measured
correctly. A large literature exists documenting the difficulty of correctly estimating
"true" production costs in multiproduct firms in other industries. Fundamental cost
estimation problems such as allocating costs in joint production or calculating true
economic depreciation rates for assets that may be expensed or depreciated according to
standard accounting formulas are no different for hospitals. Such detailed cost estimation
is practically infeasible anyway. Medicare’s cost estimates for setting DRG prices are
obtained from "ghost" bills for hospital charges that would have been generated if the
beneficiary were a private patient.\textsuperscript{19} Reimbursement updates for a DRG are based on
the average "weight" of reported charges per admission in the DRG relative to average
charges for all Medicare admissions.\textsuperscript{20} To the extent that charges are not everywhere
proportional to true costs, the reimbursement system tends to favor treatments for which
true cost-to-charge ratios are low; if true costs are far enough below reported costs, the
unstable dynamics of Figure 9 may result.

\textsuperscript{19}The relationship of hospital charge data to "true" costs is probably declining. Most
hospitals provide special discounts to many large payors (e.g., Blue Cross, HMOs, PPOs).
Stated charges to residual third-party payors may be higher as a result (McGuire and Pauly,
1991), and in any event bear less of a direct relationship to actual hospital costs of care.

\textsuperscript{20}Charge-based weights were first used in the fiscal year 1988 PPS DRG updates. Prior
to that, cost-based weights were used, where costs were calculated from reported hospital
charges using hospital-specific cost-to-charge ratios (see below).
In particular, the reimbursement system favors DRGs that rely more heavily on capital-intensive treatments such as operative procedures or laboratory tests. These DRGs have the lowest measured cost-to-charge ratios (Rogowski and Byrne, 1990). Other features of PPS also favor more capital-intensive treatments. Teaching hospitals receive an indirect medical education adjustment to their DRG payments proportional to their ratio of interns and residents to hospital beds. Since the adjustment is proportional, it provides larger increments to reimbursement for admissions in more intensive DRGs. Finally, Medicare payments for hospital capital expenditures were cost-based through 1991: Medicare reimbursed hospitals for 85% of its "share" of capital purchases (i.e., 0.85 times the proportion of Medicare admissions at the hospital times the capital purchase). The pass-through payment system for capital costs is now being gradually phased out over a ten-year period ("prospective" capital payments will be included in DRG payments), but this system reduces the cost of investment to the hospital (the variable b in Section II, above). Thus, particularly for intensive DRGs, reported costs (and prices) may be greater than true marginal costs to the hospital.

The dynamic instability of intensity choices is further complicated by the mechanism for updating Medicare prices. The "conversion factor" between DRG relative weights and dollar payment levels is set so that if the current period's DRG admission patterns are identical to the prior period's DRG admission patterns, aggregate hospital payments will increase at a target growth rate. This updating mechanism has consequences for the dynamic reallocation of resources to health problems between single-DRG health problems and health problems for which DRGs are available for multiple intensity levels. Suppose that all treatments for health problem A are aggregated into a
single DRG at price \( \bar{p}_A(t) \), and that treatments for health problem B are divided into a less intensive DRG at price \( \bar{p}^0_B(t) \) and a more intensive DRG at price \( \bar{p}^1_B(t) > \bar{p}^0_B(t) \). Assume that the number of patients with the health problem in each period \( n_A \) and \( n_B \) is fixed and that production of care for A is competitive, so that \( \bar{c}_A(t) = \bar{p}_A(t) \) (the dynamic problem is worse if it is not). Assume that the current (price, cost) state is such that the use of the more intensive treatment for problem B is increasing (that is, \( \bar{\theta}_B \) is decreasing). The current price for a DRG is a function of its relative weight \( \omega(t-1) \) in the previous period (average cost per admission in the DRG divided by the average cost of all admissions) times the conversion factor \( \phi(t) \) which solves

\[
\hat{c}(t-1) \cdot g(t) = \phi(t) \cdot \left( n_A \cdot \omega_A(t-1) + n_B \cdot [F(\hat{\theta}_B(t-1)) \cdot \omega_B^0(t-1) + (1-F(\hat{\theta}_B(t-1))) \omega_B^1(t-1)] \right)
\]

where \( \hat{c}(t-1) \) is total cost in the previous period, and \( g(t) \) is the exogenous target growth rate for the current period. If the rate of change of \( F(\hat{\theta}_B(t-1)) \cdot (c_B^0-c_B^1) \) exceeds \( g \), then \( \phi(t) \) will decrease over time, leading to a decline in price (and cost) for treatment of health problem A and a reallocation of resources to health problem B. Even if the production of A is competitive, the intensity of treatment for problem A will decline over time due to an externality effect of increasing intensity for problem B induced by the update rule.\(^{21}\)

Thus, in general, PPS does not lead to dynamic cost-intensity equilibria with any particularly desirable properties, if it leads to cost equilibria at all. A critical policy

\(^{21}\)In recent years, PPS updates have been based on target growth rates lower than measured hospital cost inflation. To the extent that this reflects true price ratcheting, it can be captured in the phase diagrams above by a counterclockwise rotation of the \( P=0 \) line. Thus, it tends to lead to treatment equilibria at lower intensity levels and is less likely to result in unstable growth; the qualitative conclusions are unchanged.
question is whether better static and dynamic properties are possible in practice through feasible improvements in PPS pricing rules.

In theory, potentially major improvements in efficiency are possible through modifying the pricing rules. The preceding analysis describes two major types of health problems: those for which hospitals face perfect competition or for which physicians acting as patient agents can control intensity choices, and those for which hospitals face upward-sloping demands for intensity and can choose optimal intensity levels. In the former case, the regulator need only set a single price for all alternative treatments for the health problem. For example, in the case of two possible intensity choices with costs $c^0$ and $c^1$, the first-best intensity level is $\theta^* = c^1 - c^0 = \Delta c$. Thus the optimal $\tilde{p}^*$ solves

$$F(\hat{\theta}^*) \cdot [\tilde{p}^* - c^0] + [1 - F(\hat{\theta}^*)] \cdot [\tilde{p}^* - c^1] = 0$$

(10)

Hospital production will maximize patient welfare subject to this budget constraint.

If hospitals choose intensity and face upward-sloping demand, then the optimal $\theta^*$ can be implemented by solving for a set of possible $(\bar{p}^0, \Delta \bar{p})$ choices using the formula of equation (6). Note that this requires pricing the less intensive treatment above its marginal cost and setting $\Delta \bar{p} < \Delta c$ (as noted previously, when $\Delta \bar{p} = \Delta c$, the hospital is
indifferent between intensity choices).\textsuperscript{22} All these solutions leave positive profits to the hospital, because demand is upward-sloping in intensity; the regulator would need an additional instrument such as the ability to enforce a particular level of technological capacity to achieve first-best intensity without profits. Profits may be costly, so that one dollar of hospital profits costs \((1 + \lambda)\) dollars in social welfare. In this case the regulator must choose \(p = (\overline{p}^0, \Delta \overline{p})\) to

\[
\max_{\overline{p}^0, \Delta \overline{p}} \int_{\hat{\theta}} \theta(p) \left[ \mu(\theta) - c^0 \right] dF(\theta) + \int_{\hat{\theta}(p)} \theta \left[ \mu(\theta) + \theta - \Delta c^1 \right] dF(\theta)
- \lambda \left(F(\hat{\theta}(p)) \cdot (\overline{p}^0 - c^0) + [1 - F(\hat{\theta}(p))] \cdot (\overline{p}^0 + \Delta \overline{p} - c^1)\right)
\]

\[\text{s.t. } \hat{\theta}(p) : F(\hat{\theta}(p)) \cdot (\overline{p}^0 - c^0) + [1 - F(\hat{\theta}(p))] \cdot (\overline{p}^0 + \Delta \overline{p} - c^1) = \frac{f(\hat{\theta}(p)) \cdot \delta(p)}{\eta_{\theta}} \cdot [\Delta c - \Delta \overline{p}]\]

The constraint for \(\hat{\theta}(p)\) is hospital incentive compatibility from equation (5): the hospital will choose an intensity level to maximize its objective function given the prices set by the regulator. The first line is the regulator's objective of choosing the intensity level that maximizes net benefits; if the regulator could mandate \(\hat{\theta}\), he would solve this program to

\textsuperscript{22}For the a numerical example developed in footnote 13, any particular \(\theta\) can be implemented by solving for \(\overline{p}^0\) and \(\Delta \overline{p} = \overline{p}^1 - \overline{p}^0\) in the equation

\[
\hat{\theta} = 1 - \frac{1}{2} \cdot \frac{(\overline{p}^0 - c^0)}{(\Delta \overline{p} - \Delta c)}
\]

where \(\Delta c = c^1 - c^0\). Note that increasing \(\overline{p}^0\) leads to higher equilibrium intensity, and increasing \(\Delta \overline{p}\) makes \(\hat{\theta}\) more responsive to a given change in \(\overline{p}^0\). The first-best intensity choice \(\theta^* = \Delta c\) can be implemented by any pair of administered prices \((\overline{p}^0, \Delta \overline{p})\) satisfying

\[
\overline{p}^0 = (c^0 + 2[\Delta c - \Delta c^2]) - (2[1 - \Delta c]) \Delta \overline{p}
\]

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choose $\theta^* = \Delta c$. The second line is the hospital's profit multiplied by its social cost $\lambda > 0$. Note that the incentive compatibility constraint can be written as a restriction on the form of the hospital's profit function. Since the left side of the constraint is increasing in $\theta$ for standard distributions, a tradeoff exists between pricing more generously to increase intensity and giving hospitals more profits. If the incentive constraint can be solved for $\theta$ in closed form, the program in (11) can be solved by substituting the constraint into the maximand and taking first-order conditions with respect to prices.

Although it is unlikely in practice that demand and treatment effect distributions can be specified precisely enough to derive an exact optimal price set, the qualitative features of optimal pricing for treatment intensity provide some insights of practical value. First, price differentials for alternative treatments are necessary only when hospital production equilibria deviate significantly from maximizing patient welfare. If demand

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23The additional individual rationality constraint of nonnegative profits and the requirements of positive prices are assumed to be satisfied to simplify exposition.

24For example, for the demand function and treatment effect distribution studied in footnotes 13 and 22, substituting the incentive compatibility constraint for the hospital's choice of $\theta(\overline{p}, \Delta \overline{p})$ into the social welfare function and taking first order conditions yields

\[
\overline{p}^0 = c^0 + \frac{1 - \Delta c}{3} - \frac{\lambda}{6};
\]

\[
\Delta \overline{p} = \Delta c - \frac{1}{6};
\]

\[
\theta^* = \Delta c + \frac{\lambda}{2}.
\]

Note that $\overline{p}^0 > c^0$ (for values where an internal solution is optimal) and $\Delta \overline{p} < \Delta c$. If $\lambda = 0$, the first-best intensity level is optimal. As hospital profits become more costly ($\lambda$ increasing), the optimal intensity level and hospital profits fall. For this example, second-order conditions are satisfied at the optimum.
for hospital services is perfectly elastic, or if the treatment technology is such that physicians are able to act as near-perfect agents for patients, then first-best outcomes can be achieved with a single aggregated price for the health problem. Even if the regulator does not know the cost of achieving the optimal $\theta^*$, he need only know the direction of $\theta^*$ from the current equilibrium $\theta$ to improve welfare. Since any $\bar{p}$ leads to an equilibrium, if costs for each component of intensity are not observed perfectly, the regulator can iterate to a desired intensity level by increasing or decreasing price, respectively, to increase or decrease equilibrium intensity. Aggregated prices are most likely to be optimal when the nature of health problems makes demand more elastic and where hospital investment decisions do not provide tight control over marginal technology use ("lower-tech" treatments that are not specialized to a particular health problem). For diseases whose treatment primarily involves nonspecific technologies, the regulator need only get the price right for the bundle of DRGs.

For health problems such that markets are less competitive and specific hospital investments in technological capacity are important, disaggregated prices related to cost differences for alternative treatments may be optimal. This result is similar to the general conclusion in Pope (1989) that optimal pricing rules involve some cost sharing.\textsuperscript{25} However, administered price rules that provide high differential reimbursement for more intensive treatment alternatives -- for example, reimbursement of the full cost difference

\textsuperscript{25}Pope addressed a similar question, incentives to provide quality when hospitals face upward-sloping demand, but did so in a static framework without accounting for technological factors or dynamic implications. Ellis and McGuire (1988), Pope (1990), and Newhouse (1992) also concluded that some cost sharing is optimal when hospitals face different severity mixes of patients (a topic not addressed here). None of these studies addressed the technology-based cost sharing inherent in current PPS rules.
between alternative intensity levels -- lead to use of the intensive technology in "marginal" cases and provide more pressure for intensity growth over time. In contrast, the price differential in an optimal system is only a fraction of the cost differential, coupled with an increase in the price level of the less intensive alternative above cost to provide nonnegative profits. Clearly, disaggregated pricing rules as steep as they are at present for some health problems invite cost and intensity growth that is unlikely to be desirable.

Steeper $\dot{P}=0$ rules (in contrast to steeper $\dot{C}=0$ curves) are also less likely to lead to unstable equilibria with continued intensity growth. Steeper $\dot{P}=0$ rules are less dependent on observed market costs in the previous period. (In the limit, a vertical $\dot{P}=0$ rule is independent of observed costs.) If market equilibrium intensity is known to be too high, a $\dot{P}=0$ rule that is near vertical and to the northeast of the current cost level (e.g., price below observed cost) will almost certainly result in intensity and cost reductions over time. While the case described above in which the only equilibrium was at the minimal quality level indicates the danger of a dynamic pricing rule that is too "high-powered," if observed treatment intensity is too low, a similar steep $\dot{P}=0$ rule to the right of observed cost will tend to lead to marginal increases in intensity but will be unlikely to result in continued dynamic cost growth. Thus, the practical pricing implications of the noncompetitive case are similar to those for the competitive case.

Intuitively, the steepness of the $\dot{P}=0$ rule should increase with the precision of the regulator’s knowledge about the marginal effectiveness of treatment intensity. All of the directions for improvement in PPS dynamic adjustment rules outlined above require some knowledge of whether current intensity of hospital production is greater or less than the desired intensity level. Given the limited state of knowledge about the outcome
consequences of most medical technologies, marginal or otherwise, this assumption may seem strong. But in the absence of financing reforms that change the incentives facing patients or physicians, using even limited knowledge of treatment effectiveness to guide the dynamic path of treatment intensity seems necessary to improve welfare. In fact, the price changes themselves, coupled with a mechanism to monitor outcomes for health problems, may be able to provide some much-needed information on marginal effectiveness (see McClellan and Newhouse, 1993, for a presentation of methods for estimating marginal treatment effectiveness in observational data). In any event, one conclusion from this analysis is clear: the current payment system does not lead to any particularly desirable relationship between the marginal costs and effectiveness of intensive technologies. In the next section, I consider aggregate empirical evidence on the dynamics of hospital production under PPS in terms of this analytic framework.

IV. Preliminary Empirical Evidence

The model developed in Sections II and III has the following empirical predictions. First, if hospital care for treating a health problem is competitive, or if physician control of technology use leads to production decisions that maximize intensity given price, costs should track price over time. Second, whether or not hospital production maximizes patient welfare, hospitals have minimal incentives to limit dimensions of treatment intensity that involve technologies reimbursed in distinct cost-based DRGs. Third, if demand for hospital services is not perfectly elastic in intensity, dynamic changes in treatment intensity are likely to occur independent of any exogenous technological change. In particular, dynamic intensity growth is likely for health
problems where reimbursement differences reflect cost differences, leading to steeper
equilibrium price-cost relationships, or where measured marginal production costs
overstate true costs. Finally, for health problems grouped into true diagnosis-based
DRGs, declines in intensity over time are likely because the PPS price update mechanism
tends to increase the share of reimbursement devoted to health problems in which cost
increases can occur through shifts to more intensive DRGs.

Exogenous technological progress is also viewed as a principal cause of growth in
health care costs (Newhouse, 1993). While the development of a formal model of
hospital technology adoption decisions in the context of the model presented here awaits
further work, 26 some important implications for technology diffusion are evident. For
health problems with multiple DRGs for different levels of treatment intensity,
innovations are favored that shift the net benefit distribution to permit "marginal" patients
to be treated in more intensive DRGs. For example, innovations that reduce operative
mortality and morbidity for specifically-reimbursed surgical procedures will be adopted
and will lead to dynamic cost increases through more intensive treatment of the disease.
For diseases without intensive treatment-based DRGs, such technologies are less likely to

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26Most biomedical research is conducted not by the clinical divisions of hospitals but by
their biomedical research divisions and separate research organizations. Funding for
biomedical research, primarily from the Federal government, is largely independent of
Medicare funding for patient care. Consequently, technology diffusion rather than innovation
itself has greater consequences for medical costs. In a standard model of diffusion, the firm
compares its expected profit stream from investing in the innovation this period to the
expected profit stream associated with waiting until the next period (Reinganum, 1989).
Firm heterogeneity leads to heterogeneity in observed adoption times and frequency of use.
Incentives for technology adoption include the reimbursement rules and demand responses
associated with the technology. Thus, the intuitive predictions of the model developed here
involve greater diffusion of the types of technologies noted in the text.
be adopted. In these cases, the adoption of cost-reducing technologies may complement the dynamic decline in costs outlined previously.

To illustrate the practical consequences of the structure of the DRG reimbursement system, I first present evidence on one particular health problem, acute myocardial infarction (AMI, or heart attack). This is a very common health problem in the elderly which accounts, directly or indirectly, for much of the mortality and hospital use associated with coronary heart disease. The data are derived from all hospital discharge abstracts filed over a two year period by all elderly Americans hospitalized with a new AMI in 1987. The sample thus includes data from 522,506 hospitalizations for 205,021 elderly AMI patients (see McClellan and Newhouse, 1993, for details of the dataset creation process). Table 1 summarizes demographic characteristics and some important treatment intensity decisions for these patients. In 1987, approximately 23% of elderly AMI patients underwent cardiac catheterization, an invasive procedure, and approximately 13% of these patients underwent a further intensive revascularization procedure, percutaneous transluminal coronary angioplasty (PTCA) or coronary artery bypass graft (CABG) surgery. Approximately 87% of patients spent at least one day in a specialized coronary or intensive care unit bed (CCU/ICU), including 84% of patients who did not undergo any invasive procedure (last column).

These intensive treatments have different implications for hospital reimbursement. Admissions for AMI patients who do not undergo intensive procedures are categorized into DRG 121 (AMI with complicating conditions), 122 (AMI without complicating conditions), or 123 (AMI, expired). The three DRGs differ somewhat in reimbursement levels, reflecting patient disease severity (ideally independent of hospital treatment
choices) that is correlated with cost of care. Both revascularization procedures, PTCA (DRG 112) and CABG (DRGs 106 and 107), involve distinct DRGs with much higher reimbursement levels that reflect the incremental costs of the intensive treatments. In contrast, although one might imagine a DRG for "AMI with coronary care unit admission," there is no incremental reimbursement for treatment involving specialized coronary care unit beds. The implications for DRG classification of the initial hospitalizations of AMI patients are presented in Table 2, which shows that only 92% of all AMI patients and only 88% of male patients aged 65-74 were initially hospitalized in an AMI-related DRG. The other AMI patients were mostly categorized in more intensive DRGs based on the use of invasive or surgical treatments. Table 2 also shows that the share of treatment-based DRGs is even larger when all hospitalizations within 30 days of the AMI are considered. AMI patients are specifically excluded from the catheterization DRGs (124 and 125), but over 1% of patients are hospitalized in these DRGs within a month of their AMI.

Table 3 reports means and standard deviations for hospital utilization,\textsuperscript{27} reported hospital costs,\textsuperscript{28} and reimbursement\textsuperscript{29} for AMI patients grouped by which treatments they received. These statistics are reported for all hospital admissions during three time

\textsuperscript{27}Number of admissions, number of total hospital days, and number of ICU or CCU days were calculated from Medicare claims.

\textsuperscript{28}Reported costs for each hospitalization were calculated by multiplying the reported departmental charges for a hospitalization by the PPS cost-to-charge ratio for that hospital department and summing the resulting cost estimates across all departments. As noted above, these reported costs are not perfect measures of "true" average incremental costs to the hospital and so should only be interpreted qualitatively.

\textsuperscript{29}Reimbursement rates were calculated for each admission by summing DRG-based payments and DRG outlier payments (if any).
intervals after AMI: within 30 days, within 90 days, and within one year. Compared to patients not undergoing invasive procedures, patients undergoing one or more of the procedures used hospitals more intensively (in terms of number of admissions, total days, and intensive-care days) and incurred substantially higher costs. But DRG reimbursement totaled a relatively constant proportion of reported costs, regardless of procedure use. For example, within 90 days of AMI, total DRG reimbursement for patients not undergoing procedures was 89% of reported costs ($6,177 versus $6,953 on average), for patients undergoing catheterization only was 82% of costs ($8,749 versus $10,697), for patients undergoing catheterization and PTCA was 89% of reported costs ($12,146 versus $13,614), and for patients undergoing catheterization and CABG was 94% of reported costs ($23,708 versus $25,221). Thus, for these intensive procedures used in the management of AMI patients, PPS reimbursement tracks costs quite closely on average.\(^{30}\)

In contrast, Table 4 reports summary statistics for patients grouped on the basis of whether or not they stayed in a specialized CCU or ICU bed for more than two days during their acute AMI treatment. Patients with acute CCU/ICU stays of two days or less had costs significantly lower than those of patients with stays over two days. Reimbursement differences between the two groups were much more modest, however, so that patients receiving two days or less of CCU/ICU treatment had average

\(^{30}\)The slightly larger proportion of cost-bearing for patients undergoing catheterization only is likely to be a reflection of DRG structure as well. For patients admitted with AMI, only if catheterization occurs during a subsequent admission does it provide additional reimbursement for the hospital. Table 2 demonstrated that some patients are readmitted soon after their initial AMI admission to undergo catheterization, which then constitutes a non-AMI DRG.
reimbursement levels 29% higher than average costs of hospital care within 90 days of AMI ($5,133 versus $3,971), while average reimbursement was only 77% of costs for patients receiving more than two days' CCU/ICU treatment ($6,802 versus $8,855). While this pattern is expected under prospective payment -- patients requiring more CCU/ICU days are sicker than those who do not -- the pattern is quite different from that observed for intensive technologies with separate DRGs. Because DRG payments are largely independent of CCU/ICU use, additional CCU days lead to relatively little additional hospital reimbursement.

The association\textsuperscript{31} between reimbursement and treatment intensity for AMI illustrates the financial incentives for hospital investments in medical technologies. Implementing the capacity to perform CABG, PTCA, or cardiac catheterization, as well as choosing the quantity of CCU beds to support, are all hospital investment decisions that may have substantial effects on physician decisions for AMI treatment. Analogous investments in intensive technologies are prerequisites for intensive hospital treatments of other health problems. In the context of the model developed in Section II, these reimbursement policies will affect hospital investment choices and in turn the treatment intensity levels chosen by physicians. With this framework, I now turn to a broader

\textsuperscript{31}These results do not distinguish patient selection effects from true differences in resource use, costs, and reimbursement resulting from the alternative treatments. The Appendix presents preliminary evidence from least-squares and instrumental-variables estimation of costs of treatment that the patients receiving procedures are relatively healthy and consequently would have lower resource use and somewhat lower reimbursement than those who do not receive intensive procedures. The principal subject of this paper -- the average relationship of payment and treatment intensity decisions -- does not require demonstration of these causal relationships.
analysis of trends in hospital treatment patterns and costs before and after the adoption of
the Medicare Prospective Payment System.

Prior to 1982, Medicare payment to hospitals consisted of fixed per diem payments
for room, board, and basic nursing services, plus "reasonable cost" reimbursement for all
special services (laboratory and radiologic tests, intensive care costs, operating room
costs, etc.). Rates determined through detailed cost monitoring rules. Broadly speaking,
reasonable-charge reimbursement amounted to a disaggregated administered price system,
with correspondingly weak incentives to trade off profits against patient treatment
intensity.\footnote{Some states had ratesetting boards that set "target" average payments per admission
prospectively. However, the target payments were adjusted by the hospital's case-mix index,
an index of the average intensity of cases treated at the hospital. Using more intensive
procedures increased the hospital's case-mix index, leading to increases in the average
reimbursement targets that paralleled the increases in costs.}

This mechanism encouraged hospitals to adopt technologies that increased
patient stays, and it encouraged investments in hospital beds toward the maximum level
desired by physicians. Figure 10 shows aggregate trends in admission rates per 1,000
elderly Medicare beneficiaries since 1977.\footnote{The statistical data used to construct this and subsequent
figures and tables on hospital utilization trends were provided by the Health Care Financing
Administration, to whom I am once again grateful. Most of these data have been published
previously in Latta and Keene (1989) and Latta and Helbing (1991).} Medicare admissions increased steadily
before 1983.

The Tax Equity and Fiscal Responsibility Act (TEFRA) of 1982 introduced a new
set of hospital cost control measures in fiscal year 1983. Under TEFRA, a hospital's
historic average costs per discharge in 1982, trended forward and adjusted for case mix,
provided a "target" cost for reimbursement in 1983. Case-mix adjustment is similar in principle to DRG weights; in fact, the relative weights developed for DRGs provided the basis for a hospital's case-mix index under TEFRA. Thus, reimbursement was adjusted for the average intensity of admission types at the hospital (e.g., bypass surgery is a more intensive case than AMI without intensive procedures). TEFRA thus began a movement away from regulated prices for specific services and towards pricing at the more aggregated level of the admission itself, with reimbursement adjustments based on the types of admissions at the hospital.

This process continued with the implementation of PPS beginning in fiscal year 1984. PPS featured a four-year phasein during which "prospective" hospital payments consisted of a weighted average of hospital-specific TEFRA payments and national average costs within the DRG, with the hospital-specific component declining to zero. The adoption of PPS was associated with a one-time reduction in lengths of stay and hospital costs, which was accompanied by the decline in elderly admissions shown in Figure 10. The Figure demonstrates one of the "puzzles" of PPS: Why did admission

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34Actual hospital payments were based on how the average cost per hospital admission compared to the target for the fiscal year. Average cost less than the target was reimbursed at cost plus half the difference between actual and target costs (limited to a 5% incentive payment). Average cost greater than the target was reimbursed at the target plus 25% of excess costs (with a mechanism for additional payments in exceptionally high-cost cases).

35The Figure is not meant to imply that reduced admissions alone accounted for all of the cost reductions associated with PPS implementation; reductions in lengths of stay and in costs per admission were also important. After the one-time reduction, however, lengths of stay have stabilized and costs per admission have increased. The relationship of PPS adoption to time trends in Part A hospital costs, Medicare costs more generally, and other measures of hospital financial performance have been well-documented; see Coulam and Gaumer (1991) for a detailed review. Here, I present only some selected evidence related to the model of the previous sections.
rates decline, rather than intensity per admission? Some authors have suggested that, where technically feasible, outpatient treatment became relatively more attractive to hospitals, and growth rates in outpatient and physician costs increased after PPS adoption (Gianfrancesco, 1990; Holohan, Dor, and Zuckerman, 1991). But these increases were considerably smaller than the reductions in inpatient costs, and in any event hospitals could still have increased revenues by increasing admissions for more healthy patients.

However, the result is consistent with the model developed here. A fundamental feature of true prospective payment is that it eliminates congruence between physician and hospital objectives. Thus, whether physicians or hospital managers control clinical decisions such as patient admissions matters, and the minimal observed responses of skimming and dumping (Newhouse, 1989) and of specialization within medical diagnoses demonstrate that admission and length of stay decisions are primarily controlled by physicians. As noted in Section II, if hospitals can only establish general capacity constraints or utilization guidelines, physicians will allocate bed days based on their own assessment of maximizing net benefits. Thus, hospitals will choose bed supply so that the revenue from increased profitable admissions from the marginal bed equals the cost of increased expected lengths of stay and increased probability of unprofitable admissions resulting from physician allocation decisions. Hospitals cannot choose how the marginal bed-day will be used. In contrast to hospital price regulation before TEFRA, in which reasonable costs per hospital day could be "passed through" to payors, increasing bed supply to the point where marginal patient benefits are near zero is costly.

The response to PPS suggests that marginal bed-days prior to PPS were largely devoted to longer lengths of stay, which under PPS became unprofitable. A contraction
of bed supply for Medicare patients, to the point where additional admissions (and
revenue) constituted a larger share of marginal bed days, was optimal. As a result,
lengths of stays declined, admissions of "marginal" patients declined, and the marginal
hospital day was spent on a sicker patient. Some contraction of aggregate demand for
hospital care (as opposed to demand for care at specific hospitals) may have accompanied
the lower equilibrium intensity of treatment, also contributing to the admission decline.
This model obviously simplifies physician-hospital relationships: hospital managers can
and do influence physician effort costs or incentives for specific allocations of hospital
bed days. But it appears to capture a key feature of PPS effects not predicted by models
that assume hospital control of admission and length of stay decisions.

Figure 11 demonstrates that the change in hospital admission rates associated with
PPS implementation reflects the composite effects of two much more striking trends. The
Figure divides admissions into two types of DRGs: admissions in which no major
surgical procedures were performed, and surgical admissions. While not exact, surgical
admissions comprise the bulk of the separate treatment-based payment groups under PPS
(and prior to PPS were a principal source of higher case-mix adjustments). In contrast to
the diagnosis-based nonsurgical DRGs, in which greater intensity does not lead to greater
reimbursement, PPS adoption did not result in significant differences in physician and
hospital incentives for producing these treatments. According to the model in Section II
and the analysis of price regulation in Section III, these intensive treatments will be used
in all patients that physicians believe will benefit from treatment. Before 1982, both
surgical and nonsurgical admission rates were increasing steadily. Beginning in 1982,
nonsurgical admission rates began to fall, with a dramatic drop following PPS
implementation. This drop may in part reflect coding changes, since recording surgical procedures will lead to greater DRG reimbursement. But hospital reimbursement before PPS was also affected by surgical procedures performed, and the respective upward and downward trends have continued in the years after PPS adoption.

These very different trends explain all of the real growth in hospital treatment intensity under PPS and are consistent with the model developed here. Reimbursing more intensive treatment alternatives at cost -- in this case, surgical versus nonsurgical treatments -- supports hospital investment in enough surgical capacity to treat all patients who physicians believe will have any benefit from the more intensive treatment. If reported marginal costs for hospitals overestimate true marginal costs, and if hospital capital investments to support surgical treatments are subsidized, PPS payment rules may encourage dynamic increases in intensity involving these treatments. In any event, technological improvements to increase the fraction of patients with a health problem who are expected to benefit from the treatments will lead to dynamic intensity growth. In contrast, equilibrium intensity and hence demand may fall over time for diagnosis-based DRGs, according to the mechanisms described in Section III.

Other data on hospital performance under PPS is consistent with these effects. In terms of revenue-cost margins, hospitals with small sizes and low case-mix indices have fared much worse than large teaching hospitals under PPS, and they also have had much smaller increases in intensity (Coulam and Gaumer, 1991). While these trends are widely attributed to "PPS pressure," they may simply reflect the greater difficulty of small hospitals to support intensive treatments that lead to higher-intensity DRG reimbursement. Finally, the Prospective Payment Assessment Commission (1992) has concluded that PPS
led not to hospital specialization but to *diversification* into performing a wider variety of more intensive procedures. While not expected, diversification into intensive surgical procedures is actually a plausible consequence of DRG incentives and patient or physician demand.

Indeed, direct evidence on the diffusion patterns of specific technologies also supports the model. Figure 12A plots the diffusion of cardiac catheterization laboratories and open-heart surgery facilities over time. The diffusion rates for these intensive technologies used in the treatment of coronary heart disease were unchanged, or may even have increased slightly, after the adoption of PPS. Treatments using both of these intensive technologies are reimbursed in separate DRGs. In contrast, Figure 12B plots the diffusion rate for another technology, beds in specialized cardiac intensive care units, which is not associated with a treatment-based DRG. While the pattern is complex, investment in CCU beds increased prior to 1982 and decreased after 1984.

Table 5 summarizes changes in admissions and hospital treatment intensity between 1983 and 1988 for some common health problems for which alternative diagnosis- and treatment-based DRGs exist. The Table includes all health problems that are indications for the principal inpatient surgical procedures reimbursed separately under PPS, as well as the alternative nonsurgical DRGs. In general, the use of technologies

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36 The data used to construct the following figures were obtained from the American Hospital Association’s Annual Survey of Hospitals, multiple years.

37 For many DRGs, separate groups exist for cases with and without "complicating conditions." The DRGs with complications are reimbursed at somewhat higher rates than those without, with the goal of providing "fair" reimbursement for sicker patients within the diagnosis group as well as incentives for upcoding or "DRG creep." Both prices influence hospital investments in intensive technologies. To abstract from coding instability that severely affected admission patterns in DRGs with versus without complicating conditions
that constituted treatment-based DRGs for each of these health problems increased substantially between 1983 and 1988. For example, the use of CABG and PTCA as intensive treatments for heart disease doubled between 1983 and 1988, reflecting the increased investment in cardiac surgery capacity and the complete cost sharing documented above. Other intensive DRG-based treatments for health problems that showed substantial increases in utilization rates included valve replacement procedures as a treatment for heart valve diseases, cholecystectomy as a treatment for gall bladder disease, open reductions in the treatment of hip fracture, discectomy in the treatment of back pain, and prostatectomy in the treatment of benign prostatic hypertrophy.

Hospitalizations in treatment-based DRGs for diseases without alternative hospital treatments -- such as joint replacement for arthritis and chemotherapy for cancer -- also increased substantially. Altogether, the surgical admission rate for elderly Medicare beneficiaries increased by a third between 1983 and 1988, while the nonsurgical admission rate fell by one half.

Table 6 summarizes changes in admissions and intensity between 1983 and 1988 for some common "single DRG" diseases, those that do not have distinct DRGs for more intensive treatments. Three of these health problems -- chronic obstructive pulmonary disease, pneumonia and pleurisy, and bronchitis and asthma -- show intensity increases, though the large changes in admission rates for these respiratory diseases imply that underlying coding changes make it difficult to compare the 1983 and 1988 populations. For most of these health problems, however, average intensity was virtually unchanged or

during this period, I group DRGs with and without complicating conditions together for the analyses that follow.
fell, and admissions declined. Treatment intensity changes thus seem much more limited for health problems where hospitals face single prices regardless of intensity decisions.

These findings, based entirely on aggregate statistical data on Medicare hospital utilization, are obviously preliminary. Further analysis of more detailed data on the intensity of treatment of health problems that differ in reimbursement incentives and in the types of alternative technologies available for treatment is clearly required. But these findings indicate that hospitals have responded and are continuing to respond quite dramatically to PPS incentives for treatment intensity. The nature of the responses is not puzzling in a simple model that accounts for the consequences of differences in objectives and decisionmaking power for hospitals and physicians, of quality competition among hospitals, and of the incentives for producing intensive treatments in the DRG reimbursement system.

V. Conclusions

This paper began by presenting the fundamental empirical puzzles of the Prospective Payment System for Medicare hospital reimbursement. Why have Medicare admission rates declined? Why has intensity per discharge and intensity per beneficiary continued to increase at rates comparable to those before PPS? And why aren’t diagnosis-related groups more related to diagnoses? To address these questions, I reviewed some features of the treatment of health problems in the elderly and the internal organization of the hospital that are not readily captured by standard models of hospital behavior. I developed a simple formal model that incorporates differences in hospital and physician objectives, quality competition among hospitals, and the relationship of hospital
technologies to hospital and physician control. I then considered the static and dynamic implications of price regulation in the model, including both current PPS rules and an optimal system. With these theoretical results, I reexamined aggregate empirical evidence on the effects of PPS, finding that the "puzzles" were not so puzzling after all.

Though the empirical evidence is preliminary, there are a number of important conclusions. First, as Harris (1979) originally suggested, physicians play an important role in hospital production. Differences between physician and hospital incentives for using hospital bed days, coupled with physician control of hospital resource allocation, prevented hospitals from exploiting features of the DRG payment system that would have led to greater profits. While the model of physician and hospital incentives developed here is a simplification of complex nonmarket relationships, it suggests that physician incentives should be incorporated in models of hospital responses to regulation and, logically, in the regulation of hospital production itself. Second, hospitals have responded quite dramatically to PPS, to the point that intensive surgical treatments now dominate hospital care for the elderly. All growth in the case mix index of Medicare admissions since PPS implementation appears attributable to increasing use over time of the particular intensive technologies that are reimbursed separately under PPS. While these trends may be attributable to exogenous technological change, the model of hospital incentives for investing in intensive technologies for the treatment of health problems suggests they are not. This conclusion contrasts with the conventional view that exogenous change is driving hospital costs, but it supports a recent study by Cox (1993) which found that only a small fraction of the growth in Medicare physician payments between 1986 and 1990 was attributable to new technologies. Most intensity growth may
in fact represent dynamic equilibrium changes in the use of existing technologies, or marginal "process" improvements that increase the number of suitable candidates for these technologies. In contrast, intensity and admissions have remained constant or fallen for most diseases that do not involve treatment-based DRGs. Since younger male elderly patients tend to be the best candidates for surgical procedures, the payment incentives may be leading to a concentration of intensive hospital resources in this demographic group. Whether these substantial changes in treatment intensity have had significant consequences for patient outcomes is beyond the scope of this paper but is an important topic for future work.

Third, feasible reforms in the structure of PPS reimbursement would be likely to mitigate these trends, at least for some health problems. As Section III demonstrated, increasing the reimbursement rate for the lower-intensity treatment alternative above its cost and reducing the reimbursement level for the higher-intensity alternative below its cost would provide some incentives for hospitals to invest in technologies to treat health problems where imperfect quality competition or limited physician control leads to suboptimal intensity choices with fixed prices. One complication is that not all hospitals can or should offer all intensive treatments. However, the differential payment above low-intensity production costs could be transferred with the patient when he is referred from the less intensive to the more intensive hospital. This mechanism would provide adequate reimbursement for providing the more intensive treatment to the receiving hospital while still permitting the sending hospital to face appropriate marginal reimbursement incentives. A more problematic situation involves intensive treatments such as hip replacement, where the alternative treatment does not require hospitalization.
In this case, if appropriate physician incentives or hospital outpatient treatment incentives cannot be incorporated into the payment schedule, reimbursement at cost may in fact be second-best. Clearly, however, trends in hospital care under PPS suggest that further evaluation of the payment system from the standpoint of incentives for treating a health problem is warranted.

Finally, these results should be reassuring for those who have wondered why price incentives have not been more effective. In fact, the incentives seem to have been well understood by hospitals. Far more dramatic reforms are now under consideration that would alter the nature of physician incentives as well as physician-management residual control and bargaining power in the determination of internal production decisions. Since both price incentives and physician control appear to matter, bringing Medicare price incentives into closer agreement with policy goals for medical treatment intensity and costs may provide an important alternative or supplement to the proposed reforms.
APPENDIX

In the text, I documented substantial differences in hospital costs and reimbursements associated with different treatment intensity decisions. These average differences are a combination of differences between patients receiving different treatments and the differences in resource use (and payment) associated with the different treatment arms themselves. While the endogeneity of the relationship between treatment decisions and costs or payment does not affect the subject of the paper, distinguishing patient selection effects from the true effect of treatment decisions on costs and reimbursement is required for marginal cost-benefit analyses of the use of intensive technologies to treat health problems.

In this Appendix, I present preliminary evidence on the marginal costs of treatment intensity for acute myocardial infarction in the elderly. In a related paper (McClellan and Newhouse, 1993) I have shown that the health status of elderly AMI patients who receive invasive procedures is substantially better than those who do not. Such unobserved differences might suggest that the true cost differences are even larger than observed differences, since healthier patients would tend to require less intensive care. Moreover, costs and reimbursement appear highly correlated, and it seems unlikely that patients with higher costs resulting from unobserved differences in health status (leading to more hospitalizations or more intensive treatments) would have lower reimbursement. On the other hand, healthier patients may survive longer when intensive treatments are used, leading to higher costs, possibly without additional PPS reimbursement.
Since the use of catheterization and revascularization procedures are highly correlated (McClellan and Newhouse, 1993), the following results analyze the differences in cost and reimbursement arising from the decision of whether treat patients with invasive procedures after AMI (that is, catheterization possibly followed by CABG or PTCA). As was evident in Table 1, patients undergoing invasive procedures after AMI are considerably younger and more likely to be white and male than patients who do not. Tables A1 and A2 adjust for these observable differences among patients receiving different treatments by grouping patients on the basis of observable demographic characteristics. Groups were based on age intervals (65-69, 70-74, 75-79, 80-84, 85-89, 90 and over), male or female sex, black or white race, urban or rural residence, and full interactions of all these variables. Separate effects for state of residence were also included in the models. Heteroskedasticity corrections were performed using the methods of White (1980).

Table A1 presents the results of regressions in levels for hospital use, costs, and DRG payments for hospitalizations occurring within 30 days and 90 days after AMI. (As Tables 3 and 4 suggested, models estimated for longer time intervals showed no significantly different patterns.) The grouped-data framework used leads to consistent estimates of average effects and their standard deviations, in spite of the nonnormality of the process generating the data at the individual level.\textsuperscript{38} For reference, the Table reports the average cost of treating a white male urban patient aged 65-69 in New York at a low-volume hospital without catheterization. For each regression, the average consequences

\textsuperscript{38}Due to the very large sample sizes in each cell, the estimates are unlikely to be sensitive to outliers.
of treatment with catheterization, treatment at a high-volume hospital, and residence in a rural area are reported. Rural residence may lead to lower costs because less intensive treatments are typically available (even after controlling for observed differences in intensity) and because hospitals face lower input prices.\textsuperscript{39}

The estimated effects in Table A1 are consistent across the different measures of hospital use, costs, and reimbursement. The "reference patient" has utilization and costs that are lower than average over all AMI patients. (Estimates for each demographic subgroup are not reported in the Table for brevity.) Hospital days and costs increase with age until after age 80, when they begin to decline. For example, during the 90-day episode of care after AMI, patients aged 75-79 who do not undergo invasive procedures have an average of 10 percent more hospital days (1.4 days) and 10 percent higher total costs ($785) than a male patient aged 65 to 69; female patients aged 65-69 have 9 percent more days (1.2 days) and 8 percent higher costs ($570). In these least-squares estimates, the hospital cost differences for older patients and for younger female patients do not translate into higher hospital reimbursement levels.\textsuperscript{40} One reason may be that these patients are most likely to receive invasive procedures, which lead to significantly more hospital days, more intensive hospital days, much higher total costs ($7,301 more within 30 days and $8,309 more within 90 days), and much higher reimbursement levels ($6,344

\textsuperscript{39}Input price indices at the county level are currently under development.

\textsuperscript{40}In the least-squares regressions, age has only a trivial relationship to reimbursement level in spite of the fact that, in 1987, patients age 70 and over qualified for reimbursement at the higher level (DRG 123, "with complications") strictly on the basis of age. In the IV regressions below, the positive relationship between age and reimbursement is present but modest. The lower "profitability" of older AMI patients is interesting in light of the findings reported elsewhere (McClellan, 1993) that large hospitals and hospitals that perform invasive procedures tend to attract younger Medicare patients.
more within 30 days and $7,503 more within 90 days). These results largely parallel the "unadjusted" results of Table 5: invasive procedure use is associated with higher costs that are almost fully reimbursed. In contrast, high-volume hospitals do not receive more reimbursement for the more intensive treatments other than invasive procedures that they typically offer, and their average costs also do not differ significantly from low-volume hospitals. On average, the economies of scale of high-volume hospitals do not translate into lower costs; instead, these hospitals appear to provide more intensive treatments (such as more use of CCU and ICU beds) which do not lead to additional reimbursement.

Table A2 reports the results of the same least-squares grouped-data models estimated using logs of the dependent variables rather than levels.\textsuperscript{41} The results do not differ substantively from those reported in Table A1.\textsuperscript{42} For example, for the 90-day episode of care for a typical "reference" patient, the effect of catheterization is to increase hospital days from 9.9 to 18.4, to increase CCU/ICU days from 2.6 to 4.8, to increase total costs from $4,817 to $11,271, and to increase total DRG payments from $6,063 to $12,457. High-volume hospitals and rural hospitals also show the same pattern of effects as in Table A1.

\textsuperscript{41}Since approximately 13% of patients had no CCU/ICU days, a constant of 0.1 was added to the patient's CCU/ICU totals for each time increment.

\textsuperscript{42}Regressing in logs rather than levels improves the fit of the model slightly and "downweights" the impact of skewness in the underlying cost distributions on predictions. However, the principal policy implications of this paper relate to arithmetic average effects. Thus, Table 6A and the corresponding IV results below provide more direct estimates of the average and total cost effects of a change in policy on Medicare costs for treating AMI in each demographic cell of large numbers of elderly patients, even though they may be less useful for predicting effects at the individual level. A more comprehensive evaluation of policy consequences through least-squares and IV quantile regressions in levels is planned for future work.
Thus, correcting for observed correlates of health status does not affect the apparent relationship of invasive procedure use to both costs and reimbursement. This is not surprising, since observed (endogenous) average costs within a DRG such as that for PTCA or CABG provide the basis for calibrating DRG weights, and hence the price incentives for hospitals. Nonetheless, the estimates may still reflect unobserved patient differences in health status. Instrumental-variables (IV) methods were used to obtain estimates of the effects of invasive procedure use on hospital payments that do not reflect such unobserved differences. The IV estimation methods are described in detail in McClellan (1993) and McClellan and Newhouse (1993). The instruments used are the patient’s differential distances to alternative types of "intensive" hospitals -- the differences between the patient’s distance to any acute-care hospital providing AMI treatment versus a hospital performing catheterization, a hospital performing catheterization and revascularization procedures, and a high-volume hospital. These instruments influence the probability that the patient receives alternative levels of treatment intensity for reasons independent of health status. They provide the basis for IV estimation of the average effects of the alternative treatments in "marginal" patients, those whose treatment intensity was influenced by the value of the instruments (see McClellan and Newhouse, 1993, for methodologic details and a battery of specification tests of the identifying assumption).

Using these IV methods to estimate consequences for reimbursement is complicated by the fact that -- as the previous Tables have demonstrated -- patients likely to receive catheterization are likely to receive more intensive treatments in other dimensions as well. Use of these correlated treatments could potentially lead to an
overestimate of the effect of catheterization on reimbursement. However, evidence presented thus far has suggested that the other aspects of treatment intensity -- such as treatment at a high-volume hospital or use of a CCU or ICU bed -- have little impact on the DRG payments received by hospitals. Since performing an invasive procedure is required to shift an AMI patient into a significantly higher DRG, the estimated effect of invasive procedure use on reimbursement should approximate the true effect. For this reason, and because other reported hospital costs do not reflect actual payments to hospitals for treating elderly AMI patients, the following estimates concentrate on DRG payments.

IV estimates of the average effect of invasive procedure use and the other "treatments" on hospital payments are presented in Table A3. The first panel presents IV estimates of average effects on hospital payments for the same aspects of treatment intensity analyzed using least-squares methods in Table 6A. For all time intervals after AMI, base hospital reimbursement for the "reference" patient is somewhat smaller, and the effect of invasive procedure use is larger, than in the corresponding least-squares models. For example, for the 90-day episode of care after AMI, the IV estimate of the average effect of catheterization on reimbursement ($9,178) is approximately 20 percent larger than the least-squares estimate of the average effect ($7,583). For the same time interval, the IV estimate of hospital payments for the "reference" patient ($6,792) is 12 percent smaller than the least-squares estimate ($7,708). These results are consistent with the selection of relatively healthy patients for invasive procedures. Since these patients would require fewer hospitalizations and less intensive treatment than the average AMI patient, the least-squares estimate is confounded by somewhat higher hospital
reimbursement for the less healthy patients who do not undergo invasive procedures.\textsuperscript{43} Higher-intensity treatment at high-volume hospitals shows a small positive correlation with reimbursement. The effect of rural residence on cost is considerably less dramatic, reflecting the significantly lower use of intensive procedures (and hence intensive DRGs) in rural AMI patients.

The IV log regressions show larger proportional effects. As in the level regressions, the "marginal" decision to catheterize an AMI patient leads to an increase in hospital payments for AMI treatment of well over 100 percent. For example, the coefficient of 8.45 for the "reference" patient translates to DRG payments during the 90-day episode of care of $4,964; in this patient, catheterization increases the payment to $16,814. These preliminary IV results demonstrate that the least-squares estimates do not appear to overstate the true effects of invasive procedure use for hospital payments. Indeed, combining these IV estimates of Medicare payments with estimates of the marginal effects of these procedures calculated previously (McClellan and Newhouse, 1993) yields marginal cost-benefit ratios for the procedures that are very high (a conservative lower bound over $200,000 per two years' life saved).\textsuperscript{44}

\textsuperscript{43}This result is also supported by a somewhat stronger relationship between age (which is associated with more hospital use) and DRG reimbursement than was evident in the least-squares results.

\textsuperscript{44}These results should be viewed as preliminary. As noted above, they do not yet account for cross-sectional price differences that are correlated with likelihood of catheterization; such price differences may also account for the small but significant association of treatment at a high-volume hospital with higher payments in the IV but not least-squares models. Further, they do not conclusively demonstrate that the additional DRG payments are strictly the result of performing more procedures, as opposed to more aggressive hospitalization policies that are correlated with performing procedures. Current research using cross-sectional price indices and dynamic hospital production function models is examining these effects. While a portion of the IV-estimated difference in intensity
Though these results on the relationship between hospital costs and reimbursement for the treatment of AMI patients are preliminary, several important patterns are clear. First, the existence of distinct treatment-based DRGs for the invasive procedures used in the management of AMI -- especially PTCA and CABG -- as well as the possibility for hospitals to readmit or transfer patients to receive invasive procedures leads to almost complete reimbursement of the hospitals' average incremental costs for producing these treatments. Medicare PPS thus provides minimal financial obstacles to the adoption of catheterization or revascularization technologies by hospitals, as well to their use by physicians in cases where the expected benefits of invasive procedures may be quite small. In contrast, intensive treatments such as days spent in specialized CCU or ICU beds do not lead to significant increments to reimbursement, and patients receiving these treatments are more likely to lead to losses in the relatively low-intensity diagnosis-based DRGs for AMI.

---

appears attributable to differences in price levels, the effect appears quite modest. Further, the main difference between patients near and far from catheterization appears to be specifically in hospitalizations in procedure-associated DRGs. Thus, while revised IV estimates of the effect of catheterization may be mildly smaller, it does not appear that the OLS estimates overstate the effect of catheterization on hospital reimbursement. The least-squares estimate of the marginal cost-benefit ratio is approximately $160,000 per two years' life saved; increasing the estimated cost consequences by 10 percent above this (still substantially less than the preliminary IV estimates here) yields the $200,000 ratio in the text.
FIGURE 2

ALTERNATIVE REGULATED PRICE AGGREGATION LEVELS

DISAGGREGATED

| Administered Prices for All Specific Services | Medicare Physician Fee Schedule | Medicare Hospital Prospective Payment System | Pure Diagnoses-Based Payment System | HMO |

AGGREGATED
FIGURE 5

FIGURE 6
FIGURE 10
HOSPITAL DISCHARGE RATES FOR THE ELDERLY
FIGURE 11
SURGICAL AND NONSURGICAL DISCHARGE RATES FOR THE ELDERLY

- Surgical Discharge Rate
- Nonsurgical Discharge Rate

Year

100 125 150 175 200 225 250
FIGURE 12A
DIFFUSION OF CARDIAC CATHETERIZATION AND OPEN-HEART SURGERY

FIGURE 12B
CARDIAC INTENSIVE CARE UNIT BEDS
<table>
<thead>
<tr>
<th></th>
<th>ALL PATIENTS (N=205,021)</th>
<th>NO PROCEDURES (N=155,880)</th>
<th>CATH ONLY (N=22,902)</th>
<th>CATH AND PTCA (N=10,837)</th>
<th>CATH AND CABG (N=15,402)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Patient Characteristics</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>50.36</td>
<td>53.75</td>
<td>41.07</td>
<td>41.02</td>
<td>36.37</td>
</tr>
<tr>
<td>Black</td>
<td>5.65</td>
<td>6.08</td>
<td>5.69</td>
<td>3.19</td>
<td>2.96</td>
</tr>
<tr>
<td>Age in Years (Standard Deviation)</td>
<td>76.11 (7.26)</td>
<td>77.49 (7.28)</td>
<td>71.71 (5.11)</td>
<td>71.51 (5.15)</td>
<td>71.47 (4.79)</td>
</tr>
<tr>
<td>Rural</td>
<td>29.45</td>
<td>30.56</td>
<td>26.40</td>
<td>24.45</td>
<td>26.32</td>
</tr>
<tr>
<td>Technology Use</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Catheterization within 90 Days</td>
<td>22.81</td>
<td>0</td>
<td>100.0</td>
<td>100.0</td>
<td>100.0</td>
</tr>
<tr>
<td>PTCA within 90 Days</td>
<td>5.30</td>
<td>0</td>
<td>0</td>
<td>100.0</td>
<td>0</td>
</tr>
<tr>
<td>CABG within 90 Days</td>
<td>7.74</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>100.0</td>
</tr>
<tr>
<td>Acute Treatment in CCU</td>
<td>86.56</td>
<td>83.99</td>
<td>92.07</td>
<td>96.70</td>
<td>97.21</td>
</tr>
</tbody>
</table>
### TABLE 2:
**DISTRIBUTION OF AMI PATIENT ADMISSIONS AMONG DIAGNOSIS-RELATED GROUPS**

<table>
<thead>
<tr>
<th>DRG</th>
<th>ALL PATIENTS (N=205,021)</th>
<th>MALE PATIENTS AGED 65-7 (N=55,570)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Initial AMI Admission (N=205,021)</td>
<td>All Admissions Within 30 Days (N=251,575)</td>
</tr>
<tr>
<td>AMI (121, 122, 123)</td>
<td>92.0</td>
<td>81.1</td>
</tr>
<tr>
<td>CABG (106, 107)</td>
<td>2.2</td>
<td>4.9</td>
</tr>
<tr>
<td>PTCA (112)</td>
<td>2.8</td>
<td>3.9</td>
</tr>
<tr>
<td>Catheterization without AMI (124, 125)</td>
<td>0</td>
<td>1.2</td>
</tr>
<tr>
<td>Other Cardiovasc Procedures (mainly 109, 115)</td>
<td>2.5</td>
<td>2.8</td>
</tr>
<tr>
<td>Other</td>
<td>0.5</td>
<td>6.1</td>
</tr>
<tr>
<td>Time Interval After AMI</td>
<td>ALL PATIENTS (N=205,021)</td>
<td>NO PROCEDURES (N=155,880)</td>
</tr>
<tr>
<td>-------------------------</td>
<td>--------------------------</td>
<td>---------------------------</td>
</tr>
<tr>
<td><strong>Hospital Admissions</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Within 30 Days</td>
<td>1.22 (0.48)</td>
<td>1.12 (0.35)</td>
</tr>
<tr>
<td>Within 90 Days</td>
<td>1.46 (0.77)</td>
<td>1.29 (0.63)</td>
</tr>
<tr>
<td>Within 1 Year</td>
<td>1.95 (1.39)</td>
<td>1.78 (1.31)</td>
</tr>
<tr>
<td><strong>Hospital Days</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Within 30 Days</td>
<td>12.06 (10.59)</td>
<td>10.85 (9.92)</td>
</tr>
<tr>
<td>Within 90 Days</td>
<td>14.13 (13.70)</td>
<td>12.45 (12.76)</td>
</tr>
<tr>
<td>Within 1 Year</td>
<td>18.38 (19.69)</td>
<td>16.76 (19.19)</td>
</tr>
<tr>
<td><strong>ICU/CCU Days</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Within 30 Days</td>
<td>5.28 (6.09)</td>
<td>4.46 (5.11)</td>
</tr>
<tr>
<td>Within 90 Days</td>
<td>5.83 (6.92)</td>
<td>4.80 (5.66)</td>
</tr>
<tr>
<td>Within 1 Year</td>
<td>6.77 (8.27)</td>
<td>5.73 (7.15)</td>
</tr>
</tbody>
</table>
### TABLE 3, CONT.:  
**HOSPITAL UTILIZATION, COSTS, AND REIMBURSEMENT FOR ELDERLY AMI PATIENTS IN 1987**

<table>
<thead>
<tr>
<th>Time Interval After AMI</th>
<th>ALL PATIENTS (N=205,021)</th>
<th>NO PROCEDURES (N=155,880)</th>
<th>CATH ONLY (N=22,902)</th>
<th>CATH AND PTCA (N=10,837)</th>
<th>CATH AND CABG (N=15,402)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Total Hospital Costs</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Within 30 Days</td>
<td>7,702 (7,529)</td>
<td>6,073 (5,505)</td>
<td>8,992 (6,880)</td>
<td>11,413 (7,136)</td>
<td>19,663 (12,634)</td>
</tr>
<tr>
<td>Within 90 Days</td>
<td>9,096 (9,188)</td>
<td>6,953 (6,694)</td>
<td>10,697 (8,699)</td>
<td>13,614 (8,985)</td>
<td>25,221 (13,285)</td>
</tr>
<tr>
<td>Within 1 Year</td>
<td>11,364 (7,529)</td>
<td>9,198 (9,878)</td>
<td>13,416 (12,187)</td>
<td>16,024 (11,958)</td>
<td>26,964 (15,456)</td>
</tr>
<tr>
<td><strong>Total Hospital Reimbursement</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Within 30 Days</td>
<td>6,810 (5,704)</td>
<td>5,418 (3,501)</td>
<td>7,141 (4,985)</td>
<td>9,880 (5,471)</td>
<td>18,235 (9,690)</td>
</tr>
<tr>
<td>Within 90 Days</td>
<td>8,098 (7,066)</td>
<td>6,177 (4,443)</td>
<td>8,749 (6,384)</td>
<td>12,146 (6,888)</td>
<td>23,708 (8,794)</td>
</tr>
<tr>
<td>Within 1 Year</td>
<td>10,078 (9,196)</td>
<td>8,118 (7,338)</td>
<td>11,155 (9,161)</td>
<td>14,479 (9,425)</td>
<td>25,208 (10,497)</td>
</tr>
</tbody>
</table>
TABLE 4:  
HOSPITAL UTILIZATION, COSTS, AND REIMBURSEMENT 
FOR ELDERLY AMI PATIENTS IN 1987

<table>
<thead>
<tr>
<th>Time Interval After AMI</th>
<th>ALL PATIENTS (N=205,021)</th>
<th>ACUTE ICU/CCU USE WITHOUT PROCEDURES (N=155,880)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>TWO DAYS OR LESS (N=60,707)</td>
</tr>
<tr>
<td><strong>Hospital Admissions</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Within 30 Days</td>
<td>1.22 (0.48)</td>
<td>1.06 (0.26)</td>
</tr>
<tr>
<td>Within 90 Days</td>
<td>1.46 (0.77)</td>
<td>1.19 (0.52)</td>
</tr>
<tr>
<td>Within 1 Year</td>
<td>1.95 (1.39)</td>
<td>1.58 (1.16)</td>
</tr>
<tr>
<td><strong>Hospital Days</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Within 30 Days</td>
<td>12.06 (10.59)</td>
<td>7.08 (7.97)</td>
</tr>
<tr>
<td>Within 90 Days</td>
<td>14.13 (13.70)</td>
<td>8.24 (10.96)</td>
</tr>
<tr>
<td>Within 1 Year</td>
<td>18.38 (19.69)</td>
<td>11.67 (17.24)</td>
</tr>
<tr>
<td><strong>ICU/CCU Days</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Within 30 Days</td>
<td>5.28 (6.09)</td>
<td>0.87 (0.83)</td>
</tr>
<tr>
<td>Within 90 Days</td>
<td>5.83 (6.92)</td>
<td>1.03 (1.60)</td>
</tr>
<tr>
<td>Within 1 Year</td>
<td>6.77 (8.27)</td>
<td>1.53 (3.22)</td>
</tr>
</tbody>
</table>
TABLE 4, CONT.:
HOSPITAL UTILIZATION, COSTS, AND REIMBURSEMENT FOR ELDERLY AMI PATIENTS IN 1987

<table>
<thead>
<tr>
<th>Time Interval After AMI</th>
<th>ALL PATIENTS (N=205,021)</th>
<th>ACUTE ICU/CCU USE WITHOUT PROCEDURES (N=155,880)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>TWO DAYS OR LESS (N=60,707)</td>
</tr>
<tr>
<td><strong>Total Hospital Costs</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Within 30 Days</td>
<td>7,702 (7,529)</td>
<td>3,379 (2,789)</td>
</tr>
<tr>
<td>Within 90 Days</td>
<td>9,096 (9,188)</td>
<td>3,971 (4,025)</td>
</tr>
<tr>
<td>Within 1 Year</td>
<td>11,364 (7,529)</td>
<td>5,673 (7,452)</td>
</tr>
<tr>
<td><strong>Total Hospital Reimbursement</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Within 30 Days</td>
<td>6,810 (5,704)</td>
<td>4,637 (2,314)</td>
</tr>
<tr>
<td>Within 90 Days</td>
<td>8,098 (7,066)</td>
<td>5,133 (3,245)</td>
</tr>
<tr>
<td>Within 1 Year</td>
<td>10,078 (9,196)</td>
<td>6,695 (6,120)</td>
</tr>
</tbody>
</table>
### TABLE 5:
CHANGES IN HOSPITAL TREATMENT PATTERNS FOR COMMON HEALTH PROBLEMS IN THE ELDERLY

<table>
<thead>
<tr>
<th>SURGICAL TREATMENT DRGs</th>
<th>ALTERNATIVE NONSURGICAL DRGs</th>
</tr>
</thead>
<tbody>
<tr>
<td>DRG</td>
<td>Description</td>
</tr>
<tr>
<td>4</td>
<td>Decompression of spinal canal</td>
</tr>
</tbody>
</table>

**SPINAL NERVE COMPRESSION**

Medical treatment outside hospital

<table>
<thead>
<tr>
<th>CEREBROVASCULAR DISEASE</th>
</tr>
</thead>
<tbody>
<tr>
<td>DRG</td>
</tr>
<tr>
<td>5</td>
</tr>
<tr>
<td>14</td>
</tr>
<tr>
<td>15</td>
</tr>
</tbody>
</table>

\(^1\) During the time period, new clinical evidence suggested these procedures were often ineffective.
TABLE 5. CONT.:
CHANGES IN HOSPITAL TREATMENT PATTERNS FOR COMMON HEALTH PROBLEMS IN THE ELDERLY

<table>
<thead>
<tr>
<th>SURGICAL TREATMENT DRGs</th>
<th>ALTERNATIVE NONSURGICAL DRGs</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1988 Discharges</td>
</tr>
<tr>
<td></td>
<td>(Weight % Change from 1983)</td>
</tr>
<tr>
<td>DRG</td>
<td>Description</td>
</tr>
<tr>
<td>-----</td>
<td>--------------------------------------------------</td>
</tr>
<tr>
<td>106</td>
<td>Coronary artery bypass graft (CABG) with catheterization</td>
</tr>
<tr>
<td>107</td>
<td>Coronary artery bypass graft (CABG) without catheterization</td>
</tr>
<tr>
<td>112</td>
<td>Percutaneous transluminal coronary angioplasty (PTCA)²</td>
</tr>
<tr>
<td>124</td>
<td>Non-AMI cardiac catheterization with CC</td>
</tr>
<tr>
<td>125</td>
<td>Non-AMI cardiac catheterization without CC</td>
</tr>
</tbody>
</table>

CARDIAC RHYTHM IRREGULARITY

<table>
<thead>
<tr>
<th>DRG</th>
<th>Description</th>
<th>Weight</th>
<th>1988 Discharges</th>
<th>DRG</th>
<th>Description</th>
<th>Weight</th>
<th>1988 Discharges</th>
</tr>
</thead>
<tbody>
<tr>
<td>115</td>
<td>Pacemaker implantation with CC¹</td>
<td>4.05</td>
<td>58,300 (+6.5)</td>
<td>138</td>
<td>Cardiac arrhythmia with CC</td>
<td>0.85</td>
<td>254,705 (+11.2)</td>
</tr>
<tr>
<td>116</td>
<td>Pacemaker implantation without CC¹</td>
<td>2.77</td>
<td></td>
<td>139</td>
<td>Cardiac arrhythmia without CC</td>
<td>0.59</td>
<td></td>
</tr>
</tbody>
</table>

¹ During the time period, new clinical evidence suggested these procedures were often ineffective.
² Some other surgical procedures for coronary heart disease account for a small proportion of admissions in this DRG.
### TABLE 5. CONT.:
CHANGES IN HOSPITAL TREATMENT PATTERNS FOR COMMON HEALTH PROBLEMS IN THE ELDERLY

<table>
<thead>
<tr>
<th>SURGICAL TREATMENT DRGs</th>
<th>1988 Discharges</th>
<th>ALTERNATIVE NONSURGICAL DRGs</th>
<th>1988 Discharges</th>
</tr>
</thead>
<tbody>
<tr>
<td>DRG Description</td>
<td>Relative Weight</td>
<td>(% Change from 1983)</td>
<td>DRG Description</td>
</tr>
<tr>
<td>104 Cardiac valve procedure with pump and cardiac catheterization</td>
<td>7.34</td>
<td>12,015 (+1869.5)</td>
<td>135 Cardiac congenital and valve disorders with CC</td>
</tr>
<tr>
<td>105 Cardiac valve procedure with pump, without catheterization</td>
<td>5.78</td>
<td>12,010 (+18.0)</td>
<td>136 Cardiac congenital and valve disorders without CC</td>
</tr>
<tr>
<td>148 Major small and large bowel procedures with CC</td>
<td>3.24</td>
<td>142,750 (+53.1)</td>
<td>None</td>
</tr>
<tr>
<td>149 Major small and large bowel procedures without CC</td>
<td>1.83</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### CARDIAC VALVULAR DISEASE

### SMALL AND LARGE INTESTINAL DISORDERS

### GALL BLADDER AND BILIARY DISORDERS

3 C.D.E. = Contrast Dye Enhancement, an intraoperative radiologic procedure.
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>161</td>
<td>Inguinal/femoral hernia repair with CC</td>
<td>0.75</td>
<td>78,150 (-31.2)</td>
<td>None</td>
<td></td>
</tr>
<tr>
<td>162</td>
<td>Inguinal/femoral hernia repair without CC</td>
<td>0.50</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td><strong>INGUINAL/FEMORAL HERNIA</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>209</td>
<td>Hip replacement</td>
<td>2.41</td>
<td>209,080 (+78.0)</td>
<td>None</td>
<td></td>
</tr>
<tr>
<td></td>
<td><strong>ARTHROSIS OF HIP</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>210</td>
<td>Open reduction of hip/femur fracture with CC</td>
<td>2.18</td>
<td>139,310 (+29.3)</td>
<td>235 Fracture of femur</td>
<td>1.21</td>
</tr>
<tr>
<td>211</td>
<td>Open reduction of hip/femur fracture without CC</td>
<td>1.61</td>
<td>236 Fracture of hip</td>
<td>0.90</td>
<td></td>
</tr>
<tr>
<td></td>
<td><strong>HIP FRACTURE</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>214</td>
<td>Intervertebral discectomy with CC</td>
<td>2.14</td>
<td>62,550 (+87.1)</td>
<td>243 Back problem</td>
<td>0.67</td>
</tr>
<tr>
<td>215</td>
<td>Intervertebral discectomy without CC</td>
<td>1.38</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td><strong>BACK PAIN</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DRG Description</td>
<td>Relative 1988 Discharges</td>
<td>BREAST CANCER</td>
<td>ALTERNATIVE NONSURGICAL DRGs</td>
<td></td>
<td></td>
</tr>
<tr>
<td>--------------------------</td>
<td>--------------------------</td>
<td>---------------</td>
<td>-----------------------------</td>
<td></td>
<td></td>
</tr>
<tr>
<td>DRG Description</td>
<td>Relative Weight</td>
<td>1988 Discharges</td>
<td>% Change from 1983</td>
<td>1988 Discharges</td>
<td>% Change from 1983</td>
</tr>
<tr>
<td>257 Total mastectomy with CC</td>
<td>1.04</td>
<td>59,155</td>
<td>(+44.1)</td>
<td>None</td>
<td></td>
</tr>
<tr>
<td>258 Total mastectomy without CC</td>
<td>0.85</td>
<td>7,700</td>
<td>(-28.1)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>259 Subtotal mastectomy with CC</td>
<td>1.00</td>
<td>342,570</td>
<td>(+35.5)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>260 Subtotal mastectomy without CC</td>
<td>0.60</td>
<td>9,685</td>
<td>(-32.3)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>DRG Description</th>
<th>Relative 1988 Discharges</th>
<th>BENIGN PROSTATIC HYPERPLASIA</th>
</tr>
</thead>
<tbody>
<tr>
<td>DRG Description</td>
<td>Relative Weight</td>
<td>1988 Discharges</td>
</tr>
<tr>
<td>336 Transurethral prostatectomy with CC</td>
<td>1.08</td>
<td>207,570</td>
</tr>
<tr>
<td>337 Transurethral prostatectomy without CC</td>
<td>0.75</td>
<td>348</td>
</tr>
</tbody>
</table>

TABLE 5. CONT.
### TABLE 5. CONT.
### CHANGES IN HOSPITAL TREATMENT PATTERNS FOR COMMON HEALTH PROBLEMS IN THE ELDERLY

<table>
<thead>
<tr>
<th>SURGICAL TREATMENT DRGs</th>
<th></th>
<th>ALTERNATIVE NONSURGICAL DRGs</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>DRG</td>
<td>Description</td>
<td>Relative Weight</td>
<td>1988 Discharges</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(%) Change from 1983</td>
<td></td>
</tr>
<tr>
<td>409</td>
<td>Radiotherapy⁴</td>
<td>1.08</td>
<td>8,530 (+85.8)</td>
</tr>
<tr>
<td>410</td>
<td>Chemotherapy⁴</td>
<td>0.47</td>
<td>137,890 (+248.3)</td>
</tr>
</tbody>
</table>

**CANCER (NONSURGICAL TREATMENTS)**

| SURGICAL DISCHARGE RATE PER 1,000 ELDERLY | 191 | (+33.6) |
|                                          |    |        |

**NONSURGICAL DISCHARGE RATE PER 1000 ELDERLY**

121 (-50.0)

⁴ Though these cancer therapies comprise treatment-based DRGs, they are not surgical procedures.
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>11</td>
<td>Multiple Sclerosis/</td>
<td>1.01</td>
<td>0.93</td>
<td>-.08</td>
<td>4,785 (-23.5)</td>
</tr>
<tr>
<td></td>
<td>Cerebellar Ataxia</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>12</td>
<td>Degenerative Nervous System Disorders</td>
<td>1.11</td>
<td>0.95</td>
<td>-.16</td>
<td>28,840 (-54.9)</td>
</tr>
<tr>
<td>22</td>
<td>Hypertensive Encephalopathy</td>
<td>0.79</td>
<td>0.70</td>
<td>-.09</td>
<td>11,925 (+15.6)</td>
</tr>
<tr>
<td>87</td>
<td>Pulmonary Edema and</td>
<td>1.55</td>
<td>1.57</td>
<td>+.02</td>
<td>68,265 (+7.4)</td>
</tr>
<tr>
<td></td>
<td>Respiratory Failure</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>88</td>
<td>Chronic Obstructive Pulmonary Disease</td>
<td>1.04</td>
<td>1.13</td>
<td>+.09</td>
<td>92,275 (-66.2)</td>
</tr>
<tr>
<td>89-90</td>
<td>Simple Pneumonia/ Pleurisy</td>
<td>1.08</td>
<td>1.21</td>
<td>+.13</td>
<td>405,760 (+26.7)</td>
</tr>
<tr>
<td>96-97</td>
<td>Bronchitis/Asthma</td>
<td>0.78</td>
<td>0.93</td>
<td>+.15</td>
<td>266,450 (+31.2)</td>
</tr>
<tr>
<td>127</td>
<td>Heart Failure/Shock</td>
<td>1.04</td>
<td>1.02</td>
<td>-.02</td>
<td>537,875 (+17.6)</td>
</tr>
<tr>
<td>128</td>
<td>Deep Venous Thrombophlebitis</td>
<td>0.86</td>
<td>0.85</td>
<td>-.01</td>
<td>30,725 (-19.0)</td>
</tr>
<tr>
<td>174-175</td>
<td>Gastrointestinal Hemorrhage</td>
<td>0.91</td>
<td>0.92</td>
<td>+.01</td>
<td>168,810 (+22.0)</td>
</tr>
<tr>
<td>176-178</td>
<td>Peptic Ulcer Disease</td>
<td>0.79</td>
<td>0.80</td>
<td>+.01</td>
<td>38,610 (-34.2)</td>
</tr>
<tr>
<td>316</td>
<td>Renal Failure</td>
<td>1.33</td>
<td>1.28</td>
<td>-.05</td>
<td>39,935 (-27.7)</td>
</tr>
</tbody>
</table>
TABLE A1:
LEAST-SQUARES ESTIMATES OF COST AND REIMBURSEMENT CONSEQUENCES
OF AMI TREATMENT INTENSITY
(ARITHMETIC MEAN REGRESSIONS)

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>AVERAGE EFFECTS OF ALTERNATIVE TREATMENTS¹</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>REFERENCE PATIENT²</td>
</tr>
<tr>
<td>Hospital Days</td>
<td>12.98</td>
</tr>
<tr>
<td>Within 30 Days of AMI</td>
<td>(.11)</td>
</tr>
<tr>
<td>Hospital Days</td>
<td>14.93</td>
</tr>
<tr>
<td>Within 90 Days of AMI</td>
<td>(.14)</td>
</tr>
<tr>
<td>CCU/ICU Days</td>
<td>4.42</td>
</tr>
<tr>
<td>Within 30 Days of AMI</td>
<td>(.06)</td>
</tr>
<tr>
<td>CCU/ICU Days</td>
<td>4.66</td>
</tr>
<tr>
<td>Within 90 Days of AMI</td>
<td>(.07)</td>
</tr>
<tr>
<td>Total Hospital Costs</td>
<td>6,245</td>
</tr>
<tr>
<td>Within 30 Days of AMI</td>
<td>(70)</td>
</tr>
<tr>
<td>Total Hospital Costs</td>
<td>7,204</td>
</tr>
<tr>
<td>Within 90 Days of AMI</td>
<td>(87)</td>
</tr>
<tr>
<td>Total DRG Payments</td>
<td>6,644</td>
</tr>
<tr>
<td>Within 30 Days of AMI</td>
<td>(52)</td>
</tr>
<tr>
<td>Total DRG Payments</td>
<td>7,708</td>
</tr>
<tr>
<td>Within 90 Days of AMI</td>
<td>(64)</td>
</tr>
</tbody>
</table>

¹Standard errors are in parentheses.

²The reference patient is a white urban male aged 65-69 residing in New York, treated without intensive procedures at a low-volume hospital.
<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>Reference Patient&lt;sup&gt;2&lt;/sup&gt;</th>
<th>Invasive Procedure Use</th>
<th>High-Volume Hospital</th>
<th>Rural Residence</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hospital Days</td>
<td>2.23</td>
<td>.82</td>
<td>.022</td>
<td>-.049</td>
</tr>
<tr>
<td>Within 30 Days of AMI</td>
<td>(.009)</td>
<td>(.004)</td>
<td>(.004)</td>
<td>(.004)</td>
</tr>
<tr>
<td>Hospital Days</td>
<td>2.29</td>
<td>.62</td>
<td>.017</td>
<td>-.052</td>
</tr>
<tr>
<td>Within 90 Days of AMI</td>
<td>(.009)</td>
<td>(.005)</td>
<td>(.004)</td>
<td>(.005)</td>
</tr>
<tr>
<td>CCU/ICU Days</td>
<td>.84</td>
<td>.72</td>
<td>.078</td>
<td>-.21</td>
</tr>
<tr>
<td>Within 30 Days of AMI</td>
<td>(.015)</td>
<td>(.008)</td>
<td>(.007)</td>
<td>(.008)</td>
</tr>
<tr>
<td>CCU/ICU Days</td>
<td>.95</td>
<td>.62</td>
<td>.075</td>
<td>-.19</td>
</tr>
<tr>
<td>Within 90 Days of AMI</td>
<td>(.013)</td>
<td>(.007)</td>
<td>(.006)</td>
<td>(.007)</td>
</tr>
<tr>
<td>Total Hospital Costs</td>
<td>8.41</td>
<td>.82</td>
<td>.031</td>
<td>-.20</td>
</tr>
<tr>
<td>Within 30 Days of AMI</td>
<td>(.008)</td>
<td>(.004)</td>
<td>(.004)</td>
<td>(.004)</td>
</tr>
<tr>
<td>Total Hospital Costs</td>
<td>8.48</td>
<td>.85</td>
<td>.026</td>
<td>-.20</td>
</tr>
<tr>
<td>Within 90 Days of AMI</td>
<td>(.041)</td>
<td>(.004)</td>
<td>(.004)</td>
<td>(.004)</td>
</tr>
<tr>
<td>Total DRG Payments</td>
<td>8.62</td>
<td>.66</td>
<td>.027</td>
<td>-.20</td>
</tr>
<tr>
<td>Within 30 Days of AMI</td>
<td>(.005)</td>
<td>(.003)</td>
<td>(.002)</td>
<td>(.003)</td>
</tr>
<tr>
<td>Total DRG Payments</td>
<td>8.71</td>
<td>.72</td>
<td>.018</td>
<td>-.200</td>
</tr>
<tr>
<td>Within 90 Days of AMI</td>
<td>(.005)</td>
<td>(.003)</td>
<td>(.003)</td>
<td>(.003)</td>
</tr>
</tbody>
</table>

<sup>1</sup>Standard errors are in parentheses.

<sup>2</sup>The reference patient is a white urban male aged 65-69 residing in New York, treated without intensive procedures at a low-volume hospital.
TABLE A3:
INSTRUMENTAL-VARIABLES ESTIMATES
OF THE CONSEQUENCES FOR HOSPITAL REIMBURSEMENT
OF AMI TREATMENT INTENSITY DECISIONS

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>REFERENCE PATIENT</th>
<th>INVASIVE PROCEDURE USE</th>
<th>HIGH-VOLUME HOSPITAL</th>
<th>RURAL RESIDENCE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total DRG Payments</td>
<td>5,866</td>
<td>8,050</td>
<td>293</td>
<td>-869</td>
</tr>
<tr>
<td>Within 30 Days of AMI</td>
<td>(104)</td>
<td>(325)</td>
<td>(47)</td>
<td>(36)</td>
</tr>
<tr>
<td>Total DRG Payments</td>
<td>6,792</td>
<td>9,178</td>
<td>294</td>
<td>-1,048</td>
</tr>
<tr>
<td>Within 90 Days of AMI</td>
<td>(162)</td>
<td>(446)</td>
<td>(57)</td>
<td>(44)</td>
</tr>
<tr>
<td>Total DRG Payments</td>
<td>9,082</td>
<td>9,657</td>
<td>357</td>
<td>-1,367</td>
</tr>
<tr>
<td>Within 1 Year of AMI</td>
<td>(221)</td>
<td>(612)</td>
<td>(78)</td>
<td>(60)</td>
</tr>
<tr>
<td>Total DRG Payments</td>
<td>11,058</td>
<td>10,589</td>
<td>447</td>
<td>-1,610</td>
</tr>
<tr>
<td>Within 2 Years of AMI</td>
<td>(277)</td>
<td>(765)</td>
<td>(98)</td>
<td>(75)</td>
</tr>
</tbody>
</table>

**Arithmetic Mean Regressions (Levels)**

**Geometric Mean Regressions (Logs)**

<table>
<thead>
<tr>
<th>Dependent Variable</th>
<th>8.45</th>
<th>1.17</th>
<th>0.05</th>
<th>-.16</th>
</tr>
</thead>
<tbody>
<tr>
<td>Within 30 Days of AMI</td>
<td>(.013)</td>
<td>(.03)</td>
<td>(.005)</td>
<td>(.004)</td>
</tr>
<tr>
<td>Total DRG Payments</td>
<td>8.51</td>
<td>1.22</td>
<td>0.05</td>
<td>-.16</td>
</tr>
<tr>
<td>Within 90 Days of AMI</td>
<td>(.015)</td>
<td>(.04)</td>
<td>(.005)</td>
<td>(.004)</td>
</tr>
<tr>
<td>Total DRG Payments</td>
<td>8.74</td>
<td>1.09</td>
<td>0.05</td>
<td>-.16</td>
</tr>
<tr>
<td>Within 1 Year of AMI</td>
<td>(.017)</td>
<td>(.05)</td>
<td>(.006)</td>
<td>(.005)</td>
</tr>
<tr>
<td>Total DRG Payments</td>
<td>8.90</td>
<td>1.02</td>
<td>0.05</td>
<td>-.16</td>
</tr>
<tr>
<td>Within 2 Years of AMI</td>
<td>(.019)</td>
<td>(.05)</td>
<td>(.007)</td>
<td>(.005)</td>
</tr>
</tbody>
</table>

1 Standard errors are in parentheses.

2 The reference patient is a white urban male aged 65-69 residing in New York, treated without intensive procedures at a low-volume hospital.
REFERENCES


Pauly, Mark V., 1980, Doctors and Their Workshops, Chicago: Chicago University Press.


CHAPTER THREE

THE EFFECT OF HOSPITAL CHARACTERISTICS
ON MEDICAL TREATMENT INTENSITY:
ACUTE MYOCARDIAL INFARCTION IN THE ELDERLY

Substantial variations exist across geographic areas in the intensity of treatment of virtually all common health problems (e.g., Glover, 1948; Wennberg and Gittelsohn, 1973; Chassin et al., 1986). These small-area variations are not explained by adjusting for differences in demographic, socioeconomic, or other observable characteristics that might be expected to influence the demand for medical care (at least at the level of county averages). For example, Wennberg (1990) studied the use of common hospital treatments in sixteen cities with medical schools, where practice patterns presumably would most closely reflect the current state of medical knowledge. He documented large variations in the use of some common surgical treatments, after adjustment for observable population characteristics. For many procedures, the coefficient of variation in use was near 0.5 or greater. Similarly, adjusted hospital admission rates for common diseases differ substantially across geographic areas (Wennberg, McPherson, and Caper, 1984; Wennberg et al., 1987). Coefficients of variation greater than zero are expected, due to the stochastic nature of health problems and heterogeneity in patient preferences. But observed variations are far too large to be explained by random events.

The documentation of area variations in practice patterns mainly raises further questions. Wennberg (1984) has argued that observing such variations in treatments without any corresponding variations in outcomes suggests that the lowest rates are best.
But in the absence of clinical trials or longitudinal studies of outcomes across areas, the evidence on the absence of relationships between treatments and outcomes is limited. Similarly, estimated welfare losses associated with variation from a socially-optimal intensity choice may be large (Phelps and Mooney, 1991). But even if the right intensity level were known, the literature provides little guidance as to how it can be achieved. If the variations are not related to any observable population characteristics, in particular to variables that might respond to policy manipulations, the policy implications of these findings are unclear.

Presumably, changes in physician treatment decisions must be achieved through modifying physician beliefs about efficacy or modifying provider incentives given beliefs. Almost by default, uncertainty about the effects of alternative treatments in similar patients has been hypothesized to be the cause of the area variations (Wennberg, Barnes, and Zubkoff, 1982; Phelps, 1992). If acquiring information on the effectiveness of alternative medical treatments is costly, if physicians can share experience about treatment effectiveness, or if physicians experience disutility from deviating from group norms, then variations in medical treatment decisions will be positively correlated within an area and among nearby areas. For example, Phelps and Mooney (1991) describe a model of physician "schools of thought" about correct procedure rates. In this model, physician prior beliefs about the "correct" rates for performing a treatment given a disease are summarized by a beta distribution. The physician's beliefs are updated by the experience (procedure rates) of all doctors in the community, leading to an equilibrium community norm. The principal empirical prediction is that new doctors who may have a distinct practice style will converge to the community pattern over time. But the model does not
specify how such community norms develop, or how policies might influence them. The model also has no role for the relationship between treatment decisions and the subsequent outcomes observed by clinicians; their Bayesian updating formula only holds if all outcomes are weighted equally or if outcomes are independent of treatment choice.

Further, physician beliefs alone do not determine treatment intensity choices. A physician may believe that all of his patients with coronary heart disease should receive bypass surgery. But only a fraction of his patients will actually receive this level of intensity if he only has access to limited hospital surgical capacity. Similarly, if the more intensive treatment entails significant financial costs (e.g., through the absence of any marginal reimbursement) or effort costs (e.g., through bureaucratic obstacles), then he may decide the more intensive treatment for some "marginal" patients is not worth it. In general, the existing literature on static and dynamic variations in medical practice patterns has not distinguished the effects of investments in technological capacity, of physician incentives to use alternative levels of treatment intensity, and of physician beliefs about the outcome consequences of intensity choices.

These features of the production of medical care imply that actual intensity choices for the treatment of a disease can be decomposed as follows:

\[ \text{Intensity Choices} = \text{Beliefs} \times \text{Access} \times \text{Costs} \]

1Here, I assume that patients are fully insured, prefer more intensive treatments (as long as they are not harmful), and seek care for their illness to focus on decisions by suppliers. Obviously, patients with a health problem may decide not to seek treatment or not to pursue more intensive services during a treatment episode. While incentives affecting the demand for care are also of much policy interest, they are beyond the scope of this paper.
\[
\Pr(X, H, I, V, r) = \Pr(X) \cdot \Pr(H|X) \cdot \Pr(I|X, H) \cdot \Pr(V|X, H, I) \cdot \Pr(r|X, H, I, V)
\]

That is, the joint distribution of the probability that a patient with characteristics \( X \) and health state \( H \) will receive treatment intensity \( r \) from a physician with beliefs about the consequences of treatment intensity \( V \) who practices at a facility with technological capacity \( I \) is given by the product of: the marginal distribution of patient characteristics \( X \), the probability of the health state conditional on \( X \), the probability of receiving treatment at facility \( I \) given \( X \) and \( H \), the distribution of physician beliefs about the impact of treatment given \( X \), \( H \), and \( I \), and the treatment intensity choice \( r \) given all of these characteristics.\(^2\) The model is complicated further by the fact that some characteristics of \( X \) and \( H \) are not observed. For example, sicker patients with a given health problem may choose to visit more intensive facilities. Treatment choices for these patients may differ not because physician beliefs differ but because their health status suggests a different treatment course is optimal.

Elsewhere (McClellan, 1993), I have addressed the consequences for treatment intensity choices of facility investments in specific intensive technologies. There, I argued that the existence of capacity constraints for specific technologies implies that hospital or medical office managers, not physicians themselves, can determine the average level of treatment intensity for a health problem. Trivially, the use of magnetic resonance scanners, cardiac catheterization and cardiothoracic surgery, chemotherapy, or any other intensive technology will differ between hospitals based on whether they have these

\(^2\)The choice of treatment intensity given the other variables is deterministic, unless physicians weigh the value of two or more treatments equally. This choice may be influenced by financial and effort incentives as noted above.
technological capacities. However, patients requiring these technologies who are initially treated elsewhere can be referred to the more intensive facilities for further treatment. To the extent that treatment patterns differ across these types of providers, however, transfers and referrals will not equalize the distribution of treatment intensities. The type of provider that initially treats the health problem will matter.

Here, I present empirical evidence on the interaction between the availability of intensive technologies and practice patterns. The availability of intensive technologies, especially for costly capital equipment, varies considerably across health care providers. Many studies have documented differences in practice patterns between providers that are associated with technology availability. For example, Hillman et al. (1990) documented differences in the use of radiologic services for apparently similar patients treated at physician offices with and without radiologic equipment. More generally, as in the case of breast cancer, differences in the propensity to use intensive treatments appear to be related to other provider characteristics (e.g., Noren et al., 1980; Adamson et al., 1989). For example, Greenfield et al. (1992) noted significant differences in treatment intensity between general internists and specialists for similar clinical problems, after adjusting for many observed characteristics of the patients (the study also showed an apparent effect of financial incentives). While all of these studies found significant differences in treatment patterns across provider types, none addressed whether the differences in treatment patterns reflect unobserved patient selection effects. That is, patients treated at physician offices with radiologic facilities are probably not the same as those treated at facilities without, and even relatively detailed surveys or record abstracts (e.g., Kravitz et al.,

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may not be able to capture all these differences in the clinical features of specific cases.

Ideally, to determine the effect of technology availability on treatment decisions, patients with similar clinical problems would be randomized to treatment by different types of providers. Then exogenous differences in practice patterns could be identified, and any consequences for patient outcomes could be attributed to the differences in practice patterns. In this paper, I examine treatment intensity choices for patients with acute myocardial infarction (AMI) as a function of the technologies available at the hospital to which they were initially admitted. I find substantial differences in treatment intensity choice. However, patients treated at different kinds of hospitals show mild differences in observable health characteristics, suggesting some sorting on the basis of unobserved health characteristics. I use instrumental-variables (IV) methods to identify true differences in treatment intensity. These distance-based instruments consist of estimates of a patient’s differential access to hospitals with alternative levels of treatment intensity available. The IV results demonstrate that although some patient sorting occurs across hospital types, the availability of more intensive treatments leads to a much greater propensity to use these technologies in AMI patients. Further, systematic differences in diagnostic patterns -- specifically, the diagnosis of health problems for which the intensive technologies are appropriate treatments -- parallel the differences in treatment decisions.

These methods provide further insights into differences in treatment intensities that have been well-documented for demographic groups, including blacks, women, and rural patients. Many studies have documented differences in the use of catheterization and revascularization procedures for patients with coronary heart disease on the basis of sex
(e.g., Ayanian and Epstein, 1991) and race (e.g., Goldberg et al., 1992); differences due to residence in rural areas are also well-known. However, because these studies did not incorporate models of hospital choice, they did not develop any substantial evidence on whether the differences across demographic groups are the result of differences in access to intensive treatments, and perhaps clinically inappropriate, or differences in the clinical presentation of disease. Similarly, these studies have not documented any relationship between intensity of treatment and outcomes within demographic groups.

Identifying the effect of hospital type on treatment intensity provides important new evidence on these issues. The IV methods permit the intensity differences to be decomposed into "within" and "between" hospital components, in terms of the framework in equation (1). This decomposition has important implications for policy, since policies to influence access to hospitals (through regulation of technology availability, programs to improve hospital networks, etc.) are quite different from policies to influence treatment decisions within hospitals. Further, if valid, the IV methods identify differences in intensity decisions that are independent of unobserved differences in patient health status. Consequently, they permit the identification of the average effect of the intensive treatments in "marginal" patients, patients whose intensity choice was influenced by their access to hospitals where the technologies were available. Thus, the consequences for outcomes of marginal differences in technology use in the population of patients with the disease can be measured directly. These methods are potentially applicable to many other health problems which involve the use of costly intensive treatments that are not everywhere available.
This empirical analysis also provides a foundation for further work on area variations in treatment patterns. This work identifies an average effect of technological capacity on treatment decisions. As equation (1) indicates, this average effect is composed of two parts. First, technology availability permits doctors to use intensive treatments that they believe provide net benefits for patients but were unable to perform due to binding capacity constraints. Second, technology availability may have direct effects on their beliefs about treatment effectiveness. If physicians are uncertain about the effects of the treatment, then technology use may increase over time as physicians gain more experience (specifically, if they observe good outcomes in patients who receive the intensive treatment compared to those who do not).

Finally, to the extent that area practice patterns truly exist beyond the level of hospitals, technology adoption will have a "neighborhood" effect. That is, as physicians gain experience with the technology and revise their practice patterns, the beliefs and treatments of physicians at nearby facilities will also change. Thus, technology adoption provides a natural experiment to identify any effects on the practice patterns of neighboring physicians.

The outline of the remainder of the paper is as follows. The next section briefly reviews the management of AMI in the elderly and summarizes the comprehensive patient-level data on treatment intensity in the United States in 1987 that will be used in the empirical analysis. Section II presents descriptive comparisons of the effects of hospital technological capacity on intensity of AMI treatment. Section III describes the IV estimation strategy to control for unobserved differences in patients across hospital types that might affect treatment decisions. Section IV presents the results of least-
squares and IV estimation for the effects of technological capacity on treatment intensity and diagnostic patterns. The results consistently show a dramatic effect of technology availability on treatment intensity for AMI patients, though some patient selection among hospital types is evident. Section V outlines the direction for future work on the relationship of hospital characteristics to treatment intensity, area practice patterns, and patient outcomes. Section VI concludes with a discussion of policy implications.

I. The Intensity of Treatment of AMI in the Elderly

Acute myocardial infarction (AMI) is a leading cause of morbidity, mortality, and medical expenditures in the elderly. McClellan and Newhouse (1993) summarize the many dimensions of treatment intensity that may affect AMI costs and outcomes. In this paper, I concentrate on the use of major invasive procedures: cardiac catheterization, percutaneous transluminal coronary angioplasty (PTCA), and coronary artery bypass graft (CABG) surgery. These are the most intensive procedures that are widely used in the treatment of coronary heart disease, and they account for much of the cost of AMI treatment (McClellan, 1993). Catheterization, a diagnostic procedure to evaluate the patient’s likelihood of benefiting from a revascularization procedure, involves injecting radiopaque dye into the blood vessels supplying the heart to study the adequacy of blood flow to the heart muscle. PTCA and CABG are revascularization techniques, therapeutic procedures to restore compromised blood flow that has been previously identified by catheterization. PTCA features the inflation of a balloon in the compromised vessel; because it is performed via catheter, it is not a major operation. CABG, which involves
grafting veins and/or arteries from other parts of the patient's circulatory system into the coronary vessels to "bypass" occluded areas, is a major open-heart surgical procedure.

The development of the analytic dataset consisting of information on characteristics, treatments, outcomes, and costs for all elderly Americans hospitalized with a new diagnosis of AMI in 1987 (N=205,021) is described in McClellan and Newhouse (1993), McClellan (1993) and Udvarhelyi et al. (1993). Table 1 summarizes the characteristics (Table 1A) and treatment intensity choices (Table 1B) for the elderly AMI patients. Column 1, describing the entire sample of patients, shows that approximately half of the patients in the sample were female, 5.6 percent were black, and 29 percent lived in rural areas. Approximately 46 percent of patients were treated initially at hospitals that had the capacity to perform catheterization. Approximately 23 percent of patients underwent catheterization within the 90-day episode of care following their AMI, and approximately 13 percent of patients underwent a revascularization procedure (CABG or PTCA).

The remaining columns of Table 1 summarize the characteristics and use of intensive procedures in particular demographic groups. Compared to male patients, female patients were older, had a higher proportion of blacks, had higher incidence of comorbid diseases such as dementia and diabetes.3 They were considerably less likely

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3 Information on comorbid diseases was obtained by categorizing the secondary diagnosis codes present on each patient’s discharge abstract for the initial AMI hospitalization. Making inferences based on comorbid disease information for particular patients is complicated. Comorbid diseases tend to be undercoded in patients who die acutely after AMI, and milder diseases tend to be overcoded in patients who are less severely ill. See McClellan and Newhouse (1993) for more details. Consequently, comorbid disease information is used in a largely qualitative way in the analysis that follows. Including covariates based on comorbid diseases in the regressions reported below did not affect the results.
than male patients to undergo catheterization and revascularization procedures (especially CABG), and they were slightly less likely to be admitted to catheterization hospitals. Compared to white patients, black patients were slightly younger, more likely to be female, and more likely to live in urban areas. Black patients were also much less likely than whites to undergo catheterization and revascularization procedures, despite a significantly higher incidence of initial treatment at a catheterization hospital. For example, during the 90-day episode of care after AMI, the catheterization rate in blacks is 24 percent lower than in whites (17.5% versus 23.1 percent), and the revascularization rate is 48 percent lower (7.0% versus 13.4%). Patients living in rural areas were more likely to be white and male, and they were less likely to undergo catheterization and revascularization procedures. The lower rate of intensive procedure use was associated with a much higher probability of initial treatment at a small hospital without catheterization facilities.

Table 2 examines the relationship between the type of hospital where AMI patients were initially admitted and the incidence of intensive procedure use, to provide the first preliminary evidence on the association between technology availability and choice of treatment intensity. Hospital type was defined empirically based on the volume of intensive procedures performed on AMI patients: hospitals that performed at least five catheterizations on AMI patients in 1987 were defined as catheterization hospitals, hospitals that in addition performed at least ten revascularization procedures (PTCA) were
defined as major revascularization hospitals, and hospitals that did not empirically provide these services were defined as non-catheterization hospitals. 4

The first part of Table 2 summarizes differences in the observable characteristics of patients admitted initially to the different types of hospitals. Hospitals that performed procedures were much less likely to treat patients from rural areas, and they had a larger share of black patients as well. Revascularization hospitals treated a slightly smaller share of female patients. These hospitals also treated patients who were younger on average and who had a lower incidence of some common chronic diseases (except for cancer).

The second part of Table 2 summarizes differences in the use of intensive procedures for AMI patients across hospital types. The differences are striking: during the 90-day episode of care after AMI, patients initially admitted to major revascularization hospitals were over 2.3 times more likely to undergo catheterization as those initially admitted to noncatheterization hospitals (36.3% versus 15.6%). Patients initially treated at catheterization hospitals that do not perform many revascularization procedures were between these extremes (24.6% catheterization rate within 90 days of AMI). Differences in use of revascularization procedures were also dramatic: patients admitted to revascularization hospitals are 2.5 times more likely to undergo revascularization procedures within 90 days than patients admitted to noncatheterization hospitals, and are almost 1.8 times more likely to undergo revascularization as patients admitted to catheterization hospitals. The difference consists of greater use of both revascularization

4 Cutoffs greater than two were used to avoid miscategorization on the basis of coding errors by hospitals. Few facilities were affected by changes in the volume levels used to classify hospitals, and using lower volume cutoffs had no effect on results.
procedures, but it is larger for PTCA use than CABG use (e.g., 90-day PTCA rate of 11.3% for revascularization hospitals versus 2.8% for noncatheterization hospitals). The very large differences in the use of catheterization during the initial hospital stay -- ranging from zero at noncatheterization hospitals to 16.4% at catheterization hospitals to 32.7% at major revascularization hospitals -- shows that these differences in procedure use are attributable to differences in treatment decisions during the initial admission. These differences diminish over time but remain substantial even at long intervals after AMI.

The comparisons of intensity choices across hospital types suggest that the availability of intensive technologies may have a fundamental effect on hospital practice patterns. However, they do not preclude the possibility that the hospital admission decision is subject to selection bias: patients who appear likely to benefit from catheterization may be selectively referred to hospitals that have these technologies. Indeed, the differences in sex and age across hospital types suggest some selection of this type may be occurring in terms of observable characteristics. These mild differences do not seem sufficient to explain the dramatic differences in treatment patterns. However, since patient characteristics observable in Medicare claims data represent only a small fraction of the information on health status available to emergency response teams and physicians, it is conceivable that large unobserved differences could account for the systematic differences in AMI treatment intensity across hospital types. In any event, quantifying the proportion of systematic treatment variation attributable to technology availability would be useful for policy purposes. The next section outlines IV methods to
identify the contributions of selection effects and systematic differences in practice patterns to these observed effects.

II. The Use of Instrumental-Variables Methods to Identify Exogenous Differences in Practice Patterns

Hospital choice may reflect patient selection: patients with more severe health problems or who are better candidates for intensive procedures may select hospitals where more intensive treatments are available. In an observational dataset such as the Medicare claims files, failure to capture these variations in health status will lead to biased estimates about the effect of hospital type on intensity choice. Such selection bias can be captured in the following model, which imposes no parametric structure on the process determining admission choice:

\[ r^n_i = \mu + h_i \]  \tag{2}

\[ r^c_i = r^n_i + \eta^c_i \]

where \( \mu \) is the mean rate of procedure use in the population admitted to a noncatheterization hospital, \( h_i \) is a mean-zero random variable that represents the patient’s health status, \( r^n_i \) is an indicator for use of the intensive treatment if the patient were initially admitted to a "nonintensive" hospital, \( r^c_i \) is an indicator for use of the

\[ ^5 \text{In fact, some patient characteristics that are correlated with treatment intensity (age, sex, race) are observed in the data. In these models estimated below,} \]  \( \mu \)  \[ \text{is a conditional mean for all patients with a given set of observable characteristics -- that is, for all patients who "look" identical in the observational data -- but the basic idea is the same.} \]
intensive treatment if the patient were initially admitted to an "intensive" hospital, and $\eta_i$ is the effect of practice pattern differences across hospital types on the patient's intensity of treatment. Both $h_i$ and $\eta_i$ are unobserved stochastic terms from the standpoint of the analyst, and for any individual only $r^n_i$ or $r_i$ will be observed.\(^6\)

If patients select different hospital types on the basis of unobserved characteristics, a true practice pattern effect cannot be identified using actual admission choices and treatment intensity decisions. In large observational studies, only $E[r^n|c=0]$ and $E[r^c|c=1]$ can be estimated consistently, where $c$ is an indicator for whether the patient was admitted to an intensive hospital. Patient selection implies that $E[r^c|c=1] \neq E[r^c|c=0]$ and $E[r^n|c=0] \neq E[r^n|c=1]$: observed differences in average intensity across hospital types reflect both average selection effects and average practice pattern effects. As described in Imbens and Angrist (1991) and McClellan and Newhouse (1993), IV estimation can consistently identify average marginal effects in this context, where the "margin" is over patients whose hospital choice is influenced by the value of the instrument. Details of the generalized method of moment (GMM) estimation strategy used to estimate these models are in Angrist (1991) and McClellan and Newhouse (1993).\(^7\)

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\(^6\)This framework nests the more familiar (and more restrictive) latent-index models for IV estimation with limited dependent variables. The Appendix describes a corresponding latent-index framework for the models and compares it to the estimation framework used in the paper. Latent-index models assuming both linear probability and probit distributions yielded identical results to the more robust models presented in the text.

\(^7\)In this paper, I use the same instrumental variables to identify the effect of technology availability on practice patterns as I used in a companion paper (McClellan and Newhouse, 1993) to estimate bounds on the marginal effects of intensive treatments on patient outcomes. As noted in McClellan and Newhouse and in the text below, differential distances "randomize" patients to different likelihoods of admission to hospitals with alternative levels
The instrumental variables used to predict hospital admission independent of disease severity were based on estimates of each patient's differential distances to alternative types of hospitals. Differential distance measures first required estimation of patient distances to the alternative hospital types (noncatheterization, catheterization, and major revascularization). To estimate these distances for individual patients, I linked zip codes for all patient residences and hospitals in the United States to approximate latitude and longitude coordinates using a commercial software package. I then used an algorithm to estimate patient-hospital distances from the coordinates and choose the minimum distance from each patient zip code among all the hospitals of the relevant type.  

The resulting distributions of patient distances to the alternative hospital types are shown in Figures 1 and 2. Figure 1, which plots the cumulative distribution of patient distances to the nearest acute-care hospital, shows that most patients do not live very far from a hospital. Over 40% of AMI patients lived in the same zip code as a hospital, over

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of treatment intensity available. Here, I use these methods to examine the direct consequences of treatment at alternative hospital types for use of intensive procedures. In McClellan and Newhouse (1993), I address the more complicated problem of estimating the outcome consequences of these exogenous differences in treatment intensity. For that case, I develop a framework in that paper for estimating the effect of intensive procedures along with any unobserved but correlated aspects of treatment intensity and quality of care at the more intensive hospitals. For this case, estimation of effects is direct. Later in this paper I outline the direction for future work on identifying hospital effects on treatment intensity, which will permit narrower bounds on the marginal benefits of particular medical technologies.

See McClellan and Newhouse (1993) for details. Successful matches were obtained for 98.6% of the original sample. The resulting analytic sample (N=205,021) was also used in the descriptive results presented thus far in the paper.

A relevant acute-care hospital was defined as a hospital treating at least ten elderly AMI patients during 1987. Approximately 98% of patients were admitted initially to such hospitals.
80% of patients lived within ten miles of a hospital, and almost all patients lived within 25 miles of a hospital. Figure 2 plots the cumulative distribution of patient distances to the nearest catheterization or revascularization hospital. Approximately half of elderly AMI patients lived within five miles of such an intensive hospital, over 80% lived within 30 miles of one, and almost 95% of patients lived within 50 miles of one. Thus, though the distribution of patient distances to a catheterization hospital is skewed to the right compared to distances to any hospital, few patients in the United States are "very far" from intensive treatments.

For each of the intensive hospital types (catheterization and revascularization), a patient's differential distance was estimated to be the difference between the patient's distance to the nearest intensive hospital and the patient's distance to the nearest hospital. For example, consider two patients who each live five miles from a catheterization hospital. For the first patient, the catheterization hospital is also the nearest hospital, so her differential distance is zero. For the second patient, a lower-intensity hospital is located only two miles away, so her differential distance is three. Differential distances reflect a simple underlying model of facility choice, in which patients prefer hospitals that are closer and hospitals that have more intensive treatments available.

Table 3 compares patient characteristics, hospital admission choices, and treatment intensity decisions for patients grouped on the basis of differential distance to a catheterization hospital. This Table provides the basic results present in the more formal estimation results to follow. Approximately half of the elderly AMI patients have differential distances to catheterization of two miles or less. Compared to patients with differential distances of greater than two miles, the patients differentially near to
catheterization are more likely to be black and slightly more likely to be female. But in
terms of other observable correlates of health status -- age and comorbid diseases -- they
appear virtually identical to the far group.\textsuperscript{10} In spite of these minimal differences in
observable health characteristics, patients differentially near to catheterization are much
more likely to be admitted initially to catheterization or revascularization hospitals (75.2% versus 16.5%), and they are also much more likely to be treated with intensive
procedures. The difference in catheterization rates within 90 days of AMI is
approximately 33 percent (26.0% versus 19.6%), which parallels a 32 percent difference
in revascularization rates (14.8% versus 11.2%).

These differences in treatment intensity for patients who appear quite similar in
dimensions other than type of admitting hospital suggest that the systematic practice
pattern differences associated with the availability of intensive technologies are large.
Nonetheless, the simple two-group comparison does not permit full evaluation of the
effects of differences in access to intensive hospitals versus treatment intensity decisions
conditional on admission within particular demographic groups. Rural patients are
concentrated in the far group, and rural patients may have lower procedure rates for
reasons other than site of initial admission. For example, rural patients tend to live
farther in terms of absolute distances from catheterization hospitals, and consequently may
have lower demand for catheterization due to transportation costs. Finally, splitting the
sample into two groups is unlikely to exploit all of the statistical power in differential
distances to catheterization and revascularization hospitals to predict treatment intensity.

\textsuperscript{10}See McClellan and Newhouse (1993) for a more extensive discussion of the medical and
statistical validity of using differential distance as an instrument for treatment choice.
Thus, in this two-group comparison, it is difficult to quantify precisely how much of the difference in procedure use is attributable to differences in practice patterns between catheterization and revascularization hospitals. The next section uses GMM IV estimation techniques to address these issues.

III. Least-Squares and Instrumental-Variables Estimation of Hospital Effects

This section presents the results of GMM estimation of the simple model described in equation (2) of the effects of availability of intensive technologies on hospital treatment intensity choices. The large number of observations in the sample permits estimation of models with complete interactions of all demographic covariates. The specific groups used in estimation were: age 65-69, age 70-74, age 75-79, age 80-84, age 85-89, and 90 and over, female or male sex, black or nonblack race, rural or urban residence, and full interactions of all of these variables. In addition, average effects for each state of residence were included in the models.\textsuperscript{11} For the IV models, patients were also grouped based on their differential distances to a catheterization and revascularization hospitals. For each of these differential distances, IV groups were based on the following intervals (in miles): 0, 0-1, 1-2, 2-4, 4-6, 6-8, 8-10, 10-12, 12-15, 15-18, 18-21, 21-25,

\textsuperscript{11}The 49 indicators for state of residence (states except Alaska plus the District of Columbia) were highly significant in all specifications estimated, but results did not differ from models in which no state effects were included.
25-30, 30-40 and over 40.\textsuperscript{12} Thus, both the least-squares and IV results below estimate average effects in large groups using fully-interacted ANOVA models, without parametric or distributional assumptions. Heteroskedasticity-consistent estimates were obtained using the techniques of White (1980) for least-squares estimation and of White (1982) for IV estimation.\textsuperscript{13}

Figure 3 extends the two-group comparisons of Table 3 to the full set of IV groups. The Figure plots the residual probability of admission to a catheterization or revascularization hospital as a function of differential distance to one of these hospitals, after adjusting for all observable patient characteristics (the area of the circles is proportional to the size of the groups). The relationship between differential distance and admission is very strong: patients with a differential distance of zero are have a probability of admission to a catheterization or revascularization hospital approximately 75 percentage points greater than patients with large differential distances. (The probability of admission to a catheterization or revascularization hospital for the entire sample is 45.9\%). Thus, the range of variation induced by the instruments is almost complete, so that the IV estimate of the effect of type of hospital on treatment intensity approaches the average effect over the entire population (that is, the "margin" consists of the average effect over 75\% of all patients).

\textsuperscript{12}These intervals were chosen to provide large enough groups of approximately equal size who differed in their physical access to the more intensive hospitals. The clustering of some patients at a differential distance of zero makes that group larger than the others, but the remaining groups are comparable in size.

\textsuperscript{13}Many alternative intervals for grouping on the basis of demographic variables and instruments were explored. None led to significantly different results.
Figure 4 provides the intuition for the IV estimates to follow by plotting the residual admission probabilities of Figure 3 against the corresponding residual probabilities of catheterization. Type of hospital at admission has a strong linear relationship with procedure use (associated with a ten percentage point variation in the latter around the population mean catheterization rate of 22.8%). The figure demonstrates that IV estimation using differential distances to more intensive hospitals permits the identification of a strong independent effect of technology availability at hospitals on hospital practice patterns.

Tables 4 and 5 quantify this hospital effect. For comparison, Table 4 first presents least-squares estimates of the effect of patient characteristics on treatment intensity decisions without accounting for hospital characteristics. Each column describes estimated probabilities of catheterization during the patient’s initial hospitalization (including transfers, however long the hospital stay; column 1) and during three time intervals after AMI (7, 30, and 90 days; columns 2 through 4). Table 4 has two panels, one presenting estimates for nonblacks (N=193,445) and one presenting estimates for blacks (N=11,576). The average catheterization rate for a reference patient (male, urban resident, age 65-69) is shown in the first row, and the weighted-average effects of rural residence and female sex in the second and third rows. These least-squares estimates confirm the descriptive results in Table 2. For all time intervals after AMI, blacks are less likely to undergo catheterization than whites, and the differential increases at longer time intervals. For both blacks and nonblacks, rural residence is associated with a much lower catheterization rate. The rural-urban difference diminishes over time, but does not diminish as much for blacks as nonblacks. Female sex is associated with a lower
catheterization rate, especially for nonblacks, and the male-female difference increases with time.

Table 5 summarizes how much of these differences in treatment intensities can be attributed to differential practice patterns across hospitals. Two columns, one with least-squares (LS) estimates and the other with IV estimates of hospital effects, correspond to each column in Table 4. The first half of Table 5 presents estimates for nonblacks, and the second half of Table 5 presents estimates for blacks. In this table, hospital types are defined so that the effects of admission to a revascularization hospital is in addition to the effect of admission to a catheterization hospital. For nonblacks, the least-squares estimates of the effects of technology availability are very close to the aggregate differences of the descriptive statistics in Table 2. Compared to initial admission to a noncatheterization hospital, initial admission to a catheterization hospital increases the probability of catheterization by 16 percentage points, and initial admission to a revascularization increases the average probability of catheterization by 31 percentage points. Type of hospital at initial admission completely accounts for the lower catheterization rate in rural AMI patients: the effects of rural residence on procedure use are approximately zero. In contrast, the sex differential in intensive procedure use is slightly larger than in Table 4. These least-squares estimates do not account for patient selection to the alternative hospital types. The IV estimates which do account for hospital selection lead to hospital effects that are 10 to 20 percent smaller than the LS estimates (and the baseline catheterization probabilities are correspondingly higher). Thus, even for an acute health shock such as AMI, some patient selection occurs across hospital types on the basis of characteristics that are not observed in Medicare claims data. Even after
correcting for the systematic differences in patient mix, however, the IV estimates still suggest a very large effect of technology availability on treatment intensity.

The second half of Table 5 shows similar patterns for black patients. However, differential admission rates to catheterization and revascularization hospitals do not explain lower catheterization rates among blacks. At all time periods, baseline catheterization rates for blacks are substantially lower than for whites, and these differences increase with time after AMI. For example, during an initial hospitalization at a revascularization hospital, the IV estimate of the average probability of catheterization for urban male black patients is 7.1 percentage points lower than for white urban male patients. By 90 days after AMI, the rate differential increases to 10.4 percentage points. Especially for longer time intervals, the differences primarily reflect lower use of catheterization regardless of the initial hospital admission type. For time intervals beyond 7 days after AMI, the IV-estimated hospital effects are larger for nonblacks than blacks, but the difference disappears at longer time intervals.14 In addition, unlike whites, blacks living in rural areas have a slightly lower likelihood of catheterization even after accounting for differences in likelihood of admission to more intensive hospitals. Black females are also less likely to be catheterized, but the sex differential does not grow as rapidly over time as it does for white females.

These results demonstrate that technology availability at hospitals is associated with large, systematic differences in treatment intensity, and that these differences are not attributable to unobserved case mix variation across hospitals. For nonblacks, differences

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14The IV-estimated incremental effect of admission to a revascularization hospital is approximately as large for blacks as for nonblacks beyond 7 days (though it is measured relatively imprecisely).
in site of initial hospital admission entirely explain the lower use of catheterization in rural patients. Thus, demand-side factors such as absolute distance seem unimportant compared to supply-side factors in treatment intensity variations. For blacks and women, lower treatment intensity choices arise independently of access to more intensive hospitals; within-hospital differences in practice patterns for these demographic groups lead to lower intensity of treatment. The next section presents evidence on systematic differences in diagnostic patterns across hospital types that correspond to these treatment intensity differences.

Before turning to that issue, I briefly explore the differences in treatment intensity associated with race. For blacks, lower intensity occurs despite the greater geographic access to intensive hospitals evident in Table 3. As the trends in baseline probabilities of catheterization in Table 5 indicate, the differences in intensity associated with race increase over time (from a difference of 5.8 percentage points within 7 days of AMI to a difference of 11.6 percentage points by 90 days; during the initial hospitalization, the difference is only 1.6 percentage points). Two hypotheses with different policy implications are consistent with these findings. First, the evolution of coronary heart disease in blacks may be different than in nonblacks, so that the increasing intensity differentials over time simply reflect more rapid progression of heart disease in nonblacks. Second, access barriers to followup care may be greater for blacks, leading to increasing intensity differences over time (and, for example, a residual effect of rural residence that is not present for whites).

The difference in probability of catheterization between blacks and nonblacks is paralleled by a difference in the use of revascularization procedures also attributable to
treatment differences that are independent of hospital type for longer time intervals. For example, the IV estimate of the average 90-day revascularization rate in 65-69 year old urban males is 7.0 percentage points lower in blacks than whites. This is a 50% differential in revascularization rates, comparable to the difference in catheterization rates. But this aggregate difference is not attributable to the higher probability of revascularization for patients admitted to revascularization hospitals for nonblacks (7.0 percentage points) versus blacks (6.8 percentage points). The composition of the incremental revascularization procedures also differs slightly by race. Whites treated at revascularization hospitals have an average 90-day PTCA rate that is 6.3 percentage points higher than whites treated initially at noncatheterization hospitals, and an average CABG rate that is 3.3 percentage points higher. For blacks, the difference in PTCA rates is 3.9 percentage points and in CABG rates is 2.9 percentage points. Thus, although both revascularization procedures are used less frequently in blacks regardless of admission site, treatment at a revascularization hospital has a larger proportionate effect on the use of CABG than PTCA in blacks.

The implications of these demographic differences await further research. First, differences in treatment intensity may be due to unobserved factors correlated with the observed demographic characteristics. McClellan, Smith, and Skinner (1993) show that some of the racial differences in treatment intensity are associated with patient income differences that are correlated with race, rather than race itself. Moreover, the core policy issue is whether the within-hospital intensity differences for blacks and women have adverse consequences for outcomes. The intensity differential will not lead to outcome differences if the nature of heart disease or responsiveness to intensive treatment
differs for these groups, or if the treatments provide little marginal benefit, as suggested by the results of McClellan and Newhouse (1993) for all elderly patients. These hypotheses cannot be distinguished directly in this analysis, but they will be distinguished in subsequent studies of the outcome consequences of these variations in treatment within specific demographic groups. These issues are discussed in more detail in Section V.

IV. The Relationship Between Technology Availability and the Diagnosis of Illness

Table 3 implied that the incidences of serious complicating diseases in elderly AMI patients were not significantly correlated with differential distance. This absence of correlation with observable aspects of health status provides some evidence that differential distance is a valid instrument. However, the incidence of one complicating disease not reported in Table 3 did have a significant negative correlation with differential distance. The incidence of stable angina, like the use of catheterization, was significantly higher in patients with differential distances to catheterization of two miles or less (27.7% versus 22.0%). Angina is a diagnosis of chest pain specifically caused by coronary heart disease. "Stable" angina, as the name implies, is a milder and less worrisome condition than "unstable" or worsening angina, which is associated with a high risk of AMI and is a classic indication for catheterization and revascularization. Stable angina may be a chronic condition, and patients with symptomatic coronary artery disease might choose to reside closer to catheterization hospitals for convenience of treatment. Such patient sorting on the basis of health status would tend to invalidate the use of differential distance as an instrument.
Alternatively, the apparent difference may reflect a relationship between treatment aggressiveness and discharge coding practices: standards for use of surgical procedures at hospitals performing catheterization may differ from those at hospitals that do not perform the procedures.\textsuperscript{15} Patients initially admitted to catheterization hospitals who show marginal evidence of continuing chest pain may be more likely to be categorized as "angina" patients and catheterized.\textsuperscript{16} In fact, the apparent correlation of the incidence of angina with differential distance is attributable to differences in physician and hospital behavior associated with technology availability.

First, Figure 5, which plots mean residual catheterization rates and angina diagnosis rates by differential distance intervals, shows the two rates are highly correlated. The correlation is considerably higher than between angina and absolute distance to a catheterization hospital; the opposite pattern would be expected if the incidence of angina reflected true variation in patient location decisions.

Additional evidence comes from actual hospital admission and treatment patterns, conditional on differential distance. If true differences in patient health account for variation in likelihood of catheterization with distance, then the likelihood of catheterization should not differ much for patients living near catheterization hospitals by

\textsuperscript{15}McClellan and Newhouse (1993) describe a battery of tests of the potential correlation of differential distances and health status. Those tests find no evidence of failures with significant consequences for the estimated results. Consequently, they reinforce the evidence presented below that the correlation between the apparent incidence of angina and differential distance is a diagnosis coding effect.

\textsuperscript{16}Catheterization is medically appropriate for four major diagnoses: AMI (present in all patients in the sample), stable angina, unstable or progressive angina, and chest pain of undetermined cause (a highly unlikely diagnosis in AMI patients, who have clear evidence of coronary artery disease).
whether their initial admission happens to be to a catheterization hospital or not. After stabilization, patients requiring catheterization could be transferred to nearby catheterization hospitals for treatment. However, if practice patterns differ across hospital types in association with technology availability, then patients initially admitted to catheterization hospitals would be considerably more likely to undergo catheterization than patients from a similar differential distance initially admitted to noncatheterization hospitals. Greater differential distance would lead to a smaller likelihood of both angina diagnosis and catheterization because the probability of initial admission to a catheterization hospital would decline.

Table 6 presents these conditional probabilities. In fact, differences in catheterization use and stable angina coding between catheterization and noncatheterization hospitals are very large, independent of differential distance. For patients near catheterization facilities, small differences in demographic characteristics and comorbid diseases show the mild selection effect documented in the previous section. That is, a patient living close to a catheterization hospital is mildly more likely to be admitted to it if he appears to be a "good candidate" for surgical procedures. Such selection effects are more pronounced for patients living far from catheterization facilities: admission to a catheterization hospital when other hospitals are much closer is more likely to reflect a specific intention to treat. In contrast to the mild differences in all these observable

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17By definition, stable angina is not an emergent condition requiring immediate surgical treatment.

18Of course, some selection of hospital types at initial admission is possible; that is why IV estimation is required for estimating effects. The goal here is to determine whether the diagnosis of angina shows a far stronger association with hospital characteristics than any other patient characteristic, and thus is not clinically plausible.
characteristics, the probability of catheterization is more than 100% greater for AMI
patients initially admitted to catheterization hospitals, independent of differential distance.
Differences in the coding of stable angina are almost as striking: the coding of the
diagnosis parallels the actual use of intensive procedures and has little direct relationship
to patient location.

Further evidence supporting an endogenous coding effect comes from split-sample
IV estimations of the models of treatment effects in McClellan and Newhouse (1993).
Splitting the sample based on the presence (N=50,976) or absence (N=160,111) of stable
angina to test for coefficient stability leads to a decisive rejection. For patients with
stable angina, the "first stage" estimates of the effect of differential distance on
catheterization decisions are considerably larger, implying that catheterization decisions
for angina patients are more elastic with respect to distance than decisions for other
patients. The IV estimates of the average effect of catheterization for stable angina
patients, -.133 (standard error .041) for one-year mortality and -.176 (.043) for two-year
mortality, are also much larger. Though quite large, these estimates are plausible:
patients with angina have additional heart muscle at risk of damage, so surgical
procedures might be particularly useful. However, for patients without the diagnosis of
angina at initial discharge after AMI, the estimated effect of catheterization on one-year
mortality is +.291 (.097) at one year and +.249 (.097) at two years. These estimates
are not clinically plausible. Instead, grouping on the basis of angina appears to generate
two samples in which unobserved variations in health status are correlated significantly
with the instruments. If patients with relatively less severe coronary disease are more
likely to be diagnosed with angina and catheterized if they are treated at catheterization
hospitals, these econometric results simply reflect the restriction of the angina sample to patients with relatively poorer health status as differential distance increases. The resulting correlation between unobserved health status and the value of the instrument invalidates IV estimation of the endogenously-split samples.

These patterns suggest that many elderly AMI patients are in a borderline category that tends to be diagnosed with angina and undergo catheterization if they are initially admitted to catheterization facilities but not otherwise. The availability of intensive technologies at hospitals is associated not only with more intensive treatment of patients, but also with systematic differences in diagnostic practices.

V. Implications of Differences in Practice Patterns Across Hospitals for Future Work

The evidence of major differences in patterns of diagnosis and treatment intensity in AMI patients provides the foundation for future work on the relationship of hospital characteristics, treatment intensity, and patient outcomes. This work will expand and further integrate the analysis of the relationship of hospital characteristics to treatment intensity choices (described here), the analysis of the relationship of treatment intensity to patient outcomes (McClellan and Newhouse, 1993), and the analysis of provider incentives to use alternative levels of treatment intensity in the production of care for health problems (McClellan, 1993). The research will integrate recent developments in the analysis of panel data with group effects with the recent developments in the estimation of average treatment effects applied already. It will rely on large,
comprehensive datasets currently under development that summarize all utilization of medical care by the elderly with a set of common health problems (such as AMI, coronary heart disease, cerebrovascular disease, and cancer) over a long time period (1984-1992). In this section, I summarize the methods that will be used to extend the results described in this paper.

This analysis has considered the relationship between hospital characteristics and treatment intensity for three types of hospitals: noncatheterization hospitals, catheterization hospitals, and major revascularization hospitals. These technological capacities are important dimensions of the intensity of treatment of acute myocardial infarction. But many other provider characteristics may influence treatment intensity and patient outcomes, both directly and through their effects on technology adoption decisions. These characteristics include hospital ownership, teaching status, size, volume, and the availability of other intensive treatments such as coronary care unit beds. Assume for the moment that hospital choice by patients is not endogenous and consider a parametric model of treatment intensity as a function of hospital characteristics comparable to the model in (2):

$$r_{ist} = Z_{ijt} \gamma + X_{ist} \beta + \alpha_{i} + \mu_{s} + \varepsilon_{ist}$$  (3)

where $r_{ist}$ is an index of treatment intensity for patient $i$ living in state $s$ who develops the health problem at time $t$, $Z_{ij}$ summarizes the characteristics of hospital $j$ treating the patient, $\gamma$ is the effect of hospital characteristics on treatment intensity choices, $X$ is a vector of patient characteristics, $\beta$ is the effect of patient characteristics on intensity choices, $\alpha_{i}$ is a time effect, $\mu_{s}$ is a state effect, and $\varepsilon_{ist}$ is a stochastic error term. This is the estimation model underlying the results in Section III, except that the large sample
size permitted estimation of separate models for different demographic groups and that
dynamic effects (changes in t) were not analyzed. Separate models for particular
demographic groups will also be estimated in future work, but the basic idea is easier to
describe with fewer free parameters. In fact, hospital choice for AMI treatment is mildly
dependent with respect to unobserved heterogeneity in patient health status. But the IV
techniques developed in this paper can also be used as exogenous predictors in the panel
models.

While hospital characteristics can be viewed as exogenous from the standpoint of
an individual patient with a health problem (subject to the patient selection as described
below), hospital decisions to adopt technologies are a function of factors including
competition, payment levels, regulation, and patient mix (Newhouse, 1987; Baumgardner,
1991; Weisbrod, 1991; McClellan, 1993). The hospital type $Z_X$ can in turn be modeled
as a function of these characteristics of the hospital environment, either as panel models
with limited dependent variables (e.g., whether hospital $j$ has adopted technology $Z$ in
period $t$) or as hazard models for time to adoption. Hospital characteristics such as size
and ownership, changes in hospital reimbursement (such as the adoption of the Medicare
Prospective Payment System or reformulation of DRG reimbursement rates for intensive
treatments for the health problem), measures of hospital competition, and the composition
the population in the hospital’s service area (income, racial composition, and insurance
status) are all covariates of interest. In addition, determinants of the relationship between
technology availability and practice patterns, captured by $\gamma$ in terms of equation (3), will
be modeled explicitly as a function of physician and hospital incentives to provide
alternative levels of treatment intensity for the health problem. In particular, random-
coefficient models for $\gamma_s$ (e.g., Card and Krueger, 1991) will be used to identify the consequences of cross-sectional and time-series variation in payment for physician services.

Analyzing technology adoption decisions by hospitals also permits more direct studies of "neighborhood" effects on the endogenous variable, treatment intensity (Griffith, 1988; Case, 1991). For example, if opening a catheterization laboratory leads physicians at the hospital to revise their beliefs about the appropriate use of catheterization, then physicians at neighboring hospitals should also be affected.\textsuperscript{19} A spatial effect can be incorporated in the model described above by including an additional term $W\mathbf{r}$, where $W$ is a weighting matrix for the vector of intensity decisions $\mathbf{r}$ for all patients and weights are proportional to influence (e.g., patients treated at nearby hospitals would contribute positive weights). While such neighborhood effects can be absorbed into fixed area effects to allow consistent estimation of the other parameters of the model, as was done in Section III, modeling the spatial processes explicitly would provide some insights into the actual importance of area practice patterns. These effects are quantitatively important, even after accounting for variation in hospital types across areas: in all specifications estimated above, all state effects were highly significant. However, estimation of spatial models will be inconsistent if the conditioning variables $X$ are correlated with unobserved hospital-specific effects, leading to serious identification

\textsuperscript{19}Note that this effect is different from any effect of technology adoption on hospital competition. Competition would increase the probability of catheterization for patients treated at nearby hospitals by increasing the likelihood that the neighboring hospital would open a catheterization facility itself. In contrast, in a neighborhood effect, the intensity of treatment of patients admitted to neighboring hospitals would be influenced independent of technology adoption by those hospitals.
problems in cross-sectional studies of neighborhood effects (Manski, 1992). In contrast, by using changes in hospital characteristics which lead to changes in practice patterns at a given hospital, fixed hospital effects can be differenced out. The resulting model of the effect of changes in practice patterns at a hospital on changes in practice patterns at neighboring hospitals (using changes in practice patterns in areas where no technology adoption occurred to control for time trends) will be consistent even in the presence of such correlation.

All of these modeling extensions will provide further insights into the relationship between hospital characteristics and treatment intensity decisions, and on the determinants (if any) of area practice patterns. However, the extensions will also provide additional evidence on the relationship of treatment intensity to patient outcomes. The panel datasets will provide much larger samples to which the IV estimation techniques developed in McClellan and Newhouse (1993) can be applied, so that treatment effects for specific demographic groups can be estimated. The panel models also permit a more direct method to control for hospital-specific effects on outcomes. Models of treatment intensity and outcomes for patients admitted to a hospital before and after it adopts a particular intensive technology will be estimated, thereby controlling for hospital-specific quality effects. For example, during the time period for which Medicare claims data are being processed, over 500 hospitals adopted intensive technologies such as the capacity to perform cardiac catheterization and revascularization procedures. Comparing AMI patients treated by a hospital before and after catheterization or revascularization became
available allows a hospital-specific effect to be differenced out, identifying the effect of the intensive technology.\textsuperscript{20}

\section*{VI. Conclusions}

This paper has demonstrated that the availability of intensive medical technologies at hospitals leads to large differences in treatment intensity decisions. Though some studies have documented differences in procedure use associated with technology availability, they were generally unable to control for the likely differences in patient mix across facilities that confounded results. Using differential distances to predict intensity independent of these unobserved aspects of health status permits much stronger conclusions here: patients initially admitted to a hospital with the capacity to perform surgical cardiac procedures are much more likely to undergo those procedures than patients admitted to non-catheterization hospitals. Similarly, the availability of catheterization also leads to a large difference in the propensity to categorize patients as having a diagnosis for which the technology is indicated. This latter finding has important implications for both peer review procedures and the validity of research on treatment of health problems such as chest pain that are "soft calls" in clinical parlance. While phenomena like DRG creep are well known responses to reimbursement (Carter, Newhouse, and Relles, 1990), no previous studies have documented such large diagnosis

\textsuperscript{20}As usual, IV comparisons based on patients likely to be admitted to particular hospitals can be used to control for changes in patient mix associated with technology adoption. For example, technology adoption may change the likelihood of admission as well as outcomes for patients near to the hospital, and modeling hospital choice permits both effects to be identified.
effects when reimbursement issues are not directly involved. Further, peer review organizations generally do not disallow catheterizations based on reported diagnoses. The effect here appears to result from a more fundamental interaction of technology availability with norms of clinical practice. The availability of technology matters for the dynamics of medical practice patterns and for growth in health care costs.

In addition, the results provide considerable evidence for the validity of the differential-distance IV approach to estimating effects of treatments on outcomes, as a complement to randomized trials (McClellan and Newhouse, 1993). Since different types of hospitals tend to use different intensity bundles (i.e., hospital effects differ significantly for reasons exogenous to patient health status), differential distance can be used to analyze the magnitude of treatment differences for similar patients that is associated with technology availability.

The methods developed here represent a first step toward understanding the underlying causes of area variations in medical practice patterns. The framework permits an empirical decomposition of three factors that appear to be important contributors to observed area variations, each of which has quite different implications for policy:

1. Variations attributable to *provider characteristics*: Controlling for endogenous patient selection of hospitals, do hospital characteristics such as technology availability significantly influence treatment intensity choices?

2. *Within-provider* variations in treatment intensity: Does less intensive treatment in certain groups such as blacks, women, or rural patients arise from differences in decisions within a hospital, or reduced access to hospitals with more intensive technologies available?
(3) Variations in treatment intensity attributable to *neighborhood effects*: Do the practice patterns of nearby providers significantly affect the practice patterns of a given provider?

This empirical work has concentrated on questions (1) and (2), and demonstrates that the pure "area" effects in (3) may be smaller than suspected. To provide direct evidence on (3), panel data is required; as outlined in Section V, the estimation techniques used here can be extended directly to panel models. Panel analysis will also provide evidence on why hospitals adopt intensive technologies, leading to considerable variation in access to intensive treatments across areas. While this application has involved the treatment of acute myocardial infarction, the methods are potentially applicable to the analysis of other clinical problems for which intensive technologies are not available everywhere.
Appendix:

A Comparison of Generalized Method of Moments and Latent-Index Instrumental Variables Models

The grouped-data GMM framework used to estimate the IV models in the text subsumes parametric latent index models as special cases. Both the linear probability IV model and the probit IV model (e.g., Maddala, 1983, Chap. 8) are examples of such parametric latent-index models. These models use specific parametric and distributional assumptions not required for GMM estimation, and hence they are more likely to misspecify the underlying processes generating the data. Thus, the following discussion is more relevant as a practical guide to choosing among parametric IV methods; the GMM models actually estimated in the text provide consistent estimates of "local average" effects for observations affected by changes in the value of the instrument without making any parametric assumption beyond the existence of group means.

The models estimated in the text use GMM techniques to identify the effect of an endogenous treatment (in this case, the effect of admission to a particular type of hospital on treatment intensity). Alternatively, the models could be estimated using a latent-index specification. The form of the second-stage model is $r_i = F_i (x_i, c_i, q_i, h_i; \alpha, \gamma)$, where $\alpha$ is the constant additive treatment effect, $\gamma$ is a vector of covariate parameters to be estimated, and $h_i$ is an error term that includes unobserved aspects of the individual's health status. Similarly, hospital admission choice $q_i$ is also a function of $x_i, c_i$, and a set of unobserved factors captured in an error term $h_i$: $q_i = F_q (x_i, c_i, h_i; \beta)$, where $\beta$
parameterizes the function. The dependent variables in these equations are observed as binary indicators.

This system of equations is probably not identified because \( E(h'_i \mid q_i) \neq 0 \), as described in Section III of the text. A simple parameterization is \( h'_i = h_0^i + \epsilon'_i \), where \( h_0^i \) is an index of health status observed by medical personnel making treatment decisions and \( \epsilon'_i \) is a random error, and similarly \( h'_i = \theta h_0^i + \epsilon'_i \). Observation of instruments such as differential distances to alternative hospital types \( d_i \) that are correlated with procedure choice by a relation such as \( q_i = \text{F}_q(x_{ri}c_{ri}d_{ri}h_0^i) \) but are uncorrelated with \( h'_i \) and thus do not directly affect the \( \text{F}_r(.) \) equation determining outcomes may permit unbiased estimation of the effect of \( q_i \). In addition to Conditions 1-4 outlined in the Appendix to McClellan and Newhouse (1993), specification of this influence requires rather general but important assumptions about \( \text{F}_q(.) \) and \( \text{F}_r(.) \). Angrist (1991b) has derived sufficient conditions for estimation of average treatment effects using linear models that involve the additive separability of the expectations of these functions conditional on the observed covariates and the (unobserved) latent index. If either of the conditions

\[
(i) \quad E[\text{F}_q|x_{ri}c_{ri}d_{ri}h_0^i] = G_{q1}(x_{ri}c_{ri}d_{ri}) + G_{q2}(h_0^i)
\]

\[
(ii) \quad E[\text{F}_r|x_{ri}c_{ri}q_{ri}h_0^i] = G_{r1}(x_{ri}c_{ri}q_{ri}) + G_{r2}(h_0^i)
\]

(A1)

hold, where the \( G(.) \) denote conditional expectation functions, then the average treatment effect can be estimated consistently using a linear specification.

Such conditions are implicitly assumed in a wide variety of linear IV contexts, but IV estimation with models involving limited dependent variables raises additional consistency issues. Often, the observed binary response in these models is assumed to

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be a nonlinear function of an unobserved latent index. The corresponding system of equations is

\[ q_i^* = \beta_0^s + x_i \beta_1^s + c_i \beta_2^s + d_i \beta_3^s + h_i^q, \]

\[ q_i = 1 \text{ if } q_i^* > 0 \]
\[ = 0 \text{ if } q_i^* \leq 0; \]

\[ r_i^* = \gamma_0 + x_i \gamma_1 + c_i \gamma_2 + q_i \gamma_3 + h_i^r, \]

\[ r_i = 1 \text{ if } r_i^* > 0 \]
\[ = 0 \text{ if } r_i^* \leq 0; \]

Distributional assumptions are required for the individual error terms \( h_i^q \) and \( h_i^r \). For example, the system might be estimated by maximizing a bivariate probit likelihood function in which the joint distribution of \((h_i^q, h_i^r)\) is parameterized by \(G(., .; \theta, \gamma, \rho)\), where \( \rho \) is the correlation of \( h_i^q \) and \( h_i^r \) (Ashford and Sowden, 1970). The computational expense of multivariate maximum likelihood techniques is very high even with considerably smaller datasets and simpler models than those estimated here. Much more importantly, however, the coefficient estimates obtained through these methods are very sensitive to the assumption that the latent indices are distributed as bivariate normal (or as any other specific distributional structure). Even if the latent indices can be approximated by linear functions of the observed covariates, bivariate normality imposes substantial a priori structure on how changes in covariates of the "first-stage" \( q \) equations affect the "second-stage" \( r \) equation. If these structural assumptions are false, then the resulting coefficient estimates may be seriously inconsistent (Goldfield and Quandt, 1968; Kelejian, 1972).
For analyses using relatively small numbers of observations, the efficiency gains possible with such structural assumptions may outweigh inconsistency concerns. With very large datasets and cases where selection bias may have large effects, consistency and robustness are more critical concerns than marginal gains in asymptotic efficiency. While many econometric studies of the relative asymptotic efficiency of nonlinear estimators have been published, few studies have assessed the robustness of these nonlinear methods to departures from the underlying distributional assumptions. Intuitively, in the absence of strong prior knowledge of the nature of the nonlinearity in the structural system, estimators that primarily rely on plausible exclusion restrictions rather than distributional assumptions are less likely to lead to serious consistency errors. In this category are probit models that reflect the Angrist separability conditions in their latent index structure:

\[ q_i^* = \beta_0 + x_i\beta_1 + c_i\beta_2 + d_i\beta_3 + h_i^*, \]

\[ q_i = 1 \text{ if } q_i^* > 0 \]
\[ = 0 \text{ if } q_i^* \leq 0; \]

\[ r_i^* = \gamma_0 + x_i\gamma_1 + c_i\gamma_2 + q_i^*\gamma_3 + h_i^*, \]

\[ r_i = 1 \text{ if } r_i^* > 0 \]
\[ = 0 \text{ if } r_i^* \leq 0; \]

An advantage of this formulation is that misspecification of the first stage may not have serious consequences for consistency of the second stage coefficient estimates. In two-stage procedures, correct specification of the first stage is not necessary for consistent second-stage estimates; what is necessary is that the resulting predicted values are
uncorrelated with the second-stage errors (Kelejian, 1972). Two-stage methods based on (A3) are thus considerably more robust than (A2).²¹

Can (A3) be justified in the context of the present econometric problem? Heckman (1977) distinguishes between the discrete effect of a genuine shift associated with use of a "treatment" and the continuous effect of underlying "sentiment." In the context of medical care, treatment intensity for a specific patient clearly undergoes a discrete shift based on whether or not he is admitted to an intensive hospital; in spite of its favorable robustness properties, the latent index function seems less relevant to the patient's intensity choice. But relevant policy implications of procedure effectiveness, especially in datasets with limited clinical detail such as claims information, are more closely related to epidemiology than to clinical decisionmaking at patient level: how does the tendency to use specific procedures--medical practice patterns--influence aggregate patient outcomes? Variations in practice patterns as a function of observed covariates may be appropriately captured in an unobserved latent index q* that influences the likelihood of observing a particular admission choice. The index q* is a parameterization of the expected propensity for admission for the patient; similarly, the r* index is a parameterization of the patient's likelihood of receiving intensive treatment. Both are continuous, unobserved variables; only the realizations of hospital admission q and treatment intensity r are observed. Most policy interventions -- for example, restricting the diffusion of certain medical technologies -- will influence the treatment of individual

²¹Some empirical papers have used two-stage techniques in which nonlinear transformations of the fitted values from the first stage, for example Φ(ŷₖ) or a 0/1 binary function of ŷₖ, are used in the second stage. In general, in systems where the differences between endogenous and true coefficient estimates are substantial, these methods will be inconsistent for the reasons noted: the expectation of a function is not equal to the function of an expectation.
patients only through their effect on $q^*$. Consequently, though a model based on latent
index functions has limited application to individual patients, it may be the best
formulation from the standpoint of policy relevance and consistency.\(^{22}\)

Many of the difficulties of consistent nonlinear IV specification--such as the use of
discrete shifts versus latent indices and the imposition of nonlinear identifying restrictions
contained in distributional assumptions--are specific to models with nonlinear functional
form assumptions. If a linear probability structure is modeled, the latent index model
may be less conceptually objectionable since the latent index and the predicted
probabilities are identical. Moreover, identification of the equation system clearly results
from separability assumptions such as exclusion restrictions. In a series of Monte Carlo
simulations, Angrist (1991) demonstrated that the bias in coefficient estimates from linear
IV models compared favorably to probit maximum likelihood models even when the true
distribution was nonlinear. The approximations were particularly good for observations
concentrated in the linear range of the nonlinear distributions. Even in a nonlinear range,

\(^{22}\) Mallar (1977) and Maddala (1983, Chap. 8) describe two-stage techniques for estimation
of the system in (10) if the residuals conditional on the instruments are uncorrelated. Modeling
correlations between these residuals, as before, requires estimation of a full bivariate maximum
likelihood model and is sensitive to the cross-equation structure imposed (Stern, 1989). Methods
for calculating the correct covariance matrix are described in Maddala (1983, p. 247) and Stern
(1989, Appendix). The covariance matrix formula in Maddala contains an error in the definition
of the $Z$ matrix: $Z_{i} = [X_{i1}, X_{i2}]$, for $i,j = 1,2$ and $i \neq j$. Moreover, calculation of the covariance
expectation term in Maddala's $W_4$ matrix involves maximization of a joint density function (i.e.,
nonzero correlation between errors); if the errors are uncorrelated, then $W_4 = 0$.

Alternative nonlinear IV estimation strategies have been described which are asymptomatically more efficient than the two-stage methods (Amemiya, 1978; Lea, 1981; Newey,
1987). Whether these alternative methods are worthwhile depends on their additional
computational cost and the magnitude of the efficiency and robustness consequences relative to
the two-stage IV methods. Limited empirical evidence suggests the gains over the two-stage
procedures are small. Since the potential computational and robustness expenses are large, the
nonlinear models estimated in this study were two-stage probits.

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if the sample size is large and the effect of the endogenous variable modest, a linear approximation was benign. Problems with a linear specification include the fact that it may also represent a potential misspecification of the true distribution and that estimation yields some predicted probabilities beyond the [0,1] interval as well as heteroskedastic error terms. Heteroskedasticity does not affect the consistency of the coefficient estimates, and efficient estimation methods consistent in the presence of heteroskedasticity can be used (White, 1982). Whether the predictions out of range and the assumption of linearity have serious empirical consequences in part can be tested by comparing the linear, nonlinear, and GMM results. In this study, various two-stage probit and linear specifications were estimated, and in all cases the resulting coefficient estimates led to identical estimated effects. For these reasons, as well as ease of interpretation, only GMM results are presented in the text.
FIGURE 1:
CUMULATIVE DISTRIBUTION OF PATIENT DISTANCES TO THE NEAREST ACUTE-CARE HOSPITAL

FIGURE 2:
CUMULATIVE DISTRIBUTION OF PATIENT DISTANCES TO THE NEAREST CATHETERIZATION HOSPITAL
FIGURE 3:
THE RELATIONSHIP BETWEEN DIFFERENTIAL DISTANCE AND PROBABILITY OF ADMISSION TO A CATHETERIZATION HOSPITAL.
FIGURE 4:  
THE EFFECT OF ADMISSION TO A CATHETERIZATION HOSPITAL ON PROBABILITY OF CATHETERIZATION
FIGURE 5:
DIFFERENTIAL DISTANCE, PROBABILITY OF CATHETERIZATION,
AND PROBABILITY OF DIAGNOSIS WITH ANGINA

○ Res Prob(90-Day Cath)  △ Res Prob(Angina Diagnosis)
# TABLE Ia:
CHARACTERISTICS OF ELDERLY AMI PATIENTS

<table>
<thead>
<tr>
<th></th>
<th>ALL PATIENTS (N=205,021)</th>
<th>FEMALE PATIENTS (N=103,240)</th>
<th>MALE PATIENTS (N=101,781)</th>
<th>BLACK PATIENTS (N=11,576)</th>
<th>WHITE PATIENTS (N=193,445)</th>
</tr>
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<tbody>
<tr>
<td>Female</td>
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<td>(7.44)</td>
<td>(6.80)</td>
<td>(7.36)</td>
<td>(7.25)</td>
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<td>Urban Patients (N=144,641)</td>
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<td>---------------------------</td>
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<td></td>
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</tr>
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<td>50.4</td>
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<td>0.0</td>
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<tr>
<td>Cancer</td>
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<tr>
<td>Dementia</td>
<td>0.99</td>
<td>0.94</td>
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<td>1.94</td>
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<tr>
<td>Cerebrovascular Disease</td>
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<td>MALE PATIENTS (N=101,781)</td>
<td>BLACK PATIENTS (N=11,576)</td>
<td>WHITE PATIENTS (N=193,445)</td>
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<td>5.44</td>
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<tr>
<td>CABG Within 7 Days</td>
<td>3.70</td>
<td>2.69</td>
<td>4.74</td>
<td>2.12</td>
<td>3.80</td>
</tr>
<tr>
<td>CABG Within 90 Days</td>
<td>7.74</td>
<td>5.61</td>
<td>9.91</td>
<td>4.01</td>
<td>7.96</td>
</tr>
<tr>
<td></td>
<td>ALL PATIENTS (N=205,021)</td>
<td>RURAL PATIENTS (N=60,380)</td>
<td>URBAN PATIENTS (N=144,641)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>--------------------------------</td>
<td>--------------------------</td>
<td>---------------------------</td>
<td>---------------------------</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Admit to Catheterization Hosp.</td>
<td>45.9</td>
<td>18.7</td>
<td>57.2</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Catheterization During Initial Hospitalization</td>
<td>12.0</td>
<td>6.39</td>
<td>14.4</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Catheterization Within 7 Days</td>
<td>15.9</td>
<td>11.9</td>
<td>17.5</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Catheterization Within 30 Days</td>
<td>19.8</td>
<td>16.8</td>
<td>21.1</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Catheterization Within 90 Days</td>
<td>22.8</td>
<td>20.3</td>
<td>23.8</td>
<td></td>
<td></td>
</tr>
<tr>
<td>PTCA Within 7 Days</td>
<td>3.87</td>
<td>3.00</td>
<td>4.23</td>
<td></td>
<td></td>
</tr>
<tr>
<td>PTCA Within 90 Days</td>
<td>5.30</td>
<td>4.40</td>
<td>5.67</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CABG Within 7 Days</td>
<td>3.70</td>
<td>2.98</td>
<td>4.00</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CABG Within 90 Days</td>
<td>7.74</td>
<td>6.89</td>
<td>8.10</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
### TABLE 2:
**PATIENT CHARACTERISTICS AND INTENSIVE PROCEDURE USE BY SITE OF INITIAL ADMISSION**

<table>
<thead>
<tr>
<th></th>
<th>NON-CATH HOSPITAL (N=110,933)</th>
<th>CATH HOSPITAL (N=40,382)</th>
<th>MAJOR REVASC. HOSPITAL (N=53,706)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Patient Characteristics</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>50.9</td>
<td>51.6</td>
<td>48.2</td>
</tr>
<tr>
<td>Black</td>
<td>5.05</td>
<td>6.13</td>
<td>6.52</td>
</tr>
<tr>
<td>Age</td>
<td>76.4</td>
<td>75.9</td>
<td>75.6</td>
</tr>
<tr>
<td>(Standard Deviation)</td>
<td>(7.29)</td>
<td>(7.22)</td>
<td>(7.20)</td>
</tr>
<tr>
<td>Rural</td>
<td>44.3</td>
<td>11.8</td>
<td>12.2</td>
</tr>
<tr>
<td>Cancer</td>
<td>1.80</td>
<td>1.95</td>
<td>2.04</td>
</tr>
<tr>
<td>Pulmonary Disease</td>
<td>11.1</td>
<td>11.0</td>
<td>9.75</td>
</tr>
<tr>
<td>Dementia</td>
<td>0.99</td>
<td>1.00</td>
<td>0.89</td>
</tr>
<tr>
<td>Diabetes</td>
<td>18.4</td>
<td>18.4</td>
<td>16.8</td>
</tr>
<tr>
<td>Renal Disease, Uncomplicated</td>
<td>1.97</td>
<td>1.98</td>
<td>1.76</td>
</tr>
<tr>
<td>Cerebrovascular Disease</td>
<td>4.94</td>
<td>4.64</td>
<td>4.64</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Intensive Procedure Use</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Catheterization</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>During Initial Hospital Admission</td>
<td>0</td>
<td>16.4</td>
<td>32.7</td>
</tr>
<tr>
<td>Catheterization within 7 Days</td>
<td>6.53</td>
<td>18.8</td>
<td>32.9</td>
</tr>
<tr>
<td>Catheterization within 30 Days</td>
<td>12.1</td>
<td>21.8</td>
<td>34.3</td>
</tr>
<tr>
<td>Catheterization within 90 Days</td>
<td>15.6</td>
<td>24.6</td>
<td>36.3</td>
</tr>
<tr>
<td>PTCA within 7 Days</td>
<td>1.38</td>
<td>2.14</td>
<td>10.3</td>
</tr>
<tr>
<td>PTCA within 90 Days</td>
<td>2.82</td>
<td>4.13</td>
<td>11.3</td>
</tr>
<tr>
<td>CABG within 7 Days</td>
<td>1.94</td>
<td>2.85</td>
<td>7.99</td>
</tr>
<tr>
<td>CABG within 90 Days</td>
<td>5.93</td>
<td>8.38</td>
<td>11.0</td>
</tr>
</tbody>
</table>
### TABLE 3:
DESCRIPTIVE STATISTICS BY DIFFERENTIAL DISTANCE TO A CATHETERIZATION OR REVASCULARIZATION HOSPITAL

<table>
<thead>
<tr>
<th>RATE (%)</th>
<th>≤2 miles (N=102,744)</th>
<th>&gt;2 miles (N=102,277)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Patient Characteristics</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>51.2</td>
<td>49.5</td>
</tr>
<tr>
<td>Black</td>
<td>7.1</td>
<td>4.20</td>
</tr>
<tr>
<td>Age in Years (Standard Deviation)</td>
<td>76.1 (7.29)</td>
<td>76.1 (7.22)</td>
</tr>
<tr>
<td>Rural</td>
<td>7.25</td>
<td>51.7</td>
</tr>
<tr>
<td>Cancer</td>
<td>1.93</td>
<td>1.85</td>
</tr>
<tr>
<td>Pulmonary Disease</td>
<td>10.4</td>
<td>10.9</td>
</tr>
<tr>
<td>Dementia</td>
<td>0.99</td>
<td>0.94</td>
</tr>
<tr>
<td>Diabetes</td>
<td>18.0</td>
<td>18.0</td>
</tr>
<tr>
<td>Renal Disease, Uncomplicated</td>
<td>1.98</td>
<td>1.85</td>
</tr>
<tr>
<td>Cerebrovascular Disease</td>
<td>4.78</td>
<td>4.82</td>
</tr>
<tr>
<td>Intensive Procedure Use</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Admit to Catheterization Hosp.</td>
<td>34.0</td>
<td>5.4</td>
</tr>
<tr>
<td>Admit to Revascularization Hosp.</td>
<td>41.2</td>
<td>11.1</td>
</tr>
<tr>
<td>Catheterization During Initial Hospital Admission</td>
<td>18.3</td>
<td>5.72</td>
</tr>
<tr>
<td>Catheterization within 7 Days</td>
<td>20.5</td>
<td>11.1</td>
</tr>
<tr>
<td>Catheterization within 30 Days</td>
<td>23.5</td>
<td>16.2</td>
</tr>
<tr>
<td>Catheterization within 90 Days</td>
<td>26.0</td>
<td>19.6</td>
</tr>
<tr>
<td>PTCA within 7 Days</td>
<td>4.88</td>
<td>2.85</td>
</tr>
<tr>
<td>PTCA within 90 Days</td>
<td>6.30</td>
<td>4.30</td>
</tr>
<tr>
<td>CABG within 7 Days</td>
<td>4.50</td>
<td>2.90</td>
</tr>
<tr>
<td>CABG within 90 Days</td>
<td>8.54</td>
<td>6.94</td>
</tr>
</tbody>
</table>
TABLE 4:
LEAST-SQUARES ESTIMATES OF THE EFFECTS OF PATIENT CHARACTERISTICS ON TREATMENT DECISIONS FOR ELDERLY AMI PATIENTS

<table>
<thead>
<tr>
<th>Probability of Catheterization (Percent)</th>
<th>(1) DURING INITIAL HOSPITALIZATION</th>
<th>(2) WITHIN 7 DAYS</th>
<th>(3) WITHIN 30 DAYS</th>
<th>(4) WITHIN 90 DAYS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nonblack Patients</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Prob. (Catheterization) for Reference Patient¹</td>
<td>23.4 (0.3)</td>
<td>29.8 (0.3)</td>
<td>36.3 (0.3)</td>
<td>41.4 (0.4)</td>
</tr>
<tr>
<td>Rural Residence Effect²</td>
<td>-11.1 (0.2)</td>
<td>-8.5 (0.2)</td>
<td>-6.8 (0.2)</td>
<td>-5.8 (0.2)</td>
</tr>
<tr>
<td>Female Effect³</td>
<td>-2.9 (0.1)</td>
<td>-3.6 (0.2)</td>
<td>-4.3 (0.2)</td>
<td>-5.0 (0.2)</td>
</tr>
<tr>
<td>Black Patients</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Prob. (Catheterization) for Reference Patient¹</td>
<td>19.1 (1.1)</td>
<td>22.5 (1.2)</td>
<td>26.7 (1.3)</td>
<td>30.1 (1.4)</td>
</tr>
<tr>
<td>Rural Residence Effect²</td>
<td>-11.3 (0.8)</td>
<td>-9.4 (0.8)</td>
<td>-7.9 (0.9)</td>
<td>-7.5 (0.9)</td>
</tr>
<tr>
<td>Female Effect³</td>
<td>-2.2 (0.6)</td>
<td>-2.3 (0.6)</td>
<td>-2.8 (0.7)</td>
<td>-3.3 (0.7)</td>
</tr>
</tbody>
</table>

¹ The "reference patient" is a male aged 65 to 69 living in an urban area.

² The reported effect of rural residence is an average of the estimated rural residence effects for each demographic cell of rural patients, weighted by the number of patients in the cell.

³ The reported effect of female sex is an average of the estimated female effects for each demographic cell of female patients, weighted by the number of patients in the cell.
<table>
<thead>
<tr>
<th>Probability of Catheterization (Percent)</th>
<th>During Initial Hospitalization Within 7 Days</th>
<th>Within 30 Days</th>
<th>Within 90 Days</th>
</tr>
</thead>
<tbody>
<tr>
<td>LS</td>
<td>IV</td>
<td>LS</td>
<td>IV</td>
</tr>
<tr>
<td>(1) Nonblack Patients</td>
<td>(2) Within 7 Days</td>
<td>(3) Within 30 Days</td>
<td>(4) Within 90 Days</td>
</tr>
<tr>
<td>8.4</td>
<td>18.1 (0.3)</td>
<td>26.9 (0.3)</td>
<td>32.8 (0.4)</td>
</tr>
<tr>
<td>0.3</td>
<td>0.3 (0.3)</td>
<td>0.7 (0.3)</td>
<td>0.5 (0.3)</td>
</tr>
<tr>
<td>-0.4</td>
<td>-0.4 (0.3)</td>
<td>-0.4 (0.3)</td>
<td>-0.4 (0.3)</td>
</tr>
<tr>
<td>-2.4</td>
<td>-2.4 (0.1)</td>
<td>-3.2 (0.2)</td>
<td>-4.0 (0.2)</td>
</tr>
<tr>
<td>-1.2</td>
<td>-1.2 (0.1)</td>
<td>-1.2 (0.2)</td>
<td>-1.2 (0.2)</td>
</tr>
<tr>
<td>16.0</td>
<td>14.5 (0.3)</td>
<td>10.4 (0.2)</td>
<td>8.6 (0.2)</td>
</tr>
<tr>
<td>0.2</td>
<td>0.2 (0.2)</td>
<td>0.2 (0.2)</td>
<td>0.2 (0.2)</td>
</tr>
</tbody>
</table>

1 The "reference patient" is a male patient aged 65 to 69 living in an urban area who is admitted to a non-catheterization hospital.
2 The reported effect of rural residence is an average of the estimated rural residence effects for each demographic cell of rural patients, weighted by the number of patients in the cell.
3 The reported effect of female sex is an average of the estimated female effects for each demographic cell of female patients, weighted by the number of patients in the cell.

ESTIMATES OF THE EFFECTS OF HOSPITAL TECHNOLOGY AVAILABILITY ON TREATMENT DECISIONS FOR ELDERLY AMI PATIENTS...
<table>
<thead>
<tr>
<th></th>
<th>(1) DURING INITIAL HOSPITALIZATION</th>
<th>(2) WITHIN 7 DAYS</th>
<th>(3) WITHIN 30 DAYS</th>
<th>(4) WITHIN 90 DAYS</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>LS</td>
<td>IV</td>
<td>LS</td>
<td>IV</td>
</tr>
<tr>
<td>Prob. (Catheterization) for Reference Patient(^1)</td>
<td>7.7</td>
<td>8.2</td>
<td>12.9</td>
<td>13.7</td>
</tr>
<tr>
<td>Rural Residence Effect(^2)</td>
<td>-1.9</td>
<td>-2.4</td>
<td>-1.6</td>
<td>-2.3</td>
</tr>
<tr>
<td>Female Effect(^3)</td>
<td>-2.5</td>
<td>-2.5</td>
<td>-2.5</td>
<td>-2.5</td>
</tr>
<tr>
<td>Effect of Admission to Catheterization Hospital</td>
<td>12.6</td>
<td>11.1</td>
<td>10.0</td>
<td>7.5</td>
</tr>
<tr>
<td>Additional Effect of Admission to Revasc. Hospital</td>
<td>10.0</td>
<td>10.9</td>
<td>9.0</td>
<td>11.1</td>
</tr>
</tbody>
</table>

\(^1\) The "reference patient" is a male patient aged 65 to 69 living in an urban area who is admitted to a noncatheterization hospital.

\(^2\) The reported effect of rural residence is an average of the estimated rural residence effects for each demographic cell of rural patients, weighted by the number of patients in the cell.

\(^3\) The reported effect of female sex is an average of the estimated female effects for each demographic cell of female patients, weighted by the number of patients in the cell.
TABLE 6:
PATIENT CHARACTERISTICS AND INTENSIVE PROCEDURE USE
BY TYPE OF HOSPITAL AT INITIAL ADMISSION
FOR PATIENTS DIFFERENTIALLY NEAR AND FAR FROM CATHETERIZATION

<table>
<thead>
<tr>
<th>Differential Distance to Catheterization Hospital ≤ 2 mi (N=102,744)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non-Cath Hospital (N=25,479)</td>
</tr>
<tr>
<td>Share of Patients in Diff. Distance Group</td>
</tr>
<tr>
<td>Female</td>
</tr>
<tr>
<td>Black</td>
</tr>
<tr>
<td>Age (Standard Deviation)</td>
</tr>
<tr>
<td>Diabetes</td>
</tr>
<tr>
<td>Cancer</td>
</tr>
<tr>
<td>Pulmonary Disease, Uncomplicated</td>
</tr>
<tr>
<td>7-Day Cath.</td>
</tr>
<tr>
<td>90-Day Cath.</td>
</tr>
<tr>
<td>Stable Angina</td>
</tr>
<tr>
<td>Unstable Angina</td>
</tr>
<tr>
<td>Stable Angina</td>
</tr>
<tr>
<td>Unstable Angina</td>
</tr>
</tbody>
</table>

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<table>
<thead>
<tr>
<th>DIFFERENTIAL DISTANCE TO CATHETERIZATION HOSPITAL &gt; 2 mi (N=102,277)</th>
<th>NON-CATH HOSPITAL (N=85,454)</th>
<th>CATH HOSPITAL (N=5,499)</th>
<th>REVASC. HOSPITAL (N=11,324)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Share of Patients in Diff. Distance Group</td>
<td>83.55</td>
<td>5.38</td>
<td>11.07</td>
</tr>
<tr>
<td>Female</td>
<td>50.25</td>
<td>48.77</td>
<td>43.93</td>
</tr>
<tr>
<td>Black</td>
<td>4.27</td>
<td>4.02</td>
<td>3.83</td>
</tr>
<tr>
<td>Age (Standard Deviation)</td>
<td>76.31 (7.25)</td>
<td>75.54 (7.13)</td>
<td>74.49 (6.83)</td>
</tr>
<tr>
<td>Diabetes</td>
<td>18.2</td>
<td>18.2</td>
<td>16.2</td>
</tr>
<tr>
<td>Cancer</td>
<td>1.83</td>
<td>2.18</td>
<td>1.86</td>
</tr>
<tr>
<td>Pulmonary Disease, Uncomplicated</td>
<td>11.09</td>
<td>11.47</td>
<td>9.73</td>
</tr>
<tr>
<td>7-Day Cath.</td>
<td>6.59</td>
<td>20.49</td>
<td>40.97</td>
</tr>
<tr>
<td>90-Day Cath.</td>
<td>15.92</td>
<td>26.64</td>
<td>44.21</td>
</tr>
<tr>
<td>Stable Angina</td>
<td>19.51</td>
<td>27.59</td>
<td>38.07</td>
</tr>
<tr>
<td>Unstable Angina</td>
<td>3.94</td>
<td>6.04</td>
<td>7.60</td>
</tr>
<tr>
<td>Stable Angina</td>
<td>24.62</td>
<td>46.55</td>
<td>54.71</td>
</tr>
<tr>
<td>Unstable Angina</td>
<td>10.35</td>
<td>11.67</td>
<td>11.75</td>
</tr>
</tbody>
</table>
REFERENCES


Carter, Grace, Joseph P. Newhouse, and Daniel Relles, 1990, drg creep


Newhouse, Joseph P., 1988, "Has the Erosion of the Medical Marketplace Ended?" *Journal of Health Policy, Politics, and Law*.


