# APPLICATIONS OF DECISION ANALYSIS TO HEALTH CARE

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# APPLICATIONS OF DECISION ANALYSIS TO HEALTH CARE

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# SUMMARY

This dissertation deals with three problems in health care. In the first, we consider the incentives to change prices and capital levels at hospitals, when private payers depend on hospitals to provide services for patients. We develop an optimal control model of prices and capital formation over time, and analyze the expected effects from the structure built into the assumptions.

In the second, we focus on the flow of nosocomial infections in an intensive care unit. Nosocomial infections are a sub-set of healthcare acquired infections, namely those caught while a patient at a hospital. In the U.S. these infections occur on the order of two million per year, of whom roughly one hundred thousand die. In our discrete-event simulation we investigate the relative impact of hand-hygiene and isolation policies, and incorporate cost. We find that hand-hygiene is a more powerful tool, provided compliance with hand-hygiene policy can reliably be improved.

In the third essay, we analyze a proposed change in diversion policies at hospitals, in order to increase the number of patients served, without an increase in resources. We use a continuous time Markov chain model to show that our policy decreases the time a hospital spends on diversion under our scheme. We then use data to parameterize a discrete-event simulation, in order to add revenue to the model. As expected, the hospital increases its revenue by reserving some beds for high-paying patients. However, another simulation of two hospitals, show that the policy increases the number of low-paying patients served by the system overall, a result due to the avoidance of system-wide ambulance diversion.

# CHAPTER I

# INTRODUCTION

Health care in the U.S., especially the plight of uninsured and the rising costs, is a prominent political topic in the current presidential campaign. Costs have grown much faster than the general CPI. The system is highly complex, with a large number of interested parties. Many find the intimate link between health and financial resources troubling.

In this dissertation, we address some of the aspects of this system, unravel some of the incentives, and examine potential solutions to specific problems. The common thread is provided not only by the topic of health care, but by the focus on incentives faced by each party, and by the explicit inclusion of financial aspects.

## *1.1 Repeated Negotiations in Health care: Hospitals and Payers*

Health care costs in the U.S. have been characterized as exploding, and they are certainly much higher as a percentage of GDP than other OECD nations. Since Clinton's failed reform in the early nineties, political fixes have been suggested, and in the current presidential campaign (2008), almost every candidate has a plan for health care.

The current system, dominated by employer benefits, came about when the federal government imposed wage caps during World War II. Employers responded by competing for workers using benefits, and the popularity of health benefits made it impossible to remove the linkage after the war. The fact that firms may deduct health costs pre-tax, while individuals may not, gives employees a strong incentive to demand health benefits from the firms. However, aside from the tax advantage, there is no obvious reason why health benefits should have any link to employment. Given the vulnerability of the unemployed, it is easy to argue the opposite.

The tax shelter for firms, the fact that patients were only responsible for small co-pays, the constrained supply of physicians, are among the reasons that have been put forward to explain the troubling price increases in health care in the decades after WWII. Health Maintenance Organizations (HMO's) were introduced to emphasize preventive care, and to control costs. Given that these entities are largely for profit, benefit from patients' limited use of health care, and also to shifting costs to providers, it is not surprising that HMO's are not universally popular with patients and doctors. Also, in the last few years, cost increases have accelerated, in spite of the prevalence of HMO's.

We therefore consider the role of the private payers, and what incentives these have with regard to the provision of hospital care to their patients. The critical assumption is that HMO's sell hospital provided services at a markup. We recognize that this is an approximation, since prices tend to be fixed over the contract period, typically one year. Nevertheless, it is not a stretch to imagine that higher hospital prices one year, will lead to higher HMO charges in the following years.

In order to examine the effects of such assumptions on prices, we develop and analyze an optimal control model. Over time, we find that prices and the hospital capital stock grow proportionally, and without bound. This explosive behavior is clearly only an approximation, since the pain of such excessive price increases will lead to political fixes, especially when there is no functioning market discipline. Still, we observe the explosive growth in prices, and many have also noted the remarkable growth in medical capital. We find a limited amount of empirical support for the model, but suggest it is one step in understanding the link between HMO's, hospitals, capital stock, and prices.

## 1.2 A Simulation Model to Compare Strategies for the Reduction of Healthcare-Associated Infections

Infections that are acquired at a healthcare institution is defined as a "healthcare associate infection", or HAI. In the past, specifically hospital acquired infections were termed *nosocomial*. In the US, there are approximately two million such infections per year, of which roughly one hundred thousand lead to death. The situation in the rest of the world is also serious. The problem is exacerbated by various pathogens' growing resistance to antibiotics. The term *pathogen* is used for all organic entities that may cause an infection. Pathogens come and go like fashion, and currently Methicillin-resistant Staphylococcus aureus (MRSA) and Vancomycin-Resistant Enterococcus (VRE) are most troubling.

Since it is difficult to measure precisely when a patient was exposed to an infectious pathogen, and many individuals may be asymptomatic, it is hard to even know whether or not a given infection is an HAI. Clearly, individuals may be exposed to pathogens outside of hospitals or long-term care facilities, in which case the infection is classified as community acquired. Finally, the attachment of a pathogen to an individual only leads to the individual being *colonized*, not necessarily infected. The interaction of the infection with treatment, immune system and illness, and other patients and visitors, make it extremely challenging to decide what impact any given HAI may have.

In spite of the measurement difficulties, the growing toll of HAI's is a problem Congress recognizes. It is therefore considering different regulations. The CDC is required to do cost versus benefit analyses for new regulations on public health, and the end goal of this stream of research is an economic analysis of the various approaches to constrain HAI's.

Various measures include forced reporting, isolation and quarantine, limiting the use of anti-biotics, and expanding the use of prosaic measures such as hand-hygiene.

All of these have champions and detractors, and in order to make a first start, we consider the flow of pathogens through an ICU, using cost data from Cook County Hospital.

We simulate the flow of patients, visitors, and health-care workers (HCW), as well as pathogens, through the ICU, and measure the cost of treatment. This enables us to differentiate the effects of hand-hygiene and isolation, and to assess an overall cost of an HAI.

In the future, we expect to build models for different types of hospitals across the nation. These models will be used as input into a larger cost-benefit analysis of regulation to combat HAIs.

## *1.3 The Effect of Flexible Hospital Contracts on Emergency Department Diversion*

There are fewer hospital beds and emergency departments (ED) in the U.S. today than there were ten years ago, without a similar decrease in demand. ED overcrowding is becoming a nationwide problem, not least because EDs are crucial in disaster response, as well as the only medical resource for the uninsured. One major cause of ED overcrowding is boarding, i.e. the practice of holding on to patients in the ED, while waiting for a bed to open up in the regular hospital wards. Although the uninsured only lay legal claim to beds in the ED, the privately insured, and those insured under Medicare and Medicaid (M/M), often remain in the ED for significant waiting periods. When medical conditions warrant, the ED physician in charge may place the ED on ambulance diversion (AD). This means 911 operators are not to send ambulances to the ED, although walk-ins still occur. Since there is some effort in going on and off AD, hospitals leave the AD in place until conditions have improved, i.e. beds have opened up. Operations research methods, especially queuing models, appear appropriate to model the system of ED and hospital beds.

The opportunity to model the system and include variance of demand, as well as the mean level of demand, would in itself help in planning future capacity. However, there is a simpler avenue, similar to changing software, while retaining the hardware. The Federal government has immense purchasing power via the M/M contracts, and dictate terms of contracts with hospitals. Two aspects of these contracts are especially salient. First, the prices paid are significantly lower than those paid by private insurers. Second, if a hospital takes one M/M patient, the hospital must take every such patient. This rigidity appears fair, but may not be necessary.

In metro areas with at least two hospitals in close proximity, ambulances often may deliver patients to one or the other hospital based on a number of factors, e.g. insurance, personal physician preferences, or family preferences. Physicians tend to prefer that EMS personnel not make medical decisions, but otherwise, the routing of patients to different hospitals is routine. This gives an opportunity to lower overcrowding by adding one degree of freedom to the contract between hospitals and the Federal government.

Specifically, we suggest that the Federal government allow M/M patients to be diverted before the hospital goes on full AD. This would have the following expected benefits: 1. The hospital would lessen the arrival rate of patients, while retaining the highest-revenue private patients. 2. The federal government would gain hospitals that are off AD more, and hence better prepared for disaster. To the extent that the hospitals increase revenue, the government may also choose to decrease the amount paid for service for M/M patients. 3. Patients benefit through the hospital being off AD and better disaster preparedness as well. The uninsured and the privately insured patients only benefit from this method. Those insured by the government benefit from the improved disaster preparedness, but may have a more constrained choice of hospital. This method is therefore limited to systems that have multiple hospitals within a metropolitan area.

In order to operationalize this method, we specify a fixed level of hospital ward beds that must be freed up before a hospital will go off full AD. In addition, we suggest a secondary partial diversion (PD) level, at which point the hospital selectively diverts M/M patients. We model this using a Markov process, and find that as expected, we are able to significantly decrease the time spend on AD, with a very minor change.

Using data from DeKalb Medical Center in Atlanta to parameterize a simulation model, we also found that revenue for the hospital increased for certain levels of partial diversion. Hence we have found a method that is simple to implement due to the pricing power of the federal government, and which both decreases overcrowding and increases revenue and supply. Against the loss of choice for M/M patients, we must therefore weigh the opportunity to decrease ED overcrowding, increase disaster preparedness, increase revenue for hospitals, and increase average overall capacity of hospitals.

# CHAPTER II

# REPEATED NEGOTIATIONS IN HEALTHCARE: HOSPITALS AND PAYERS

## *2.1 Introduction*

Policy makers have a difficult problem in designing health systems. In order to understand the effects of structural variables on health outcomes at the aggregate level, feedback effects over time are important. In this paper, a dynamic model of the iterated negotiations between hospitals and payers is analyzed to capture the goal of the hospital to provide more services, and the payers to maximize profit over the long-term. The latter effect drives a price for hospital services sufficiently high that it allows hospitals to increase their capital stock, while the additional cost to payers is recouped later. The key result of this model is that prices will grow proportionately to the capital stock. Even without new medical technology, the model suggests that prices will grow explosively, rather than reaching an equilibrium.

### 2.1.1 Overview

From a systems engineering perspective, the U.S. health care sector may be regarded as system designed to reach multiple goals, both for individuals and in aggregate. Applying such a perspective, which has roots more than half a century old ([57]), means using operations research tools to model and improve the system. The decision variables for the policy makers are the parameters that enter whichever sub-system that is being studied. In this paper, we focus on the relationship between hospitals and private payers over time. More narrowly, we investigate how the structure of the hospital-payer system and the contract process impact the prices and capital base over an infinite horizon.

Hospitals and payers such as health maintenance organizations (HMO's) agree to contracts that specify services and prices. These contracts are typically for one year in duration ([8]), but are often extended or minimally amended ([78]). Both parties expect to enter into a new contract after any current contract expires, and this expected continuation can have both intuitive and unexpected effects on the negotiations. We wish to explore the implications of repeated negotiations on yearly contracts between hospitals and payers.

In general, hospitals provide prices for the uninsured, take Medicare and Medicaid prices as given, but negotiate with payers such as HMO's and PPO's over the terms of yearly contracts ([78]). Medicare and medicaid patients provide far less revenue ([69]), and self-insured often do not pay at all ([77]). Since both parties depend on each other, each has an incentive to make sure the other is financially viable. In particular, payers are aware that they depend on selling the services hospitals provide to future patients, and so would like to see increased capital expenditures to facilitate more medical products on offer ([38]). Patients are insulated from the direct costs of their demand for medical services through medical insurance and the traditional deference shown to doctors regarding their own treatment. Hence the structure of health care markets is unusual.

The purpose of this study is to examine the impact of incentives that hospitals and payers operate under through repeated negotiations. We assume that hospitals take the prices that payers offer, since these are generally profitable ([76]), and invest surplus in capital. Insurance firms are assumed to maximize the net present value of their cash flow and select prices to drive capital formation. Patients are assumed to do as their doctors order, and utilize the services hospitals provide, and through small co-pays are largely shielded from the cost of providing those services. Firms are not assumed to exert major cost-cutting pressure. To make the problem tractable, we assume continuous time pricing decisions are made, so that the solution to the maximization problem is really a price function of time, or a price path.

In the following we provide a brief review of the literature. A mathematical model captures the simplified incentives of the parties involved. This model is presented in Section 3 with steady state and long term implications. Data from a regional hospital is used to compare with the model implications in Section 4. Finally we consider what implications this model suggests, and indicate future directions of study.

## *2.2 Literature Review*

Inflation in U.S. health care costs have been a matter of concern for decades, and remains a common topic in both the popular press and academic journals. In a recent edition of BusinessWeek, Tom Daschle ([35]) states that “The biggest frustration during my 26 years in Congress was our failure to address the health cost crisis.” In a recent survey ([4]), The Economist stated the U.S. health-care system was in a crisis and close to collapse. The survey further pointed out two key points. First, the traditional explanations for increasing medical costs are not entirely convincing. Technology improvement is not limited to the U.S. and could be dedicated to cost-saving, e.g., through better handling of data. Nor is an aging population, with resultant increased demand for health services, a problem unique to the U.S. Second, the market for medical technology is insulated from budgets. In fact, the survey suggests there is little reason to treat health as a classic competitive market.

In the Operations Research literature, health systems are instead regarded as tools that may be adjusted to reach a goal ([57]). A large number of studies have been undertaken, e.g. more than a hundred surveyed ([88]) in Decision Analysis alone prior to 1980. Public interest goals include minimizing the discounted cost from infection in an epidemic ([94]) or the average cost of a policy to stabilize a population ([111]). Morey and Dittman ([105]) examine the profit incentives for hospitals to respond to

Medicare reimbursement, and close by recommending that their optimization model be used as a "policy analysis tool for federal administrators". In each of these cases, a model is created which allows policy makers to decide which goals to strive for, and how to implement policies to do so.

Economic research has also addressed the issue of the health of the US health care system. For example, Banks et. al ([9]) suggested that health care outcomes in the USA were worse than in England, in spite of spending approximately twice as much per person ($5274 versus $2164), and measured in biological markers for disease rather than self-reported measures. An OECD overview of the U.S. health system ([42]) documents the remarkably high spending levels compared to health expenditures in other developed nations. The review points out that the U.S. system has both strengths and weaknesses: there is ample capacity and choice, but costs are excessive, outcomes are less than commensurate with expenditures, there is an efficiency loss from the regulation and complexity of the system, and there is unequal service across the population.

Why the U.S. has such a high, and rapidly increasing, level of health care expenditure, is considered an important question. Cutler ([34]) goes so far as to suggest empirical evidence to study health costs is paramount within health economics. Unfortunately, hospitals define their products and prices as they wish ([76]), and instead of price and quantity data, researchers can only apply expenditures ([66]).

Although technology may well be the driver of cost increases ([108]), it is exacerbated by weak competition between insurers ([34]). Further, the technology invested in is not primarily cost-saving, and in fact, using the technologically advanced equipment requires a great deal of expensive labor ([4]). In a published lecture, Fuchs ([61]) suggests supply factors are crucial drivers of expenditures. In a recent paper (2005), Bodenheimer ([16]) shows that health care costs in the U.S. continue to grow faster than inflation, and provides several possible hypotheses.

The literature on health care economics is much larger than what is relevant to this study, as we limit ourselves to the study of incentives and institutions. We recognize that equity plays a distinct role in health delivery ([100]), and that operational efficiency in health ([1]) may be relevant. Nevertheless, in this paper we only consider how repeated negotiations between hospitals and payers may influence the incentives of price development.

Fuchs ([61]) states that in some of the health care literature there is a view that "refuses to accept the notion that resources are inherently scarce". This perspective also leads to an expansive attitude towards investment in hospital capacity: any perceived need is sufficient rationale to invest. Further, vacant capacity tends to stimulate demand ([118]). Nevertheless, there is at least a "quasi-market" ([14]) for hospital care in the U.S., and so we assume that hospitals wish to provide as much, and as high-quality, care as possible.

From the economic point of view, incentives guide actions, and financial gain plays a role in the behavior of health care providers in several ways. First, even non-profit hospitals need to earn enough to invest in new medical technology. Leone and Horn ([95]) found that hospitals will adjust their income to be just barely positive. Physician behavior has also been found to depend on many different factors. For example, Yip ([159]) found that coronary bypass grafts responded to changes in Medicare fees. Rizzo and Zeckhauser ([121]) showed that physicians react to a loss of income even if unable to change prices, e.g. by shortening appointments. Similarly, Gruber and Owings ([74]) found that when ob/gyns lost income due to decreased fertility, they compensated with increased cesarean sections. It appears that some physicians, at least partially, adjust to incentives. Legal risk also affects physician behavior. Kessler and McClellan ([84]) found evidence for physicians practicing defensive medicine, which was weakened when tort reform lessened physicians legal exposure ([85]). Under these circumstances, it does not seem unreasonable to treat physicians as applying all available resources to treat an illness.

On the other hand, patients also have complex incentives in health care. Royalty and Hagens ([126]) found that patients were insensitive to price with regard to health insurance. Strombom et al.([139]) found price sensitivity to insurance premiums, especially among the younger and healthier. Similarly, Buchmueller ([21]) found a price elasticity to out-of-pocket expenditures between -0.2 and -0.3. Patients are also sensitive to their doctors recommendations, as documented by Lien et al. ([96]) for alcohol abuse treatment. The latter two effects lead us to treat patients as simply following a physicians recommendations in this paper.

Medicare and Medicaid are treated as free-riders on the private sector ([69]). This merely suggests that the federal government pays what is required to purchase the services needed, but no more. And since Medicare and Medicaid have a menu of prices that hospitals may either take or leave, and if they do take it, they must accept all such patients, we treat these actors as fixed in the repeated negotiations between hospitals and payers. Government also has a hand in regulating hospitals, with multiple regulators yielding sub-optimal outcomes ([120]), but we ignore this complicating factor in this paper.

The remaining economic actors are the hospitals and the payers, and these are the main actors in this study. The HMO's and PPO's that pay hospitals for service are here regarded as traditional for-profit companies. As such, Bodenheimer ([16]) suggests

> Payers generally wish to reduce the dollars flowing into health care, while providers and suppliers want to increase those dollars. Payers want to contain costs; providers and suppliers resist cost containment.

However, the structure of the product is such that HMO's are concerned with patients over the contract time, and as such are not merely focused on current costs. In game theory terms, what happens if the suppliers act strategically? Rizzo ([119]) found “that preventive care is substantially higher with HMO coverage than with traditional fee-for-service reimbursement”. Further, HMO’s market penetration was correlated with lower hospitals admissions ([60]). This indicates that payers are interested in the net present value of the patient over the terms of the contract, as opposed to simplistically containing the costs of serving the patients perceived needs. We extend this temporal awareness to the price that payers apply to reimburse hospitals.

Turning to the hospitals, the empirical support for their behavior is mixed. There is some evidence that while doctors are meant to be the decision-makers, managers also have some input ([15]). There does not appear to be a strong impact on hospital prices if physicians are tied to the hospitals ([27]). It is clear that hospitals do have some negotiating power with payers, but that they are offering lower prices and taking on more risk than in previous years ([68]). Consistent with that finding, Krishnan ([89]) found that prices increased when hospitals merged, and that this effect was stronger if the merged hospitals had an increased market share. Regarding the issue of for-profit versus nonprofit ownership, Kessler and McClellan ([86]) document how increased hospital competition leads to increased social welfare, and found that for-profit hospitals had a slightly lower cost, but virtually the same output ([87]).

Hospitals’ investment and cost structure are of particular relevance to this paper. Anderson et. al. ([3]) examine the relationship between capital and operating costs. Previous studies ([137, 44, 11]) had explicitly estimated the increased operating costs from new investment the previous year, and these estimates ranged from 22 to 50 cents. Taking into account the interdependence of capital and operating costs, e.g. through automation, this increased cost was estimated to be much lower, and possibly nothing more than capital costs ([113, 62]). After comparing six models, Anderson et. al. estimate that costs do increase with investment, but not as much as the initial models suggest ([3]).

In a series of papers from the financial literature, Wedig et. al. consider how hospitals invest, both theoretically and empirically ([152, 154, 153]). They find evidence that the regulations, non-profit nature of most hospitals, and agency problems between investing hospitals and donors, lead to investment that is driven by debt targeting, rather than based on profitability or societal cost-benefit analysis. In a paper especially relevant to this study, Wedig et. al. ([154]) extended Feldstein's model ([55]) which assumed that nonprofit hospitals maximize the present value of "a utility function in the quantity and quality of care". In this model, the hospitals are constrained only by a break-even constraint; i.e. they will invest all they can in additional capacity. In sum, hospitals appear to focus on efficiency and expanding services, and otherwise appear less motivated by economic incentives than payers.

Modeling the interaction of the actors in the health care drama has often focussed on maximizing social welfare. European studies often consider how the state may optimally allocate health care expenditures, e.g. via tax or caps ([106]). Insurance contracts have been considered in light of moral hazard ([65]), and optimal contracts have been constructed between patients and physicians ([99]). Dynamic models have also been used, e.g. by Claxton and Thompson ([29]) to model optimal clinical trials. Optimal control models have been used in Operations Research settings to study the control of epidemics ([94]), and to design policies to manage illicit drug use ([142]). The paucity of data and the complexity of the situation have led to sophisticated models, with fewer empirical studies.

## 2.3 Assumptions and model formulation

In this section we consider the structure of the repeated negotiation process and construct a representational model for a single payer and health care service. We then look at the steady state and long run implications of the model as well as perform comparative statics. Finally we extend the model a duopoly and then to $N$ payers.

### 2.3.1 Assumptions

There are a number of participants in the health care arena including:

- Hospitals provide services and desire increased health spending in order to invest and expand those services.
- Private insurers sell health care and contract with hospitals to gain access to operating rooms, MRI machines, etc.
- Consumers demand health care, but provided they have insurance, pay only a small co-pay.
- Firms provide health care and make the expense opaque.
- The government pays a significant portion of US health care and pays a low price due to its buying power.

There are two main negotiators with some flexibility in this complex situation: hospitals and payers. The government tends to make unilateral decisions. For example, hospitals cannot negotiate Medicaid reimbursement rates, but can only decide whether to accept Medicaid patients or not. Consumers that have insurance are mostly insulated from the cost of providing the health care they consume due to the averaging effects of the insurance system.

Therefore the system is opaque to consumers, and the firms' role is limited to providing that shield. Payers and hospitals, on the other hand, require a contract both find acceptable. Hospitals depend on the payers to ensure profitability because the prices the government pays are very low and uninsured patients simply do not pay. Therefore hospitals are dependent on the large, private, payers. The payers, conversely, have some choice in hospitals, but not so much that they are happy to fail to come to some agreement on the terms of a contract.

The key items of interest are therefore:

1. Both parties expect to negotiate a new contract after the current contract expires;

2. The profitability of the hospital determines the equipment purchased, and hence to the services offered in the future.

The last point leads to a dynamic element in the negotiations. We assume that the payers mark up the cost of the services the hospital provides, and hence make more profit in the future if the hospital is capable of offering more services.

In order to make the mathematics tractable, the model is set in continuous time, with investment and capital as flow and stock functions. An optimal control approach is applied, of which there are several recent examples ([150, 56, 53]).

### 2.3.2 Notation

In order to describe this scenario more concisely, we introduce some notation (see table 16). The variables below are typically functions of time $t$. Hospitals have a capital stock, $K(t)$, that generates health services, and which depreciates at a rate of $\delta$, assumed to be between zero and one. To build its capital stock, a hospital invests its "profit" as $I(t)$. We assume costs $C(t)$ are also proportional to capital with a constant multiplier of $z$. Although in general capital is often used to substitute for labor, in hospitals there is a great deal of labor that is required to use the machinery, e.g. MRI machines.

We assume consumer demand, $Q(t)$ is linear in $P(t)$, and if a hospital provides a service, consumers will demand it. We let $q$ represent the multiplier to capital $K(t)$ that gives the total demand if the price is zero, i.e. $qK(t)$. We let $A$ be the multiplier to the price that decreases demand. Technology is assumed to increase demand by adding new techniques, but this is exogenous and is assumed to have an impact through $q$ and $A$. Hence both of these parameters are treated as constants in the model.

**Table 1:** Notation

| | |
|---|---|
| $t$ | The time period |
| $Q(t)$ | The quantity of health care services demanded by consumers. |
| $K(t)$ | The capital of the hospital, generating the health care services |
| $\delta$ | Capital retention (one minus the depreciation rate); $\delta\epsilon\langle 0,1\rangle$ |
| $I(t)$ | Amount invested by the hospital |
| $C(t)$ | The hospital's costs |
| $z$ | Multiplier of capital to find costs, assumed positive |
| $A$ | Constant multiplier to $P(t)$ that determines the decrease in demand $Q(t)$ |
| $q$ | Constant multiplier to $K(t)$ that determines zero-price demand $Q(t)$ |
| $P(t)$ | Price of health care services as paid to the hospital |
| $m$ | Margin payers mark up $P(t)$ when charging firms for health care insurance |
| $r$ | Payer's discount rate, assumed constant and positive |
| $\pi(t)$ | Payer's profit |
| $F(t)$ | Payer's fixed costs |
| $c$ | Co-pay, as a percentage |

Payers wish to maximize profits, and they use the prices, $P(t)$ of hospital services to pursue that goal. $P(t)$ is a vector with a price for each service. We further assume that $m$ represents the constant markup that payers apply, so that the firms which pay for the consumers health care is met with the price $(1+m)P(t)$. In order to discount future cash flow, the payers use a rate of $r$. We assume the payers make a profit of $\pi(t)$. To simplify, we initially assume payers have a zero fixed cost $F(t)$, and no variable cost.

To defray some of the cost of the services provided by the hospital to the patient, firms require that consumers pay a co-pay $c$. We assume $c$ to be a percentage of cost, rather than a fixed amount. Then the price a consumer faces is $c(1+m)P(t)$.

### 2.3.3 Model

We assume there is a single health care service, so the price vector $P(t)$ is a scalar. Based on our assumptions, demand is linear in $P(t)$:

$$Q(t) = qK(t) - Ac(1+m)P(t) \tag{1}$$

For notational simplicity, let $a = Ac(1+m)$.

Supply, however, depends only on capital, and so is fixed in the short term. In the long run, capital grows with investment and declines with depreciation.

$$\dot{K}(t) = \delta K(t) + I(t) \tag{2}$$

We assume hospitals invest their entire profit, and so:

$$I(t) = P(t) \cdot Q(t) - zK(t)$$

Substituting in the expression for demand, we find that investment becomes:

$$I(t) = qP(t)K(t) - aP(t)^2 - zK(t)$$

Similarly, inserting investment into (2) yields a new expression for capital growth.

$$\dot{K}(t) = qK(t)P(t) - aP(t)^2 - (\delta - z)K(t) \tag{3}$$

This model indicates that the key variable is the price of health care paid by the payers to the hospital. Since the hospitals are dependent on the payers, one might initially think that payers would reduce $P(t)$ to a bare minimum. But that would mean fewer services in the future, and so the payers also have an incentive to make sure the hospital invests enough to provide the future services the payers rely on to stay in business. Instead of a single-period model, payers must regulate the path of the capital stock $K(t)$ by judiciously choosing $P(t)$ in every period.

Since we assumed the payer has no variable or fixed costs, i.e. $F(t) = 0$, the profit equation is dependent on the margin, $m$:

$$\pi(t) = mP(t)Q(t) = mqK(t)P(t) - a)P(t)^2 \tag{4}$$

However, the payer does not seek to maximize single-period profits, but instead to maximize the total expected profit over an infinite horizon.

To make the model tractable, we assume continuous time instead of a series of negotiations, and that the price function is the control, while $K(t)$ is the capital stock. We discount using $r$ over an infinite time horizon, and apply a boundary condition of $K(0) = K_0$.

Further, we assume

$$\dot{K} = \delta K + I$$

where $I = PQ - zK$, i.e. the hospital invests all of its profit in capital. Let $b = \delta - z$ , so that the change in the stock of capital becomes

$$\dot{K} = bK + qPK - aP^2$$

The profit for the payer is therefore the markup percentage of the revenue, or $\pi = mQP$. Discounting this at $r$ yields a net present value of profit of:

$$NPV = \int_0^\infty e^{-rt}(mqKP - maP^2)dt$$

The problem becomes to find a price function $P(t)$ that maximizes $NPV$ subject to our constraints:

$$\max_{P(t)} \quad \int_0^\infty e^{-rt}(mqKP - maP^2)dt \tag{5}$$

$$s.t. \quad \dot{K} = bK + qPK - aP^2 \tag{6}$$

$$K(0) = K_0 \tag{7}$$

This is an optimal control problem, so we define the Hamiltonian equation:

$$H = e^{-rt}(mqKP - maP^2) + \lambda(bK + qPK - aP^2) \tag{8}$$

Solution of this control problem yields the following Theorem. The proofs of all Theorems are provided in the Appendix.

**Theorem 1:** For a single payer and health care service under the assumptions provided, the solution for price $P(t)$, capital $K(t)$, and the multiplier $\lambda(t)$ through time is given by:

$$K(t) = \frac{1}{\left(\frac{1}{K_0} + \frac{q^2}{4ab}\right)e^{-bt} - \frac{q^2}{4ab}} \tag{9}$$

$$P(t) = \frac{q}{2a}\frac{1}{\left(\frac{1}{K_0} + \frac{q^2}{4ab}\right)e^{-bt} - \frac{q^2}{4ab}} \tag{10}$$

$$\lambda(t) = e^{-A(t)}\left(\int f(t)e^{A(t)}dt + C\right) \tag{11}$$

It is of interest to study the impact of capital stock on the change in capital and pricing. Considering (47), we find that $\dot{K}(t) > 0$ for all positive values of the capital stock. Hence the change in capital is zero at $K = 0$, but for capital values greater than zero, the capital stock will grow without bound. Since the price is proportional to the capital stock (46), this leads to the following corollary:

**Corollary 1:** Whenever the capital stock exceeds the steady-state value of zero, both the price and the capital will increase exponentially.

In other words, in this model, there is no positive steady state solution that is self-correcting.

#### 2.3.4 Comparative Statics

Since $P(t)$ is proportional to $K(t)$ (46), the number of relationships to consider under comparative statics is simplified. However, for the parameters that make up the constant of proportionality, $q/2Ac(1+m)$, we have a somewhat more complex relationship.

We begin by introducing another helper function, $\Gamma(t)$, so that $K(t) = (\Gamma(t))^{-1}$. We first examine the difference in capital stock with respect to the sensitivity of demand to price:

$$\frac{\partial K}{\partial A} = \left(\frac{q^2}{4c(1+m)(\delta - z)}\right)\left(\frac{1}{A^2}\right)\left(e^{(z-\delta)t} - 1\right)\Gamma^{-2} \tag{12}$$

This derivative is negative, because $(\delta - z)$ is positive by assumption, the second and third factors are positive due to the square, and the third is negative because $z-\delta < 0$, and time is positive. Since a more sensitive demand will reduce the future profit from increasing the investment in capital, we get the following intuitive observation.

*Observation 1:* If demand is relatively more sensitive to price, then capital decreases for all $t$.

Using the expressions for $K$ and $\partial K/\partial A$, we get the following relationship for $\partial P/\partial A$:

$$\frac{\partial P}{\partial A} = \frac{q}{2Ac(1+m)}\frac{\delta K}{\delta A} - \frac{q}{2c(1+m)A^{-2}K(t)} \tag{13}$$

This derivative is also negative, because (12) showed that $\partial K/\partial A$ is negative, the proportionality constant $q/2Ac(1+m)$ must be positive, capital must be positive, and $A^2$ is clearly positive. This provides a second observation.

*Observation 2:* A more steeply sloping demand curve lowers the price path for all $t$.

Analogously, the derivative of capital with respect to the markup percentage is also negative:

$$\frac{\partial K}{\partial m} = \left(\frac{q^2}{4c(1+m)(\delta - z)}\right)\left(\frac{1}{(1+m)^2}\right)\left(e^{(z-\delta)t} - 1\right)\Gamma^{-2} \tag{14}$$

Examining the effect of markup on price, we find:

$$\frac{\partial P}{\partial m} = \frac{q}{2Ac(1+m)}\frac{\partial K}{\partial m} - \frac{q}{2Ac(1+m)^2}K(t) \tag{15}$$

This expression is negative, providing a third observation.

*Observation 3:* An increase in the markup percentage lowers the price path.

This observation is counterintuitive, but is the result of taking more profit out earlier in time, and hence having a lower capital stock at every given time, rather than lowering prices for a given supply of medical services.

Similarly, if the co-pay percentage increases, the capital stock path falls:

$$\frac{\partial K}{\partial c} = \left(\frac{q^2}{4A(1+m)(\delta - z}\right)\left(\frac{1}{(c)^2}\right)\left(e^{(z-\delta)t} - 1\right)\Gamma^{-2} \tag{16}$$

In exactly the same way as before, the effect of co-pay percentage on price is also negative:

$$\frac{\partial P}{\partial c} = \frac{q}{2Ac(1+m)}\frac{\partial K}{\partial m} - \frac{q}{2A(1+m)}c^{-2}K(t) \tag{17}$$

This leads to a forth (though intuitive) observation.

*Observation 4:* An increase in co-pay percentage dampens demand, resulting in a drop in price.

### 2.3.5 Extensions to a Multi-Payer game

Since hospitals in this model are price takers, extending the game to multiple hospitals is the same as increasing capacity. We first extend the results to a duopoly. In this case market share is defined to be a function of the prices:

$$S_i(t) = \frac{P_j}{P_i + P_j} \tag{18}$$

This gives a market share that is bounded between zero and one, and is higher for lower price. The approach has the advantages of being simple and allowing share to change depending on price, without the extreme reaction that a Bertrand style model would entail. However, this functional form implies discontinuous jumps in the market share if prices change discontinuously. In addition, the extension to $N$ payers is difficult, as we discuss in the next section. To further isolate the effect of market share, we assume $a_1 = Ac_1(1+m_1) = a_2 = Ac_2(1+m_2) = a$.

With these assumptions, we let the demand faced by each payer to equal the share of its monopoly demand: $Q_i = S_i(qK - aP_i)$. This has the results in overall demand: $Q = qK - aP_1P_2/\bar{P}$. As in the monopoly model, the hospital invests its profit, so the change in capital becomes:

$$\dot{K}(t) = bK + \frac{2qKP_1P_2}{P_1+P_2} - aP_1P_2 \tag{19}$$

Again, $b = \delta - z$. Since profit to the payer is still the focus, we find that profit equation:

$$\pi_1(t) = m_1P_1(t)Q_1(t) = m_1q\frac{P_1P_2}{P_1+P_2}K(t) - m_1a\frac{P_2{P_1}^2}{P_1+P_2} \tag{20}$$

Which gives the revised maximization problem:

$$\begin{aligned}
\max_{P_1(t)} \quad & \int_0^\infty e^{-rt}(m_1q\frac{P_1P_2}{P_1+P_2}K(t) - m_1a\frac{P_2{P_1}^2}{P_1+P_2})dt \\
s.t. \quad & \dot{K} = bK + \frac{2qKP_1P_2}{P_1+P_2} - aP_1P_2 \\
& K(0) = K_0
\end{aligned}$$

This is also an optimal control problem, so we define the Hamiltonian equation:

$$H = e^{-rt}(m_1q\frac{P_1P_2}{P_1+P_2}K(t) - m_1a\frac{P_2{P_1}^2}{P_1+P_2}) + \lambda(bK + \frac{2qKP_1P_2}{P_1+P_2} - aP_1P_2) \tag{21}$$

and find optimality conditions:

$$
\begin{aligned}
\dot{K} &= bK + \frac{2qKP_1P_2}{P_1+P_2} - aP_1P_2 && (22)\\
\dot{\lambda} &= -H_K && (23)\\
H_{P_1} &= 0 && (24)
\end{aligned}
$$

These become:

$$
\begin{aligned}
\dot{K} &= bK + \frac{2qKP_1P_2}{P_1+P_2} - aP_1P_2 && (25)\\
\dot{\lambda} &= -e^{-rt}m_1q\frac{P_1P_2}{P_1+P_2} - \lambda(b + \frac{2P_1P_2}{P_1+P_2}) && (26)\\
0 &= e^{-rt}m_1P_2(qK\frac{P_2}{(P_1+P_2)^2} \\
&\quad - aP_1\frac{P_1+2P_2}{(P_1+P_2)^2}) + \lambda P_2(2qK\frac{P_2}{(P_1+P_2)^2} - a) && (27)
\end{aligned}
$$

If we add the further requirement that our two payers are identical, we find the following Theorem.

**Theorem 2:** For a duopoly: i) prices are lower than monopoly prices for any level of capital invested and ii) price is proportional to capital stock and will grow without bound.

As noted previously, the duopoly model of share as a function of price does not easily generalize. As a remedy, one can model the system as having two state variables, share as well as capital, with an additional optimality condition equation and an additional boundary condition, ($S(0) = S_0$). We make this assumption in the following section.

*2.3.5.1 Extension to an N-Payer game*

Extending the market share formula and assuming that there are $N$ identical payers gives:

$$S_i = \frac{\sum_{j \neq i} P_j}{\sum_k \sum_{j \neq k} P_j} \tag{28}$$

We assume positive prices, $P_i > 0, \forall i \in 1, \ldots, N$, and $S_i \in< 0, 1 > \forall i \in 1, \ldots, N$. To further simplify, we assume payers are identical, and so $\sum_k \sum_{j \neq k} P_j = (N - 1) \sum_{k=1}^{N} P_k = N(N-1)\bar{P}$. If we fix the other payers prices to be $P$, we find that $S_i = \frac{P}{(N-1)+P_i}$. Finally, for identical payers, each payer's initial share is $1/N$, and each payers $a_i = a$.

With these assumptions, the change in capital is:

$$\dot{K} = bK + \frac{N-1}{N}(qK - aP)P + \frac{P_i P(qK - a_i P_i)}{(N-1)P + P_i}$$

and the profit for the i'th payer is:

$$\pi_i = m_i Q_i P_i = \frac{m_i P_i P(qK - a_i P_i)}{(N-1)P + P_i}$$

So again, the problem is to maximize expected net present value of profit:

$$\begin{aligned} \max_{P_i(t)} \quad & \int_0^\infty e^{-rt} \pi_i dt \\ s.t. \quad & \dot{K} = bK + \frac{N-1}{N}(qK - aP)P + \frac{P_i P(qK - a_i P_i)}{(N-1)P + P_i} \\ & K(0) = K_0 \end{aligned}$$

This gives a somewhat more complex Hamiltonian:

$$H = e^{-rt} \left( \frac{m_i P_i P(qK - a_i P_i)}{(N-1)P + P_i} \right) + \lambda(bK + \frac{N-1}{N}(qK - aP)P + \frac{P_i P(qK - a_i P_i)}{(N-1)P + P_i}) \tag{29}$$

The optimality conditions ([83]) are once again:

$$\begin{aligned}\dot{K} &= bK + \frac{N-1}{N}(qK - aP)P + \frac{P_i P(qK - a_i P_i)}{(N-1)P + P_i} \\ \dot{\lambda} &= -H_K \\ H_P &= 0\end{aligned}$$

Solution of this control problem yields the following Theorem.

**Theorem 3:** For $N$ identical players, capital stock will grow without bound, even when there is no growth in external demand or technological change.

In order to test whether this result holds in practice, we perform an empirical analysis in the next section.

## *2.4 Empirical analysis*

Numerical support proves somewhat difficult as price and quantity are not directly observable ([66]). However, there exist some data-sets are available from public sources. In this section we use data from the Mergent database; we first perform a simple hypothesis test, and then apply the data to parameterize the model.

### 2.4.1 Statistical support

The model suggests that prices are proportional to capital (see 46). This leads to the hypotheses that a linear statistical model would have an intercept of zero and a constant slope:

$$Price = \beta_0 + \beta_1 Assets + \varepsilon \tag{30}$$

This type of hypothesis test requires a null hypothesis that the specified model is correct, rather than the preferred approach of assuming a simpler model to hold. Therefore, the conclusion is limited to finding whether or not the data is consistent with the model.

**Table 2:** Data Used in Numerical Analysis: Assets in millions per year

| **Company Name** | 2005 | 2004 | 2003 | 2002 | 2001 | 2000 |
|---|---|---|---|---|---|---|
| Amsurg Corp. | 527 | 425 | 356 | 299 | 241 | 190 |
| Community Health Systems, Inc. (New) | 3934 | 3632 | 3350 | 2809 | 2460 | 2213 |
| HCA, Inc. | 22225 | 21465 | 21063 | 18741 | 17730 | 17568 |
| Health Management Associates, Inc. | 3988 | 3507 | 2979 | 2364 | 1941 | 1772 |
| Lifepoint Hospitals Inc | 3224 | 887 | 799 | 733 | 554 | 488 |
| MedCath Corp. | 763 | 754 | 749 | 741 | 606 | 486 |
| SunLink Health Systems Inc (US) | 65440 | 63152 | 59453 | 48571 | 56514 | 23128 |
| Tenet Healthcare Corp. (US) | 9812 | 10078 | 12298 | 13814 | 12995 | 13161 |
| Triad Hospitals, Inc. | 5736 | 4981 | 4735 | 4381 | 4165 | 1400 |
| United Surgical Partners Int. | 1028 | 922 | 870 | 727 | 556 | 331 |
| Universal Health Services, Inc. | 2858 | 3022 | 2772 | 2323 | 2114 | 1742 |

With large data-sets it may be possible to explore and test more complex alternative formulations, but we are limited to accounting data. Although such data reflects law as opposed to economic principles, we are assume that the accounts are accurate. We use public accounting filings to find total assets and revenue, and the Bureau of Labor Statistics to find both the hospital Consumer Price Index (CPI), as well as the general CPI to strip out economy-wide inflation from the hospital price index. Two levels of tests are performed.

#### *2.4.1.1 Aggregated hospital hypothesis test*

First, we aggregate the hospitals' total assets from the Mergent database and use the general CPI to adjust the hospital CPI ([22]). The index, therefore, indicates real hospital prices, as opposed to nominal. This yields the graph of assets (in millions of USD) and a real price index, normalized to 2000 (see Tables 2, 3, and 4).

Although the sample size is small, the linear model (30) provides a fit with adjusted $R^2 = 0.92$ and a P-value for the hypothesis test that the slope is zero of 0.000044. The P-value for the hypothesis test that the intercept is zero is 0.07018, i.e. we fail to reject the null hypothesis that the intercept is zero at a 5% level of significance.

**Table 3:** Data Used in Numerical Analysis: Revenue in millions per year

| **Company Name** | 2005 | 2004 | 2003 | 2002 | 2001 | 2000 |
|---|---|---|---|---|---|---|
| Amsurg Corp. | 391 | 334 | 301 | 251 | 202 | 143 |
| Community Health Systems, Inc. (New) | 3738 | 3332 | 2834 | 2200 | 1693 | 1337 |
| HCA, Inc. | 24455 | 23502 | 21808 | 19729 | 17953 | 16670 |
| Health Management Associates, Inc. | 3588 | 3205 | 2560 | 2262 | 1879 | 1577 |
| Lifepoint Hospitals Inc | 1855 | 996 | 907 | 743 | 619 | 557 |
| MedCath Corp. | 758 | 692 | 542 | 477 | 377 | 332 |
| SunLink Health Systems Inc (US) | 128 | 112 | 99 | 87 | 41 | 32 |
| Tenet Healthcare Corp. (US) | 9614 | 9919 | 13212 | 13913 | 12053 | 11414 |
| Triad Hospitals, Inc. | 4747 | 4450 | 3865 | 3541 | 2669 | 1235 |
| United Surgical Partners Int. | 474 | 389 | 431 | 332 | 238 | 134 |
| Universal Health Services, Inc. | 3935 | 3938 | 3643 | 3258 | 2840 | 2242 |

**Table 4:** Data Used in Numerical Analysis: Price Index

| **Index** | 2006 | 2005 | 2004 | 2003 | 2002 | 2001 | 2000 |
|---|---|---|---|---|---|---|---|
| CPI (Hospitals) | 166.2 | 157.9 | 149.9 | 141 | 128.9 | 119.7 | 112.3 |
| CPI (All prices) | 198.3 | 190.7 | 185.2 | 181.7 | 177.1 | 175.1 | 168.8 |
| Estimated Price Change Index | 0.838 | 0.828 | 0.809 | 0.776 | 0.728 | 0.684 | 0.665 |
| Normalized Estimate | 126 | 124 | 122 | 117 | 109 | 103 | 100 |

Running the regression without an intercept, i.e. fitting $Price = \beta_1 Assets + \varepsilon$, we find an adjusted $R^2 = 0.69$. Results of both models are shown in Tables 5 and 6.

For completeness, we further test for nonlinearity by adding a quadratic term: $Price = \beta_0 + \beta_1 Assets + \beta_2 Assets^2 + \varepsilon$. We were unable to reject $H_0 : \beta_2 = 0$ at any reasonable level of significance, as the p-value was 71%. The results are shown in Table 7.

These results are not conclusive, but the fact that the proportional model does account for most of the variation in price, while the intercept does not provide significant additional explanatory power, provides some support for the model.

**Table 5:** Excel OLS output for Price index regressed on Total Assets

SUMMARY OUTPUT

| Regression Statistics | |
|---|---|
| Multiple R | 0.9646 |
| R Square | 0.9305 |
| Adjusted R Square | 0.9166 |
| Standard Error | 3.0232 |
| Observations | 7 |

ANOVA

| | df | SS | MS | F | Significance F |
|---|---|---|---|---|---|
| Regression | 1 | 612.04 | 612.01 | 66.96 | 0.00044 |
| Residual | 5 | 45.70 | 9.14 | | |
| Total | 6 | 657.71 | | | |

| | Coefficients | Standard Error | t Stat | P-value |
|---|---|---|---|---|
| Intercept | 25.17 | 10.97 | 2.30 | 0.0702 |
| Total Assets | 1.85E-09 | 2.26E-10 | 8.18 | 0.00044 |

**Table 6:** Excel OLS output for Price index regressed on Total Assets with zero constant

SUMMARY OUTPUT

| Regression Statistics | |
|---|---|
| Multiple R | 0.9259 |
| R Square | 0.8573 |
| Adjusted R Square | 0.6906 |
| Standard Error | 3.9550 |
| Observations | 7 |

ANOVA

| | df | SS | MS | F | Significance F |
|---|---|---|---|---|---|
| Regression | 1 | 563.86 | 563.86 | 36.05 | 0.00184 |
| Residual | 5 | 93.85 | 15.64 | | |
| Total | 6 | 657.71 | | | |

| | Coefficients | Standard Error | t Stat | P-value |
|---|---|---|---|---|
| Intercept | 0 | #N/A | #N/A | #N/A |
| Total Assets | 2.36E-09 | 3.08E-11 | 76.78 | 3.28E-10 |

**Table 7:** Excel OLS output for Price index regressed on Total Assets with quadratic term

SUMMARY OUTPUT

| Regression Statistics | |
|---|---|
| Multiple R | 0.9660 |
| R Square | 0.9332 |
| Adjusted R Square | 0.8998 |
| Standard Error | 3.3139 |
| Observations | 7 |

ANOVA

| | df | SS | MS | F | Significance F |
|---|---|---|---|---|---|
| Regression | 2 | 613.79 | 306.89 | 27.94 | 0.00446 |
| Residual | 4 | 43.93 | 10.98 | | |
| Total | 6 | 657.71 | | | |

| | Coefficients | Standard Error | t Stat | P-value |
|---|---|---|---|---|
| Intercept | 72.82 | 119.26 | 0.61 | 0.5744 |
| TotalAssetsInMillions | -0.0002 | 0.0051 | -0.0386 | 0.971 |
| TAIM SQRD | 2.17E-08 | 5.40E-08 | 0.4016 | 0.708 |

#### *2.4.1.2 Individual hospital hypothesis tests*

It is also possible to examine individual hospitals. Since we do not have access to price data at this level, we substitute revenue, and note that equation (30) suggests a quadratic relationship between revenues and assets for each hospital $i$: $Revenue_i = \beta_{i,2} Assets_i{}^2$. When we add a constant term for each of the ten hospitals that we have data for, i.e. $Revenue_i = \beta_{i,0} + \beta_{i,2} Assets_i{}^2$, we find an average positive intercept. Applying a simple test for means, we find a p-value for the null hypothesis that the average intercept is zero of 6.12%. Full results are shown in Table 8.

Alternatively, we may use a non-parametric signs test and note that all the estimated intercepts were positive. The probability of all the intercepts being one sign, assuming a 1/2 probability of either sign if the true population mean intercept is zero, is binomially distributed and approximately 0.00195. This would suggest that something is missing from the model, which is not surprising, given the rather strong

**Table 8:** Excel worksheet with intercepts and tests $H_0 : \beta_0 = 0$

| Company Name | Intercepts |
|---|---|
| Amsurg Corp. | 146919457.2 |
| Community Health Systems, Inc. (New) | 326100919.1 |
| HCA, Inc. | 5755455601 |
| Health Management Associates, Inc. | 1269493867 |
| Lifepoint Hospitals Inc | 705721853.2 |
| MedCath Corp. | 57643421.05 |
| SunLink Health Systems Inc (United States) | 16767071.74 |
| Triad Hospitals, Inc. | 1005770491 |
| United Surgical Partners International Inc. | 122547558.3 |
| Universal Health Services, Inc. | 1567040636 |
| | |
| Avg | 1097346088 |
| StDev | 1725848661 |
| Standard Error | 520362950 |
| STS | 2.1088 |
| P-value for $H_0 : \beta_0 = 0$ | 0.0612 |
| | |
| Binomial Prob of all positive intercepts | 0.000977 |
| Binomial Prob of all pos or all neg intercepts | 0.001953 |

assumptions we made to simplify the mathematics.

### 2.4.2 Numerical example

In constructing the numerical example, we rely on accounting data, as well as published papers. From the SEC ([134]) accounting forms we find an average capital retention rate of $\bar{\delta} = 0.961$ with a standard deviation of $s_\delta = 0.013$ and an average cost parameter of $\bar{z} = 0.7165$ with a standard deviation of $s_z = 0.0514$. For convenience, we set the co-pay percentage of price to $c = 0.05$, the markup percentage to $m = 1$ and initial capital base to $K_0 = 1000$. This leaves the demand parameters, $A$ and $q$, which we do not observe and turn to the literature for reasonable estimates. Santerre and Neun ([129]) summarize a number of papers ([109, 47, 33, 37, 115, 54]) and suggest that an own-price elasticity between -0.1 and -0.7 is reasonable. As this is our only information on demand, we select $q = 1$, $A = 300$ at price $P = 10$. Even with this ad hoc parametrization, we observe the explosive growth in capital invested (see figure 1).

This figure includes two boundary graphs, one in which the cost multiplier ($z$) is two standard deviations below the mean, and the other two standard deviations above. Note that the pattern is unchanged. For the other parameter estimate with a standard deviation, the capital retention rate $\delta$, the graphs were too close to each other to be useful. We also tried arbitrary deviations from the remaining parameters in the capital equation, with similar results. Only when the co-percentage $c$ was lowered did the model explode substantially quicker. Since it is the quality of explosive growth that is of interest, this effect was not remarkable.

## 2.5 Conclusion

We developed a dynamic model of repeated negotiations between hospitals and payers. Under certain assumptions,we arrived at an optimal control problem, which yields solutions for price and capital. The price path equation (46) gives an optimal price

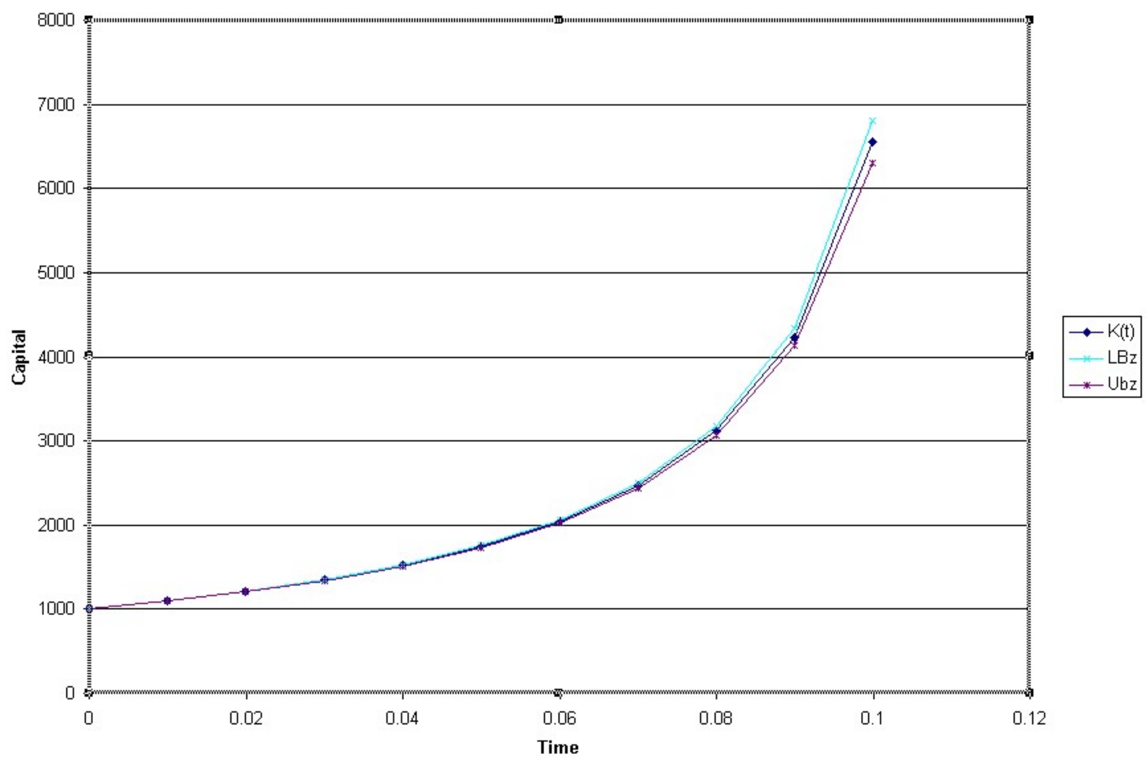


**Figure 1:** Numerical illustration of capital growth in this model

that is proportional to the hospitals' capital stock. This means that as the supply of hospital services increase, prices also increase, as opposed to the usual dynamic of falling prices with expanding supply.

The solution for capital (9) is not obviously explosive, but when we examine the long run and steady state solutions (2.3.4), we find that capital only has one meaningful equilibrium, at zero. An equilibrium of zero is not useful, but when we examine the time derivative of capital versus capital (47, we note that the derivative is positive, i.e. the capital stock is increasing over time, and increases faster for greater capital stock. This means the equilibrium is unstable, and an increase from the steady state will lead to an explosion of both price and capital devoted to health services.

The remainder of the comparative statics show that capital and price are sensitive to the slope of the demand function ($A$), the markup percentage ($m$), and the co-pay percentage ($c$). The directions of change are intuitive, which is reassuring, given the simplifications of the model.

An extension to multiple payers was attempted in 2.3.5. Doing the same for hospitals would not change the model, as these are price takers in the this scenario. The effect of having each insurance firm know that the price they pay will benefit other payers equally in the future, leads to a public goods problem. As one would expect, multiple payers lead to lower investment and also lower prices. The dynamics of the model remain unchanged from the single payer model, so even if more payers means it takes longer for the explosion in capital and prices to arrive, the final result is the same. Given the tremendous growth in health care expenditures, and unprecedented portion of U.S. GDP devoted to health, the model appears to provide a possible explanation for the twin phenomenon of beneficial capacity growth and traumatic increase in health care costs Americans are experiencing.

The data examined is in accordance with the model, but no stronger conclusion may be drawn. Given the strong assumptions we made, and the limited data available, even this result is encouraging. The prediction from the model that prices will be proportional to capital has some support. But the more important implication, that health care prices are exploding, seems obvious to most observers ([4, 42]).

The major contribution of this paper is to point out that even if payers act purely out of self-interest, and without technological change, the incentives appear to be in place for an expenditure explosion in health care capacity and prices. To our knowledge, this result is new, and it is not an obvious conclusion. One policy implication is that the qualitative aspects of the system will not change without structural redesign.

# CHAPTER III

# A SIMULATION MODEL TO COMPARE STRATEGIES FOR THE REDUCTION OF HEALTHCARE-ASSOCIATED INFECTIONS

## *3.1 Introduction*

Cook County Hospital, like many hospitals in the U.S. and worldwide, is pursuing a developing strategy to combat healthcare-associated infections (HAIs). Annually, the human toll in the U.S. is approximately two million infected, of which over 100,000 die. An interdisciplinary team of researchers from Georgia Tech, the CDC, and Cook County Hospital, with backgrounds in engineering, economics and medicine, analyze the flow of pathogens. We combine infection rates and cost data to build a discrete event simulation model for the purpose of capturing the complex relationships between hand-hygiene, isolation, demand, and costs. We find that both hand-hygiene and isolation policies have a significant impact on rates of infection, with a complex interplay between factors. This suggests a systems-level approach to infection-control procedures will be required to contain healthcare-associated infections.

### 3.1.1 Overview

A healthcare-associated infection (HAI) is defined as one where there is no evidence that the patient was infected (or colonized) at the time of admission [48]. The infections we consider in this study are a subset of HAI, namely the hospital acquired, or nosocomial, infections. Roughly two million patients contract HAIs each year in the United States alone, of which more than 100,000 die [101]. Dealing with these infections costs more than thirty billion dollars per year, most of which must be borne by hospitals, since they are not part of any recognized treatment. The problem is becoming increasingly complicated, due to the emergence of resistant pathogens [81]. In addition, there is evidence that the liberal use of antibiotics is resulting in evolving resistance in pathogens [36].

The federal government is considering regulating infection control, but as of now, various states have taken the lead [156]. For example, the Pennsylvania Health Care Cost Containment Council (PHC4) now reports on HAIs online (www.phc4.org). The idea that report cards on hospitals infection rates may help has been slow to win acceptance, but is being considered by a number of other states [156]. In addition, the Centers for Medicare and Medicaid Services (CMS) recently announced new rules for hospital inpatient cost reimbursement in response to a provision of the Deficit Reduction Act of 2005, which requires hospitals to begin reporting secondary diagnoses that are present on admission by October 1, 2007 [25]). Under the new rule, diagnostic related payments to hospitals would be reduced or not provided for certain hospital-acquired conditions.

In the U.S. health system, where hospitals have a financial and legal incentive to conceal HAIs, it has been especially difficult to monitor the problem [75]. In addition, the risk factors change depending on patient characteristics, ailments, local frequencies of pathogens, and infection controls. This leads to research on very specific types of HAIs [127, 23]. Different types of patients also have different risks for developing HAIs [58]. Hence even if the problem is significant and potentially solvable, it is also complex and in need of some level of aggregation.

We therefore seek to address the following research questions:

- Does the system of infections in a hospital behave as a set of independent problems, or do the relationships between parts change depending on the state of the system? For instance, does greater compliance with hand-hygiene measures reduce costs?

- What are the relative merits of isolation versus hand-hygiene?
- How do infection control measures impact hospitals costs?

To address these questions, we combine data from Cook County Hospital [122] with parameter estimates from the literature to build a simulation model of HAIs in an intensive care unit (ICU). We compare the costs, benefits, efficacy, and efficiency of various strategies for HAI reduction including screening and isolation.

The paper is organized as follows. We first provide an overview of the literature that provides the basis for our study. We describe our research design, and how it relates to the literature. Then we discuss the data used in the model, followed by the simulation model. After describing the different experiments based on the model, we assess the economic impact of different approaches to infection control. Finally, we give preliminary recommendations for policy, along with an overview of proposed future research.

## *3.2 Literature Review*

The literature on HAIs is very large, spanning both medical and economics journals, and with varied approaches. We will draw on the health and economics literature, in which pathogens and treatments are the focus.

### 3.2.1 Public Health and Medical Literature

HAIs can be classified by pathogen or by what is infected. The major types of infections are surgical site infections (SSI), pneumonia, bloodstream infections (BSI), urinary tract infections (UTI) and a catch-all class of Other [48]. Catheters in particular contribute to BSI, but these may be managed, as one study found mean rates of catheter related BSI dropped from 7.7 to 1.4 per 1000 catheter-days due to an intervention [117]. A recent review estimated that "up to 1/3 of all HAIs may be prevented by adequate cleaning of equipment" [130].

Another approach to reducing SSI is to provide feedback to the hospitals on their performance. This approach in Germany's KISS system (Krankenhaus Infektions Surveillance System), led to a relative risk of 0.54 as compared to conditions prior to installation of the outcome measures [64]. Naturally, such a system relies on the hospitals to trust that their self-reported measures will not be used against them. The efficacy of outcome measures is not limited to system-wide initiatives. St. Luke's Episcopal Health System counted incidents of hospital-acquired pneumonia, and were able to identify risk factors such as the use of intra-aortic balloon pumps, renal failure, re-intubation, and total intubation time, and reduce the rate of pneumonia from 6.5% in FY96 to 2.8% in FY01 [80]. However, they noted that a "major obstacle" was to keep staff aware and involved in the infection control program. A larger program involving 56 hospitals decreased SSI rates from 2.3% to 1.7% over three months by applying correct antibiotics (within one hour of surgery), keeping the patient at correct temperature, blood sugar and blood-oxygen, and even correct hair removal [39].

Which pathogens are most troubling at any one time changes as bacteria migrate and develop resistance, and as technology provides both new avenues for microbes to attack, as well as new tools, methods, and pharmaceuticals to combat various agents of infection. Currently, the main problem pathogens in the U.S. are Methicillin-resistant Staphylococcus aureus (MRSA) and Vancomycin-Resistant Enterococcus (VRE) [46].

Although Staphylococcus aureus is a widespread bacterium, the current problem is primarily with Methicillin-resistant strains. MRSA has been estimated to increase length-of-stay (LOS) by 50% and the cost of hospitalization by 100%, when compared to the susceptible strain, MSSA [98]. MRSA tends to stay in hospitals that have been infected, and carriers may harbor MRSA for more than three years [128]. Asymptomatic carriers may contribute a great deal to the spread of MRSA, which argues in favor of screening [149]. However, others find that isolating MRSA patients either alone or in cohorts does little to reduce the risk of cross-infection [26]. Of course, both those results are compatible with the argument that health-care workers spread the bacterium; the number of manipulations does appear to increase the spread [45].

VRE, on the other hand, has become a significant problem only since 1990 [143, 17]. Just as with other HAIs, VRE leads to greater LOS and cost [140], and similar to MRSA, VRE cross-colonization is easy, and colonization may persist for some time [17].

In addition to the VREs and MRSAs, there are a number of other major pathogens, and an even larger group of so-called zoonotic diseases (e.g. hantavirus, anthrax, hemorrhagic fevers such as Ebola, plague and rabies) [151]. Since pathogens follow cycles and modeling can easily become intractable with too fine a structure, we will not go into more detail on individual microbes. It is important to retain risk factors that are common to HAIs, such as LOS, hand hygiene, and colonization among health-care workers (HCW) [144]. In addition, it is important to include resistance to antibiotics and biocides [30].

#### *3.2.1.1 Medical Treatments*

There are two major lines of research in the control of HAI: surveillance and avoidance. Surveillance techniques observe and report on the record of the hospital, while avoidance techniques help to hinder infection. In our simulation model, we focus on screening and hand-hygiene, as different approaches to avoiding HAIs.

**Surveillance** This may be done either at the level of the hospital or of all patients, i.e. the system. In addition, surveillance may be passive, inspecting patients or records, or active, which involves culturing samples from asymptomatic patients and health care workers (HCW). There is no nationwide surveillance system in the U.S., but six states had systems in 2005 [10], and 39 have considered legislation [156]. Although it is not clear that all HAIs are being reported, hospitals that do report their performance are not penalized, while those that fail to report risk $1000 dollar per day fines. In addition to the importance of trust that their reports will not be used against them, it is important to take into account risk-adjusted patients, so that hospitals cannot "improve" their performance by cherry-picking cases [156].

**Screening** It is difficult to know when to classify an infection as healthcare-associated. If an active approach to screening all patients and HCW is applied, cultures must be taken to test for different pathogens. In one study in Israel, a country where MRSA is endemic, such an approach cut the cases of bacteremia in half [136], while a U.S. study found a cost-effective reduction in the incidence of MRSA [28].

**Isolation** If carriers and those with infection can be isolated, either privately or in cohorts, then such quarantine might control outbreaks. For individual patients, each test costs approximately $30, and comprehensive screening is estimated to cost $300 [43]. Isolating MRSA-colonized patients is given credit for working in the Netherlands, Denmark and Finland [51, 50]. However, a study in the UK found no effect [26]. Two reviews of the literature found some support for isolation in response to MRSA [31], but no robust economic evaluation [32]. Similarly, a survey of German hospitals found that isolation did help control MRSA [63]. From a system-design perspective, it seems that isolation may primarily benefit the entire health-care system, while hand-washing may be most important for individual patients.

**Hand Hygiene** The issue of hand hygiene is sufficiently important for the Centers for Disease Control and Prevention (CDC) to provide a Morbidity and Mortality Weekly Report (MMWR) guideline [19]. In short, these recommend washing visibly dirty hands, and otherwise using alcohol-based hand rubs, as well as gloves in certain cases. Rates of adherence to hand-hygiene guidelines are typically less than 50% [147], so measures to improve compliance may have a significant impact. Although [92] found that gels were no better than traditional methods, the fact that an increase in the number of sinks, and therefore a reduction in the inconvenience in hand-washing, had no significant impact on compliance [147], suggests that alcohol gels are a better choice. An alternative may be to use gloves, which has similar efficacy, but is cheaper and easier to comply with than hand-washing [145]. It has been noted that improved hand-hygiene will have a secondary positive impact, in reducing the need for antibiotics and retarding the evolution of resistant strains of pathogens [155].

### 3.2.2 Economics

The framework for general economic analysis of health care [133], and to the problem of HAIs specifically, has been discussed in several papers. The economics of HAIs are especially challenging due to measurement difficulties and the uncertainties associated with cost-allocation and quantifying[124, 123, 71, 72]. Research has estimated fixed costs to represent 84% of hospital costs [123, 71], which leads to questions of how to assess such costs, as well as the benefits from infection control programs and regulations. [101] provides a useful summary of the financial and human cost of hospital acquired infections. A briefing for the Association for Professionals in Infection Control and Epidemiology (APIC) also provided an overview of the financial impact for hospitals, emphasizing that due to the increase in LOS from HAI, the opportunity cost should also be counted, for hospitals running close to capacity [107]. Since HAIs extend the stay of patients in hospitals, but do not usually require additional surgeries or alternative treatment, several studies indicate that hospital acquired infections primarily have the effect of increasing LOS [13, 73]. This has led to the argument that only marginal costs should be included, as long as the perspective is the hospitals

[72]. [73] also makes the argument that quality-adjusted life-years (QALY) should be employed to measure the benefits of infection control. Clearly, extra mortality is also a relevant cost [158], although this cost is not borne by the hospital.

The literature on HAIs is primarily based on specific transfers and pathogens, without consideration for the complex interactions within a hospital setting. Our focus is on the dynamics of the system as a whole. The contribution of this paper then is to develop insights from HAIs in a hospital setting, accounting for the relatively complex set of interactions, to develop insights that can help establish effective policies.

## *3.3 Data*

The data we use in in this work are based on the CARP study [122], conducted at Cook County Hospital located in Chicago, Illinois. In the overall data-set we have records for the hospitalization of 1,254 patients, with information on the patients' age, whether or not they died during hospitalization, if they had surgeries, spent any time in the ICU, and had a confirmed or suspected HAI in their urinary tract, bloodstream, surgical site, lungs, or elsewhere. We further have available the LOS, two severity of illness scores (the Apache III and the Charlson), in addition to various costs. These have been carefully constructed through actual hospital outlays and procedures, and include fixed charges for admittance ($635.33) and treatment in the emergency department ($250.45). Variable costs include a charge for the LOS, charges for procedures done at the bedside (i.e. without an operating room), charges for use of an operating room, and charges for blood, pharmaceutical, and radiological laboratory tests.

Since we are limiting this study to ICU's, we first reduce our data-set to the 212 patients who were in the ICU. Of these, 33 died, 70 developed a confirmed HAI based on the CDC guidelines, and a further 20 lacked one indicator, and so are counted as

**Table 9:** ICU Summary Statistics

| | ICU | | With HAI | | No HAI | |
|---|---|---|---|---|---|---|
| | LOS | Cost | LOS | Cost | LOS | Cost |
| Mean | 15.73 | 38072.54 | 23.65 | 59711.30 | 10.43 | 23589.91 |
| Standard Deviation | 15.10 | 38610.31 | 19.16 | 49996.29 | 8.16 | 17398.89 |
| Count | 212 | | 85 | | 127 | |

suspected of having an HAI. Due to overlap, the total number patients classified as having any HAI is 85, or approximately 40% (see Table 9). A t-test for differences in means gives p-values of 0.000 for LOS and total cost, confirming that the difference in means between patients with and without HAI is statistically significant.

We use the data to provide parameter estimates and a method to assign costs. The LOS is modeled through a probability of discharge, which we estimate using maximum likelihood means for a geometric distribution of length of stay (LOS): $\hat{\theta} = N/\sum_{i=1}^{N} LOS_i$ for both those infected, and those not infected. This gives $\hat{\theta}_{NoHAI} = 0.095291$ and $\hat{\theta}_{HAI} = 0.042289$. These are adjusted slightly, to make the LOS for infected and uninfected patients conform with the CARP patients.

Finally, upon patient exit, costs are assessed using the CARP data. After running several regressions, the best parsimonious fit for total costs is (see Table 18):

$$\widehat{TotalCost} = 3028.81 + 445.9 * HAILOS + 1944.2 * LOS \tag{31}$$

Here $HAILOS = AnyHAI * LOS$, i.e. an interaction effect to increase the average daily cost once infected. This gives an $R^2 = 0.88$, after we remove one outlier.

The total costs we use since we do not have what the patients incur for specific categories such as pharmacological costs. However, the CARP data gives us valuable validation through both the average LOS and the average total cost incurred.

This aggregate approach ignores the types of HAI, the demographics, and the breakdown of costs into LOS, consults, drugs, diagnostics, etc. However, since we are focused on the effect of HAI on overall costs, we use the total costs attributed to the patients.

### *3.4 Simulation*

Discrete event simulation is used to model the process by which pathogens, patients and visitors enter an ICU, interact with HCW and each other, infect, become infected and cured of both primary disease and their additional infections, and finally are discharged and assigned costs. Note that those who carry an infection agent are *colonized*, and that there is an incubation period between colonization and infection, during which the pathogen may spread from an asymptomatic patient, HCW, or visitor.

We incorporate the various pieces described above to shed light on the research questions, in particular the complex interactions between the various parts of the infection process. We simulate rather than pursue a closed-form approach, because the large number of interacting factors means we must trade precision for greater realism. This approach allows us to include all the various factors mentioned above, which we need to address the research questions.

We incorporate location, patient demographics, and variable bed-occupancy into the simulation. We construct a base model using an ICU [26], along with the CARP data to provide ICU rates of HAI in a U.S. hospital, as well as total cost data.

The ICU has ten rooms, in which two doctors and four nurses provide transportation for the pathogens. The HCWs mix in random groups of one doctor and two nurses, and spread the pathogens between patient locations and HCWs. These HCWs, patients and visitors all move on a network between an entrance (and exit), and individual and cohort rooms (see Figure 2).

We alter the base model to allow for screening and isolation in two formats:

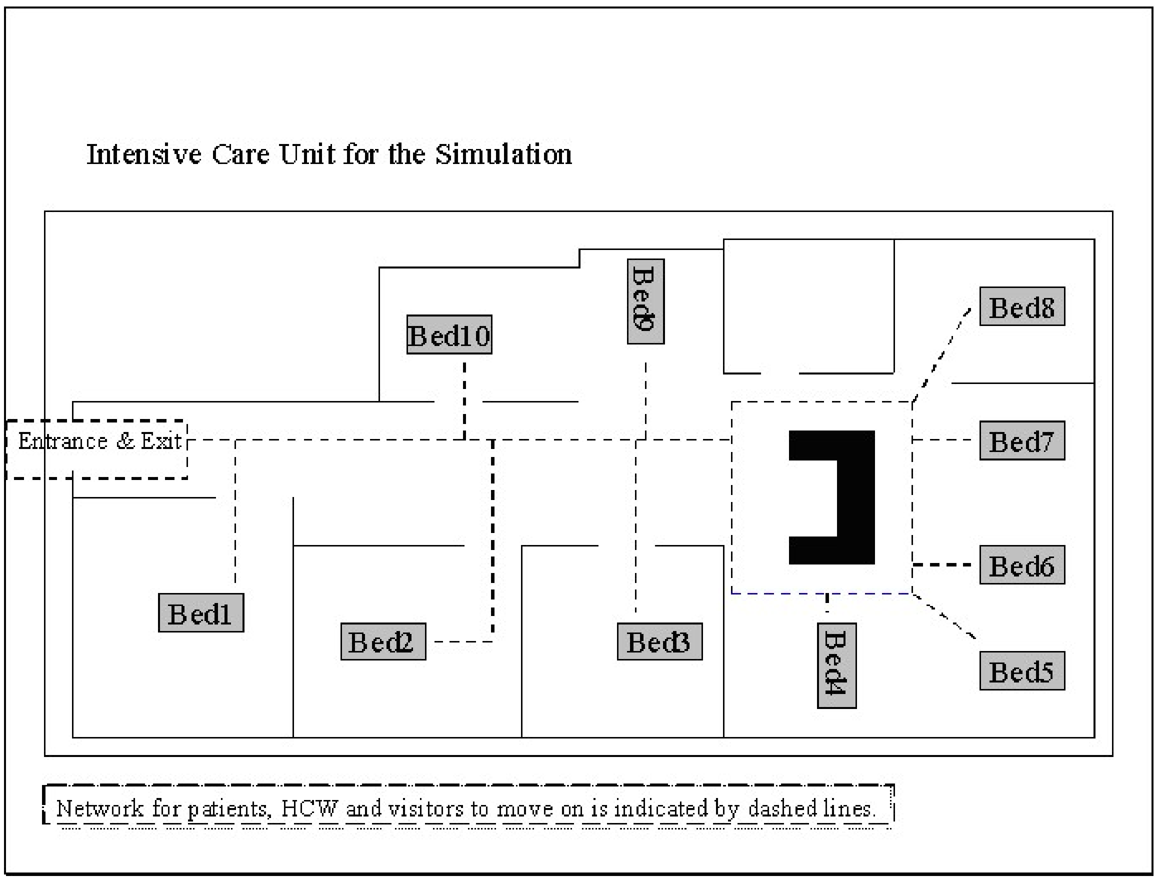


**Figure 2:** ICU Schematic

1. An additional isolation ward is added.

2. An isolation ward is carved out of the available space.

Hand-hygiene efficacy (HHE) and compliance is modeled through the assumption that there is a hand-hygiene station in every patient room, and that HCWs attempt to cleanse their hands, with a positive probability of success. We use an efficacy parameter to quantify the probability of removing any colonization, and represent both the probability of cleansing hands, and that the effort is successful.

We focus on the dynamic aspects of the movement of pathogens, and so limit ourselves to one generic pathogen. Although this is a simplification, it is reasonable due to the level of aggregation we utilize. Specifically, we do not include surgeries, intravenous devices, different pharmaceutical products, which we would require in order to benefit from differentiated pathogens. In the following we describe each of the models and report on the results.

### 3.4.1 Base Model

The base model takes the ICU as given, but allows both patients and visitors to bring colonizations of resistant and susceptible pathogens into the locale. The health care workers then probabilistically spread the pathogen to different locations. In order to keep some measure of control with the model, only the locations transfer the pathogens, but we adjust the parameters to force the infection rates in the simulation to mimic those seen in the data (See Table 10).

Using MedModel [79] structures, the discrete event simulation is formulated using the following elements:

- Locations: Ten beds, along with visitor stations for each bed; one entrance for patients, and another for visitors. The locations capture the transmission of pathogens by passing along colonizations.

- Entities: Patients and visitors. Both can be colonized with susceptible or resistant pathogens, but only patients are assumed to arrive with actual infections.

- Path networks: The movement of the patients, visitors, nurses and doctors are constrained to a network between locations (see 2). Although we have a geographical model of the ICU, we do not allow the simulation to use all the possible locations, as that would draw processing time, without adding useful results.

- Resources: Doctors and nurses. These can be colonized, but infected HCWs are assumed to stay away from the ICU [12, 135]. Colonized individuals can then spread the pathogen to other locations.

- Processing: Entities are processed when they move from one location to another, and while they remain at a given location.

  1. Visitors bring pathogens from the outside, and can pass those along to the locations visited.

  2. Patients are treated by the health care workers, and since this is an ICU, the patients are seen frequently. The simulation process selects one doctor and two nurses at random for each patient care event. Each visit provides an opportunity for pathogens to move between the HCW, locations, and patients. In addition, a patient can stochastically develop or be cured of an infection, and also has a probability of discharge. As mentioned above, this probability falls substantially when the patient is infected, but not from a colonization. The probabilities were selected to imitate the data from Cook County Hospital (see 3.3).

  3. Upon a patient's exit there is a cleanup of the location if the patient was infected, in order to limit the colonization. The exit process also captures

data, such as the LOS, which infections had been caught, and calculates the total cost for that patient.

- Arrivals: The rate at which patients and visitors arrive at the entrance. Arrivals are modeled using exponential distributions.

- Variables: Global variables track the incidence of colonization for HCWs, locations, patients and visitors. In addition, global variables count various items of interest, such as the number of the different types of patients entered and discharged, infections and colonizations, lengths of stay, and the state of occupancy in the ICU.

- Parameters are given constant values within each simulation run, representing the probabilities of colonization, infection, cure, etc.

### 3.4.2 Model with Area Reserved for Isolation

In this model, we remove three beds next to the entrance (beds 8, 9 and 10) from the base model, and turn these into an isolation ward. Patients are first screened, then go to the isolation ward or the regular entrance. This significantly lowers capacity, but provides a model directly comparable to the base model, as no more room is devoted to the ICU.

### 3.4.3 Model with Additional Isolation Ward

In this model we add a separate isolation ward to the base model. This increases capacity, since valuable beds are no longer used for de-colonization purpose. We recognize that this solution may be somewhat unrealistic, as patients with a need to be in an ICU would also require intensive care in any isolation facility, but it allows for another direct comparison with the base model.

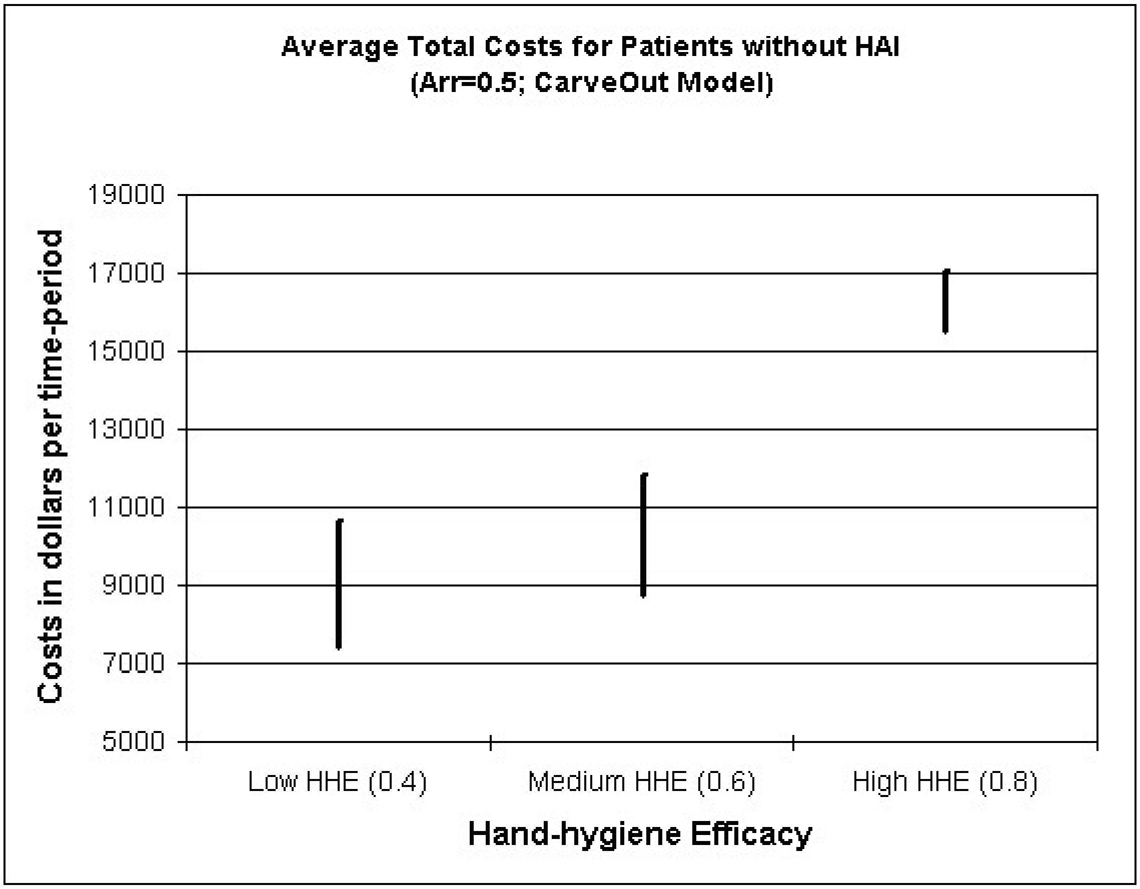


**Figure 3:** Average Total Cost v. HHE in Patients without HAI

## *3.5 Analysis*

We seek to understand the interplay between hand-hygiene (HHE), isolation, arrival rates and costs on the dynamic flow of HAIs. We therefore simulate different scenarios of isolation, namely, none (Base), an isolation ward carved out of the main ICU (Carve-out), and with an added isolation ward (Plus-Screen). We use high, medium, and low levels for the hand-hygiene (HHE) and arrival rate (Arr) parameters. The simulations are replicated 50 times for 100 days, after a warm-up period, for each scenario. The parameter values, as well as the calculated means and standard deviations are provided in tables 12,13, and 14. Total costs and lengths of stay remain in line with results from the CARP data set.

We observe that higher overall infection rates increase costs, reduce capacity, and increase lengths-of-stay. However, we note that the relationships do not appear to be linear, and are sometimes surprising when we focus solely on subsets of patients, e.g. those who did not catch an HAI. The apparently nonlinear relationships include the relationship between the number of discharged patients (total, with and without HAI) versus HHE, LOS and average cost versus HHE, and the proportion of time the ICU is full versus HHE. There is no reason to assume linearity, but we emphasize this point because previous statistical models used to assess the impact of HAIs on costs have been linear, and in fact uncoupled from LOS [73].

Note that as the patients' interarrival time decreases (e.g. Arr=0.1 rather than Arr=1.0), the proportion of time the ICU is full increases. Only when there is a significantly lower patient inflow does the ICU have spare capacity. In addition, a significant increase in volume occurs only at the highest level of HHE.

Another capacity related effect is due to the physical locations of the screens. When we add an additional screen to the base model, there is a slight increase in the patient throughput. Since we do not allow for patient healing during isolation, this estimate is conservative, and solely due to the decrease in HAIs. When the screen is carved out of the ICU, however, capacity and throughput drop significantly, in line with expectations. The effects are mirrored for those with and without HAIs. However, the number discharged who ever had an HAI does not drop significantly when the isolation room is added. Instead, the additional throughput is comprised of patients who do not contract HAIs. We note here that visitors are not screened, and bring in a steady stream of pathogens from the community.

In order to assess the numerical effects of the different parameter values, we average across the different scenarios (Table 15). We cautiously interpret these results, and note that a standard deviation is meaningless due to the fact that these are arbitrarily selected parameter-settings. Nevertheless, we do observe that the effect of changes in HHE is monotonic for each variable.

It appears clear that an increase in HHE is an unmitigated benefit. However, it is of interest to note that under our specifications, and with low arrival rates, an increase in HHE increases overall throughput, while the absolute number of patients who ever contract HAIs remains roughly constant. This counterintuitive result is not surprising in light of the overall increase in volume, but would suggest that an effort to decrease the absolute number of patients who contract HAI's through increased efficacy of hand-hygiene, would simply not work. There would be a benefit, but this would have the effect of greater throughput, rather than fewer patients with HAI. This result suggests that isolated measures of success in controlling infections may be misleading, and a system-wide perspective is needed.

The most counterintuitive results are arguably that higher efficacy in hand-hygiene leads to longer lengths of stay, and higher costs, for patients who never contract an HAI. We assume no additional costs for the increased HHE, so the effect comes from the dynamics of the model. We also note that the relationship holds across all the scenarios. The key to understanding this result is to bear in mind that the mean LOS is conditional on the event that the patient did not catch an HAI. When HHE increases, more patients that would otherwise have gotten an HAI are treated until discharge without being infected, even though it may take longer. Said another way, when infections are rampant, it is a rare patient who is lucky enough, and recovers swiftly enough, to avoid an infection. Only those swift patients are counted among the group that were discharged without contracting an HAI, so they must have a short average LOS. Conversely, LOS falls for those who did contract an HAI, because with better cleanliness, they are less likely to catch another infection.

Returning to cost, we note that LOS is the primary driver, which explains why the same relationship holds for the average total cost per patient. We do note that the CARP data as presently utilized uses an allocated mechanism, so true variable costs have not been calculated. However, since doing so would increase the benefit from freeing up capacity, the approach currently utilized underestimates the impact of HAIs on cost. We cannot compare the change in costs for the added isolation ward, nor from carving out such a ward, as we do not have these figures. Since the main effect appears to be on capacity and revenue, we must base our conclusions on increased service to patients. However, since our simulation period is 100 days, we note that the average increase in patients served over the full year is 192.3, while the percentage of time the ICU is full declines from 95% to 82%.

## 3.6 Discussion

On the basis of these simulation models, we can draw several useful observations.

*Observation 1: Both hand-hygiene and isolation policies have a strong impact on rates of HAIs, capacity, and costs.*

The effects of better compliance with hand-hygiene infection control is different when capacity is tight, versus when there is slack in the system. This is intuitive for any change that increases or decreases the average throughput of the hospital. Since variable costs comprise less than a fifth of a hospitals costs [123, 71], average per-patient costs may decline with a successful infection-control program. However, overall costs will increase due to the program itself, and due to the shift in patients that do or do not acquire HAI, it is not clear that per-patient average costs will decrease for every class of patient.

*Observation 2: Hand-hygiene and isolation policies interact, so that the relative merits of the two approaches change for each scenario.*

We are not surprised to find that drastically reducing capacity by carving out an isolation ward left the ICU full much more often than under the base model or the model with an added isolation ward (see tables 12, 13, 14). Although costs were generally higher when we added isolation policies, we had to expect that, since we merely added this feature. In order to draw a strong conclusion, we would have to compare the added cost from isolation to the cost of hand-hygiene campaigns, and this data was not available. Since hand-hygiene is often poor, but may be improved through inexpensive alcohol-gels, while ICU isolation wards require significant capital expenditure, the small difference in results between isolation-ward models and the base models suggests the benefits to cost ratio is greater for hand-hygiene improvements. The burden of proof, therefore, must lie with those recommending isolation wards over hand-hygiene.

*Observation 3: The relationships between arrival rates (i.e. demand), physical structure, hand-hygiene efficacy, and length of stay are complex, and unlikely to be adequately modeled with a single linear equation. Therefore, the infection control problem does not decompose into a set of independent problems.*

The non-linear nature of the system we simulate is difficult to model in closed-form, which means that any linear approximation will only be valid for a limited interval of parameter values. As an example, this means that if compliance with hand-hygiene regulations is increased from 30% to 50%, a linear model to predict performance changes may be invalid. A simulation that incorporates such non-linear relationships remains usable.

*Observation 4: When increasing HHE, the change in the dynamic system is too complex to model with a linear approximation.*

For example, based on our simulation, we would predict that the average length of stay, as well as average total cost per patient, for patients who do not contract an infection, would increase with greater HHE. Further, greater HHE would not lead to a lower absolute number of patients who contract an HAI. We suggest that these results are not intuitive at first glance, yet perfectly reasonable upon reflection. Such insight into a service system is valuable in analyzing different approaches to improving infection control.

*Observation 5: A systemic perspective is needed to understand infection control from a global perspective.*

It is unlikely that a hospital view-point is sufficient, since the environment remains a reservoir for pathogens, which arrive at hospitals through patients, visitors and health-care workers. In this simulation, we treated the level of infection in the environment as fixed, although a multi-hospital simulation would require linked levels of pathogens throughout a given region.

### 3.6.1 Contribution to the Literature

Our model was based on actual data, and adds to the set of studies applying simulation to health issues [59]. Although simulations are more opaque than closed-form solutions, we gain the benefit of solving a more realistic problem using simulation, even if we cannot feasibly investigate every possible set of parameter values.

The complex and dynamic nature of the infection control problem also directly addresses the current discrepancy in cost attributed to hospital acquired infections. [122] estimated that HAIs added more than fifteen thousand dollars to the treatment of the average patient, largely through extended stays. [73] recently estimated that the costs were statistically insignificant for most types of HAIs under study, and practically insignificant for one. However, the approach in [73] explicitly ignores the linked effect of LOS and infection, and attributes no impact to cost from HAI through more than 100 potential variables examined to account for cost. As such, it is hardly surprising that they found no residual effect; the structural link is ignored, and the indirect impact of HAI on cost through vehicles such as increased use of pharmaceuticals is severed. Our model strongly suggests that LOS and HAI are tightly linked, and HAIs have a significant impact on the use of hospital resources and attention from HCWs, all of which increase cost (and increase the probability of yet more infections).

### 3.6.2 Future Research

We are pursuing several avenues to improve the precision and robustness of our results. First, we seek to estimate the LOS and incidence of HAI simultaneously, and isolate the effect of these on cost. A simultaneous equation approach is one possible way to properly estimate the dynamic spiral described above.

Second, we are currently working on finding levels of variable costs that may be allocated for specific events in a simulation. This will add veracity, although given the very high proportion of hospital costs that are fixed, it is unlikely to alter the overall picture drastically.

Third, although the simulation approach is valuable, it does not consider the psychological responses of health-care workers. It is unclear why compliance rates for hand-hygiene regulations are as low as they are. In order to examine the underlying factors driving compliance with infection control procedures, we are constructing a survey-instrument. We are currently working with multiple hospitals in the Atlanta area.

Finally, this study is meant to be only a first step in evaluating the costs and benefits of different types of regulations the U.S. Congress may enact. The CDC is required to evaluate such regulations, and this was the initial impetus to the model. We therefore seek to build models for different types of hospitals, before using these sub-models as input into a nationwide study of HAIs and regulation. Currently, we have four hospitals: two from Children's Hospital of Atlanta, Athens Regional Hospital, as well as the original source of data, Cook County Hospital. cooperating with us in providing information and data.

The final outcome of this line of research is meant to be guidance for how different sets of national regulations would impact HAIs, rates, costs and benefits. Since everything outside the hospital functions as a reservoir for infections, we expect a system-wide approach will be required in order to fully control resistant pathogens.

**Table 10:** Base Model Parameters

| Parameter | Value | Comment |
|---|---|---|
| mArrivalRate | 1 | Parameter governing the rate of patient arrival. |
| mVisitorMultiplier | 3 | Visitors arrive at a rate of three times the number of patients. |
| mColonProp | 0.2 | Proportion colonized in the community. |
| mComResistProp | 0.3 | Proportion of those colonized in the community carrying a resistant strain. |
| mTreatmentTime | 0.04 | Approximate number of days between visits from HCWs. |
| mHandHygEffic | .8 | Efficacy of hand-hygiene, considered as a combination of probability of washing or using gel, with probability that pathogen is removed. |
| mLocToHCWColRate | .5 | Probability per treatment incidence of transfer from location to HCW. |
| mHCWtoPatientColRate | .5 | Probability per treatment incidence of transfer from HCW to patient. |
| mHCWtoLocColRate | .7 | Probability per treatment incidence of transfer from HCW to location. |
| mLocToPatientColRate | .8 | Probability per treatment incidence of transfer from location to patient. |
| mPatientToHCWColRate | .4 | Probability per treatment incidence of transfer from patient to HCW. |
| mPatientToLocColRate | .9 | Probability per treatment incidence of transfer from patient to location. |
| mColToInfRate | .3 | Probability per treatment incidence a colonized patient develops an infection. |
| mDisinfectLoc | .1 | Probability per treatment incidence a colonized location is disinfected. |
| mCureSProb | .4 | Probability per treatment incidence a susceptible infection is cured. |
| mCureRProb | .1 | Probability per treatment incidence a resistant infection is cured. |
| mHealthyExitProb | .06 | Probability per treatment incidence of exit if patient is healthy. |
| mInfSExitProb | .02 | Probability per treatment incidence of exit if patient has a susceptible infection. |
| mInfRExitProb | .01 | Probability per treatment incidence of exit if patient has a resistant infection. |

**Table 11:** Parameter and Variable Definitions

| Name | Definition |
|---|---|
| Arr | The mean interarrival time of patients. |
| HHE | Hand-hygiene efficacy parameter. |
| vDischargedPatients | The number of patients discharged. |
| vNumDischargedHAI | The number of patients discharged that had an HAI. |
| vNumDischargedNoHAI | The number of patients discharged that never had an HAI. |
| vAvgLOSwithHAI | The average length of stay of patients discharged that had an HAI. |
| vAvgLOSnoHAI | The average length of stay of patients discharged that never had an HAI. |
| vAvgTCwithHAI | The average total cost of patients discharged that had an HAI. |
| vAvgTCnoHAI | The average total cost of patients discharged that never had an HAI. |
| vICUfull | The average proportion of time the ICU was full. |

**Table 12:** Output from Base Model

| Arr | HHE | Statistic | Number of Discharged Patients | Number discharged with HAI | Number Discharged Without HAI | Avg LOS of patients with HAI | Avg LOS for patients without HAI | Avg TC with HAI | Avg TC no HAI | ICUfull |
|---|---|---|---|---|---|---|---|---|---|---|
| 0.1 | 0.4 | Mean | 39.46 | 37.76 | 1.70 | 23.71 | 1.43 | 59706.72 | 5201.85 | 1.00 |
| 0.1 | 0.4 | SE | 0.98 | 0.99 | 0.22 | 0.49 | 0.21 | 1172.03 | 518.45 | 0.00 |
| 0.1 | 0.6 | Mean | 46.74 | 43.80 | 2.94 | 21.31 | 1.55 | 53965.47 | 5738.28 | 1.00 |
| 0.1 | 0.6 | SE | 1.04 | 0.90 | 0.34 | 0.43 | 0.17 | 1016.22 | 398.88 | 0.00 |
| 0.1 | 0.8 | Mean | 102.48 | 78.34 | 24.14 | 12.45 | 3.72 | 32785.01 | 10259.30 | 0.99 |
| 0.1 | 0.8 | SE | 1.11 | 0.91 | 0.93 | 0.13 | 0.16 | 315.28 | 304.69 | 0.00 |
| 0.25 | 0.4 | Mean | 40.14 | 38.48 | 1.66 | 22.84 | 1.42 | 57622.88 | 4814.78 | 0.99 |
| 0.25 | 0.4 | SE | 0.98 | 0.94 | 0.28 | 0.54 | 0.27 | 1296.82 | 646.18 | 0.00 |
| 0.25 | 0.6 | Mean | 47.20 | 44.44 | 2.76 | 21.10 | 1.47 | 53464.89 | 5159.56 | 0.99 |
| 0.25 | 0.6 | SE | 1.12 | 0.99 | 0.38 | 0.45 | 0.18 | 1083.15 | 492.82 | 0.00 |
| 0.25 | 0.8 | Mean | 106.34 | 74.86 | 31.48 | 12.36 | 3.96 | 32565.22 | 10721.27 | 0.94 |
| 0.25 | 0.8 | SE | 1.15 | 1.16 | 1.29 | 0.15 | 0.15 | 369.25 | 287.85 | 0.00 |
| 0.5 | 0.4 | Mean | 40.46 | 37.96 | 2.50 | 21.87 | 1.19 | 55288.03 | 4680.92 | 0.97 |
| 0.5 | 0.4 | SE | 1.11 | 0.97 | 0.53 | 0.49 | 0.18 | 1161.24 | 463.56 | 0.00 |
| 0.5 | 0.6 | Mean | 47.72 | 43.82 | 3.90 | 20.40 | 1.73 | 51792.26 | 5905.90 | 0.95 |
| 0.5 | 0.6 | SE | 1.18 | 1.07 | 0.50 | 0.53 | 0.23 | 1276.21 | 542.43 | 0.00 |
| 0.5 | 0.8 | Mean | 100.94 | 64.42 | 36.52 | 12.44 | 4.66 | 32756.32 | 12085.96 | 0.78 |
| 0.5 | 0.8 | SE | 1.27 | 1.38 | 1.62 | 0.21 | 0.18 | 490.29 | 346.41 | 0.01 |
| 1 | 0.4 | Mean | 38.86 | 35.62 | 3.24 | 21.13 | 1.78 | 53538.45 | 5888.04 | 0.82 |
| 1 | 0.4 | SE | 1.08 | 1.00 | 0.56 | 0.53 | 0.31 | 1262.04 | 698.91 | 0.01 |
| 1 | 0.6 | Mean | 45.40 | 40.20 | 5.20 | 19.49 | 2.25 | 49606.30 | 7092.66 | 0.76 |
| 1 | 0.6 | SE | 1.16 | 1.05 | 0.79 | 0.49 | 0.26 | 1181.55 | 567.32 | 0.02 |
| 1 | 0.8 | Mean | 87.46 | 39.46 | 48.00 | 12.29 | 5.05 | 32411.16 | 12844.22 | 0.28 |
| 1 | 0.8 | SE | 1.26 | 1.77 | 2.27 | 0.25 | 0.16 | 594.36 | 318.64 | 0.02 |

**Table 13:** Output from the model with an additional isolation ward

| Arr | HHE | Statistic | Number of Discharged Patients | Number discharged with HAI | Number Discharged Without HAI | Avg LOS of patients with HAI | Avg LOS for patients without HAI | Avg TC with HAI | Avg TC no HAI | ICUfull |
|---|---|---|---|---|---|---|---|---|---|---|
| 0.1 | 0.4 | Mean | 43.08 | 40.16 | 2.92 | 25.16 | 1.87 | 63174.05 | 6169.10 | 1.00 |
| 0.1 | 0.4 | SE | 0.89 | 0.85 | 0.37 | 0.57 | 0.22 | 1356.52 | 524.91 | 0.00 |
| 0.1 | 0.6 | Mean | 49.10 | 44.46 | 4.64 | 23.32 | 3.05 | 58761.50 | 8829.71 | 1.00 |
| 0.1 | 0.6 | SE | 1.02 | 1.03 | 0.46 | 0.45 | 0.23 | 1077.90 | 480.19 | 0.00 |
| 0.1 | 0.8 | Mean | 103.76 | 77.06 | 26.70 | 14.18 | 5.01 | 36925.70 | 12765.78 | 1.00 |
| 0.1 | 0.8 | SE | 1.39 | 1.10 | 1.02 | 0.19 | 0.13 | 457.42 | 247.41 | 0.00 |
| 0.25 | 0.4 | Mean | 46.84 | 43.60 | 3.24 | 22.91 | 2.44 | 57793.02 | 7404.14 | 1.00 |
| 0.25 | 0.4 | SE | 1.14 | 0.95 | 0.45 | 0.49 | 0.32 | 1166.29 | 693.07 | 0.00 |
| 0.25 | 0.6 | Mean | 53.26 | 48.12 | 5.14 | 21.27 | 2.58 | 53863.11 | 7914.37 | 1.00 |
| 0.25 | 0.6 | SE | 1.17 | 1.01 | 0.62 | 0.38 | 0.18 | 908.44 | 386.30 | 0.00 |
| 0.25 | 0.8 | Mean | 105.70 | 70.74 | 34.96 | 14.07 | 5.50 | 36654.79 | 13714.98 | 0.99 |
| 0.25 | 0.8 | SE | 1.57 | 1.32 | 1.29 | 0.21 | 0.15 | 499.48 | 287.06 | 0.00 |
| 0.5 | 0.4 | Mean | 51.80 | 46.68 | 5.12 | 20.59 | 2.26 | 52231.42 | 7061.51 | 0.98 |
| 0.5 | 0.4 | SE | 1.28 | 1.07 | 0.67 | 0.54 | 0.21 | 1290.07 | 496.87 | 0.00 |
| 0.5 | 0.6 | Mean | 53.84 | 48.14 | 5.70 | 20.58 | 2.70 | 52214.10 | 8153.28 | 0.97 |
| 0.5 | 0.6 | SE | 1.69 | 1.65 | 0.58 | 0.65 | 0.22 | 1561.55 | 471.82 | 0.00 |
| 0.5 | 0.8 | Mean | 107.50 | 61.12 | 46.38 | 13.46 | 5.58 | 35208.61 | 13879.55 | 0.88 |
| 0.5 | 0.8 | SE | 1.46 | 1.55 | 2.23 | 0.20 | 0.16 | 474.66 | 303.86 | 0.01 |
| 1 | 0.4 | Mean | 50.80 | 44.94 | 5.86 | 18.41 | 2.59 | 47042.37 | 8064.89 | 0.79 |
| 1 | 0.4 | SE | 1.50 | 1.41 | 0.59 | 0.60 | 0.19 | 1425.49 | 367.74 | 0.02 |
| 1 | 0.6 | Mean | 60.76 | 49.44 | 11.32 | 16.62 | 3.16 | 42748.23 | 9175.49 | 0.69 |
| 1 | 0.6 | SE | 1.79 | 1.64 | 0.86 | 0.61 | 0.19 | 1460.98 | 373.67 | 0.02 |
| 1 | 0.8 | Mean | 93.08 | 32.78 | 60.30 | 12.57 | 6.03 | 33074.01 | 14759.42 | 0.30 |
| 1 | 0.8 | SE | 1.26 | 1.93 | 2.47 | 0.33 | 0.17 | 790.39 | 333.39 | 0.02 |

**Table 14:** Output from the model with an isolation ward carved out form the ICU

| Arr | HHE | Statistic | Number of Discharged Patients | Number discharged with HAI | Number Discharged Without HAI | Avg LOS of patients with HAI | Avg LOS for patients without HAI | Avg TC with HAI | Avg TC no HAI | ICUfull |
|---|---|---|---|---|---|---|---|---|---|---|
| 0.1 | 0.4 | Mean | 30.02 | 27.60 | 2.42 | 27.53 | 2.48 | 68832.41 | 7676.66 | 1 |
| 0.1 | 0.4 | SE | 0.89 | 0.86 | 0.26 | 0.89 | 0.28 | 2137.69 | 586.02 | 0.00 |
| 0.1 | 0.6 | Mean | 34.94 | 31.64 | 3.30 | 24.63 | 3.41 | 61905.13 | 9354.25 | 1 |
| 0.1 | 0.6 | SE | 0.80 | 0.75 | 0.33 | 0.54 | 0.37 | 1279.96 | 785.98 | 0 |
| 0.1 | 0.8 | Mean | 76.26 | 56.14 | 20.12 | 14.59 | 5.82 | 37906.77 | 14346.53 | 1 |
| 0.1 | 0.8 | SE | 1.33 | 0.86 | 0.91 | 0.26 | 0.18 | 624.03 | 355.40 | 0 |
| 0.25 | 0.4 | Mean | 31.54 | 27.82 | 3.72 | 26.82 | 2.57 | 67129.00 | 7604.63 | 1 |
| 0.25 | 0.4 | SE | 0.80 | 0.79 | 0.48 | 0.59 | 0.30 | 1404.22 | 677.43 | 0 |
| 0.25 | 0.6 | Mean | 35.88 | 31.78 | 4.10 | 23.99 | 3.52 | 60377.19 | 9624.01 | 1 |
| 0.25 | 0.6 | SE | 0.77 | 0.79 | 0.45 | 0.53 | 0.36 | 1258.33 | 751.24 | 0 |
| 0.25 | 0.8 | Mean | 79.38 | 50.14 | 29.24 | 14.45 | 6.41 | 37563.15 | 15486.66 | 1 |
| 0.25 | 0.8 | SE | 1.29 | 1.15 | 1.28 | 0.24 | 0.22 | 565.69 | 434.83 | 0 |
| 0.5 | 0.4 | Mean | 35.08 | 30.62 | 4.46 | 23.00 | 3.28 | 57990.86 | 9035.83 | 0.99 |
| 0.5 | 0.4 | SE | 1.07 | 0.95 | 0.52 | 0.64 | 0.38 | 1533.84 | 806.63 | 0 |
| 0.5 | 0.6 | Mean | 38.90 | 33.90 | 5.00 | 21.87 | 3.86 | 55292.43 | 10297.95 | 0.99 |
| 0.5 | 0.6 | SE | 1.23 | 1.05 | 0.69 | 0.52 | 0.36 | 1249.82 | 768.92 | 0 |
| 0.5 | 0.8 | Mean | 79.16 | 43.70 | 35.46 | 13.94 | 6.82 | 36355.71 | 16294.40 | 0.95 |
| 0.5 | 0.8 | SE | 1.39 | 1.10 | 1.62 | 0.27 | 0.19 | 646.23 | 377.79 | 0.01 |
| 1 | 0.4 | Mean | 39.16 | 34.60 | 4.56 | 19.66 | 3.00 | 50024.59 | 8738.02 | 0.91 |
| 1 | 0.4 | SE | 1.57 | 1.43 | 0.59 | 0.75 | 0.28 | 1786.62 | 569.07 | 0.01 |
| 1 | 0.6 | Mean | 42.88 | 35.94 | 6.94 | 18.97 | 3.56 | 48364.56 | 9890.36 | 0.88 |
| 1 | 0.6 | SE | 1.37 | 1.27 | 0.61 | 0.70 | 0.28 | 1666.79 | 566.46 | 0.01 |
| 1 | 0.8 | Mean | 77.38 | 30.32 | 47.06 | 13.26 | 6.30 | 34730.30 | 15266.53 | 0.67 |
| 1 | 0.8 | SE | 0.80 | 1.33 | 1.61 | 0.28 | 0.15 | 666.34 | 290.84 | 0.02 |

**Table 15:** The average effect across scenarios of changes in hand-hygiene efficacy

| HHE | Number of Discharged Patients | Number of Discharged Patients With HAI | Number of Discharged Patients without HAI | Average LOS with HAI | Average LOS without HAI | Average Total Cost with HAI | Average Total Cost without HAI | Proportion o time the IC is full |
|---|---|---|---|---|---|---|---|---|
| 0.4 | 40.60 | 37.15 | 3.45 | 22.80 | 2.19 | 57531.15 | 6861.70 | 0.95 |
| 0.6 | 46.39 | 41.31 | 5.08 | 21.13 | 2.74 | 53529.60 | 8094.65 | 0.94 |
| 0.8 | 93.29 | 56.59 | 36.70 | 13.34 | 5.40 | 34911.39 | 13535.38 | 0.82 |

# CHAPTER IV

# THE EFFECT OF FLEXIBLE HOSPITAL CONTRACTS ON EMERGENCY DEPARTMENT DIVERSION

## *4.1 Introduction*

Overcrowding in the emergency departments (ED) has led to an increase in the use of ambulance diversion (AD), during which a hospital formally stops accepting patients by ambulance. A lack of available beds in the main hospital wards lead to patients waiting in beds in the ED, a practice known as *boarding*. Boarding patients in the ED as they await open beds in the main hospital is a primary reason for overcrowding, and therefore AD. In this paper we examine the potential of a change in the contracts between the federal government and hospitals to reduce such diversions. We model the arrival and discharge of patients using a birth-death process, and identify conditions under which a Pareto improvement may be found. We illustrate the procedure using data from an urban hospital, and use a simulation model to estimate revenue effects. A simulation of a two-hospital system shows that with appropriate choices for parameters, more patients of each class is served, yielding a Pareto-improvement over the current system.

### 4.1.1 Overview

From 1992 to 2003, the number of hospital emergency rooms in the U.S. went from approximately 6000 to fewer than 4000, while emergency department visits increased from 89.8 to 108 million ([131]). Many hospital patients arrive through the emergency room, and when the hospital is at capacity, patients are *boarded* in the ED until a regular bed opens up. This exacerbates crowding of the ED. To combat this problem, the hospital may go on *diversion* (or Ambulance Diversion, AD), where ambulances are sent to other facilities.

AD is therefore an unfortunate symptom of overcrowding. Diversions cost money both to initiate and terminate, and adds to the complexity of routing critical patients, which benefits neither public, hospitals, nor government. The public benefits from having efficient hospitals with the capacity to address both routine and surge requirements. The government is interested both in the public health and in the capacity to respond to disasters. Hospitals themselves seek to serve patients, expand services, and work efficiently.

The goal in this study is to identify a method to reduce AD, and to evaluate its impact from multiple perspectives:

- Hospitals seek to reduce AD, increase patients served, attain high medical standards, and increase revenue.

- The government benefits from efficiently provided medical services, at low cost, and from open ED's that increase disaster preparedness.

- The public would like rapid service at ED's, at a high medical standard, and at low cost.

A method that benefits each party, even if side-payments are required, is a Pareto-improvement.

It is important to distinguish between capacity at the hospital ED, and beds in the main wards. The lack of beds in the main ward leads to patients accumulating in the ED, after they are otherwise ready to move to the main wards (boarding). The output from the ED is the input to the main hospital wards, so a lack of beds in the wards may be regarded as a denial of service.

As an example, consider AD at DeKalb Medical Center in Atlanta, GA ([78]). When the hospital reaches capacity, i.e. there are no beds available to accept patients

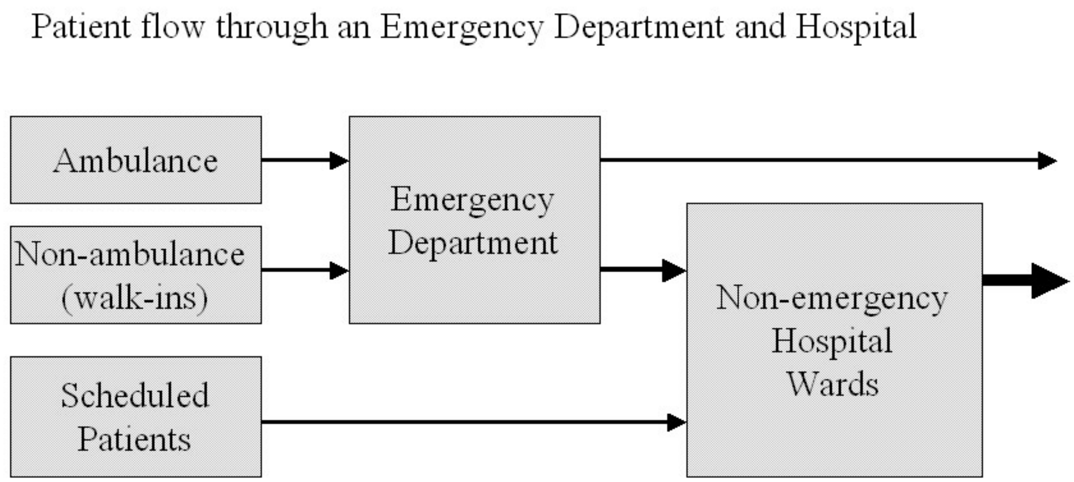


**Figure 4:** Patients moving through the ED and main hospital ward.

from the ED, the hospital goes on AD, and ambulance dispatchers are informed. Going on AD is not done lightly, and DeKalb Medical Center remains on diversion until slack capacity is generated in order that a minor surge of new patients will not overwhelm the ED again. The flow of patients is illustrated in Figure 4.

In this study, we develop an approach to lower both the rate and variability of new patient arrivals to the ED when capacity is tight, thereby lessening the probability that a hospital will have to go on diversion. The benefits include less time spent on diversion for hospitals, less crowding of ED's, enhanced government ability to respond to disasters, and better health service for the public.

There are three types of patients in the U.S.: uninsured, privately insured, and federally insured (Medicare and Medicaid). Hospital treatment for the latter is governed by very inflexible contracts, with low payments and a provision that if the hospital is to get any such patients, it must accept all such patients. On the face of it, this seems a reasonable safeguard against cherry-picking patients, but it may be counter-productive under circumstances of high demand and frequent diversions.

However, we show that introducing an additional degree of freedom to the hospital-government contracts will alleviate several burdens associated with AD. The federal government is the only entity that has one basic contract with thousands of hospitals, and so is the only entity that may realistically impact the problem so broadly. Nevertheless, our method is more general than we suggest here, since any class of patient that may be selectively routed in an ambulance may serve the purpose of federally insured patients in this paper. The scheme may therefore be applied in other health systems with changed details, but similar effects.

We readily concede that our mechanism would not be applicable in situations with emergent trauma or non-communicative patients, when immediate ED care is paramount, or when ambulance personnel cannot find out the insurance status of the patient. However, given that insurance and personal preference already partially determines hospital routing, the mechanism is not unrealistic. New information systems at hospitals and emergency call-centers are easing the flow of medical records and insurance information, and this problem of timely information flow is expected to decrease over time.

The specific policy we analyze involves a change in the contract between the federal government and hospitals, so that patients insured by Medicare/Medicaid may be routed to hospitals with more room. In addition to full AD, we add a state of partial diversion (PD), during which emergency medical services (EMS) personnel route patients identified as having Medicare/Medicaid insurance to hospitals not on diversion, either AD or PD. Physicians continue to make all medical decisions under this approach, as recommended in the guidelines for AD ([20]).

We find conditions under which an alternative contract between the federal government and hospitals afford improvements in outcomes for patients, hospitals, and the government, i.e. a Pareto improvement. We describe a practical method to route patients during periods of high demand which may even out occupied capacity in hospitals in a given area. Limiting probabilities for a Markov process are derived in order to show the potential effects, and data from DeKalb Medical Center in Atlanta is used to parameterize a numerical example, as well as to provide the framework for a simulation model. We use these quantitative analyses to estimate the scope for improvement and to indicate expected long-run effects. Finally, we expand the simulation to a two-hospital system, in order to demonstrate that more Medicare/Medicaid and uninsured patients would be served under the new scheme.

## 4.2 Literature Review

The literature on hospital and emergency room overcrowding is growing with the perception of incipient crisis ([82]), the core of which is a decrease in hospital capacity over the last ten years as the number of ED visits increase. [131] give an overview of hospital and ED overcrowding. More than six hundred studies were included in a literature review of the problem of diversion, which is an indication of academic interest ([114]). [114] point out that emergency departments constitute the designated safety net for the health system, so the current lack of surge capacity is cause for concern.

The American Hospital Association has documented the extent of the problem ([2]), showing that approximately half of ED's are operating at or over capacity in 2006 (Figure 5), more than half of all urban and teaching hospitals are experiencing at least some time on diversion (Figure 7), and the lack of beds in the main wards is cited as the primary reason by slightly more than half the hospitals experiencing some level of diversion (Figure 6).

The scope of the problem has grown significantly in recent years ([52, 131]), with more than nine out of ten ED directors considered overcrowding a significant problem ([40]). In 2003, an estimated half million diversions occurred, while the overall volume of ED visits was slightly more than sixteen million ([24]). Although this is primarily

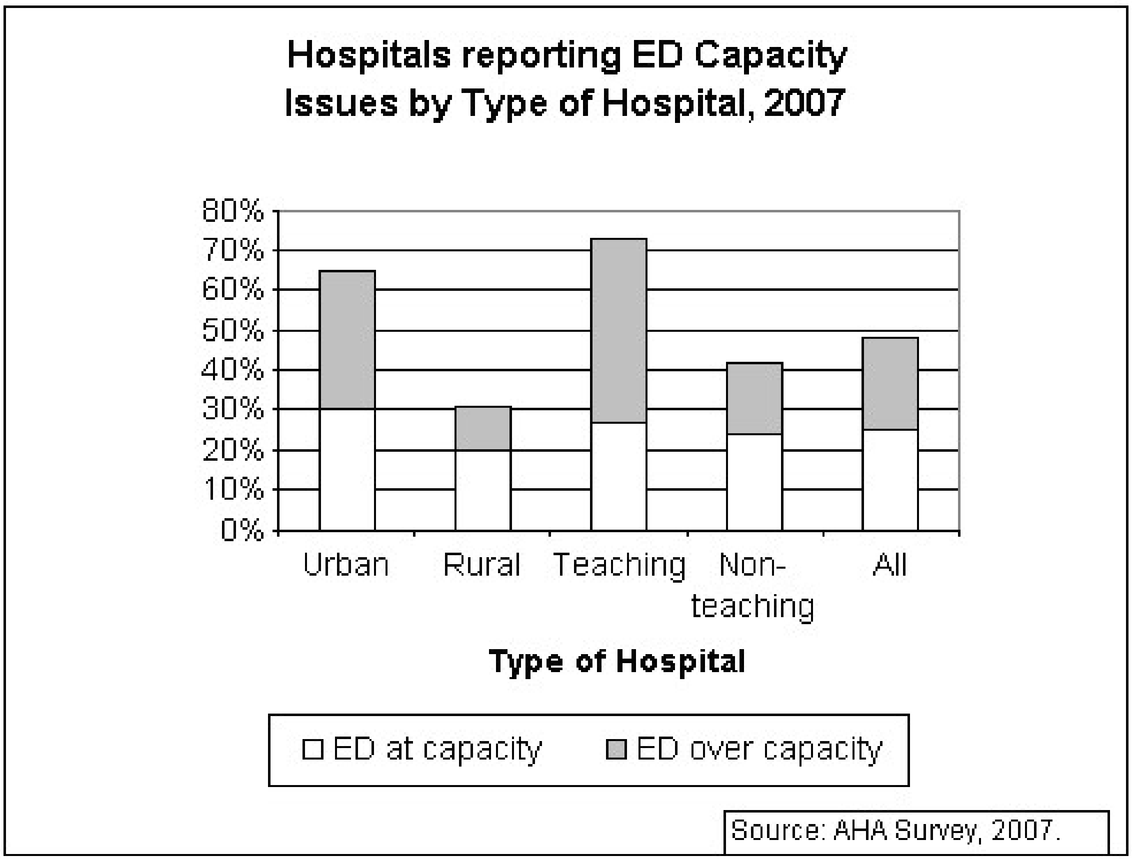


**Figure 5:** Hospital EDs at or over capacity

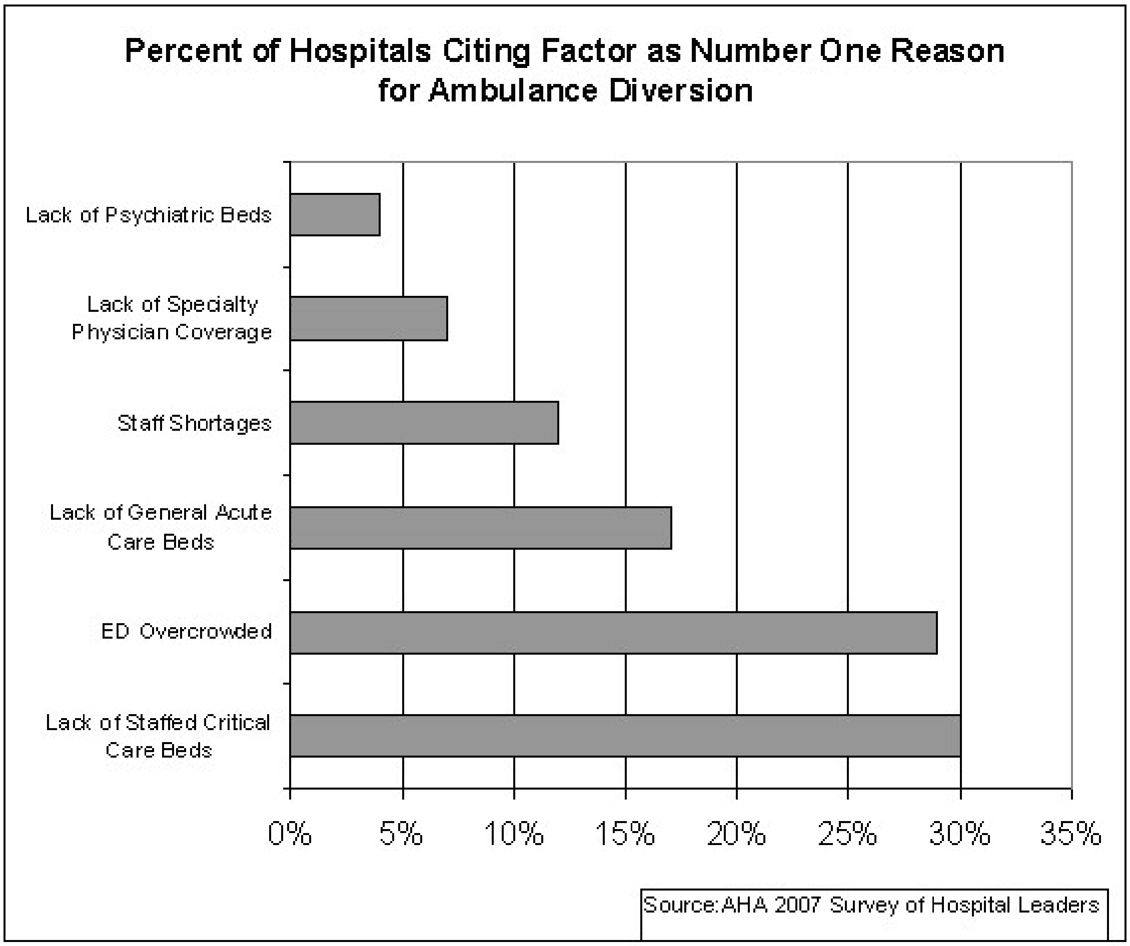


**Figure 6:** Factors Cited as Number 1 Reason for AD

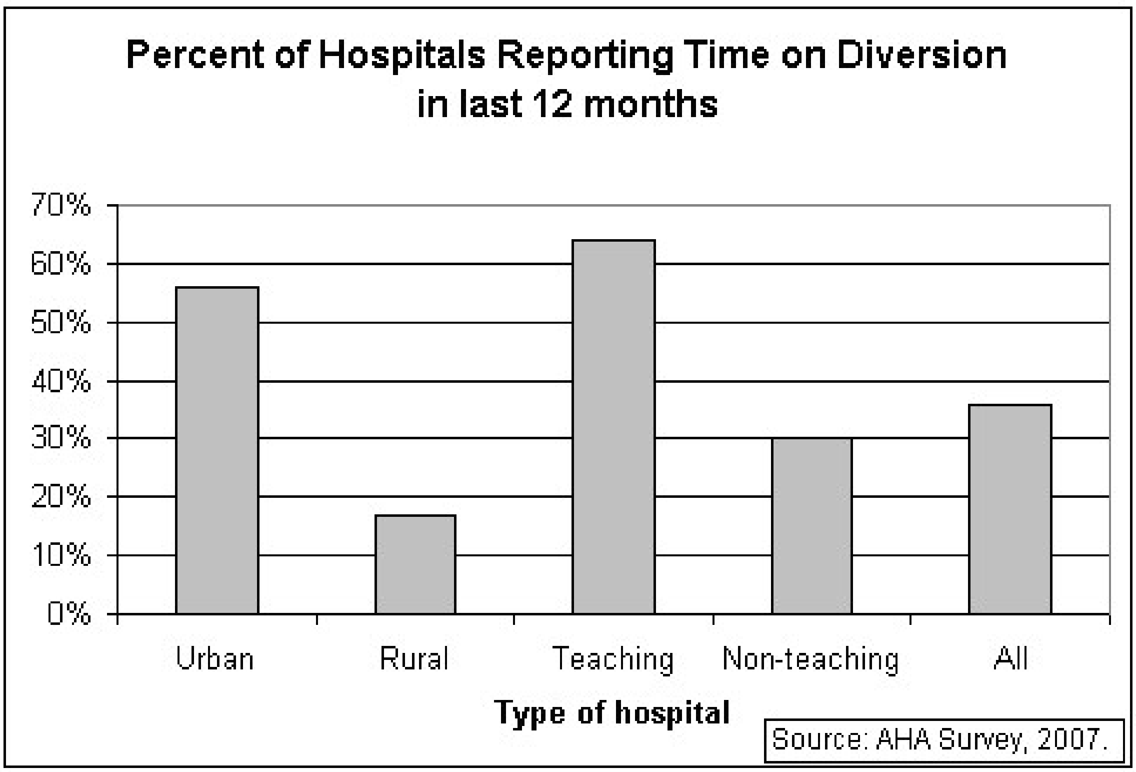


**Figure 7:** Percent of Hospitals Reporting some time on AD in 2006

a patient-safety issue, lost revenues is also considered a significant problem for many hospitals ([67]). On a per patient basis, the revenues lost to hospitals from diversion is estimated to average slightly more than one thousand dollars ([102]).

### 4.2.1 Overcrowding

Since the ED plays such a large number of roles in the U.S. health system, there are a number of suggested reasons for the causes of overcrowding ([41]), including more acute and complex cases presenting to the ED, increased patient volumes, and limited resources. The causes of overcrowding of EDs may be decomposed into three sets of problems, depending on where the patient flow is hindered ([52, 7]): i) the flow of patients into the ED, ii) patients' service times in the ED, and iii) the flow of patients out of the ED. Note that the blockage of output from the ED to the main hospital, i.e. boarding of patients in the ED, is considered a primary cause of over-crowding ([131]).

Instead of focusing only on a single hospital, several studies suggest that AD is best seen as a system-wide problem ([90, 146]), since diversion at one hospital impacts nearby hospitals. If one hospital goes on diversion, other hospitals have an incentive to do so as well, to avoid an onerous increase in traffic. In a recent experiment, two hospitals agreed to measure the impact on one hospital ED, when the other committed to remain off diversion for a week ([148]). The effect was remarkable: diversion hours fell from 19.4 and 27.7 to 1.4 and zero, respectively. A system-wide collaborative approach in Sacramento, where the hospitals committed to working together to manage patient flow, resulted in significant reductions in AD ([112]). Collaborative efforts in Rochester, New York, saw some improvement ([132]), and a 24% reduction of hours on AD in Syracuse, New York ([90]).

The studies that have been conducted support the contention that ED overcrowding and diversions are symptoms of a systemic problem ([114]). It follows that solutions to the problem may be found outside of the ED itself, a point emphasized in several studies ([91, 52, 131]). In this context, the rest of the hospital is considered ”outside of the ED”.

### 4.2.2 Proposed solutions to overcrowding

Increasing the number of beds, or creating systems to coordinate ambulance routing among hospitals, are two potential solutions to overcrowding and AD. However, AD itself is a method to handle overcrowding through a temporary reduction in input, and there is evidence that AD does reduce ED overcrowding ([91]). However, it is clearly not an ideal solution since it artificially removes access to an ED and thereby reduces effective capacity. The most obvious way to increase throughput in an ED is to add capacity. However, building new space is remarkably expensive, one estimate putting the cost at approximately one million USD per bed ([110]).

Of the proposed solutions to increase the flow of patients from the ED, several suggest increasing resources, such as ICU beds ([102]). In one hospital, increasing ICU beds from 47 to 67 decreased average daily time on diversion from 3.8 to 1.4 hours ([103]). Better management of hospital beds, as opposed to simply increasing the number of beds, is also expected to reduce ED overcrowding in general, and AD in particular ([6]).

In addition to increasing resources, there are several suggestions for more flexible use of assets. Selective diversions, e.g. for those patients that emergency medical services (EMS) personnel believe are unlikely to need critical care ([116]), is one possibility. A program to predict diversion may effectively preemptively divert in order to avoid formal diversion ([49]). Information technology may provide decision support systems to improve ED operations ([70]). In a straight-forward application of internet technology, posting an up-to-the-minute workload schedule of EDs in the Perth area was found to reduce the time spent on diversion by more than a third from 2002 to 2003 (specifically from 1788 to 1138 hours), despite an increase in demand ([138]).

Several operations management techniques have been used to help address the problem of overcrowding ([5, 82]). For example, [97] make the point that most capacity planning is done using average demand on resources, but ignores variability. This immediately suggests that reducing variability in demand would be a viable method to limit diversion, e.g. by scheduling elective surgeries ([97, 93]). [93] use a system dynamics approach to simulate admission to acute hospitals, and found that elective surgeries function as a safety valve in the UK, being canceled to allow ED patients admittance.

### 4.2.3 Current recommendations

The American College of Emergency Physicians (ACEP) have issued Guidelines for AD ([20]), which suggest that EMS agencies need working agreements to coordinate, and diversion should be a temporary situation, managed systemically, and avoided as much as possible. The guidelines explicitly allow for "selective diversion", without specifying this concept further. The guidelines suggest the decision to go on full diversion should reside with the emergency physician at the ED, without being based on financial considerations. We note that this point regards going on diversion in any one particular instance. Since the capacity of a hospital or ED is fundamentally dependent on financial resources, this caveat cannot extend to the system for hospital management over time.

### 4.2.4 Incentives to change

The literature on overcrowding and AD documents the disparate incentives the various participants operate under. Since it is unrealistic to expect a change in behavior that is contrary to a parties interests, we note some of the incentives.

The Institute of Medicine report ([82]) explicitly points out that hospitals have few financial incentives "to reduce crowding", and suggest that firm rules are needed to avoid diversion. However, [104] estimate that each hour spent on diversion cost one hospital \$ 1,086 in foregone revenue.

To put the issue of ED overcrowding and AD in perspective, consider the benefits from improving the situation. Waiting times for patients would be reduced, and fewer patients would give up and leave without medical attention ([157]). Since any hospital provided treatment must also be made available to ED patients, specialists who now avoid the ED may be enticed back to providing emergency service, and disaster preparedness would improve ([82]).

The system for responding to catastrophes is split between more than six thousand 911 centers, and there are no national training or certification for the responding EMS personnel; nor is there any single federal agency responsible ([82]). The Institute of Medicine (2006) points out that this fragmented system ensures limited accountability.

### 4.2.5 Contribution

We propose to manage diversions through a flexible contract with the federal government, which allows hospitals to selectively divert Medicare/Medicaid patients when capacity is tight. Since the federal government is by far the largest purchaser of hospital beds, it has unmatched power to set terms for service, and this change is certainly legally and practically feasible. On the operational side, EMS personnel would have a simple and non-medical basis for choosing destination hospital.

Through the avoidance of shutting down hospital capacity, such flexibility would allow patients to be spread more evenly among metro hospitals and decrease diversion time. Since privately insured patients pay more, the hospital would benefit in terms of revenue, and a decrease in price for federal patients would allow a Pareto improvement, even before the societal gains for reducing diversion is considered.

Compared to other suggested solutions, our proposal therefore increases the volume of patients served by avoiding diversion. Medical decision making is avoided in the ambulance, speeding the decision making and reducing uncertainty. The change is simple to implement, and does not require an increase in overall capacity. The main drawback of this approach is a slight reduction in choice on the part of patients selectively diverted from the hospital in question. Since we would only recommend this method in urban areas with multiple hospitals, the mechanism would not send patients outside of metro areas for emergency treatment.

To model this process, we use a continuous-time Markov process framework and derive limiting probabilities, which indicate the proportion of time a hospital spends on diversion. In order to illustrate the impact, we use data from an urban hospital (DKMC) to examine the scope for improvement, and apply this data to numerical examples. We then use the data and analysis as input for a simulation to gauge the revenue implications of this approach. Finally, we simulate a two-hospital system in order to show that more patients from every class are served under the partial diversion scheme as compared to current practice.

## 4.3 Assumptions and model formulation

In order to model the hospital's occupancy as a continuous time Markov process, we make several assumptions. We then define the state space, and formulate the model.

### 4.3.1 Assumptions

1. Base case assumptions:

   (a) The main ward of the hospital has a fixed number of beds: $N$.

   (b) There is no overflow capacity, i.e. no beds are placed in hallways.

(c) The hospital is operating in a metropolitan statistical area, with multiple ED's available to accept patients.

(d) The hospital is private, and does not function as the last resort for an area. Some public hospitals cannot go on diversion, and so this model will not apply to them.

(e) The hospital will go on full diversion only when at capacity, and remains on full diversion until some slack develops, specifically until the number of beds occupied is $M < N$. This is an interpretation of an oral description of the policy at DKMC [78], and is not to be taken as fixed or permanent policy.

2. Partial diversion assumption:

(a) Under the more flexible contract between the hospital and the federal government, the hospital may go on partial diversion earlier than at full capacity, in order to avoid full diversion. We specify $K < N$, and allow the hospital to selectively divert all patients except those with private insurance when the patient population has reached size $K$. This reduces the arrival rate to $\gamma < \lambda$. It is realistic to have multiple types of diversion, and the only new aspect to this assumption is that patients are routed to hospitals depending on federal insurance. Routing is already partially determined by insurance, so this assumption is only a small change in standard operating procedure.

3. Technical assumptions:

(a) There are two classes of patients in this model, a high revenue class consisting of the privately insured patients, and a low revenue class, made up of Medicare/Medicaid and uninsured patients.

(b) Arrivals follow a Poisson process with rate $\lambda$, and service times are exponentially distributed with mean $\mu$, with no dependence on the revenue class of the patient. With a sufficiently large metropolitan area, there is reason to assume arrivals are independently distributed with exponential inter-arrival times.

(c) Every state is recurrent and the continuous-time Markov chain is irreducible, so the Markov chain is ergodic. This means that if the hospital runs long enough, every bed occupancy level ($X$) will take place, and the hospital will spend some time on, as well as off, full diversion. This assumption assures the existence and uniqueness of the limiting probability distribution ([125]).

### 4.3.2 State Space and Notation

We indicate that the hospital is on full diversion with $\Delta = 1$, and off full diversion with $\Delta = 0$. $X \epsilon \{0, ..., N\}$ captures the number of beds occupied. The states are fully specified by the number of beds occupied, and whether or not the hospital is on full diversion: $\Omega = \{0, 1\} \times \{0, ..., N\}$. The states may therefore be visualized as on a chain of nodes, with one loop for diversion (see Figure 8). Each node is specified by the number of beds occupied, and whether or not the hospital is on full diversion. In the following, when the state is off diversion, we often denote the node using only the number of beds occupied.

The hospital goes on partial diversion at $K$ beds occupied, on full diversion when all $N$ beds have patients, and back off full diversion when $M$ beds are full. The notation for the model is summarized in Table 16.

We expect significant fluctuations in patient demand and occupancy, but since we are interested in the long-run behavior of the model, we focus on limiting probabilities.

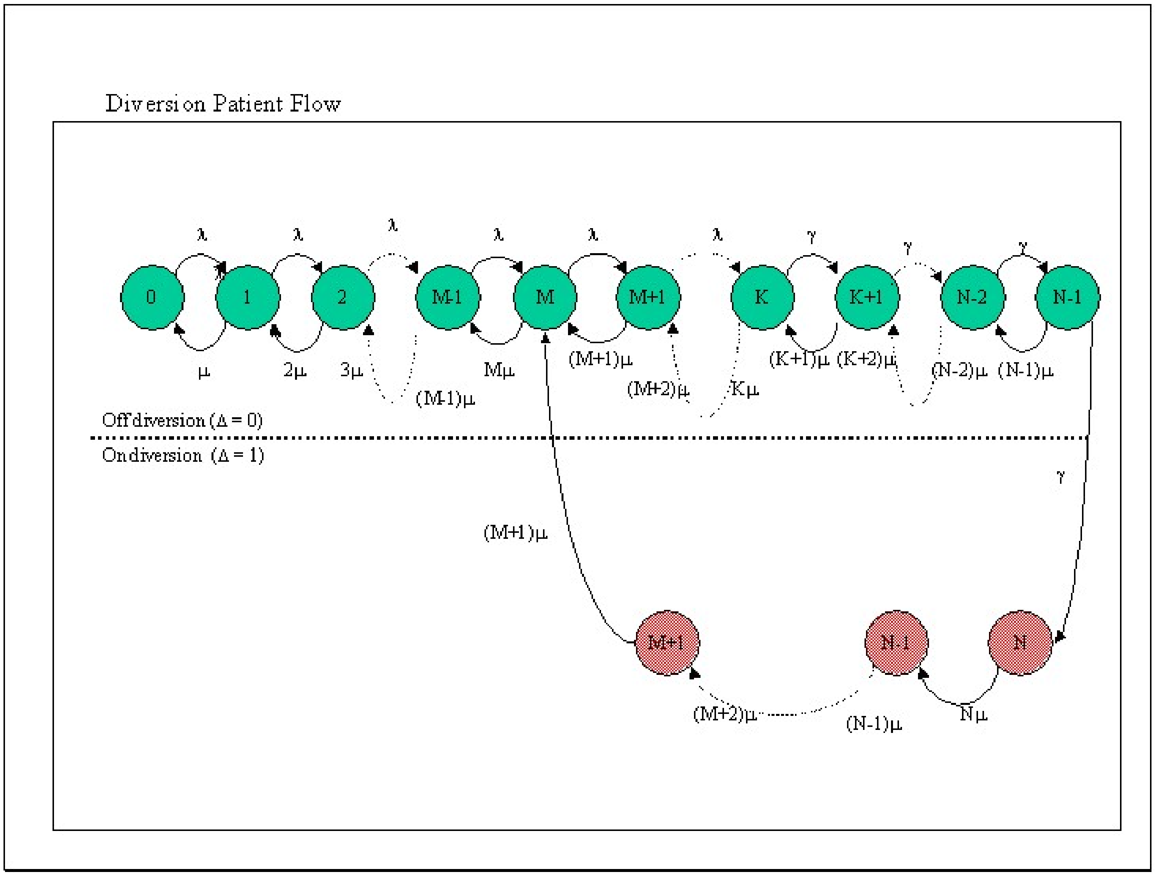


**Figure 8:** Partial Diversion Patient Flow

**Table 16:** Notation

| | |
|---|---|
| $N$ | The number of beds in the hospital. We assume the hospital goes on full diversion when capacity is reached. |
| $M$ | Diversion limit, the number of beds occupied when hospital goes off diversion. |
| $K$ | Capacity protection, when the hospital enters selective diversion. |
| $X$ | Number of beds occupied. |
| $\lambda$ | Arrival rate of patients. |
| $\gamma$ | Arrival rate of high-revenue patients ($\gamma < \lambda$). |
| $\mu$ | Departure rate of patients. |
| $\Delta$ | Indicator variable equal to 1 when the hospital is on full diversion, and zero otherwise. |
| $\Omega$ | State space; $\Omega = \{0, 1\} \times \{0, ..., N\}$. |
| $P_{i,\Delta}$ | Limiting probability of being in state $[i, \Delta]$. |
| $P_i$ | Limiting probability of being in state $[i, \Delta = 0]$. |
| $\rho_j$ | Helper parameter, equal to $\frac{\lambda}{j\mu}$ |
| $\theta_j$ | Helper parameter, equal to $\frac{\gamma}{j\mu}$ |
| $\phi$ | Helper parameter, equal to $\frac{\mu}{\gamma}$ |
| $\Gamma$ | Helper parameter, equal to $\sum_{i=0}^{N-K-1} \frac{(K-i)!}{K!} \phi^i$ |

### 4.3.3 Model

The limiting probabilities are characterized by the balance equations, which are based on the fact that for an ergodic continuous-time Markov chain, the number of exits and entries to a state must be equal. We specify the balance equations and present the solution as the limiting probabilities for the system, or the long-run proportion of time the system will be in a given state. We first provide a small example in order to motivate the discussion.

### 4.3.4 Small-Scale model

The simplest model that would exhibit the behavior of interest is a hospital with only two beds. The arrival rate overall is $\lambda$, and once one bed is occupied, only a subset of patients are brought in. The arrival rate with one bed occupied is therefore lower, and we denote the new arrival rate as $\gamma$, such that $\gamma < \lambda$. Since N is equal to 2, diversion sets in when the hospital is full, and there is only one other state in the state space, namely when one bed is occupied while the hospital is on diversion [Node (1,1)]. This gives the following set of balance equations:

$$Node(0) \quad : \quad \mu P_1 + \mu P_{1,1} = \lambda P_1 \tag{32}$$

$$Node(1) \quad : \quad \lambda P_0 = \mu P_1 + \gamma P_1 \tag{33}$$

$$Node(2) \quad : \quad \gamma P_1 = 2\mu P_2 \tag{34}$$

$$Node(1,1) \quad : \quad 2\mu P_2 = \mu P_{1,1} \tag{35}$$

The solution is:

$$P_0 = \frac{2\mu(\mu+\gamma)}{2\mu(\mu+\gamma+\lambda)+3\gamma\lambda} \tag{36}$$

$$P_1 = \frac{2\lambda\mu}{2\mu(\mu+\gamma+\lambda)+3\gamma\lambda} \tag{37}$$

$$P_2 = \frac{\lambda\gamma}{2\mu(\mu+\gamma+\lambda)+3\gamma\lambda} \tag{38}$$

$$P_{1,1} = \frac{2\gamma\lambda}{2\mu(\mu+\gamma+\lambda)+3\gamma\lambda} \tag{39}$$

$$\tag{40}$$

This small model suggests some qualitative results which also hold in the full-scale model. If we consider that selective diversion boils down to selecting an arrival rate $\gamma$ to limit the time spent on diversion, then the marginal effect of $\gamma$ on the time spent on diversion, $P_{1,1}$, is as follows:

$$\frac{\partial P_{1,1}}{\partial \gamma} = \Big(\frac{2\lambda}{2\mu(\mu+\gamma+\lambda)+3\gamma\lambda}\Big)\Big[1 - \frac{\gamma(2\mu+3\lambda)}{2\mu(\mu+\gamma+\lambda)+3\gamma\lambda}\Big] \tag{41}$$

Since $\gamma, \lambda, \mu > 0$, $\frac{2\mu\gamma+3\gamma\lambda}{2\mu^2+2\mu\gamma+2\mu\lambda+3\gamma\lambda} < 1$, both factors in Equation (41) are positive, i.e., increasing the arrival rate while on selective diversion increases the time on full diversion. This intuitive result is illustrative of the greater issue: by managing the distribution of patients such that hospitals on the verge of full diversion are partially shielded, full diversion with its concomitant problems are avoided some portion of the time. In order to assess the scope of this method, but with a full-scale model, we refer to our numerical example (see Section 4.4).

We also observe that since $\gamma < \lambda$ for all hospitals accepting Medicare/Medicaid patients under the proposed new contract, the added flexibility of applying a selective diversion limit of $K$ means the hospital may improve its performance either in revenue, or time spent off diversion, or both. Since the federal government may decrease the reimbursement rate for hospitals who choose this option, some of the benefit would accrue to tax-payers. Therefore, given our assumptions, the added flexibility this scheme provides affords a Pareto improvement for the parties to the system.

### 4.3.5 Full-Scale Model

We now turn to the full-scale model. Using the same approach as in the smaller model, but relegating the details to an appendix, we specify the balance equations, solve in terms of $P_0$, then normalize to find the limiting probabilities. The results are provided in Table 19, in the appendix.

The full-scale model is qualitatively similar to the small-scale model. Under conditions of significant demand, we find that the system spends most time close to capacity, and with a significant amount of time spent on full diversion. Figure 9 shows the probabilities for states off diversion, and Figure 10 shows the probabilities on diversion. These two figures represent a single probability distribution, using specific numbers, as described in Section 4.4.

The derived limiting probabilities show that the system will suffer from diversion if arrivals dominate departures. Since the patients have exponential service times, the rate of discharge is proportional to the number of beds occupied, $X\mu$, so a low arrival rate gives occupancies below capacity, and it is only when arrival rates dominate discharge rates at high occupancy that diversion became a significant issue. Also, as expected, when $\gamma$ is significantly smaller than the overall arrival rate, $\lambda$, the greatest effect from selective diversion is found.

## *4.4 Numerical example*

To illustrate the system and gain some intuition, we construct a numerical example based on a scaled-down version of DeKalb Medical Center in Atlanta, Georgia. We set the number of hospital beds to $N = 100$ (reduced from 535 beds), the level of occupancy when diversion ends to $M = 90$, the arrival rate at $\lambda = 12$, the rate of discharge at $\mu = 0.10$, and the rate at which the privately insured patients arrive at $\gamma = 2$. The limiting probability distribution is illustrated in Figure 9 for when the hospital is off diversion, and Figure 10 for states on diversion.

To examine the effects of different levels at which selective diversion begins, we varied parameter $K$, from $M$ to $N$. For all practical purposes, reserving just a few beds drove time spent on full diversion to zero (see Figure 11).

We therefore find that selective diversion has the potential to impact time spent on diversion. In order to assess the incentives for the hospitals, we take into account revenue, as well as the occupancy rates. We turn to empirical data to provide the input to a simulation to assess occupancy and revenue. The rationale for using simulation is that the problem becomes intractable when we add revenue. While the state space without revenue classes is of size $2N - M$, even with only two revenue classes each occupancy level may hold from 0 to its level of one patient type, and so the size of the state space grows to $\frac{1}{2}((N+1)(N+2)+(N-M-1)(N+M+2))$. In our example, with $N = 100$ beds and an occupancy level to go off diversion of $M = 90$, this gives 13695 states.

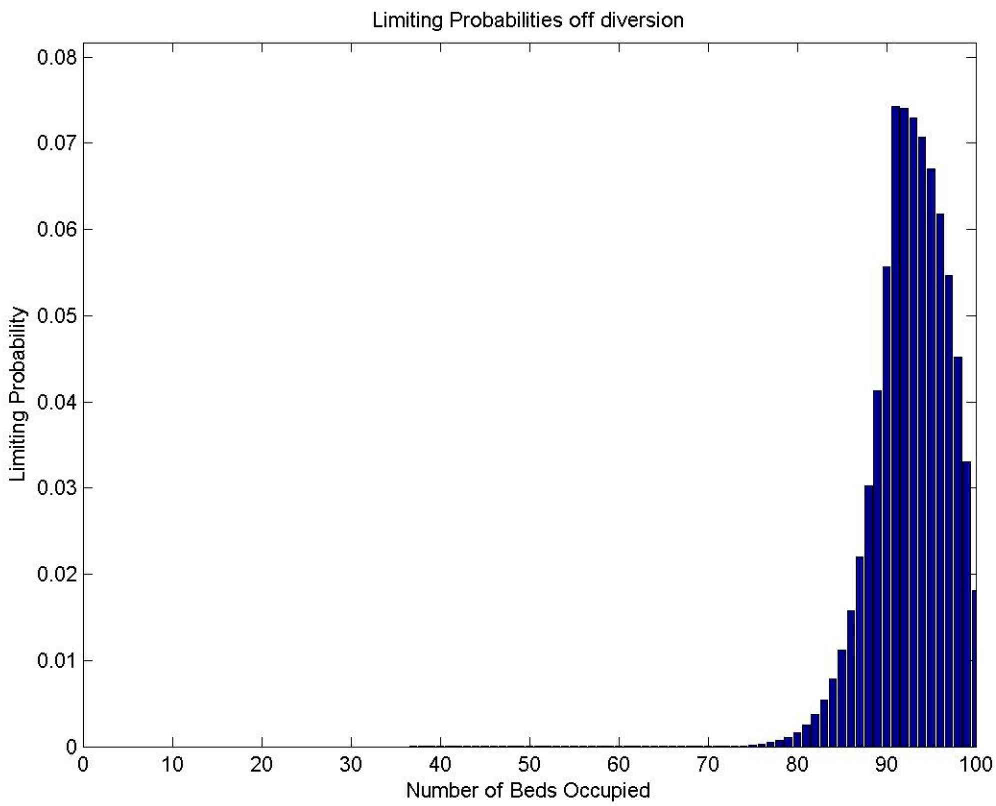


**Figure 9:** Limiting Probabilities for states off diversion

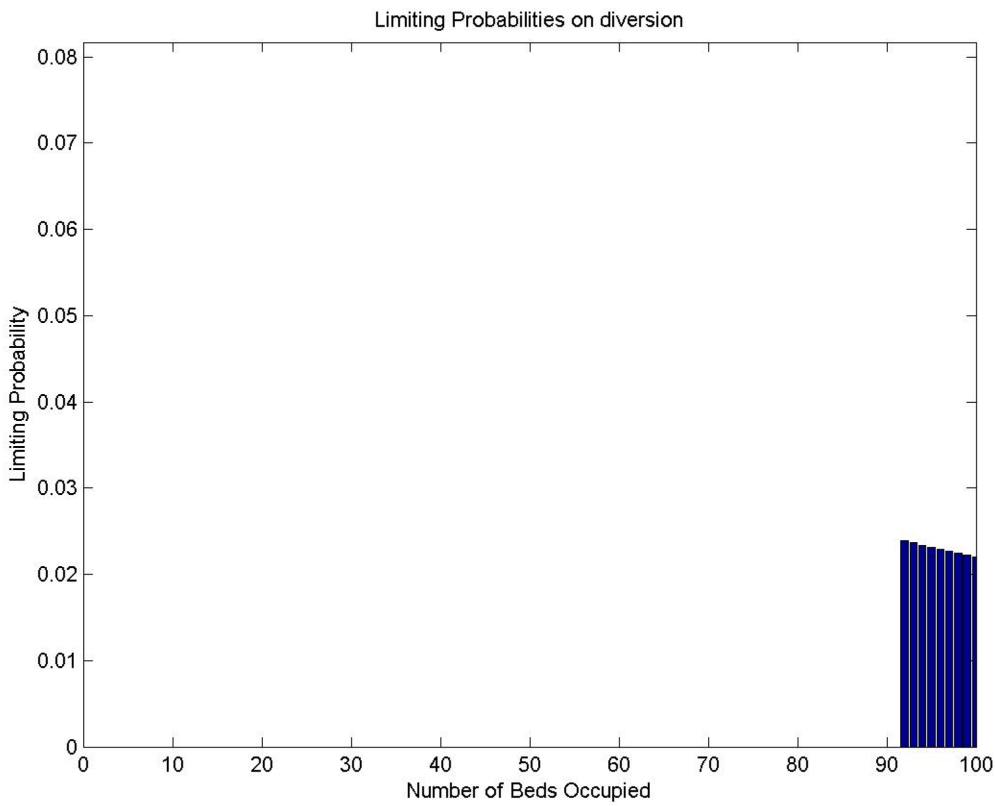


**Figure 10:** Limiting Probabilities for states on diversion

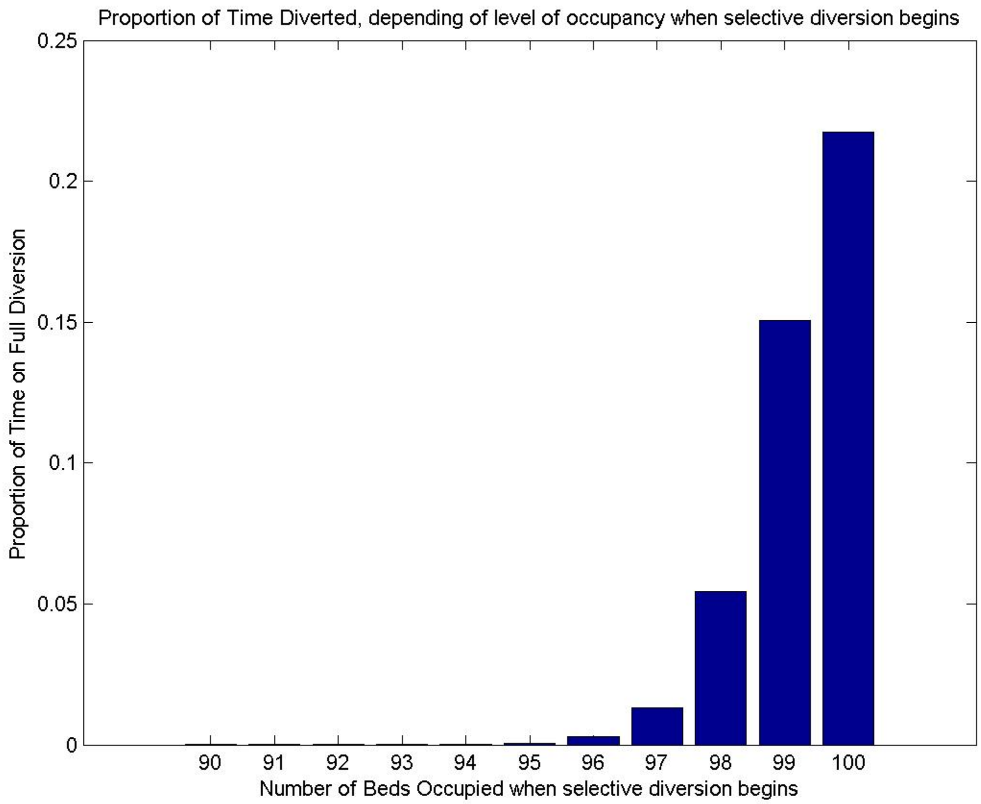


**Figure 11:** Diversion Time by Capital Protection Level

## *4.5 Empirical Study*

### 4.5.1 Data

The data was comprised of 140,720 records from 27,002 anonymous patients based on 459 days from an Dekalb Medical Center in Atlanta Georgia, which supplies more than thirty thousand services with individual charges ([78]). These data include all the patients who had their entire stay within the period of 28 March, 2004, and 30 June, 2005, so we stripped one hundred days from the beginning and end of the data-set in order to avoid the problem of understating occupancy levels. We did not have access to diversion times, but did have access to both the lengths-of-stay, the financial class of the patient, and the actual charges. These were calculated based on the percentage collected of the nominal charges, which were as low as 0.4% for one group of patients. The DeKalb Medical Center financial class corresponds to our broader designations of privately insured (HMO), Medicare/Medicaid, and uninsured.

Mean lengths of stay per type of patient varied from 1 to 140 days, while the average amount collected by type of patient varied from \$7 to \$774. The mean length of stay was 5.18 days, with a standard deviation of 7.73 days, and with an average collection of \$3,516.51 (standard deviation \$7118.16), which corresponds to an average per day charge collected of \$679.41.

### 4.5.2 Simulation

For the simulation, we begin with an initial patient population drawn from the distribution of patients in the hospital data. We assume exponential arrival and service times, but use the sample mean inter-arrival and service times to calibrate.

The hospital beds are filled on a first-come first-served basis, and when the hospital reaches capacity of 100 full beds, it ceased to accept patients, until there are 10 free beds ($M = 90$). The illustrative choice of $M$ should be sufficiently smaller than $N$ to provide some breathing space for the hospital. We then test various occupancy levels

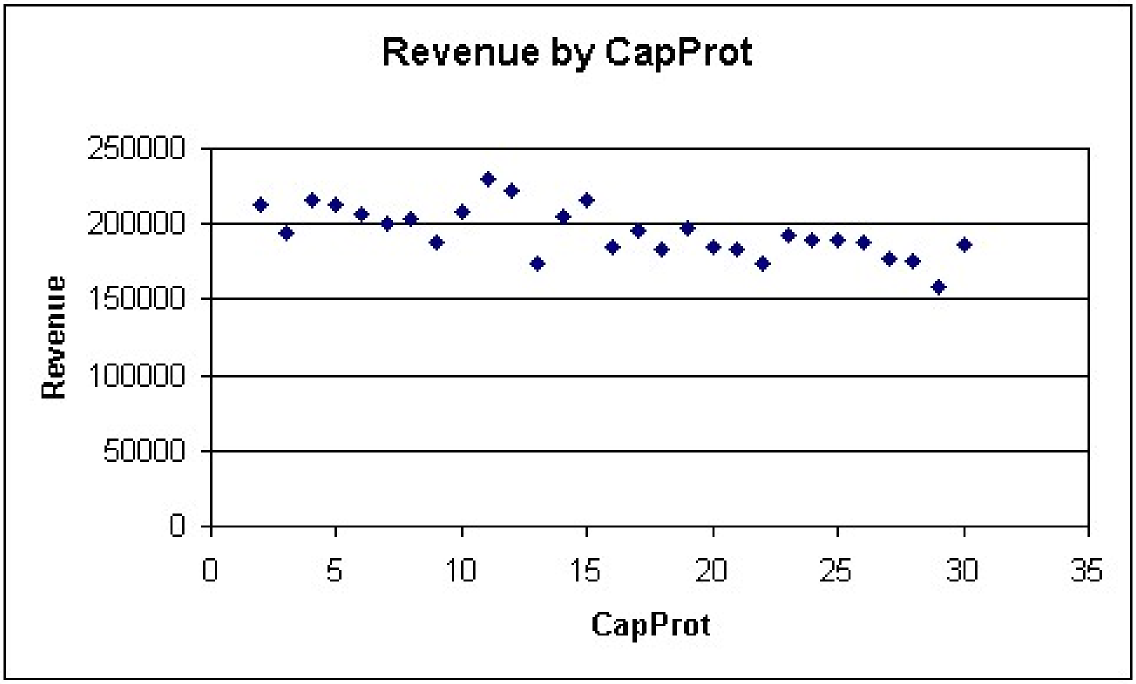


**Figure 12:** Revenue by Capital Protection Level

at which to go on partial diversion, $K$, usually from $M$ to $N$. As an experiment, we also investigate the effect of allowing $K$ to be less than $M$, to a minimum of 75. To improve the validity of the comparisons, we use common random numbers for the inter-arrival times and service times.

For brevity, we denote the number of beds reserved "Capital Protection Level", or "CapProt" in the figures. As indicated in Figure 12, there does not appear to be much effect when just a few beds are reserved, suggesting that the revenue effect is modest.

The effect on time spent on diversion is more striking. Figure 13 shows how the time spent on diversion falls to nearly zero with eight beds reserved for partial diversion. This compares to an average time on diversion without partial diversion of 12.42 days out of 100. The results for eight beds for a simulation of 100 runs of 100 days are shown in Table 17.

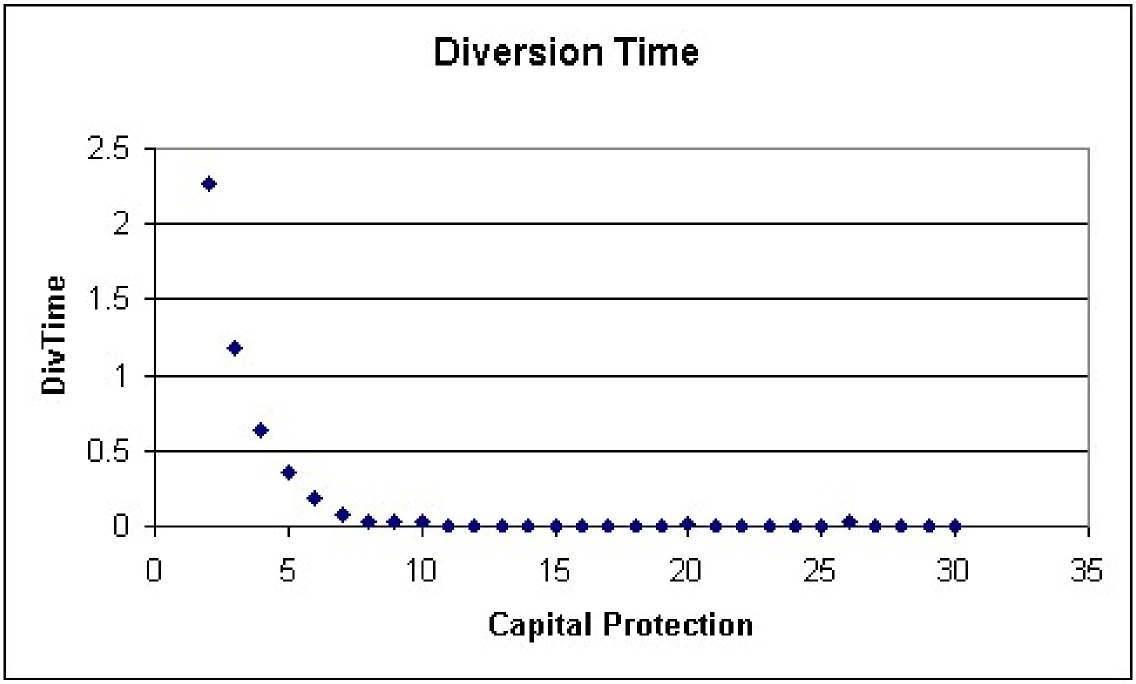


**Figure 13:** Diversion Time by Capital Protection Level

We run the simulation for $CapProt = 25$ beds to illustrate that neither the hospital nor the patients benefit from reserving too many beds: the utilization rate falls, and revenue does as well. Diversion time when 25 beds are reserved falls to an actual value of zero in the simulation, but that compares to 0.14 days out of 100 with 8 beds reserved. When compared to 12.41 without this partial diversion, we consider 8 beds reserved sufficient to resolve the problem in practice.

The difference in total number of patients served, from 1388 under no partial diversion, to 1380 with 8 beds reserved ($K = 92$) is not statistically significant. Since the different groups of patients stay different time periods, however, we note that the mean number of patients in the hospital falls slightly, from 91.9 to 89.84, which is statistically significant ($p \approx 0$).

To give the hospital an incentive to introduce this scheme, the revenue effect is crucial. With 8 beds reserved, revenue increases from \$671,976 (s=170,624) to

**Table 17:** Simulation Results for DeKalb Medical Center

| | Mean Number of Patients (SD) | Total HMO Patients | Total M/M Patients | Total Uninsured Patients | Total Patients |
|---|---|---|---|---|---|
| Without Capacity Protection | 91.9 (0.61) | 541 | 686 | 161 | 1388 |
| Capacity Protection of 25 | 74.7 (0.34) | 692 | 383 | 88 | 1163 |
| Capacity Protection of 8 | 89.84 (0.45) | 688 | 560 | 132 | 1380 |

$714,217 (s=143,670). The p-value for the one-tailed t-test that revenue did not increase was 0.02986, leading us to conclude that this change improves both metrics of performance: time spent on diversion, and revenue for the hospital. Note that revenue actually falls to $667,919 if the capacity level is increased one more bed, to nine. This suggests that hospitals may welcome the flexibility to go on partial diversion, but have a financial incentive to limit its use.

To complete the investigation we consider the effects on patients in the group selectively diverted. If these suffer, we cannot argue that the scheme is a Pareto-improvement. Since we cannot show the effect on these patients in a simulation with a single hospital, we investigate the potential for improvement in a system of only two hospitals. Note that with only one other hospital, neither will use partial diversion if the other is on full or partial diversion, so the potential for improvement is at its most limited with only two hospitals. To retain comparison with the single hospital simulation, we use two identical hospitals with $N = 100$ beds each, going off full diversion at $K = 90$ beds occupied, and with identical policies. We run the simulation over 400 iterations over a period of one year.

As we can observe from Figure 14, the total number of patients served increases for small levels of CapProt, but as expected, this benefit declines rapidly with increasing

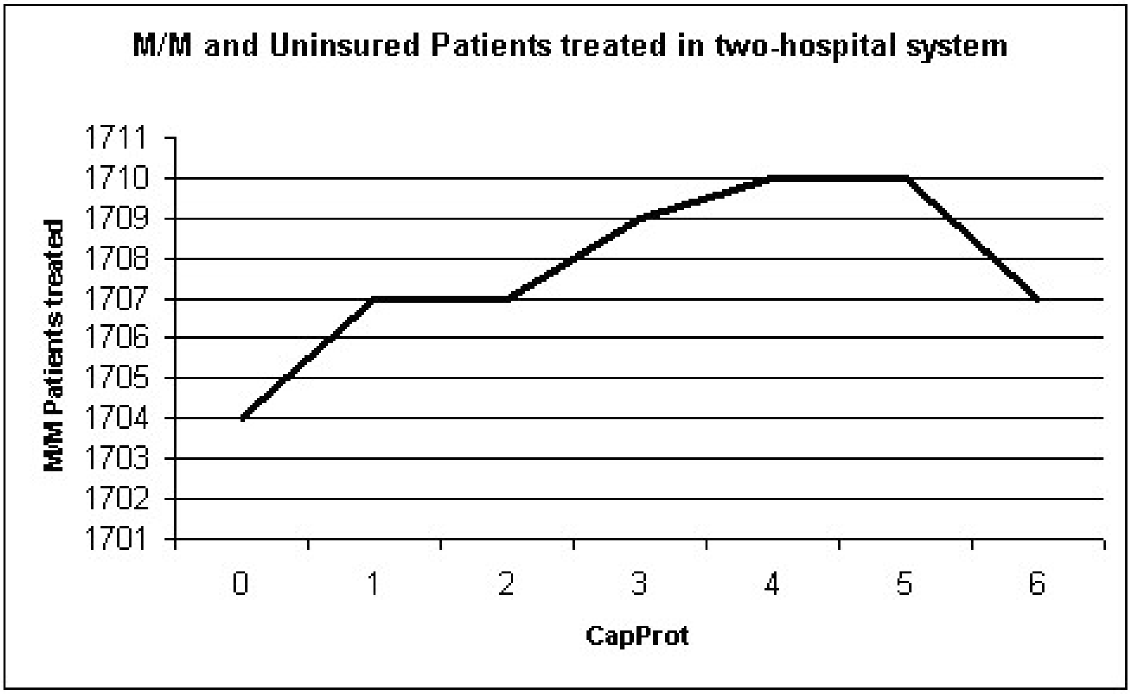


**Figure 14:** Medicare/Medicaid and Uninsured Patients served in a two-hospital system using partial diversion

numbers of beds reserved. We test the null hypothesis that the mean number of Medicare/Medicaid and Uninsured patients does not increase for $CapProt = 4$ versus the base case: $\mu_{CapProt=4} - \mu_{CapProt=0} \leq 0$. This t-test gave a p-value of 0.014. Although this increase is small, since this scheme is primarily aimed at increasing the total number of patients served, as well as hospital revenue, any increase is a bonus. In addition, if the partial diversion scheme is Pareto improving for two hospitals, it will also be improving for systems with more than two hospitals.

## *4.6 Conclusion*

Currently there are a number of policies on diversion, and various causes of ED overcrowding. With few spare beds in the main hospital wards, patients are often boarded in the ED, a common cause of diversion. The policy in the base model has the hospital go on diversion at capacity, then remain on diversion until some specified capacity has become available.

Our proposed model allows a hospital to go on partial diversion when capacity has become tight. Specifically, we suggest the federal government allow hospitals to selectively divert Medicare/Medicaid patients at a critical level, but prior to full capacity. Some of the possible objections to our partial diversion scheme are:

- Contracts cannot be changed over a large enough group of hospitals to make a difference. On the contrary, since the contracts are between hospitals and the Federal government, the latter has both the power and the reach needed.

- Ambulance routing should be made only on the basis of patient preferences and medical conditions. However, routing is already made based in part on patient preferences, and the routing of patients based on insurance information saves EMS personnel from making medical decisions the ACEP guidelines reserves for physicians.

- Financial decisions have no place in patient care. In reality, financial decisions already impact patient routing and care, especially in the routing of uninsured patients. Our proposed change would merely acknowledge this aspect of our health system. Since financial resources are required to extend treatment, we regard wanton waste of medical resources detrimental to social welfare.

- There may be no other hospitals available. However, we explicitly reserve the method to Metropolitan Statistical Areas (MSAs) ([146]) with multiple hospitals. Two hospitals in a region would suffice, as a decrease in diversion in one has been shown to significantly decrease diversion for the other ([148]). Since the method decreases overall diversion, more hospitals will be off diversion, on average. We confirmed this effect of our policy with the two-hospital simulation.

Emergency departments in the U.S. are required by law to stabilize patients, regardless of their ability to pay. Many hospitals go much further, providing treatment with little expectation of remuneration. It is important, therefore, to distinguish between policies and individual decision-making.

The change we are proposing is a systemic one, which simply uses one of the few non-medical criteria that hospitals have, in order to route a patient. It does not suggest that patients who pay less be denied care, only that they be routed to a less congested hospital. Since the change introduces one more degree of freedom, it is a truism that the system cannot perform worse if properly utilized. We have shown that if this is done, benefits may accrue to the hospitals, the government and taxpayers, and even to the general public, through the knowledge that EDs are less likely to be on full diversion.

To summarize, the primary benefits of partial diversion are:

- Patients benefit from less congested EDs and more decisive routing.
- Government and tax-payers may benefit by extracting some of the added revenues in the form of lower Medicare/Medicaid disbursements. Disaster preparedness is enhanced from the decrease in full diversion.
- EMS personnel have a simpler decision and a emergency response system that spends less time on full diversion. A follow-on benefit is that since insurance is being used to direct patients initially, there should be less insurance-related shuffling of patients to other hospitals after the initial emergency.
- Hospitals benefit from the added revenue gained when they operate near capacity, as well as the increased time spent off full diversion.

We consider the problem of diversion from the standpoint of one hospital, even though it is assumed to be in an MSA. One key factor that we did not explicitly model is that each hospital has an incentive to defect, rather than to cooperate. Nevertheless, given the purchasing power of the federal government, and that systems of hospitals have successfully come together to manage emergency care and reduce AD in the past, we believe that our proposed method has promise.

ED overcrowding has many causes and will require several solutions to solve the problem entirely. However, when this approach fits the problem, it has the advantages of being simple, feasible, and effective.

# CHAPTER V

# CONCLUSION

In this dissertation, we have addressed three problems out of many. The US system is characterized by a large number of participants, in contrast to countries with universal coverage. In addition to patients and doctors, hospitals, HMO's, State and Federal government, and others all play roles. These entities have divergent incentives, and this includes financial motives, even if the public health ethos demands that this aspect be ignored.

The problems in the system are possibly dominated by two: the spiralling cost of care, and the large fraction of the population without coverage. Cynics may argue that a lack of care is a personal preference, but given the tax structure, the government has made care differentially easy to obtain, obviating this argument. Further, many members of the public are troubled by those who suffer from medical catastrophe, especially through no fault of their own. Hence there is a public good problem with health.

The fact that the public has an interest in each citizens health, leads to several more questions. First, what is the role of government in health? We have not tried to answer that question, although the explosive cost spiral we found in our model suggests that the current system is suboptimal. The yearly contracts for health care mean that preventive care is underemphasized from the perspective of HMO's and patients, and the public would benefit from a greater emphasis on prevention. The government could, for instance, provide more preventive care.

Whenever government has to decide how to prioritize services, financial incentives come into the decision. And in order to balance these monetary considerations, we must consider how to measure the outcomes. These outcomes may be quality adjusted years of health, rather than just extended life, but some form of outcome must be captured in order to assess cost versus benefit. Currently, simply measuring results is controversial, as many health care providers fear a tendency to cherry-pick patients.

These are some of the larger questions of how to structure health care delivery in the U.S. Our problems are somewhat more limited, and with limited solutions. Nevertheless, each of these chapters lead to future work.

We consider aligning incentives over time, and with multiple players, to be the core question in chapter one. There are a number of games where the principal-agent framework is insufficient, and health, with e.g. patient-doctor-hospital, is a prime source of such problems.

Ambulance diversion is one problem tied to the decrease in hospital beds and increase in crowding. There are a number of other operations management techniques that may be brought to bear on managing the flow of patients through ED's and hospitals. On a larger scale, we may model the entire system of hospitals in a metro area, in order to distinguish between incentives to go on or off diversion. The game theoretic aspects of a system of hospitals, as well as system-wide agent-based simulations, is a natural next step in this research.

The work on health care associated infections is ongoing at a number of institutions. We expect to build models for multiple hospitals, including Cook County Hospital, Scottish Rite (Children's Healthcare of Atlanta), and Athens Regional, and use these to build a cost-benefit analysis of regulation of HAI's.

Beyond the foreseeable problems in health, we can imagine problems where genetic manipulation leads to true superbugs. Resistance itself may evolve in already existing pathogens, or biological weapons laboratories may leak deadly organisms. The encroachment on natural habitat may lead to increased outbreaks of diseases with wild reservoirs, e.g. Ebola. On a more positive note, genetic manipulation are expected to lead to new therapies, and the increasing flow of people around the world is making health care delivery a global industry. It would therefore be surprising if the flow of health care associated research questions evaporated.

# APPENDIX A

# PROOFS OF THEOREMS FOR REPEATED NEGOTIATIONS

**Proof of Theorem 1:** The necessary conditions for optimality ([83]) are:

$$\dot{K} = bK + qPK - aP^2 \tag{42}$$

$$\dot{\lambda} = -H_K \tag{43}$$

$$H_P = 0 \tag{44}$$

Since the multiplier function represents the shadow price of capital, it is restricted to $\lambda(t) \geq 0$ ([141]). This also ensures that the second order necessary condition, $H_{PP} = -2a(me^{-rt} + \lambda) \leq 0$ is met, so any solution maximizes profit. Note that the subscript on the Hamiltonian function $H$ indicates a partial derivative with respect to the subscripted variable. The first equation is simply the control equation. Evaluating $H_K$ gives the second equation as:

$$\dot{\lambda} = -(e^{-rt}mqP - \lambda(b + qP))$$

This simplifies to:

$$\dot{\lambda} + \lambda(b + qP) = -e^{-rt}mqP \tag{45}$$

Finally, the third equation simplifies substantially:

$$e^{-rt}(mqK - 2maP) + \lambda(qK - 2aP) = 0$$

$$(me^{-rt} + \lambda)(qK - 2aP) = 0$$

But this product can only be zero if one or the other factors are zero, one of which is precluded by the positive value of capital at all times. Assume $me^{-rt} + \lambda = 0$, so that $\lambda = -me^{-rt} < 0$, contrary to assumption. This leaves the second factor equal to zero, or $qK = 2aP$. Solving for P(t) yields:

$$P(t) = \frac{q}{2a}K(t) = \frac{q}{2Ac(1+m)}K(t) \tag{46}$$

Note that this states the price will increase proportionally with the capital stock, which is intuitive if we observe a spiral of ever-increasing prices, while the supply of medical services, dependent on the capital stock, only increases. This is in contrast to conventional markets, in which additional supply usually implies at least some decline in price.

We insert this solution (46) into the control equation:

$$\dot{K} = bK + q(\frac{q}{2a}K(t))K - a(\frac{q}{2a}K(t))^2$$

Collecting terms gives:

$$\dot{K}(t) = bK(t) + \frac{q^2}{4a}(K(t))^2 \tag{47}$$

and rearranging:

$$\dot{K} - bK - \frac{q^2}{4a}K^2 = 0 \tag{48}$$

which is Bernoulli's equation ([18]). We substitute $K = Z^y \Rightarrow \dot{K} = yZ^{y-1} \cdot \dot{Z}$, which yields:

$$yZ^{y-1} \cdot \dot{Z} - b(Z^y) - \frac{q^2}{4a}(Z^y)^2 = 0$$

This in turn gives:

$$\dot{Z} - \frac{b}{y}Z - \frac{q^2}{4ay}Z^{y+1} = 0$$

Since we have an additional degree of freedom, we now choose $y = -1$, which finally gives us a first order non-homogenous ordinary differential equation:

$$\dot{Z} + bZ + \frac{q^2}{4a} = 0 \Leftrightarrow \dot{Z} + bZ = -\frac{q^2}{4a}$$

Using an integrating factor of $e^{bt}$ we arrive at:

$$\dot{Z}e^{bt} + bZe^{bt} = -\frac{q^2}{4a}e^{bt}$$

$$(Ze^{bt})' = -\frac{q^2}{4a}e^{bt}$$

Integrating on both sides with respect to time gives:

$$Ze^{bt} = -\frac{q^2}{4a}\Big(-\frac{1}{b}e^{bt}\Big) + C_1$$

and dividing by the integrating factor yields:

$$Z(t) = C_1e^{-bt} - \frac{q^2}{4ab}$$

However, we recall that we chose $y = -1$ and so had $K = Z^{-1}$, which means

$$K(t) = \left(C_1e^{bt} - \frac{q^2}{4ab}\right)^{-1}$$

We apply the boundary condition $K(0) = K_0$ and find that

$$C_1 = \frac{1}{K_0} + \frac{q^2}{4ab}$$

Finally, we have the solution for capital given in 9. Inserting this into the equation for price (46) gives a solution for price only as a function of time and initial capital given in 10.

Inserting the solution for price (10) into (45) give a general linear ordinary differential equation for the multiplier:

$$\dot{\lambda} + \lambda\left(b + \frac{2K_0bq^2}{(4ab + K_0q^2)e^{-bt} - K_0q^2}\right) = \frac{2K_0bmq^2e^{-rt}}{K_0q^2 - (4ab + K_0q^2)e^{-bt}}$$

We define the following helper functions:

$$G(t) = b + \frac{2K_0bq^2}{(4ab + K_0q^2)e^{-bt} - K_0q^2}$$
$$f(t) = \frac{2K_0bmq^2e^{-rt}}{K_0q^2 - (4ab + K_0q^2)e^{-bt}}$$

This shortens the multiplier equation to:

$$\dot{\lambda} + \lambda G(t) = f(t)$$

We introduce the integrating factor $e^{A(t)}$, chosen so that it will simplify the multiplier equation, i.e. so that

$$\frac{d}{dt}(\lambda e^{A(t)}) = \dot{\lambda} e^{A(t)} + \lambda \dot{A} e^{A(t)} \tag{49}$$

To force this, we require $\dot{A}(t) = G(t)$. Therefore, we solve $A(t) = \int G(t)dt$. Integrating $b$ is trivial, and integrating the second part of $G(t)$ is aided through the substitution $u = 4ab + K_0q^2 - K_0q^2e^{-bt}$. We may select the arbitrary integration constant to make the equation as simple as possible, and therefore set it to zero. This results in

$$A(t) = bt - ln[(4ab + K_0q^2 - K_0q^2e^{bt})^2] \tag{50}$$

Inserting into the equation for the multiplier (49) gives $\lambda e^{A(t)} = \int f(t)e^{A(t)}dt + C$. We assume $A(t)$ finite, so that the general solution is given in 11.

**Proof of Theorem 2:** Equation 27 gives price as proportional to capital, which compares to the monopoly solution

46:

$$P(t) = \frac{q(e^{-rt}m + 2\lambda)}{a(3me^{-rt} + 4\lambda)}K(t) \tag{51}$$

In addition to remaining proportional to capital, we also note that if $\lambda(t) = 0$, or there is no additional benefit to investing in capital, then $P(t) = \frac{q}{3a}K(t) < \frac{q}{2a}K(t)$. While there is a positive marginal value of capital investment, i.e. $\lambda(t) > 0$,$P$ is further attenuated because $q$, $a$, $m$ and $e^{-rt}$ are all positive, so $\frac{q(e^{-rt}m+2\lambda)}{a(3me^{-rt}+4\lambda)} < \frac{q(e^{-rt}m)}{a(3me^{-rt})} = \frac{q}{3a}$, and the results follow.

**Proof of Theorem 3:** First, we find the partial derivatives:

$$
\begin{aligned}
H_K &= \frac{m_i q P_i P e^{-rt}}{(N-1)P+P_i} + \lambda\left[b + \frac{qp(N-1)}{N} + \frac{qP_iP}{(N-1)P+P_i}\right] \\
H_{P_i} &= \frac{m_i e^{-rt}\left[(N-1)qKP^2 - 2a(N-1)P^2P_i - aP{P_i}^2\right]}{[(N-1)P+P_i]^2}
\end{aligned}
$$

Notice that $H_P$ is composed of three factors, the first and third of which are positive. Therefore, the third optimality condition, $H_P = 0$, together with the requirement of positive prices, gives $P_i = a^{-1}\sqrt{a^2(N-1)^2P^2 + aPqK(N-1)} - (N-1)P$. But if this is to be a Nash Equilibrium (NE), we require that $P_i(t) \equiv P(t)$, which upon insertion yields:

$$P = \frac{q(N-1)}{a(2N-1)}K \tag{52}$$

This indicates that the optimal price is once again proportional to the capital stock. Moving to the issue of whether or not capital growth is once again explosive, we assume a NE in N identical payers with $P = \frac{q(N-1)}{a(2N-1)}K$ and $a_i = a$. Inserting into the capital growth equation and simplifying gives:

$$\dot{K} = bK + \frac{q^2}{a}\frac{N(N-1)}{(2N-1)^2}K^2 \tag{53}$$

Even assuming no growth in external demand, or technological change, this expression is zero only for $K = 0$ or for $K = \frac{-bAc(1+m)(2N-1)^2}{q^2N(N-1)}$, which is negative, provided $b > 0$. Therefore, with that assumption and based on the capital growth equation, the stock of capital will grow without bound even with N identical payers.

# APPENDIX B

# ADDITIONAL DATA AND NUMERICAL RESULTS FOR HEALTH-CARE ASSOCIATED INFECTIONS SIMULATION

## OLS Output

**Table 18:** Excel OLS output for Total Cost regressed on LOS and HAILOS

SUMMARY OUTPUT

| Regression Statistics | |
|---|---|
| Multiple R | 0.939 |
| R Square | 0.8819 |
| Adjusted R Square | 0.8807 |
| Standard Error | 13301.08 |
| Observations | 211 |

ANOVA

| | df | SS | MS | F | Significance F |
|---|---|---|---|---|---|
| Regression | 2 | 2.75E+11 | 1.37E+11 | 776.46 | 3.32E-97 |
| Residual | 208 | 3.68E+10 | 1.77E+08 | | |
| Total | 210 | 3.12E+11 | | | |

| | Coefficients | Standard Error | t Stat | P-value |
|---|---|---|---|---|
| Intercept | 3028.81 | 1477 | 2.050559 | 0.041564 |
| HAILOS | 445.9 | 113.0168 | 3.945 | 0.000109 |
| LOS | 1944.186 | 125.4174 | 15.50172 | 1.55E-36 |

# APPENDIX C

# DERIVATION OF LIMITING PROBABILITIES FOR THE FULL-SCALE MODEL IN THE AMBULANCE DIVERSION ANALYSIS

The limiting probabilities are presented in table 19. Notation used in the model is defined in Table 1. In order to find the limiting probabilities in table 19, we present the balance equations in Table 20. Note that all other states are impossible, i.e. their limiting probabilities are zero. We now use the balance equations to solve for the limiting probabilities in terms of the parameters.

State $(0, 0)$ yields :

$$\mu P_1 = \lambda P_0 \Leftrightarrow P_1 = \frac{\lambda}{\gamma} P_0 = \rho_1 P_0 \tag{54}$$

Similarly, state $(0, 1)$ gives:

$$\lambda P_0 + 2\mu P_2 = (\lambda + \gamma) P_1$$

$$2\mu P_2 = (\lambda + \gamma) P_1 - \lambda P_0 = \lambda P_1$$

$$P_2 = \frac{\lambda}{2\gamma} P_0 = \rho_2 \rho_1 P_0 \tag{55}$$

The use of the previous state to cancel out one part of the equation follows through up to and including $M - 1$ beds occupied:

$$\forall l \epsilon 1, \ldots, M-1 : P_l = P_0 \prod_{i=1}^{l} \rho_i \tag{56}$$

Note especially that this is also true for state $(0, M-1)$. Once even more beds are filled, the situation changes. Leaving aside $(0, M)$, consider the balance equation for $M+1$ beds occupied:

$$(M+2)\mu P_{M+2} + \lambda P_M = \lambda P_{M+1} + (M+1)\mu P_{M+1}$$

$$P_{M+2} = \rho_{M+2}(P_{M+1} - P_M) + \frac{(M+1)}{(M+2)} P_{M+1} \tag{57}$$

This pattern holds up to $K-1$ beds occupied:

$$P_K = \rho_K(P_{K-1} - P_{K-2}) + \frac{(K-1)}{(K)} P_{K-1} \tag{58}$$

For state $(0, K)$, however, the selective diversion causes the balance equation to shift:

$$(K+1)\mu P_{K+1} + \lambda P_{K+1} = \gamma P_K + K\mu P_K$$

$$P_{K+1} = \frac{\gamma}{(K+1)\mu} P_K - \rho_{K+1} P_{K-1} + \frac{K}{K+1} P_K$$

$$P_{K+1} = \theta_{K+1} P_K - \rho_{K+1} P_{K-1} + \frac{K}{K+1} P_K \tag{59}$$

This pattern holds until there are two beds available, but at state $(0, N-1)$, there are only two paths out: to full capacity and diversion, or back to $N-1$ occupancy:

$$\gamma P_{N-2} = (\gamma + (N-1)\mu) P_{N-1}$$

$$P_{N-1} = \frac{\gamma}{\gamma + (N-1)\mu} P_{N-2} \tag{60}$$

For state $(1, N)$, we have one arrival and one departure:

$$\gamma P_{N-1} = N\mu P_N \Leftrightarrow P_N = \frac{\gamma}{N\mu} P_{N-1} \tag{61}$$

The states under diversion are simpler, since there are only departures. So for state $(1, N-1)$, we have:

$$N\mu P_N = (N-1)\mu P_{N-1,1} \Leftrightarrow P_{N-1,1} = \frac{N}{N-1} P_N \tag{62}$$

This pattern is followed for the remainder of the states, i.e. $\forall i \epsilon M+1, \ldots, N-1$:

$$P_{i,1} = \frac{i+1}{i} P_{i+1,1} \tag{63}$$

We finally note that the sum of the state probabilities must be one:

$$\sum_{i \epsilon \{0,1\} X \{0,\ldots,N\}} P_i = 1 \tag{64}$$

In order to solve the equations above, we simplify the notation somewhat, introducing $q = P_{N-1,0}$. For the states in diversion we have only patients leaving, which we solve for $q$:

$$\begin{aligned}
P_N &= \frac{\gamma}{(N\mu)} P_{N-1} = \theta_N q & (65)\\
P_{N-1,1} &= \frac{N}{N-1} P_N = \theta_{N-1} q & (66)\\
&\vdots & (67)\\
P_{M+1,1} &= \theta_{M+1} q & (68)
\end{aligned}$$

The situation during selective diversion is twice as complex, having two entering and two departing flows. For state $(0, N-1)$, we have:

$$P_{N-1} = \frac{\gamma}{\gamma + (N-1)\mu} P_{N-2} \tag{69}$$

$$P_{N-2} = (1 + \theta_{N-1}^{-1}) P_{N-1} = q + \theta_{N-1}^{-1} P_{N-1} \tag{70}$$

Similarly, solving for $P_{N-3}$, we find:

$$P_{N-3} = (1 + \theta_{N-2}^{-1} + \theta_{N-2}^{-1}\theta_{N-1}^{-1}) q = q + \theta_{N-2}^{-1} P_{N-2} \tag{71}$$

We assume $P_L = q + \theta_{N-2}^{-1} P_{L+1}$ and solve for $P_{L-1}$, using the balance equations for the $L^{th}$ node on selective diversion:

$$\gamma P_{L-1} + (L+1)\mu P_{L+1} = L\mu P_L + \gamma P_L$$

$$\gamma P_{L-1} + \big(\gamma P_L + (L+3)\mu P_{L+3} - \gamma P_{L+2}\big) = L\mu P_L + \gamma P_L$$

$$\gamma P_{L-1} = L\mu P_L + \gamma(q + \theta_{L+3}^{-1} P_{L+3}) - (L+3)\mu P_{L+3}$$

$$P_{L-1} = q + \theta_L^{-1} P_L \tag{72}$$

$$(L+1)\mu P_{L+1} = \gamma P_L - \gamma q \tag{73}$$

Here we have used both the balance equation for node $L+1$ and the induction hypothesis. Applying this equation (72) multiple times, we find that we can state $P_L$ in terms of $q$:

$$P_L = q[1 + \theta_{L+1}^{-1} + \theta_{L+1}^{-1}\theta_{L+2}^{-1} + \ldots + \theta_{L+1}^{-1}\cdots\theta_{N-1}^{-1}] \tag{74}$$

Inserting for $\mu$ and $\gamma$, we simplify this to:

$$P_L = \frac{q}{L!}\sum_{i=0}^{N-L-1}(L-1)!(\frac{\mu}{\gamma})^i = \frac{q}{L!}\sum_{i=0}^{N-L-1}(L-1)!\phi^i \tag{75}$$

This pattern continues for lower occupancies, giving every limiting probability through $P_K$, until the critical $K^{th}$ node is reached. Then entry is at the full $\lambda$ rate, while exit is at a rate of $\gamma$.

$$\lambda P_{K-1} + (K+1)\mu P_{K+1} = K\mu P_K + \gamma P_K$$

Inserting equation (73), this simplifies to:

$$\lambda P_{K-1} + \left(\gamma P_K - \gamma q\right) = K\mu P_K + \gamma P_K$$

Cancelation gives:

$$P_{K-1} = \frac{\gamma}{\lambda}q + \frac{K\mu}{\lambda}P_K = \frac{\gamma}{\lambda}q + \rho_K^{-1}P_K \tag{76}$$

Except for the first term, this is the same form as for when selective diversion was in place. Inserting for $P_K$, in order to solve in terms of $q$, we find:

$$P_{K-1} = q\left[\frac{\gamma}{\lambda} + \rho_K^{-1}\sum_{i=0}^{N-K-1}\frac{(K-i)!}{K!}\phi^i\right] \tag{77}$$

For notational ease, we introduce $\Gamma$:

$$\Gamma = \sum_{i=0}^{N-K-1}\frac{(K-i)!}{K!}\phi^i \tag{78}$$

A similar pattern then asserts itself for occupancies down to $X = M + 1$. We begin with state $(0, K-1)$:

$$\lambda P_{K-2} + K\mu P_K = (K-1)\mu P_{K-1} + \lambda P_{K-1}$$

$$\lambda P_{K-2} + (\lambda P_{K-1} - \gamma q) = (K-1)\mu P_{K-1} + \lambda P_{K-1}$$

$$P_{K-2} = \frac{\gamma}{\lambda} q + \rho_{K-1}^{-1} P_{K-1}$$

$$P_{K-2} = q\left[\frac{\gamma}{\lambda} + \rho_{K-1}^{-1}\frac{\gamma}{\lambda} + \rho_{K-1}^{-1}\rho_K^{-1}\Gamma\right] \tag{79}$$

We solve for $P_{K-3}$ and find:

$$P_{K-3} = q\frac{\gamma}{\lambda} + \frac{\mu(K-2)}{\lambda} P_{K-2} \tag{80}$$

$$P_{K-3} = q\left[\frac{\gamma}{\lambda} + (K-2)\frac{\mu\gamma}{\lambda^2} + (K-2)(K-1)\frac{\mu^2\gamma}{\lambda^3} + (K-2)(K-1)K\frac{\mu^3\Gamma}{\lambda^3}\right]$$

As a practical solution method, equation(80) is simpler to solve in sequence. In general, however, we can solve for each occupancy $L\epsilon\{M, \ldots, K-1\}$:

$$P_L = q\left[\sum_{i=0}^{K-L-1} \frac{\gamma\mu^i}{\lambda^{i+1}} \frac{(L+1)!}{(L+1-i)!} + (L+1)(L+2)\cdots K\left(\frac{\mu}{\lambda}\right)^{K-L}\Gamma\right] \tag{81}$$

For state $(0, M)$, however, we have five flows. We insert for $P_{M+1,1}$ using equation (65), and the usual derivation yields:

$$P_M = \frac{\gamma}{\lambda} q + \rho_{M+1}^{-1} P_{M+1} \Leftrightarrow P_{M+1} = \frac{\lambda}{(M+1)\mu} P_M - \frac{\gamma}{(M+1)\mu} q \tag{82}$$

These two, inserted into the balance equation for state $(0, M)$ yield:

$$\lambda P_{M-1} + \mu(M+1)P_{M+1} + \mu(M+1)P_{M+1,1} = \lambda P_M + M\mu P_M \tag{83}$$

$$P_{M-1} = q\Bigg[1 - \frac{\gamma}{(M+1)\mu\lambda} + M\mu\Big(\sum_{i=0}^{K-M-1}\frac{\gamma\mu^i}{\lambda^{i+1}}\frac{(M+1)!}{(M+1-i)!} + \big(\prod_{j=1}^{K-M}(M+j)\big)\big(\frac{\mu}{\lambda}\big)^{K-M}\Gamma\Big)\Bigg] \tag{84}$$

Define $C_1$ such that $P_{M-1} = qC_1$ above. This gives us two equations for $P_{M-1}$, namely (84) and (56) which means we may solve for $q$ in terms of $P_0$:

$$qC_1 = P_{N-1,0}C_1 = \Big(\prod_{l=1}^{M-1}\rho_l\Big)P_0 \tag{85}$$

$$q = C_1^{-1}\Big(\prod_{l=1}^{M-1}\rho_l\Big)P_0 \tag{86}$$

Through $q$, $P_0$ and equation (86), we therefore have every limiting probability in terms of parameters and $P_0$, and so can use the fact that the sum of all the limiting probabilities must sum to one to finally solve the system. There are $N+1$ limiting probabilities off full diversion, and $N-M-1$ on full diversion, yielding $2N-M$ probabilities in all:

$$P_0 + P_1 + \ldots + P_M + \ldots P_K \ldots + P_N + P_{N-1,1} + \ldots P_{M+1,1} = 1 \tag{87}$$

This does not simplify in a fruitful way, so we use the numerical example to illustrate (see Section 4.4).

**Table 19:** Limiting Probabilities for the Full-Scale Model

| Limiting Probabilities |
| --- |
| $P_0$ is the normalizing probability |
| $P_{N-1} = q = C_1^{-1}\left(\prod_{l=1}^{M-1} \rho_l\right)P_0$ |
| $P_N = \frac{\gamma}{(N\mu)}P_{N-1} = \theta_N q$ |
| $P_{N-1,1} = \frac{N}{N-1}P_N = \theta_{N-1} q$ <br> $\vdots$ <br> $P_{M+1,1} = \theta_{M+1} q$ |
| $P_{N-2} = q + \theta_{N-1}^{-1}P_{N-1}$ |
| $P_{N-3} = q + \theta_{N-2}^{-1}P_{N-2}$ |
| $P_L = q + \theta_{N-2}^{-1}P_{L+1}$ |
| $P_{L-1} = q + \theta_L^{-1}P_L$ |
| $\vdots$ |
| $P_{K-1} = \frac{\gamma}{\lambda}q + \rho_K^{-1}P_K$ |
| $P_{K-1} = q\left[\frac{\gamma}{\lambda} + \rho_K^{-1}\sum_{i=0}^{N-K-1}\frac{(K-i)!}{K!}\phi^i\right]$ |
| $P_{K-2} = q\left[\frac{\gamma}{\lambda} + \rho_{K-1}^{-1}\frac{\gamma}{\lambda} + \rho_{K-1}^{-1}\rho_K^{-1}\Gamma\right]$ |
| $P_{K-3} = q\left[\frac{\gamma}{\lambda} + (K-2)\frac{\mu\gamma}{\lambda^2} + (K-2)(K-1)\frac{\mu^2\gamma}{\lambda^3} + (K-2)(K-1)K\frac{\mu^3\Gamma}{\lambda^3}\right]$ |
| $\vdots$ |
| $P_L = q\left[\sum_{i=0}^{K-L-1}\frac{\gamma\mu^i}{\lambda^{i+1}}\frac{(L+1)!}{(L+1-i)!} + (L+1)(L+2)\cdots K\left(\frac{\mu}{\lambda}\right)^{K-L}\Gamma\right]$ |
| $P_M = \frac{\gamma}{\lambda}q + \rho_{M+1}^{-1}P_{M+1}$ |
| $P_{M-1} = qC_1$ |
| $\vdots$ |
| $P_0 = 1 - (P_1 + \ldots + P_M + \ldots P_K \ldots + P_N + P_{N-1,1} + \ldots P_{M+1,1})$ |
| Where: |
| $q = P_{N-1}$ |
| $\phi = \frac{\gamma}{\mu}$ |
| $\theta_j = \frac{\gamma}{j\mu}$ |
| $\rho_j = \frac{\lambda}{j\mu}$ |
| $\Gamma = \sum_{i=0}^{N-K-1}\frac{(K-i)!}{K!}\phi^i$ |
| $C_1 = \left[1 - \frac{\gamma}{(M+1)\mu\lambda} + M\mu\left(\sum_{i=0}^{K-M-1}\frac{\gamma\mu^i}{\lambda^{i+1}}\frac{(M+1)!}{(M+1-i)!} + \left(\prod_{j=1}^{K-M}(M+j)\right)\left(\frac{\mu}{\lambda}\right)^{K-M}\Gamma\right)\right]$ |

**Table 20:** Balance Equations

| State (Δ, X) | Entering Rate | Leaving Rate |
|---|---|---|
| (0, 0) | $\mu P_1$ | $\lambda P_0$ |
| (0, 1) | $\lambda P_0 + 2\mu P_2$ | $(\lambda + \mu) P_1$ |
| (0, 2) | $\lambda P_1 + 3\mu P_3$ | $(\lambda + 2\mu) P_2$ |
| $\vdots$ | $\vdots$ | $\vdots$ |
| (0, M-1) | $\lambda P_{M-2} + M\mu P_M$ | $(\lambda + (M-1)\mu) P_{M-1}$ |
| (0, M) | $\lambda P_{M-1} + (M+1)\mu P_{M+1} + (M+1)\mu P_{M+1,\Delta=1} =$ $\lambda P_{M-1} + \mu(M+1)(P_{M+1,0} + P_{M+1,1})$ | $(\lambda + M\mu) P_M$ |
| (0, M+1) | $\lambda P_M + (M+2)\mu P_{M+2}$ | $(\lambda + (M+1)\mu) P_{M+1}$ |
| $\vdots$ | $\vdots$ | $\vdots$ |
| (0, K-1) | $\lambda P_{K-2} + K\mu P_K$ | $(\lambda + (K-1)\mu) P_{K-1}$ |
| (0, K) | $\lambda P_{K-1} + (K+1)\mu P_{K+1}$ | $(\gamma + K\mu) P_K$ |
| (0, K+1) | $\gamma P_K + (K+2)\mu P_{K+2}$ | $(\gamma + (K+1)\mu) P_{K+1}$ |
| $\vdots$ | $\vdots$ | $\vdots$ |
| (0, N-2) | $\gamma P_{N-3} + (N-1)\mu P_{N-1}$ | $(\gamma + (N-2)\mu) P_{N-2}$ |
| (0, N-1) | $\gamma P_{N-2}$ | $(\gamma + (N-1)\mu) P_{N-1}$ |
| (1, N) | $\gamma P_{N-1}$ | $N\mu P_{N,1}$ |
| (1, N-1) | $N\mu P_{N,1}$ | $(N-1)\mu P_{N-1,1}$ |
| $\vdots$ | $\vdots$ | $\vdots$ |
| (1, M+1) | $(M+2)\mu P_{M+2,1}$ | $(M+1)\mu P_{M+1,1}$ |

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