VARIATION IN QUALITY AND RISK:
EFFECTS ON EVALUATION AND BUDGETING

by

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A dissertation submitted to the Graduate Faculty in Economics in partial fulfillment of the requirements for the degree of Doctor of Philosophy, The City University of New York

2002

UMI Number: 3047197

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This manuscript has been read and accepted by the Graduate Faculty in Economics in satisfaction of the dissertation requirement for the degree of Doctor of Philosophy.

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Abstract

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This thesis contains three chapters that discuss various aspects of evaluation and hospital budgeting for health care. Chapter one focuses on an optimal hospital funding formula, from a hospital's perspective, and uses hedonic regression technique to estimate variation in price using various measures of product heterogeneity. Unlike traditional pricing models, cost is used as the dependent variable, where costs are estimated using a clinical costing system. Analysis was performed on 1996/97 patient level cost data from the New Children's Hospital (NCH), Sydney, Australia. The results illustrate that payment systems that use all available information of product heterogeneity dominated traditional case mix based payments, but both are superior to those reliant on bed days only.

Chapter two examines the use of portfolio theory as a theoretical foundation for Cost Effectiveness Analysis (CEA) in the evaluation of health care interventions. Here a general formula for the evaluation of a portfolio of health care interventions is derived that allows for synergies between interventions where the population effects are aggregated from individual effects. A number of special cases are presented to illustrate the nature of the formulation of modified portfolio theory. The chapter raises some important issues in CEA, especially with regard to the importance of correlations between interventions and the role of uncertainty.

Chapter three again uses hedonic regression to explain the variation of prices for coronary artery bypass graft (CABG) for individuals who are privately insured by self-insured firms. The primary data is from the inpatient component of MarketScan for 1995 and 1996 provided by the MEDSTAT group. Additional data on product heterogeneity is derived from the American Hospital Association's hospital survey and from the Area Resource File. A quality index, based upon the epidemiological literature's work on z-scores, is also estimated from Medicare data for the period 1990-93. The results indicate that there may be a potential market failure with price being responsive to uncertainty but not adverse quality. The study also finds that insurer and hospital type, a proxy for their respective bargaining powers, are significant predictors of prices.

Acknowledgements

I am indebted to many people for their assistance and encouragement for this body of work. Primarily I would like to thank my family, Terry, Margaret, and Elizabeth. I would also like to thank those that acted as surrogate family here in the USA, namely Michael Grossman, Avi Dor, Salih Neftci, Raymond Rafferty, the students and faculty at City University of New York, Graduate Center and the Weatherhead School of Management, Case Western Reserve University, Cleveland, and researchers and staff at the National Bureau of Economic Research, New York. Particular thanks must go to Carrie Davidson and Richard Grosshandler who proofread the final version of this thesis.

For chapter one, I am particularly indebted to Ralph Hanson, Maria Angelis, Christine Fan, Stuart Peacock, Michael Grossman, Robert Kaestner, and Kathy Eagar for assistance and comments. For Chapter two, I am most grateful to Michael Stewart, Madeleine King, Kees van Gool, and Michael Grossman for their advice and contributions. Aspects of this paper were presented at seminars at Australian National University, London School of Economics, McMaster University, City University of New York, and Case Western Reserve University. I would like to thank the participants of these seminars for their valuable questions and comments. For chapter three I would like to thank Avi Dor and Michael Grossman for their guidance on this project. This research was funded by an AHRQ grant to the NBER (HS10282-01 *"Medical Outcomes and the Pricing of Hospital Procedures"*).

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Introduction: Health economics and finance theory

Health Economics is a multi-disciplinary field of study that draws from welfare and microeconomics, biostatistics, epidemiology and many other disciplines (Williams, 1987). It combines both theory and empiricism (Bridges and Haywood, 2000), and often focuses on very practical and policy-related questions (Blaug, 1998; Maynard and Kanavos, 2000). With few exceptions (Gershberg et al, 2000, for example), health economists often overlook an important discipline, that is, finance theory, when considering funding and evaluation decision that parallels health economics in many ways. In finance, researchers also have to deal with principal-agent problems (Mirrlees, 1999), uncertainty (Black and Scholes, 1973; Merton, 1973), evaluation of potential investments (Sharpe, 1964), and consequences from the macro economy (Ross, 1976). Given that any purchaser of health care needs to both evaluate and budget for numerous health care interventions, health economics may benefit from applications of portfolio theory, which is very influential in financial economics (Markowitz, 1952). Portfolio theory highlights that a real tradeoff may exist between the return from an investment (or medical intervention) and its risk (variance). This would allow health economists to evaluate the interventions on more than the first moment of the distribution of outcomes (Heckman and Smith, 1995). The management of risks in health economics has been restricted to two main areas: the management of risks associated with malpractice (Danzon, 2000) and risks associated with medical outcomes (Luft and Romano, 1993). The analysis of risks from a purely financial approach is only now being discussed in the health economic literature

(Hawe and Shiell, 1995; Bridges and Hanson, 1999; Bridges et al, 2000, O'Brien and Sculpher, 2000).

This thesis utilizes various aspects of finance and economic theory to analyze two key questions. First, what are the determinants of price and are prices set so as to encourage quality without creating adverse incentives (Dranove et al, 2002)? Second, how does risk affect health care planner and policy makers decision concerning the budgeting for and evaluation of health care programs?

To analyze the first of these problems, hedonic regression analysis is utilized. Waugh (1928) was the first to explain variation in prices due to variations in quality indicators. Using linear regression, he focused on the price variation of asparagus, tomatoes, and cucumbers in a Boston market due to quality indicators. The term 'hedonic' was first coined by Court (1939) who analyzed variation in the prices of automobiles. The term was used to invoke the utilitarian ideal of welfare maximization, as Court (1939, p107) thought that commodities served to increase the '*welfare and happiness of its purchaser and the community*'. Using cross-sectional panel data, Court (1939) regressed the log of the list price against year dummies and three measures of the car's quality (weight, length and horsepower).

The hedonic method lay unused for a number of years until it was revived in the 1960s (Adelman and Griliches, 1961; Chow, 1967; Griliches, 1961). Since then, much has been written regarding the ideal functional form of such models (Berndt, 1991). Cole et al (1986) compared results from the linear, semi-log, and log-log specification, but when the dependent variable was transformed comparisons of models using goodness-of-fit were difficult to make (Berndt, 1991, p127-8). Two methods most often used for choosing between such functional forms are the Box-Cox (1964) and the Box-Tidwell (1962) methods (see Judge et al 1985, chap 20, for a detailed discussion of these methods). When one transforms the dependent variable, the regression will pass through the mean of the transformed variable and not necessarily the value of the original scale. This makes subsequent prediction problematic (see for example, Neyman and Scott, 1960). While there have been a number of methods for correction identified in the literature, these often require limiting normality assumptions to remain unbiased (Shimizu and Iwase, 1981). Duan (1983) offers a non-parametric method for retransforming the predicted values of a regression where the dependent variable has been transformed and does not need such distributional assumption.

Given that the results of the hedonic model estimated in chapter one are to be used, albeit hypothetically, for a funding model, a linear regression is used to avoid the problem of retransformation. For the model presented in chapter three a more traditional log-linear model is estimated (Berndt, 1991), as the model is not to be used for the prediction of future prices.

One other common theme across the chapters that needs to be flagged is that of the interpretation of standard errors. Rather than utilizing traditional methods of using standard errors for significance tests, they are utilized in a more Bayesian sense and focus on confidence intervals that measure the degree of risk or uncertainty in the estimation. For example, in chapter one it is shown that Aboriginal and Torres Strait Islanders (ATSI) are more costly to treat in hospital than the general population (all other things constant), but insignificantly so. A traditional approach to hypothesis testing would say that the ATSI should not be included in the funding model as it is not significantly different from zero. A finance theory approach may imply, however, that there is a moderate level of risk involved in the funding of ATSI patients and that they do need the extra funding. Also, if one expressed a different prior, that ATSI were on average $500 more expensive for example, then that value would be used as the null hypothesis, and on the basis of the empirical finding would not be rejected. This confidence interval approach is also a central component to chapter two, where it is used to express the risk of the effectiveness of interventions.

Chapter one:

Case mix funding for a Specialist Pediatrics Hospital:

A hedonic regression approach

Chapter one summary

This chapter questions the affects that Diagnosis Related Groups (DRG), which are the classification system that underpinned the implementation of the prospective payment system for inpatient care in the US, have on understanding patient level costs within a specialist pediatrics hospital in Australia. Two hedonic models are estimated using 1996/97 New Children's Hospital (NCH) patient level cost data, with and without a case mix index (CMI). The results show that a funding model that adjusts for additional measures of product heterogeneity dominate one based only on the case mix index, but they both dominate funding models based only on length of stay. The full hedonic funding model is then used to simulate a funding model for the 1997/98 NCH cost data. The proposed reimbursements (derived from the hedonic funding model) are highly correlated with the actual costs reported for that year. Bivariate regression indicates that there was cost inflation of 4.8% between the two years. In conclusion, the results of hedonic analysis provides valuable evidence for the design of funding models that account for case mix.

1.1 Introduction

In Australia, as with the US, there is a growing trend towards examining the determinants of hospital costs (Auditor-General of Victoria 1998 and Muldoon 1996). This trend can be explained by the need for hospitals to be accountable for their costs and through a desire to implement a funding system that creates incentives to further increase efficiency. For these purposes, regression analysis has been an informative tool. Culyer et al (1978) was one of the first to use a simple regression analysis of costs in a hospital setting, reporting a comparative study across British hospitals. They found a strong relationship between costs and the teaching load of the hospital. In Australia, regression analysis has been a valuable tool for identifying significant influences on hospital costs. Hindle, Degeling and van der Wel (1998) focus on within DRG variation of severity while using length of stay as a proxy for costs. Hindle, Frances and Pearse (1998) also analyzed the cost structures of small rural hospitals using regression analysis.

Traditionally, one of the limitations of regression analysis has been the paucity of quality patient level cost data. However, with the emergence and implementation of more accurate cost-accounting systems (that is, clinical costing systems), some hospitals now have a very accurate estimate of the resource cost of each individual patient. This type of data both allows for the use of more refined regression techniques and improves the performance of regression methods.

A regression analysis that relates market valuations to various physical attributes of the commodities is referred to as a hedonic regression (Rosen, 1974; Berndt, 1991). The hedonic method has been widely used in economics to analyze supply side variation in quality (see for example, Chow, 1967). It is often used in the analysis of real estate markets (Crosson et al, 1996) and to distinguish among different qualities of other consumer goods (Byron and Ashenfelter, 1995). The hedonic method is also used frequently in adjusting for quality aspects in consumer price indices (Kokoski, 1993). In health, it has been used in the modeling of hospital costs across entire hospitals rather than across individual patients (Chernichovsky and Zmora, 1986). Goldman and Grossman (1978) also used a hedonic approach to distinguish between the quality of pediatric care and the quantity of pediatric visits. In this chapter, the hedonic approach is used to estimate patient level pricing formulas at a pediatric hospital through a number of observable factors in addition to length of stay and case mix, where the dependent variable is the clinical cost data.

1.2 Analysis of New Children's Hospital (NCH) costs

The aim of this analysis was to inquire into the determinants of costs of patients admitted to the NCH using a hedonic regression approach. The analysis used all patients from the state of New South Wales (NSW) treated at the NCH in 1996/97, where patients were classified using AN-DRG version 3.1 (see Commonwealth Department of Human Services and Health & 3M Health Information Systems 1996). Exclusions from the analysis included patients that were part of the nationally funded (carve-out) program for liver transplants (DRG 5), patients from error DRGs (952, 955, and 956) and patients from costed but non-classified DRGs (locally referred to as DRG 999). Finally, all patients from DRG 780 (chemotherapy) had their costs adjusted to $640, the statewide pediatric benchmark set by NSW Health (1998a). After these deletions, there were 28, 282 observations.

The dependent variable is the estimated patient level cost reported by the New Children's Hospital. This estimated cost was calculated using a cost modelling technique that assigns costs to patients for the actual procedures that were performed. The costing methodology is derived and reviewed by NSW Health annually (see NSW Health Department 1996, 1997). For the purposes of this analysis, these reported costs could be considered the gold standard for prices, from the hospital's perspective, as this would minimise the financial risk that they face (Bridges and Hanson, 1999). The analysis will focus on the prediction of these costs using other available information about the patient. These other independent variables are outlined in table one.

Model one incorporates all explanatory variables excluding the case mix index. All variables were significant at the 1% level, except for the rurality variable which was significant at the 5% level (one tailed t-test) and ATSI, which was insignificant but of the expected sign (Ruben and Fisher, 1998 and Fisher et al, 1998).

Table 1.1: Variables used in the Analysis

Variable	Description
Cost	Estimated cost of separation
CMI	NSW 1996/97 case mix index (base weights)
LOS	Length of stay in days, same day patients given LOS = 0
Age	Age on admission in years
S.Day	Same day dummy variable, same day = 1, all other LOS = 0
Sec.diag	Number of secondary diagnoses (capped at ten, excluding V codes)
Emerg	Emergency dummy variable, admitted through emergency = 1, all other = 0
Trans	Transfer dummy variable, transferred in = 1, all other = 0
Rural	Rural dummy variable, rural area of residence = 1, other = 0
ATSI	ATSI dummy variable, Aboriginal and Torres Strait Islander = 1, all other = 0
Male	Sex dummy variable, Male = 1, Female = 0

Length of stay is one of the most important predictors of resource use. Age is also an important predictor of cost (Bridges and Hanson, 2001), with younger patients having a higher resource cost (Hanson et al, 1998). There is evidence to suggest that a same day admitted patient uses less resources than a patient with a stay of one day (overnight), this being consistent with traditional intuition that same day cases are less resource intensive.

Patients admitted through the Emergency Department (ED) had lower resource cost, holding all other variables constant. This runs against traditional logic that patients admitted through emergency stay are more costly. However, one should bear in mind that patients admitted through the Emergency Department have longer length of stay, are relatively younger and have more secondary diagnoses. It is these other variables that account for the higher costs of patients admitted through the Emergency Department.

Table 1.2: Comparison of hedonic regression models

	LOS	CMI	CMI & LOS	Model one	Model two
Intercept	220.42 (37.17)	213.19 (51.40)	-812.04 (33.91)	-306.84 (96.76)	-1673.00 (85.27)
CMI		2725.01 (21.69)	1501.48 (15.46)		1531.41 (15.96)
LOS	1074.44 (4.82)		895.24 (4.57)	1061.30 (5.26)	924.15 (19.15)
Age				-46.19 (7.65)	-12.57 (6.6)
S.Day				639.95 (81.96)	1479.58 (71.75)
Sec.Diag.				354.64 (21.76)	59.01 (19.15)
Emerg.				-734.46 (79.72)	-247.30 (69.45)
Trans.				3233.39 (186.61)	109.19 (165.38)
Rural				222.98 (126.37)	58.65 (109.82)
ATSI				281.19 (355.61)	138.33 (308.99)
Male				223.46 (70.92)	193.62 (61.62)
R^2	63.62%	35.73%	72.70%	64.64%	73.31%

Note: Standard errors in parentheses.

Patients who are transferred from another hospital into the NCH cost significantly more than do other patients. Although this result is not counter-intuitive (Butt and Shann, 1998), the magnitude of the result does attract interest. The demographic variables of patients are also important indicators of cost. Patients from rural areas are relatively more costly, as are male patients. Patients that indicated that they were from Aboriginal and/or Torres Strait Islander descent also cost relatively more. However, this result is statistically insignificant. The insignificance of the Aboriginal and Torres Strait Islander dummy variable could be due to the low number of patients who identified themselves as of Aboriginal and/or Torres Strait Islander descent upon admission to the hospital.

Model two extends upon model one by including a case mix index. The model uses the NSW 1996/97 'base weight index'. NSW Health estimates base weights using trimmed data from the majority of hospitals in the state (see NSW Health Department, 1998b). Model two explains relatively more of the variation in costs than does model one (R^2 = 73.31% as opposed to R^2 = 64.62%).

For model two, the case mix index is highly significant in predicting the patient costs, but it is not the only significant variable. Length of stay is still a significant predictor of the cost of a patient. However, the estimate is not as large as in model one. Contrary to traditional logic, same day patients are more resource intensive than patients with length of stay equal to one day (overnight), holding all other variables constant. Again, age is a predictor of cost, albeit at reduced statistical significance with younger patients costing relatively more. Cost also increases with the number of secondary diagnoses.

Patients admitted through the Emergency Department are relatively less expensive, but again the same caveats apply to the interpretation of this parameter as we presented for model one. Transfers are weakly more expensive in model two, although this coefficient is greatly reduced compared to that in model one. This evidence highlights that while transfers are more expensive, the great proportion of this cost can be explained through other explanatory variables.

Again, rural and Aboriginal and Torres Strait Islander patients are more expensive, but the coefficient estimate is insignificant from zero. Male patients are also more expensive. In hedonic regression analysis, insignificant coefficients can improve the fit of the model and need not be eliminated from the model. This is especially the case when they possess intuitive signs.

1.3 Sensitivity Analysis

The above models were assessed for possible spurious results. There was no evidence of significant multicollinearity and little evidence of heteroskedasticity, although there was a slight ballooning of variance at very high costs.

Caution was noted over the relatively small standard errors for LOS and CMI. The results indicated that these two variables are very strong predictors of costs. Using bivariate analysis, LOS predicted 63.62% of the variation in costs and CMI 35.73% of the variation in costs. Together, in a simple multivariate analysis, they predicted 72.70% of the variation in costs (Table 2). The fuller models are only marginally better in the prediction of the variation in costs (1.02% and 0.58% respectively for models one and two). The fuller models, however, may reduce incentives to select patients on the basis of other characteristics.

1.4 Simulation of 1997/98 NCH cost data

Model two was used to simulate the costs for NCH's 1997/98 financial year using patient level data to test its robustness as a funding model. As there had been a change in the NSW Health's costing standards, the 1996/97 costing methodology was used to estimate the reported costs of the patients for 1997/98. Again DRGs 5, 952, 955, 956 and 999 were removed from the data. DRG 780 was not modified. There were 27,916 observations used in the simulation.

The simulated costs from the full hedonic model were then compared to the reported patient costs for 1997/98. The correlation coefficient between the two was 0.88. Bivariate regression yields the following:

$$\textbf{Reported costs} = \underset{(30.71)}{58.352} + \underset{(0.003)}{1.048}\ \textbf{Hedonic model} \qquad [1]$$

The intercept is a marginally significant and the hedonic model is a highly significant predictor of costs (standard errors in parentheses). The model had a good fit, with an R^2 of 78.00%, indicating it would be robust as a potential funding model.

One of the problems with the model is that some simulated costs are estimated as negatives. One can consider that the minimum cost should be set at zero or some positive cost. If the minimum cost is set to zero the R^2 improves slightly to 78.04%, and if set to $100 (an arbitrary cost) the R^2 is 78.06%. Alternatively, one could use a more technical econometric specification such as using the log of cost as the dependant variable to avoid negatives (Berndt, 1991), but such transformations make prediction difficult (Duan, 1983). Also, one can interpret the estimate associated with the hedonic model as indicating inflation in costs between 1996/97 and 1997/98 of some 4.8%. This highlights that any funding policy needs to account for inflation in costs over time to be equitable.

1.5 Conclusions

NSW Health has developed their case mix index to incorporate a number of refinements beyond the standard concept of having an index that reflects the average costs (NSW Health Department 1998b). These include separate cost weights for same day, transfers (outward), long stay and private episodes. However, these refinements have been incorporated within the index and not added explicitly, as has been done in other funding models (Victorian Department of Human Service, 1998). To make adjustments more transparent, it would be better to estimate the case mix index with untrimmed data (base weights), and then derive a funding formula that incorporates the index and other measures of product heterogeneity. Hedonic regression, if used nationally or statewide, could be a valuable tool in the formulation of such a funding model. It provides a powerful tool for understanding the factors that contribute to the variation in costs. Further research could include an analysis of all NSW hospitals that produce patient level costing data to estimate a funding formula for NSW based on the hedonic methodology.

Chapter two:

Adapting Portfolio Theory for the Evaluation of Multiple Investments in Health with a Multiplicative Extension for Treatment Synergies

Chapter summary:

Portfolio theory is central to the analysis of risk in many areas of economics, but is seldom used appropriately in health economics. This paper examines the use of portfolio theory as a theoretical foundation for the implementation of Cost Effectiveness Analysis (CEA) on a number of interventions simultaneously. A number of modifications are needed to apply portfolio analysis to the economic evaluation of health care interventions. First, the method of reporting the results of a CEA, and consequently some of the underlying assumptions, need to be modified. Second, portfolio theory needs to be expressed in terms of effects on individuals aggregated to a population. Finally, one needs to allow for the possibility of synergies between the various health interventions. This chapter derives a general formula for a portfolio of health care interventions that allows for synergies between interventions where the population effects are aggregated from individual effects. A number of special cases are also derived to highlight the nature of the formulation of the modified portfolio theory. While modified portfolio theory adds a theoretical foundation to health care evaluations, it may not be operational until estimates of the correlation between interventions are available and the question of uncertainty in health care evaluation is resolved. Also, while a synergy may be present at the individual level, when aggregated over a large population, it may not be significant given the standard assumption of constant returns to scale.

2.1 Introduction

Health economics is multi-disciplinary, combining aspects of welfare economics, labour economics, econometrics, epidemiology, biostatistics, and the medical sciences. One discipline that is not often used in the economic analysis of health care is financial economics. This is despite obvious parallels between the two disciplines. Like health economics, financial economics has to contend with agency, uncertainty, forecasting, capital structure and many other areas for which standard economics must be customised to find an optimal solution.

Portfolio theory is one such tool, and while it was primarily developed for application to financial markets, it has made a significant contribution to economics as a whole. It is the standard theory utilized in economics for the management of risk and uncertainty, but despite its obvious applications, this theory is seldom used in health economics. One area of research in health economics for which portfolio theory is only now being considered is the economic evaluation of health care procedures (Hawe and Shiell, 1995; Bridges et al, 2000; O'Brien and Sculpher, 2000). This paper builds upon this emerging literature by developing a model to evaluate multiple health interventions (or investments) simultaneously. For simplicity, the paper focuses on cost effectiveness analysis only, a common evaluation tool in health economics.

Health is more complex than finance in a number of ways, and consequently, a number of modifications to traditional portfolio theory are needed. First, return on investments in health is expressed in terms of gains in the health of populations of individuals. Second, the risk of such investments equates in economic evaluation to the variance of the cost-effectiveness ratio, which is problematic to estimate. Third, each individual may receive more than one intervention concurrently, and these interventions may interact in a multiplicative fashion. That is, there may be treatment synergies.

Cost effectiveness analysis (CEA) is one of the central tools used in the economic evaluation of health care (Drummond et al, 1997; Gold et al, 1996). The objective of a CEA is to either maximize health output for a given budget or minimise cost for a given health benefit. In a CEA, two or more different health interventions are compared in terms of costs and benefits, with the benefits measured in a single dimension. For example, benefits may be measured in terms of deaths prevented, life years saved, quality adjusted life years saved, or number of smoking cessations achieved. The results of a CEA are normally reported in terms of a cost-effectiveness ratio, that is, the cost per unit of effectiveness. Often, it is optimal to report the incremental cost effectiveness ratio, the increase in cost for a one unit increase in effect.

The concepts involved in portfolio analysis are often used very loosely in health economics. The term 'portfolio' has been used in the health context to describe a collection of treatments or interventions (Lavori and Dawson, 1998; Kindig, 1988). Hawe and Shiell (1995) state that '*portfolio theory suggests that by deliberately* *diversifying the portfolio, and including high risk investments along with the safer bets, overall returns will be higher'*. While this comment remains unsubstantiated, there is some evidence that the bundling of health interventions can increase the effect in terms of health gain beyond the linear combination of the parts (Allardice et al, 1998; Gurfinkel et al. 1995; Kok et al, 1996).

This chapter adapts financial portfolio theory so as to apply it to health care evaluation. Section 2.2 discusses traditional portfolio theory and the modifications of traditional health economic evaluations needed to apply the theory. Section 2.3 presents a modified portfolio theory that allows for a synergy between interventions. We develop a population model based on the aggregation of individuals receiving one or two different health interventions. Section 2.4 presents three special cases of the general model and illustrates when a synergy based at the individual level will be felt at the population level. Section 2.5 discusses the limitations of portfolio analysis in health evaluations and offers some suggestions for further research.

2.2 Traditional Portfolio Theory

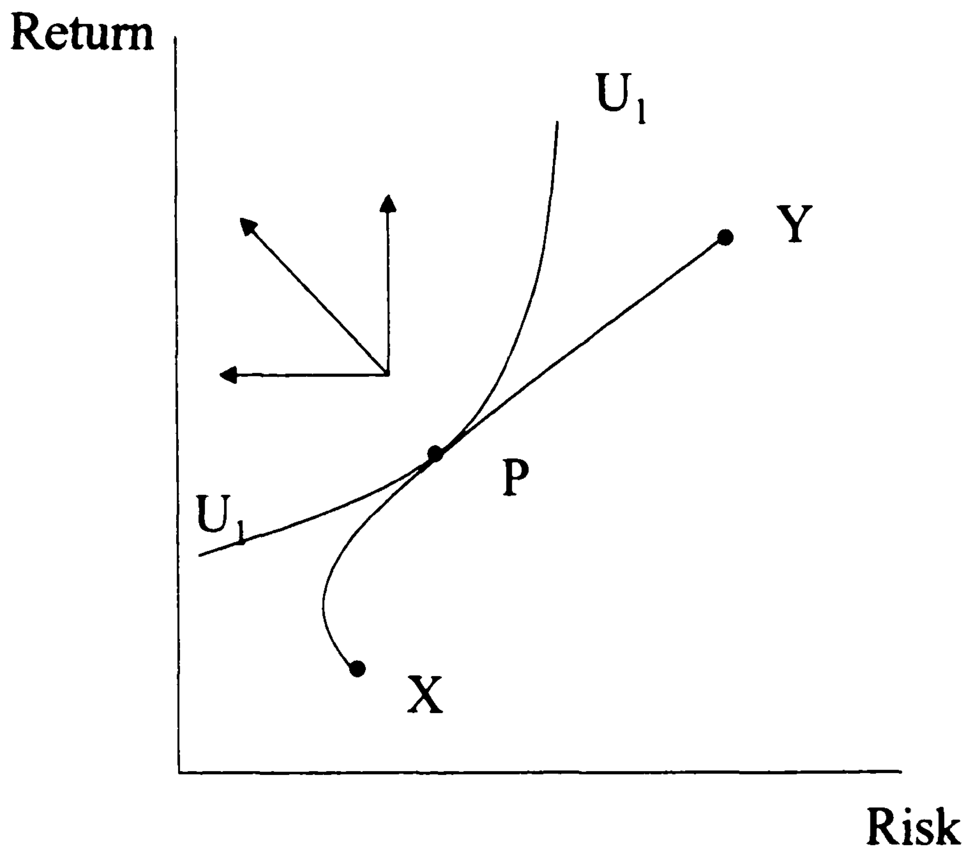
Portfolio theory is one of the central concepts of financial economics. The classic work on portfolio selection is by Markowitz (1952). It is also the basis for a number of financial market models (see Brealey and Myers, 1991 and Copland and Weston, 1988). Traditional financial portfolio theory is based on the optimal choice of investments. Any given investment's return profile can be described by the mean, the first moment, and variance, the second moment. In finance theory, these are termed the return and risk of the investment.

2.2.1 Risk / Return Objective Function

For the purposes of traditional portfolio theory, the consumer's utility is assumed to be defined over the return and risk of the portfolio of investments (Copland and Weston, 1988). That is $U = U(\mu, \sigma)$, where μ is the expected, or average, return of investments and σ is the standard deviation of that return.

The primary reason that portfolio theory is so important in financial theory is that bundling commodities into portfolios can reduce the risk of investment. If the individual is risk averse and everything else is held constant, this would increase utility. A typical depiction of this is displayed in Figure 1, where risk is on the horizontal axis and return is on the vertical axis.

Figure 2.1: The trade off between the risk and return of investments



Note: Figure 2.1 illustrates the trade off between risk and return. Point X and Y are two investments with differing risk and return profiles. The curve U_1-U_1 is an indifference curve for a representative individual, where utility is increasing in return and decreasing in risk. The curve X-Y represents differing portfolios consisting of varying amounts of X and Y only. The point P is, given the preferences illustrated, the optimal portfolio in terms of its risk and return profile. The individual can do no better than P.

In Figure 2.1, utility is increasing with return and decreasing with risk such that utility is maximized in the north-west direction. Point *X* is the risk and return if the total budget is invested in stock *X*, and point *Y* is the risk and return if the total budget is invested in stock *Y*. While *Y* has a greater return on average than *X*, it is also riskier, such that from year to year the actual return will vary and may sometimes be quite low. The curved line *XY* shows the risk and return for a portfolio of two investments *X* and *Y*, where the budget is fixed. Under portfolio theory, risk is reduced except when *X* and *Y* are perfectly correlated ($\rho = 1$) and decreased most when *X* and *Y* are perfectly negatively correlated ($\rho = -1$). Given the utility U_1 the optimal portfolio would be given by point *P*. Bridges et al (2002) demonstrates mathematically why diversifying reduces risk in the context of two investments.

2.2.2 What is the health planner's objective function?

Economic evaluations in health are most often used by centralized health planners in national health programs, although they can be used in other settings. Heckman and Smith (1995) point out that social planners should base their decisions on more than just the mean effectiveness derived from randomized trials. They suggest that higher order moments, such as variance, may be useful in the evaluation of social programs. An important question, for the purposes of this paper, is should the social (health) planner be concerned with the variance of the effectiveness of programs?

In health economics, there is no consensus on what the objective function of the health planner should be. There are two main viewpoints: the welfarist and the extra-welfarist. A common interpretation of the extra-welfarist's view is that the health planner's objective function contains only the mean health benefit. While both views concede that risk impacts on utility, only the welfarists believe that, under certain assumptions, risk should be considered by the social (health) planner. Indeed, Graff Zivin (2001) demonstrates that when individuals are risk averse and there are imperfect insurance markets (Arrow and Lind, 1970), the social planner should be risk averse too.

Since extra-welfarists are not concerned with risk, does this imply that they would not be interested in portfolio theory? Two of the three cases presented below allow for synergies between interventions, with implications for both mean effect and variance. Thus, modified portfolio theory will have implications for both welfarists and extra-welfarists.

2.2.3 Standardizing Returns in Health

One of the key problems associated with applying portfolio theory to CEA is the manner in which results, and subsequently risks, are reported. Consider the case where, at a population level, the effect and cost of a given intervention are random variables. While we can estimate a mean cost effectiveness ratio, no closed form solution exists for its variance. This problem has prompted considerable debate in health economics (Wakker and Klaassen, 1995; Polsky et al, 1997; Briggs et al, 1997; Hutubessy et al, 2001). Recent research has moved away from reporting a ratio by either looking at the problem in a two dimensional framework (Briggs and Fenn, 1998) or by specifying the trade-off between benefits and cost, for example, by using net health benefits (Stinnett and Mullahy, 1998).

One can simplify the problem by inverting the ratio and considering a deterministic cost and a stochastic effect for each intervention (Bridges et al, 2000; O'Brien and Sculpher, 2000). This will allow for the construction of Standardized Effectiveness Ratios (SER), effect divided by the cost, and subsequently the estimation of the variance of the ratio. With cost in the denominator, the budget becomes the numeraire. Thus, all measurements of effectiveness are relative to the (fixed) budget.

2.3 Modified Portfolio Theory

Suppose that each intervention targets a certain aspect of an individual's health. If an individual experiences multiple interventions, then their overall increase in health is a function of the increases of various aspects. Furthermore, suppose an increase in any aspect can be measured in a standard health unit.

2.3.1 Synergistic Combination of Two Interventions

Suppose that we are considering aspects 1 and 2 and corresponding interventions 1 and 2. If an individual experiences an increase of x health units in aspect 1 from intervention 1 and y health units in aspect 2 from intervention 2, then their overall gain in health units, g, is given by a function of x and y, for example:

$$g = x + y + kxy, \tag{1}$$

where k is a parameter measured in inverse health units that moderates the multiplicative effect. This is a plausible 'interaction' or 'synergy' model, where the two 'treatment effects' bolster each other in the 'overall effect', that is, the total increase is greater than the sum of the individual increases. For the purposes of generality, k could also be negative. That is, it may be possible for the overall effect to be less than the sum of its parts. In practice, k would a parameter that is estimated empirically.

In medicine, there is a wide range of instances where a multiplicative affect is apparent. For example, it has been demonstrated that combination drug therapies are more effective than monotherapy in the treatment of HIV (Allardice et al, 1998) and of unstable angina (Gurfinkel et al, 1995). Thus, a general model for the evaluation of multiple interventions should incorporate possible synergistic effects.

2.3.2 Random Increases in Health per Monetary Unit Spent

Suppose that the amount of an intervention is measured in monetary units spent. For an individual, we model the increase in health per monetary unit spent for the two interventions as random variables A and B, where

$$E(A)=\mu_A,\quad Var(A)=\sigma_A^2,\quad E(B)=\mu_B,\quad Var(B)=\sigma_B^2 \text{ and } Corr(A,B)=\rho \qquad (2)$$

If d monetary units of intervention 1 and e monetary units of intervention 2 are spent on an individual, the increases in the two aspects would be the random quantities dA and eB. The overall gain in health units would be given as:

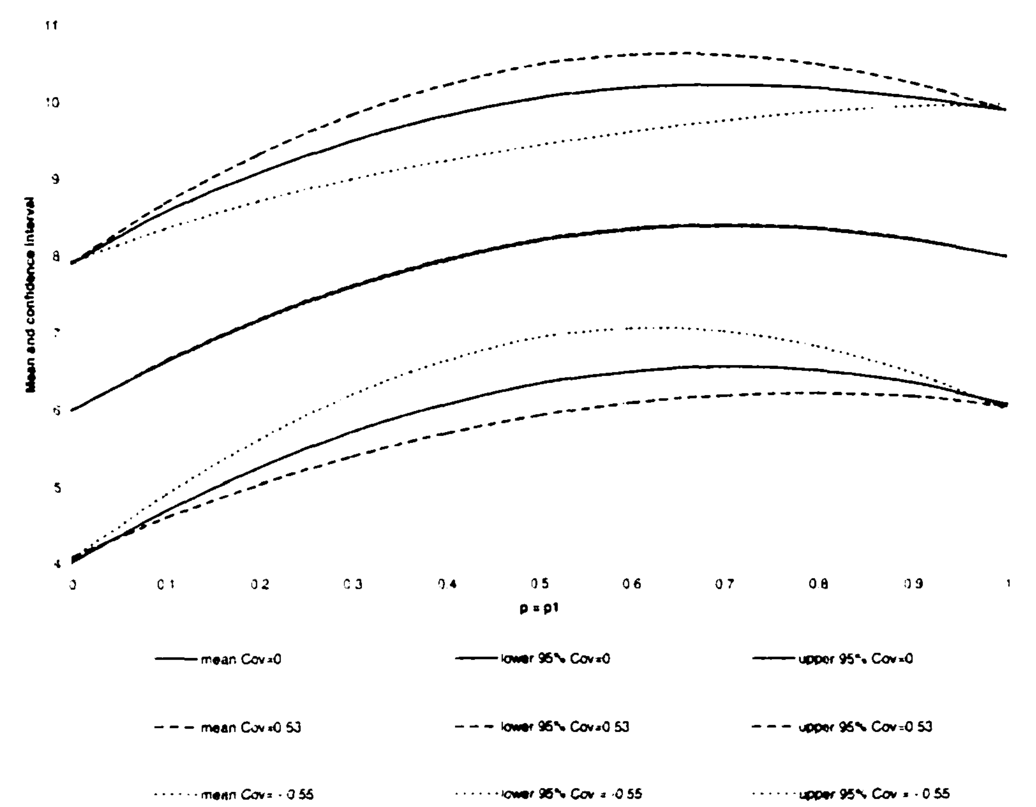
$$G = dA + eB + kdeAB. \qquad (3)$$

2.3.3 Simulation of the individual model

For positive values of the parameter k the expected value for the population ($E(G)$) will usually exceed the linear combination of its components (that is, $d=1-p$ and $e=p$) by construction. However, the nature of equation three is complicated by the multiplication of two random variables. To illustrate the implications of equation (3), particularly on its mean and confidence intervals, three simulations were run, each containing 5,000 independent observation pairs (A, B). Here A and B were normally distributed random variables with expected value 6 and 8 respectively and variance $\sigma_A^2 = \sigma_B^2 = 1$. For illustrative purposes the parameter k was set equal to 0.1. In the three simulations presented, A and B were independent ($Cov(A,B)=0$), positively correlated ($Cov(A,B) = 0.53$) and negatively correlated ($Cov(A,B) = -0.55$). In each simulation, p varied continuously from 0 to 1.

The results of the simulations are presented in Figure 2.2. For the zero covariance case, the 95% confidence intervals are almost parallel; they bow slightly inwards with the standard deviation falling from a maximum of 1.00 at $p=0$ and $p=1$ to a minimum of 0.95 at $p=0.5$. For the negative correlation case, the 95% confidence interval bows inwards relatively more than the no correlation case, which parallels classical finance theory. For the positive correlation case, the 95% confidence interval bows outward relative to the mean. This does not conform to finance theory and is in direct consequence of the multiplicative nature of the portfolio.

Figure 2.2: Simulation of multiplicative effect



Note: Figure 2.2 illustrates the mean effect and confidence intervals for a portfolio of two therapies *A* and *B*. The vertical axis is measure in units of effectiveness and the horizontal axis relates to the relative weights of the two interventions. Here intervention *A* has a mean effectiveness of 6 and *B* has a mean effectiveness of 8. Both have a unitary standard deviation. There are three levels of correlation for *A* and *B* illustrated: no correlation, positive correlation and negative correlation. The simulations have the parameter *k* set arbitrarily equal to 0.1.

The simulations illustrate two key components of equation (3). First the mean effect is responsive, albeit in a very small way, to the correlation between the two interventions. For example, when p = 0.5 the mean return is 8.20 units of E when $Cov(A,B)$=0, is reduced to 8.19 when $Cov(A, B)$ = - 0.55, and is increased to 8.21 when $Cov(A,B)$ = 0.53. Thus, positive covariance will increase the bow due to the parameter k, and under some circumstances, namely, if the covariance is highly negative and k is small, the mean effect may be lower than the linear combination of its parts, although this is unlikely. Second, the variance of the mean effect does not behave like that of classical portfolio theory. This is explored in more detail in the following sections once a formal expression for the mean effect is derived.

2.3.4 General Population Model

We now consider a population of n individuals. For the two interventions the i-th individual has random increases in health per monetary unit spent of A_i and B_i, where:

$$E(A_i) = \mu_A, \quad Var(A_i) = \sigma_A^2, \quad E(B_i) = \mu_B, \quad Var(B_i) = \sigma_B^2 \text{ and } Corr(A_i, B_i) = \rho_i .$$

That is, individuals may respond differently to the two interventions, where the unit of measurement is standardized effectiveness (specifically, health units per budgetary unit).

We assume a fixed budget is spent on the population, which for simplicity we take to be 1 monetary unit. We distribute this budget across the population as follows: p monetary units are allocated to intervention 1 and $(1 - p)$ monetary units are allocated to intervention 2. We then distribute the two interventions according to fixed distribution schemes; the i-th individual receives r_i monetary units of intervention 1 and s_i units of intervention 2, where

$$\sum_{i=1}^{n} r_i = p \quad and \quad \sum_{i=1}^{n} s_i = 1 - p.$$

Then, according to (3), G_i, the overall gain in health for the i-th individual, will be

$$G_i = r_i A_i + s_i B_i + k_i r_i s_i A_i B_i \tag{4}$$

with expectation

$$E(G_i) = r_i \mu_{A_i} + s_i \mu_{B_i} + k_i r_i s_i (\rho_i \sigma_{A_i} \sigma_{B_i} + \mu_{A_i} \mu_{B_i}) \tag{5}$$

and variance

$$\begin{aligned} Var(G_i) = {} & r_i^2 \sigma_{A_i}^2 + s_i^2 \sigma_{B_i}^2 + 2 r_i s_i (\rho_i \sigma_{A_i} \sigma_{B_i}) \\ & + 2 k_i r_i^2 s_i Cov(A_i, A_i B_i) + 2 k_i r_i s_i^2 Cov(B_i, A_i B_i) \\ & + k_i^2 r_i^2 s_i^2 \; Var(A_i B_i). \end{aligned} \tag{6}$$

Note that the coefficient k from (1) may be different for each individual. In general, $Cov(A_i, A_i B_i)$, $Cov(B_i, A_i B_i)$ and $Var(A_i B_i)$ depend on the joint distribution of A_i and B_i, but in the case where they are Normally distributed it is possible to give formulae for these in terms of $\mu_{A_i}, \mu_{B_i}, \sigma_{A_i}, \sigma_{B_i}$ and ρ_i (see Bridges et al, 2002).

The total gain in health for the population will be given as

$$G = \sum_{i=1}^{n} G_i \tag{7}$$

with mean

$$E(G) = \sum_{i=1}^{n} E(G_i) \tag{8}$$

and variance

$$Var(G) = \sum_{i=1}^{n} Var(G_i) + \sum_{\substack{i,j=1 \\ i \neq j}}^{n} Corr(G_i, G_j)\sqrt{Var(G_i)Var(G_j)}. \tag{9}$$

2.4 Special Cases of the General Model

While the above model is general in derivation, by making some limiting assumptions, we can highlight some interesting aspects of the theory. We derive three such special cases. In all three, we assume that each individual responds identically to the interventions. That is, $k_1 = k_2 = \ldots = k_n = k$ and each pair A_i and B_i has the same joint distribution, as given by (2). So then $\mu_{A_i}, \mu_{B_i}, \sigma_{A_i}, \sigma_{B_i}$ and ρ_i are respectively $\mu_A, \mu_B, \sigma_A, \sigma_B$ and ρ for each $i = 1, 2, \ldots, n$. In the first two, we also assume that there is no correlation between increases in health of different individuals, that is $Corr(G_i, G_j) = 0$ for all $i \neq j$. In the third we introduce the idea that the population consists of clusters (or peer groups) of individuals within which changes in health are correlated.

2.4.1 Special Case One

In this special case, we assume that a subset of the population receive equal shares of intervention 1 only, while the rest receive equal shares of intervention 2. Furthermore, there is no correlation between the individuals with regard to the effectiveness of the programs. Specifically, of the n individuals, the first m have $r_i = p/m$, $s_i = 0$; the other $n - m$ have $r_i = 0$ and $s_i = (1 - p) / (n - m)$, such that $r_i^x s_i^y = 0$ for $x, y \geq 1$ for all individuals.

So for $i = 1, 2, \ldots, m$ we have

$$E(G_i) = \frac{p}{m}\mu_A,\ Var(G_i) = \left(\frac{p}{m}\right)^2 \sigma_A^2$$

and for the remainder we get

$$E(G_i) = \frac{1-p}{n-m}\mu_B, Var(G_i) = \left(\frac{1-p}{n-m}\right)^2 \sigma_B^2.$$

This gives

$$\begin{aligned} E(G) &= \sum_{i=1}^{n} E(G_i) \\ &= \sum_{i=1}^{m} \frac{p}{m}\mu_A + \sum_{i=m+1}^{n} \frac{1-p}{n-m}\mu_B \\ &= \rho\mu_A + (1-p)\mu_B \end{aligned} \tag{10}$$

and since the G_i's are uncorrelated,

$$\begin{aligned} Var(G) &= \sum_{i=1}^{n} Var(G_i) \\ &= \sum_{i=1}^{m} \left(\frac{p}{m}\right)^2 \sigma_A^2 + \sum_{i=m+1}^{n} \left(\frac{1-p}{n-m}\right)^2 \sigma_B^2 \\ &= \rho^2\left(\frac{\sigma_A^2}{m}\right) + (1-p)^2\left(\frac{\sigma_B^2}{n-m}\right) \end{aligned} \tag{11}$$

which is minimised with respect to p at

$$\hat{p} = \frac{m\sigma_B^2}{(n-m)\sigma_A^2 + m\sigma_B^2} \tag{12}$$

which is neither 0 or 1 if $0 < m < n$, that is, there are two distinct and non-empty groups. In this case, when the returns are uncorrelated and each person receives only one of the interventions, the result is equivalent to classical portfolio theory. Since no individuals receive both interventions, there is no synergistic effect.

2.4.2 Special Case Two

In this special case, we assume that all individuals receive both interventions. While the total budgetary shares for each intervention may differ (namely p and $(1-p)$), each individual receives equal shares of the programs (that is, $r_i=r_j$ and $s_i=s_j$ for all $i, j \in n$). Formally, for all individuals, $r_i = p / n$ and $s_i = (1-p)/n$. So for all i, $E(G_i)=E(G_1)$ and $Var(G_i) = Var(G_1)$. Now the mean is

$$E(G_i)=\frac{p}{n}\mu_A+\frac{1-p}{n}\mu_B+k\frac{p(1-p)}{n^2}(\rho\sigma_A\sigma_B+\mu_A\mu_B)$$

and variance is

$$\begin{aligned}Var(G_i)&=\left(\frac{p}{n}\right)^2\sigma_A^2+\left(\frac{1-p}{n}\right)^2\sigma_B^2+2\rho\frac{p(1-p)}{n^2}\sigma_A\sigma_B\\&+2k\frac{p^2(1-p)}{n^3}Cov(A,AB)+2k\frac{p(1-p)^2}{n^3}Cov(B,AB)\\&+k^2\frac{p^2(1-p)^2}{n^4}Var(AB)\\&=\left(\frac{1}{n^2}\right)\left(p^2\sigma_A^2+(1-p)^2\sigma_B^2+2\rho\, p(1-p)\sigma_A\sigma_B\right)+\frac{T_2}{n^3}+\frac{T_3}{n^4}\end{aligned}$$

where

$$T_2=2k\left(p^2(1-p)Cov(A,AB)+p(1-p)^2Cov(B,AB)\right)$$

and

$$T_3 = k^2 p^2 (1-p)^2 Var(AB)$$

are grouped terms that will be of successively smaller order with respect to the population size n.

This gives

$$E(G) = nE(G_i) = \mu_A p + \mu_B (1-p) + \left(\frac{1}{n}\right) kp(1-p)(\rho\sigma_A\sigma_B + \mu_A\mu_B). \qquad (13)$$

The first two terms of equation (13) make up a classical portfolio return. The third term involves the synergy coefficient k, but it only makes a small contribution as it goes to zero as n gets large. This is because the amount spent on each individual is like $1/n$ dollars and so the multiplicative synergy contribution for each individual is like $1/n^2$. Thus, when aggregated over n individuals, the total synergistic contribution is small (like $1/n$). Thus, while a synergistic effect on return may be apparent in small populations, it is less so in larger ones. This is an example of where a social objective of maximizing population health differs from that of the individual due to aggregation.

Since the G_i' s are assumed uncorrelated, the risk becomes

$$
\begin{aligned}
Var(G) &= nVar(G_1) \\
&= \left(\frac{1}{n}\right)\left\{\left(p^2\sigma_A^2+(1-p)^2\sigma_B^2+2p(1-p)\rho\sigma_A\sigma_B\right)\right\}+\frac{T^2}{n^2}+\frac{T_3}{n^3}.
\end{aligned} \tag{14}
$$

The first term is again a classical portfolio risk, but it is small like the third term in (13). The intuition for this result is that the health planner has invested a $1/n$ share of the total investment in each individual. Thus, as n becomes large, all aspects related to risk vanish, a standard result in portfolio theory when there is no correlation between investments (see Copland and Weston, 1988). The last two terms, which contain the synergy coefficient k, are negligible by comparison, as they go to zero even faster.

2.4.3 Special Case Three

This case is identical to special case two, but here we allow for a known correlation between certain sub-groups in the population. For simplicity, we assume that the correlation within each subgroup is the same, but there are no correlations across sub-groups. Consider that there are c sub-groups (or more formally c clusters) of size n/c. Thus we can write the condition

$$
Corr(G_i, G_j) = \begin{cases} \gamma & \text{if } i-th \text{ and } j-th \text{ individual are in the same cluster,} \\ 0 & \text{otherwise} \end{cases}
$$

so each of the c clusters contribute

$$\frac{n}{c}\left(\frac{n}{c}-1\right)$$

terms to the second (double) sum in (9).

So then the formula for $E(G)$ is unchanged from (13), but the form of $Var(G)$ is now

$$\begin{aligned} Var(G) &= nVar(G_1) + c\frac{n}{c}\left(\frac{n}{c}-1\right)\gamma \; Var(G_1) \\ &= \left[n(1-\gamma) + \frac{\gamma n^2}{c}\right] Var(G_1) \\ &= \frac{\gamma}{c}\left[p^2\sigma_A^2 + (1-p)^2\sigma_B^2 + 2p(1-p)\rho\sigma_A\sigma_B\right] \\ &\quad + \left(\frac{1}{n}\right)\left\{(1-\gamma)\left[p^2\sigma_A^2 + (1-p)^2\sigma_B^2 + 2p(1-p)\rho\sigma_A\sigma_B\right] + \frac{\gamma T_2}{c}\right\} \\ &\quad + \left(\frac{1}{n^2}\right)\left\{(1-\gamma)T_2 + \frac{\gamma T_3}{c}\right\} \\ &\quad + \left(\frac{1}{n^3}\right)(1-\gamma)T_3 \end{aligned} \tag{15}$$

The important thing here is that the *leading* term in the risk in this case is of a *larger* order ($1/c$) than the leading term in the risk in the previous case ($1/n$) (see equation (14)). In this case, the risk is not necessarily small, whereas the synergy contribution to the return is asymptotically zero. In this clustered model, the risk behaves as if the population was only of size c, not n. Indeed, if the correlation between individuals in clusters is 1, the clusters behave like individuals. The return, however, behaves exactly as the previous case. This result is again standard portfolio theory, that is, in a portfolio of n securities and a fixed budget, the variance of the portfolio will only go to zero in large populations if there are no covariance terms.

2.5 Conclusion

This paper provides a theoretical foundation for the application of portfolio theory to the health care setting. To this end, the paper has applied a risk/return objective function and used a standardized effectiveness ratio. Further, the paper has considered potential interaction or synergy between interventions for individuals and the effect of this on the health of a population. Beyond deriving a general population model for the application of portfolio theory to health care evaluation with a synergy term, the paper also considered three special cases. In the simple model when part of the population gets one intervention and the rest the other, classical portfolio theory applies. When everyone gets equal shares of each of two interventions there may be a synergistic contribution to a classical portfolio return and classical portfolio risk (albeit, both are asymptotically equal to zero in large populations). However, in the third case with clusters of correlated individuals, the risk may be positive even in large populations but the synergistic term may again be trivial depending on the size of the population treated.

One aspect we did not address in this paper is the difference between uncertainty and risk. In health, this is an important definitional distinction. The term 'risk' is associated with health care interventions for which there is sufficient evidence but the level of effectiveness (or costs) varies among patients. This provides us with a measurable variance, or 'risk'. 'Uncertainty', on the other hand, refers to health care interventions for which there is insufficient evidence on either the costs or effectiveness. Often in a CEA the researcher needs to make assumptions about interventions, and a CEA should include sensitivity analysis of these assumptions to obtain an upper and lower bound for the cost effectiveness ratio (Drummond et al, 1997). However, this uncertainty about the interventions cannot easily be converted into a measure of risk, that is, a statistical variance and confidence interval. Furthermore, the correlation between two interventions and any possible synergy between them are rarely reported.

Another limitation of this paper is the complete analysis of subgroups in the population. While the analysis presented above allowed for differences in clinical effectiveness (and for these differences to be clustered), we did not consider differences in tastes. Even if one can derive a social objective function from the average preferences of individuals, the decisions made through the use of such a function may not be appropriate for some sub-groups. Sculpher and Gafni (2001) introduce a methodology for deriving and utilizing average preferences for appropriate sub-groups of society. While their method focuses on the first moment of effectiveness, it could be generalised to look at both risk and uncertainty for sub-groups. Finally, the analysis presented above lends itself more to the analysis of public health interventions of a preventative nature. It can be thought of as following a Grossman (1972) approach, where investments in health are performed at a social level rather than at an individual level. While public health interventions are more likely to fit the two pivotal assumptions of the model (namely constant returns to scale and a fixed budget), other medical and surgical interventions may need a set of different assumptions. We leave this, however, as a matter for future research.

Chapter three:

Risk and uncertainty in medical care:

Explaining price variation for coronary care

Chapter summary

This chapter examines the role that measures of product heterogeneity, including hospital quality, play in explaining variation in negotiated (transaction) prices for hospital care, again utilizing a hedonic price methodology. The empirical setting is coronary artery bypass grafts (CABG) for patients who are insured by self-insured firms and treated in private hospitals. The data is derived from several sources. Data relating to prices and patient characteristics comes from the MarketScan (provided by the MEDSTAT group) for years 1995 and 1996. A quality index is derived for each year using a lagged three-year panel from HCFA's MEDPAR data (1991-93 and 1992-94 respectively). Data from the American Hospitals Association's (AHA) survey provides hospital level variables, and the Area Resource File provides measures of market structure. The study uses a two stage regression process. In the first stage, a risk adjustment (logit) model is estimated and transformed to calculate a quality index, using a z-score framework. The second stage estimates a hedonic pricing equation that incorporates the quality index, using either traditional or decomposed z-scores, and other covariates. The results indicate that there may be a potential market failure with price being responsive to uncertainty but not to excess risk. The study also finds that insurer and hospital type, as proxies for their respective bargaining power, are significant predictors of prices.

3.1 Introduction

There has been much concern regarding various characteristics of the health care market and their effects on prices. Focusing on the supply side, prices can increase over time due to technology (Murphy, 1998) or through increases in the market power of providers that may be acquired from mergers (Keeler et al, 1999). From the demand side, utilization rates are one of the most significant factors in determining total costs (Fuchs, 1999), but price discounts may also exist at the unit price (Cutler et al, 2000).

Previous studies have examined prices in an *ad hoc* manner, with focus placed on one particular aspect of the market (Krishnan, 2001; Melnick et al, 1992, Staten et al, 1987). This paper, however, utilizes the work of Brooks et al (1997) and Dor and Watson (1995), who developed a pricing model based on a bargaining process between health care providers (hospitals and physicians) and purchasers (insurers and individuals).

In addition to the bargaining aspect of price determination, one has to account for product differentiation in the health care market (Rosen, 1974). Traditionally, product differentiation has been accounted for by separating markets on a geographic basis (Pauly and Satterthwaite, 1981; Dranove et al 1993) or more recently by limiting analysis to specific diagnosis related groups (DRGs) (Lynk, 1995; Keeler et al 1999; Dranove and Ludwick, 1999; Krishnan, 2001). This paper accounts for both of these characteristics and a third, and perhaps more important, type of differentiation, that being the quality of output (Luft and Romano, 1993; McClellan and Staiger, 1999a).

Quality, or adverse event rates, are now becoming a key component in the assessment of hospitals (Dranove et al, 2002). Large purchasers of health care, consumer groups, provider organizations, and public policy makers are all increasingly aware of the quality dimension of health care delivery (AHRQ, 1999). Often there is a dilemma for policy makers between cost-containment objectives and ensuring higher quality (Eddy, 1997).

3.2 Background

This study focuses on variation in transaction prices (as apposed to charges) in health care markets. As these are equilibrium prices, they can be explained by both supply side and demand side factors (Working, 1927). Thus the relationship between observable hospital, patient and insurer attributes and the transaction prices is estimated. The empirical setting is Coronary Artery Bypass Graft (CABG) for patients who are insured by self insured firms for the years 1995 and 1996. CABG was chosen because it is a specialized procedure where prices are usually subject to separate price negotiations between hospitals and payers, often in the form of a speciality carve-out (see Frank et al, 1995).

As prices in the Medicare program and, to a large extent, in the Medicaid program are administratively determined, we investigate pricing in the private sector only. In this study, we will focus on the actual payments received by hospitals for performing medical procedures, that is, transaction prices (Seidmann, 1990). In the past, researchers have tended to follow other traditional hedonic studies (Court, 1939) and utilized list prices or stated hospital charges, primarily because of data limitations (Staten et al, 1987; Melnick et al, 1992). Transaction prices do, however, vary across purchasers and providers and are thus more indicative of negotiated market equilibrium (Working, 1927).

Health benefits in the U.S. remain heavily employer-based, with over 60 percent of all insured individuals being enrolled through employer-sponsored plans (Mills, 2001). Self-insurance by firms occurs more frequently than is commonly perceived (NCHS, 1997). The Employer Retirement Income Security Act (ERISA) exempts self-insured plans from State regulations, specifically exempting them from paying State premium taxation and from providing State mandated benefits. Thus, self-insurance is more prevalent in multi-state firms (61 percent of all multi-state employers) than single state firms (NCHS, 1997, p11). In 1993, 40 percent of all employees who received employer-sponsored health insurance benefits were enrolled in self-insured plans. In large firms of 500 or more employees, the proportion of insured employees in self-insured plans was even higher at 63 percent (Acs et al, 1996). By 1997, these self-insurance rates declined, but remained fairly high at 33 percent and 55 percent, respectively (Marquis and Long, 1999).

The past decade or two has been characterized by a rapid growth in managed care plans. Whereas only one quarter of the privately insured population where enrolled in some form of managed care in the early 1990's the majority of enrollees are today (Gable et al, 1989; Jensen et al, 1997). However, substantial variation in the forms of managed care exist, and the decomposition within this segment of the market has been changing. In particular, the relative market share of 'closed-form' HMOs was declining in the 1990s, whereas the 'open-form' HMOs and PPOs were increasing.

3.3 Data sources

The primary source for price variation and patient level characteristics is MarketScan data from the MEDSTAT group for 1995 and 1996. Payment information includes charges, payment source and patient cost sharing. Information on various insurer types is also included to allow for an analysis of their relative bargaining power. Insurance type is limited to only self-insured firms and consequently excludes closed-form HMOs. Patient characteristics related to the episode of care (length of stay, discharge status, etc) and the patient's individual characteristics are included. The transaction prices are derived from the service level file, and only services that were related to the CABG procedure were included. If any other major procedure was performed the patient was excluded from the sample.

Additional data on product heterogeneity is derived from three other sources. First, hospital level data, such as teaching status, is derived from the American Hospitals Associations hospital survey. Second, information about the market in which hospitals are competing in, such as the Herfindahl index, is gained from the Area Resource File. Here the level of analysis is at the Metropolitan Statistical Area (MSA). Morrisey et al (1988) and Manheim et al (1993) showed that geographic boundaries defined by MSAs closely approximate the level of internal patient flows that are used by courts to define a single geographic market (Elzinga and Hogarty, 1978). Like Bazzoli et al. (1995), we find that competition measures based on MSAs yield intuitively plausible results, and we find that they dominate other market measures (Makuc et al, 1991). Finally, HCFA's Medicare and Provider Analysis and Review (MEDPAR) data is utilized to gain a measure of quality at the hospital level.

Table 3.1 reports the means of the key variables that will be used. For the purposes of pricing regressions, the dependent variables are the log of price (Berndt, 1991). The total payment for a hospital service, by the insurer, differs from what the hospital receives, as physicians are paid separately. Here, physician costs can be thought of as unavoidable transaction costs between the insurer and hospital. While it may be possible to model the situation in a 'triadic' bargaining model, for the purposes of this analysis, it is assumed that physician costs are exogenously determined. Our analysis is focusing on hospital prices, but, for completeness, we also report regression results with (log) insurer prices as the dependent variable. Also, observations with hospital or total (insurer) costs under $2,000 and exceeding $200,000 have been removed, deleting 27 observations and leaving 2181. As seen in table 1, the mean hospital price is $28,986 and insurer price is $37,778. The observed death rate in the sample of Medicare patients to calculate the quality index is approximately 5 percent.

In the data, 20% of patients have preferred provider organization (PPO) insurance, 10% have major medical fee-for-service plans, 4% have point of service HMO plans, and the remaining 66% are fee for services plans. For the hospitals, 51% are defined as major teaching centers, 26% minor teaching centers and 23% have no teaching role. The average number of secondary procedures (measured by ICD 9 procedural codes and Common Procedural Terminology (CPT) codes) performed on a particular patient is over 10 (but is capped at 14). With regard to the type of CABG, 23% received single bypass, 30% double bypass, 34% triple bypass and 23% quadruple bypass.

3.4 Conceptual model

This paper has utilized a generalized Nash-bargaining framework to derive a pricing equation for selected medical procedures for privately owned hospitals (Brooks et al, 1997 and Dor and Watson, 1995). Primarily, such a model is based upon the relative bargaining strengths of the purchaser (insurer) and the provider (hospital) and the disagreement outcomes if bargaining fails. This study does not separate out the players' 'threat points' – the lowest alternative price the hospital can receive and the highest alternative price available to the insurer. While the Brooks, Dor and Wong (1997) algorithm utilizes them in a non-linear regression, the inclusion of quality adds additional non-linearity. Subsequently, insurer and hospital type are used as a proxy for their respective bargaining powers in the estimated models.

This analysis adds to the existing literature by specifically including a measure of quality based on the hedonic health literature (Goldman and Grossman, 1978 and Bridges and Hanson, 2000). Hedonic regression analysis attempts to explain pricing variation through observable indicators (Rosen, 1974). This is achieved through a comparison of the thirty day expected and actual morbidity rates utilizing a risk adjustment method (Luft and Romano, 1993). Due to data limitations, the literature has focused on in-hospital mortality (Chernew et al, 1998; Luft and Romano, 1993; Burns and Wholey, 1992; Luft et al, 1990). Thirty day mortality is superior to in-hospital mortality measures, as it can be affected by early discharge, however, the two are highly correlated.

There appears to be some confusion about what the term risk adjustment means. Two methodological strains have developed in the literature, one that can be roughly characterized as 'epidemiological' and another that appears more commonly in health economics or policy literature. The epidemiological strain has emphasized the role of comorbidies, or the underlying distribution of medical conditions (Heller et al, 2001, DesHarnais et al, 1988, 1990, 1991), whereas the 'economics' strain has tended to focus on hospital characteristics and other factors influencing mortality (McClellan and Staiger, 1999a, 1999b). More recently, this literature has begun to address the problem of random fluctuations over time in hospital mortality by using panel data techniques (McClellan and Staiger, 1999a, 1999b). Below, we demonstrate the relationship between the two approaches. We then proceed to combine them into a single, consistent measure of hospital outcomes.

3.5 An econometric model

The system to be estimated is a two-step procedure. The first step utilizes a logistic regression to calculate predicted mortality rates, which is then compared to the actual mortality rate to calculate a quality index (Luft and Romano, 1993). In the second step, OLS is also used to estimate a pricing equation (which is the primary focus of this paper).

As mentioned above, there is a significant difference between the epidemiology and economics literature on how to model adverse quality. As an example of the epidemiological approach, Heller et al (2001) do not include hospital characteristics in their analysis of actual and expected adverse events for hospitals. However, if hospital level variables are correlated with the patient level variables and are excluded from the risk adjusting equations, then the estimation will be biased. To calculate expected mortality, a logit regression is estimated using both patient level and hospital level variables. The risk adjustment regression is discussed further in appendix A.

Consider the derivation of a quality index using the above risk adjustment method using the z-score format. Essentially a z-score asks: Does the average observed performance of a hospital significantly differ from some appropriate benchmark or expected outcome? (Luft and Romano, 1993).

Here one may utilize the central limit theorem to invoke a normal distribution for the mean death rate. Let an observed outcome for episode i at hospital j be a random variable D_{ij}. The null hypothesis is that the mean level of adverse patient events for hospital j, D_j, is equal to some expected value (conditioned upon the average level of patient level characteristics for hospital j, C_j), denoted $E[D_j|C_j]$. For simplicity, one could think that the expected level of adverse events is equal by definition to some deterministic 'gold standard'. Thus, $E[D_j|C_j]$ would not have a variance so that an adjustment to the standard error would not need to be made for a joint test. While this is a simplifying assumption, it is often used (Luft and Romano, 1997) and could be relaxed at a later stage.

Consider Z_j, a quality index for hospital j, which is the excess of the actual average mortality rate over the expected mortality rate, divided (or standardized) by the standard error of the actual mortality rate, given as $SE(D_j)$. Thus, the z-score for hospital j can be expressed as:

$$Z_j = \frac{D_j - E[D_j|C_j]}{SE(D_j)}$$

A positive value of Z_j would indicate a higher rate of actual adverse events than expected for hospital j, that is, hospital j has poor quality. Likewise, a negative value for the z-score would indicate that hospital j has high quality. Here there is no need to make an adjustment for the comparison of a discrete variable to a continuous variable, as both the mean and expected mean are measured on the continuous scale.

3.6 Results

Tables 3.2 reports results for regressions with (log) hospital price as the independent variable, and Table 3.3 reports the results for regressions with (log) insurer price. Regressions 1-3 in each table relate to pricing equations that include the z-score as the measure of hospital quality, while regressions 4-6 have the numerator and denominator entered separately as measures of excess mortality and uncertainty, respectively.

3.6.1 Risk and uncertainty

The z-score essentially reports a standardized excess mortality. The results indicate that the z-score, as a measure of quality, has positive and significant relationship with both hospital and insurer prices. This is opposite of what one might have as an *a priori* assumption. The results indicate that hospitals get rewarded financially, in terms of prices paid and received, for producing excess mortality. While one might conclude that the higher payment is 'compensation' for a higher level of severity, the z-score accounts for this through the risk adjustment, and these 'unexpected' results are robust to the inclusion of patient level severity measures, such as the number of surgical procedures.

By separating the numerator and denominator of the z-scores into what can be referred to as excess mortality and uncertainty respectively, one gains further insight into the effects of quality on price. On separation, the excess mortality variable remains positively related to prices, again a non-intuitive result, but whose significance is reduced and depends on both the model specification and the choice of the dependent variable. Uncertainty, however, is strongly significant and positively related to price. This result would be consistent with a risk aversion hypothesis, where hospitals are relatively more risk averse than insurers and thus need higher compensation for patients that have a more uncertain outcome.

3.6.2 Measures of bargaining power

In addition to measures of quality and risk, tables 3.2 and 3.3 highlight other important determinants in the bargaining process. With regard to insurance bargaining power, Preferred Provider Organizations and Major Medical Fee-For-Service receive between a 10-15 percent discount over standard Fee-For-Service providers, depending on model specification (see Halvorsen and Palmquist, 1980 for the proper interoperation of log-linear coefficient). The magnitude of the discount for Point of Service HMO is much more dependent on model specification. When hospital prices are the dependent variable, the Point of Service HMOs receive a discount between 14-23 percent over the prices for standard Fee-For-Service. When insurer prices are the dependent variable, however, the discount is approximately 12-14 percent in the full model, but much lower when regional and/or patient variables are omitted. Collectively, these results indicate that these three forms of insurance have significant bargaining power over standard Fee-For-Service insurers.

Likewise, the indicator of a hospital's bargaining power, teaching status, has the expected sign. Hospitals defined as major teaching facilities receive between a 9-15 percent premium over non-teaching hospitals when hospital prices are the dependent variable. When the insurer price is the dependent variable the premium for major teaching hospitals is greatly reduced or insignificant from non-teaching hospitals. This may indicate that major teaching hospitals internalize some physician and clinical costs that may be paid directly by insurers to non teaching hospitals. Hospitals defined as minor teaching hospitals receive payments that do not differ significantly from non-teaching hospitals when hospital prices are the dependent variable. When insurer prices are the independent variable then minor teaching hospitals have slightly lower prices, but the relationship is not always significant.

3.6.3 The market and market structure

Increases in the hospital level Herfindahl index, that is, in market concentration, are significantly related with an increase in prices. This would be consistent with the hypothesis that decreased competition is associated with higher bargaining (market) power for hospitals. From the regressions, one can deduce that a move from perfect competition (Herfindahl of 0) to monopoly (Herfindahl of 1) would see prices rise somewhere between 15-25 percent when hospital prices are the dependent variable. Furthermore, the decomposition of the z-score has the effect of lowering the coefficient estimate on the Herfindahl index. The hospital market concentration has a lower effect on insurer prices. This may be because insurer prices include physician costs and physician bargaining power is not necessarily perfectly correlated with hospital bargaining power.

The HMO penetration rate is defined as the ratio of HMO enrolees under the age of 65 with regard to the population (Wholey et al. 1997). Generally, HMO penetration is correlated with lower prices, however, the significance and magnitude of effects is dependent on model specification. Regardless of the dependent variable, the effect of HMO penetration on MSA prices is small and insignificant when regional dummies are included in the model, indicating possible multi-collinearity. When regional dummies are excluded from the model, the discounts in MSAs with higher HMO penetration are much higher and significant. When insurer price is the dependent variable, a 10 percent increase in HMO participation in the MSA would be associated with lowering general prices between 1.4-1.8 percent. When hospital prices are the dependent variable, HMO penetration has a lower effect and the significance depends upon model specification. In total, these results indicate that HMOs are not only efficient in receiving price discounts for themselves (Cutler et al, 2000) but also increase the level of competition generally.

3.6.4 Measures of patient heterogeneity

With regard to patient/procedural characteristics, tables 3.2 and 3.3 indicate that these variables have the expected signs. For each secondary procedure, the hospital and insurer prices rise approximately 3 percent, and cases that are urgent have prices that are approximately 8-9 percent higher. This increase in price for emergency care may be explained by either the fact that emergency care is often treated out of network or through a hypothesis that the demand curve is relatively more elastic, allows hospitals with bargaining power to charge a higher price. Most likely it is a combination of the two.

With regard to the number of bypasses, insurer prices for double bypass are approximately 2-3 percent higher than single bypass, but not significantly so, while insurer prices for triple and quadruple bypass are approximately 4 and 7 percent (holding other attributes constant) over single bypass surgery, respectively. The premium in hospital prices for additional bypasses is approximately half that of insurer prices and is insignificant in most specifications in table 2.

3.6.5 The regional and year fixed effects

There is some minor regional variation in prices, with the most significant discount being for the Northern/Central region, where there is a great deal of competition in cardiac care. However, due to possible multi-collinearity problems, regressions without regional variables may be more optimal. There has been no significant change in hospital or insurer prices over the study period (here prices in the analysis are measured in the same base year using a medical price index).

3.7 Discussion

This analysis is the first to include a strong measure of quality into a bargaining style pricing equation in health economics. By doing so, a potential source of market failure may have been highlighted. As with other hedonic analyses in the literature (Byron and Ashenfelter, 1995), we find that market prices do not utilize information on quality efficiently. Specifically, insurers do not use information on excess mortality measured at the hospital level to adjust their prices. Thus, hospitals do not have a correct financial incentive to increase quality.

This research also found that using a z-score structure to specify a measure of quality is sub-optimal because it incorporates both a measure of risk and uncertainty. When the z-score is decomposed, excess mortality is positively related to price (but insignificantly so in some model specifications), but uncertainty is positively correlated (and strongly significant) with both hospital and insurer prices. This indicates that hospitals are relatively more risk averse than insurers, which would have been the *a priori* assumption, and thus have to be compensated for managing a more risky portfolio of patients.

Table 3.1: Variable means and standard deviations
(N=2181)

Variable	Mean	Std Dev
Prices		
Hospital price	28985	13161
Insurer price	37778	15161
Quality indexes		
z-score	-1.36	2.73
Uncertainty	0.01	0.004
Excess mortality	-0.01	0.02
Observed death rate	0.05	0.02
Predicted death rate (with Hospital fixed effect)	0.05	0.02
Predicted death rate (without Hospital fixed effect)	0.06	0.01
Insurer characteristics		
Preferred provider organization	0.20	0.40
Major medical fee-for-service only	0.10	0.30
Point of service HMO	0.04	0.20
Hospital characteristics		
Major teaching hospital	0.26	0.44
Minor teaching hospital	0.51	0.50
Market characteristics		
MSA hospital Herfindahl index	0.13	0.13
MSA HMO penetration rate	0.18	0.11
Patient characteristics		
Double bypass	0.30	0.46
Triple bypass	0.34	0.47
Quadruple bypass	0.23	0.42
Number of secondary procedures	10.87	3.32
Urgent procedure	0.29	0.46
Regional characteristics		
Northern/central region	0.42	0.49
Southern region	0.40	0.49

Table 3.2: Pricing regressions with z-score or risk and uncertainty
Dependant variable is the log of hospital price
(N=2181)

	1	2	3	4	5	6
Z-score	0.009**	0.013***	0.012***			
	(0.00)	(0.00)	(0.00)			
Excess mortality				0.246	1.163**	0.807
				(0.52)	(0.52)	(0.54)
Uncertainty				16.154***	13.285***	15.752***
				(2.70)	(2.73)	(2.83)
Preferred provider organization	-0.125***	-0.103***	-0.091***	-0.139***	-0.114***	-0.105***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Major medical fee-for-service only	-0.133***	-0.119***	-0.116***	-0.148***	-0.133***	-0.131***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Point of service HMO	-0.229***	-0.164***	-0.138***	-0.246***	-0.177***	-0.153***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Major teaching hospital	0.119***	0.072***	0.072***	0.150***	0.093***	0.099***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Minor teaching hospital	-0.005	-0.020	-0.031	0.025	0.001	-0.003
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
MSA hospital Herfindahl index	0.191**	0.219***	0.245***	0.153***	0.187***	0.209***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
MSA HMO penetration rate	-0.029	-0.148*	-0.125	-0.002	-0.120	-0.099
	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
Number of secondary procedures	0.029***	0.027***		0.029***	0.027***	
	(0.00)	(0.00)		(0.00)	(0.00)	
Urgent procedure	0.097***	0.094***		0.093***	0.090***	
	(0.02)	(0.02)		(0.02)	(0.02)	
Double bypass	0.021	0.017		0.021	0.016	
	(0.03)	(0.03)		(0.02)	(0.03)	
Triple bypass	0.019	0.020		0.018	0.020	
	(0.02)	(0.03)		(0.02)	(0.02)	
Quadruple bypass	0.029	0.043		0.029	0.044*	
	(0.03)	(0.03)		(0.03)	(0.03)	
Regional dummies	Yes	No	No	Yes	No	No
R squared	0.156	0.123	0.044	0.175	0.139	0.064
Adjusted R squared	0.149	0.117	0.040	0.168	0.133	0.060

Note: Standard errors are presented in parentheses. Regional dummies (where applicable), time dummy and intercept omitted. *** indicates a two-tailed significance with α=0.01, ** with α=0.05 and * with α=0.10.

Table 3.3: Pricing regressions with z-score or risk and uncertainty
Dependant variable is the log of insurer price
(N=2181)

	1	2	3	4	5	6
Z-score	0.010***	0.014***	0.013***			
	(0.00)	(0.00)	(0.00)			
Excess mortality				0.531	1.630***	1.212***
				(0.42)	(0.43)	(0.45)
Uncertainty				13.957***	10.524***	13.202***
				(2.16)	(2.24)	(2.39)
Preferred Provider organization	-0.128***	-0.123***	-0.110***	-0.140***	-0.132***	-0.121***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Major medical fee-for-service only	-0.139***	-0.121***	-0.119***	-0.153***	-0.133***	-0.132***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Point of service HMO	-0.125***	-0.046	-0.016	-0.141***	-0.055*	-0.029
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Major teaching hospital	0.045**	-0.013	-0.011	0.071***	0.002	0.010
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Minor teaching hospital	-0.025	-0.047***	-0.057***	0.000	-0.031*	-0.035*
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
MSA hospital Herfindahl index	0.110**	0.147***	0.182***	0.077	0.122**	0.151***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
MSA HMO penetration rate	-0.020	-0.184***	-0.165**	0.004	-0.154**	-0.137**
	(0.06)	(0.06)	(0.07)	(0.06)	(0.06)	(0.07)
Number of secondary procedures	0.033***	0.031***		0.033***	0.030***	
	(0.00)	(0.00)		(0.00)	(0.00)	
Urgent procedure	0.079***	0.078***		0.076***	0.074***	
	(0.01)	(0.01)		(0.01)	(0.01)	
Double bypass	0.031	0.026		0.031	0.025	
	(0.02)	(0.02)		(0.02)	(0.02)	
Triple bypass	0.043**	0.044**		0.042**	0.044**	
	(0.02)	(0.02)		(0.02)	(0.02)	
Quadruple bypass	0.055***	0.072***		0.056***	0.074***	
	(0.02)	(0.02)		(0.02)	(0.02)	
Regional dummies	Yes	No	No	Yes	No	No
R squared	0.248	0.180	0.055	0.269	0.199	0.078
Adjusted R squared	0.242	0.175	0.051	0.263	0.193	0.074

Note: Standard errors are presented in parentheses. Regional dummies (where applicable), time dummy and intercept omitted. *** indicates a two-tailed significance with $\alpha=0.01$, ** with $\alpha=0.05$ and * with $\alpha=0.10$.

Appendix A: The estimation of the risk adjustment equation

To calculate the expected mortality rate for a hospital j, given their average patient mix, a logit model is estimated on HCFA MEDPAR data for all hospitals with 30-day mortality as the dependent variable and patient level characteristics as the independent variables. However, as discussed above, the estimation of such a model may be biased if an omitted hospital level variable is correlated with any of the patient level variables. Consider a dichotomous variable, D_{ij}, for the i-th patient in the j-th hospital, being the dependent variable regressed upon vectors of patient, denoted C_{ij}, and a set of hospital fixed effects, $\{h_j\}$. For estimation purposes, we can write the logit model (Gujarati, 1995, p556) that leads to an unbiased estimate of β as:

$$L_{ij} = \ln\left(\frac{D_{ij}}{1-D_{ij}}\right) = \alpha + \beta\, C_{ij} + \sum_{j} \phi_j h_j + \varepsilon_{ij}\,. \qquad \text{[A1]}$$

The actual death rate for a hospital could be calculated, given the average patient characteristics (Cramer, 1964), C_j, where there is n_j patients treated at hospital j, as:

$$L_j = \ln\left(\frac{D_j}{1-D_j}\right) = \alpha + \beta\, C_j + \phi_j + \frac{\sum_{i\in j} \varepsilon_{ij}}{n_j}\,. \qquad \text{[A2]}$$

One could then form an expected rate of death, given only the patient characteristics, C_j, as:

$$\hat{L}_j = \ln\left(\frac{E[D_j|C_j]}{1-E[D_j|C_j]}\right) = \alpha + \beta\, C_j\,. \qquad [A3]$$

To formalize the measure of quality, one can write as an identity:

$$\frac{D_j}{1-D_j} \equiv \left(\frac{E[D_j|C_j]}{1-E[D_j|C_j]}\right)\left(\frac{D_j}{1-D_j}\right)\left(\frac{1-E[D_j|C_j]}{E[D_j|C_j]}\right) \qquad [A4]$$

and taking natural logs yields

$$\ln\left(\frac{D_j}{1-D_j}\right) \equiv \ln\left(\frac{E[D_j|C_j]}{1-E[D_j|C_j]}\right) + \ln\left(\frac{D_j}{1-D_j}\right) - \ln\left(\frac{E[D_j|C_j]}{1-E[D_j|C_j]}\right) \qquad [A5]$$

Rearranging [A5] and substitution from equations [A2] and [A3] yields:

$$\ln\left(\frac{D_j}{1-D_j}\right) - \ln\left(\frac{E[D_j|C_j]}{1-E[D_j|C_j]}\right) = \phi_j + {\sum_{i\in j}\varepsilon_{ij}} \Big/ {n_j} \qquad [A6]$$

or using a McFadden (1974) styled notation one could state the an unbiased quality measure for hospital j, Q_j, as:

$$Q_j = L_j - \hat{L}_j = \phi_j + {\sum_{i\in j}\varepsilon_{ij}} \Big/ {n_j}\,. \qquad [A6a]$$

This states that the difference between the log-odds ratio for the actual death rate and for the expected death rate is equal to the hospital attributable mortality, ϕ_j, and the average error term $\sum_{i \in j} \varepsilon_{ij} / n_j$. For the purpose of this paper we have simplified the analysis so that the quality measure is not the difference of the log-odds ratios, but the difference of the implied probabilities (the actual death rate and expected death rate). Furthermore, we follow standard epidemiological methods (Luft and Romano, 1993) and standardize this measure (which we refer to as excess mortality) by the implied standard error of the actual mortality (assuming a binomial distribution).

The inclusion of a large number of dummy variables reflecting the hospital fixed effects makes the estimation by logit problematic (Greene, 2000; Chamberlain, 1980). To avoid this problem, small and similar hospitals can be clustered together so as to ensure convergence of the maximum likelihood estimates.

The summary statistics for the data, corresponding to the periods 1990-92 and 1991-3, are presented in Table A1 and the results of the two risk adjustments equations are presented in Table A2. For completeness, table A3 reports the results of a regression where the quality measure is the difference in the log-odds ratio, as defined above. Regressions 1-3 relate to hospital prices and 4-6 relate to insurer prices. It is important to note the relationship between increased adverse quality and higher prices persists.

Table A.1: Means for risk adjustment equation

Panel a: 1990-1992, 381 hospitals, 222,155 patients

Variable	Mean	Std Dev
Age	72.101	4.990
Race (Black = 1)	0.030	0.170
Sex (Female = 1)	0.346	0.476
Acute Myocardial Infarction	0.230	0.421
Diabetes	0.164	0.371
Gastrointestinal bleed	0.012	0.110
Congestive heart failure	0.167	0.373
Chronic obstructive pulmonary disease	0.115	0.320
Renal failure	0.029	0.167
Liver failure	0.001	0.033
Cancer	0.012	0.111
Cerebrovascular disease	0.074	0.262

Panel b: 1991-1993, 386 hospitals, 236,661 patients

Variable	Mean	Std Dev
Age	72.245	5.047
Race (Black = 1)	0.030	0.171
Sex (Female = 1)	0.347	0.476
Acute Myocardial Infarction	0.241	0.428
Diabetes	0.183	0.386
Gastrointestinal bleed	0.013	0.114
Congestive heart failure	0.189	0.392
Chronic obstructive pulmonary disease	0.132	0.339
Renal failure	0.035	0.184
Liver failure	0.001	0.036
Cancer	0.014	0.116
Cerebrovascular disease	0.082	0.274

Table A.2: Logit risk adjustment regressions

	1990 - 1992 N=222,155	1991 - 1993 N=236,661
Age	0.049***	0.050***
	(0.00)	(0.00)
Race (Black = 1)	0.019	0.013
	(0.05)	(0.05)
Sex (Female = 1)	0.326***	0.323***
	(0.02)	(0.02)
Acute Myocardial Infarction	0.633***	0.617***
	(0.02)	(0.02)
Diabetes	-0.327***	-0.268***
	(0.03)	(0.03)
Gastrointestinal bleed	0.094	0.107
	(0.08)	(0.07)
Congestive heart failure	0.620***	0.618***
	(0.02)	(0.02)
Chronic obstructive pulmonary disease	0.061**	0.079***
	(0.03)	(0.03)
Renal failure	1.652***	1.701***
	(0.03)	(0.03)
Liver failure	1.241***	1.377***
	(0.19)	(0.16)
Cancer	-0.207**	-0.133
	(0.10)	(0.09)
Cerebrovascular disease	0.593***	0.560***
	(0.03)	(0.03)
-2 Log L	85087.3	88581.3
Concordant	70.8%	71.7%

Note: Hospital fixed effects and intercept not reported. Standard errors in parentheses. *** indicates a two-tailed significance with $\alpha=0.01$, ** with $\alpha=0.05$ and * with $\alpha=0.10$.

Table A.3: Pricing regressions with quality score
Dependant variable is the log of hospital and insurer price
(N=2181)

	Hospital price			Insurer price		
	1	2	3	4	5	6
Quality	0.111***	0.138***	0.133***	0.112***	0.147***	0.139***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Preferred provider organization	-0.126***	-0.102***	-0.090***	-0.129***	-0.121***	-0.108***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Major medical fee-for-service only	-0.138***	-0.123***	-0.120***	-0.144***	-0.125***	-0.123***
	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	0.02
Point of service HMO	-0.225***	-0.161***	-0.134***	-0.122***	-0.042	-0.013
	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)
Major teaching hospital	0.105***	0.060**	0.060**	0.032	-0.026	-0.024
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Minor teaching hospital	-0.015	-0.030	-0.040*	-0.035**	-0.057***	-0.066***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
MSA hospital Herfindahl index	0.198***	0.224***	0.251***	0.117**	0.153***	0.189***
	(0.06)	(0.06)	(0.06)	(0.05)	(0.05)	(0.05)
MSA HMO penetration rate	-0.002	-0.103	-0.081	0.005	-0.139**	-0.121*
	(0.08)	(0.08)	(0.08)	(0.06)	(0.06)	(0.07)
Number of secondary procedures	0.030***	0.027***		0.033***	0.031***	
	(0.00)	(0.00)		(0.00)	(0.00)	
Urgent procedure	0.095***	0.092***		0.077***	0.076***	
	(0.02)	(0.02)		(0.01)	(0.01)	
Double bypass	0.021	0.017		0.031	0.025	
	(0.03)	(0.03)		(0.02)	(0.02)	
Triple bypass	0.020	0.022		0.045**	0.046**	
	(0.02)	(0.03)		(0.02)	(0.02)	
Quadruple bypass	0.033	0.047*		0.059***	0.076***	
	(0.03)	(0.03)		(0.02)	(0.02)	
Regional dummies	Yes	No	No	Yes	No	No
R squared	0.162	0.131	0.052	0.256	0.193	0.067
Adjusted R squared	0.155	0.126	0.049	0.250	0.188	0.063

Note: Standard errors, which allow for hospital/year clustering, are presented in parentheses. Regional dummies (where applicable), time dummy and intercept omitted. *** indicates a two-tailed significance with $\alpha=0.01$, ** with $\alpha=0.05$ and * with $\alpha=0.10$.

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