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The Demand for Episodes of Medical Treatment in the Health Insurance Experiment

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Janet M. Hanley, David M. Reboussin

March 1988

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PREFACE

This report contains a statistical and economic analysis of data on the demand for medical care from the RAND Health Insurance Experiment (HIE). The HIE, funded by a grant from the U.S. Department of Health and Human Services, is a large-scale social experiment designed to assess how varying patients' cost of health services affects their use of services and their health status. The experimental design for estimating the effects of financing on demand for health care is described in J. P. Newhouse, "A Design for a Health Insurance Experiment," *Inquiry*, Vol. 11, March 1974, pp. 5–27. Related economics papers include J. P. Newhouse et al., "Some Interim Results from a Controlled Trial in Health Insurance," *New England Journal of Medicine*, Vol. 305, December 17, 1981; and W. G. Manning et al., "Health Insurance and the Demand for Medical Care: Evidence from a Randomized Experiment," *American Economic Review*, June 1987. In addition, many RAND papers describe other economic results, the measurement and analysis of health effects, details of the experimental design, and data reliability issues.

This report presents final results for medical spending organized by episodes, a powerful and fairly new approach to the study of demand. It uses the methods developed in E. B. Keeler et al., *The Demand for Episodes of Medical Treatment: Interim Results from the Health Insurance Experiment*, R-2829-HHS, December 1982. Readers interested in the justification and details of the methods used here should refer to that report. The application of these methods to spending on mental health treatments is given in E. B. Keeler et al., *The Demand for Episodes of Mental Health Services*, R-3432-NIMH, October 1986. Episodes are also used in K. N. Lohr et al., "Use of Medical Care in the RAND Health Insurance Experiment: Diagnosis- and Service-Specific Analyses," *Medical Care*, Supplement, September 1986, to examine quality of care. This report also presents results from a new model that uses statistical estimates to simulate spending on episodes of treatment by a representative group of families. The results presented here should interest health economists, health services researchers, and persons involved in designing, choosing, or evaluating health insurance schemes.

SUMMARY

Those designing or choosing health insurance schemes need to know how cost sharing by users affects the use of health services. Studies of the effects of copayment that are based on nonexperimental data are flawed because of adverse selection (that is, people in chronic poor health may choose fuller coverage than most other people), and because of inevitable gaps in such data. To overcome these data problems, the federal government asked The RAND Corporation to conduct a social experiment, the Health Insurance Experiment (HIE). The HIE randomly assigned families to 14 different insurance plans, balancing the plan groups in terms of nonprice characteristics that affect use. Much effort has gone into obtaining complete and accurate data on the participants' use of health services.

The plans had different levels of cost sharing, which varied over two dimensions: the coinsurance rate (percentage paid out of pocket) and an upper limit on annual out-of-pocket expenses. The coinsurance rates were 0, 25, 50, or 95 percent. Each plan had an upper limit (the Maximum Dollar Expenditure or MDE) on annual out-of-pocket expenses of 5, 10, or 15 percent of income, up to a maximum of $1000. Beyond the MDE, the insurance plan reimbursed all covered expenses in full. On one plan, individuals faced a 95 percent coinsurance rate for outpatient services up to an individual limit on out-of-pocket expenses of $150 but all inpatient services were free.

One approach to the HIE data estimated the effects of plan on annual expenses. Such estimates are unbiased and accurate and can be extrapolated to plans similar to the 14 tested. However, annual estimates cannot readily be used to assess the effects of insurance with a different scope of coverage, a different basis for copayment, or a different deductible. In particular, we need to know the effects of "pure" price, that is, coinsurance with no limits on out-of-pocket payments.

EPISODES OF TREATMENT

To predict the effects of insurance plans other than those used in the experiment, we must know how decisions to buy medical services during the year are actually made. We have previously shown that such decisions can be analyzed in terms of episodes of treatment that contain all the spending associated with a given bout of illness, chronic condition, or well-care procedure (Keeler et al., 1982). Because most

participants have several episodes of various types in a year, relative to annual aggregates, episodic data increase precision, untangle the effects of coinsurance and deductibles, and generate new ideas on how to use copayments to meet the goals of health insurance more effectively.

To use the episodic approach, we developed procedures for grouping expenses into episodes. Grouping was based on diagnosis, treatment history (initial, repeat, or routine), referral and other linking information (for drugs, tests, and supplies), and the time between possibly related claims. Episodes were categorized (hospital, ambulatory acute, chronic, well, or dental care), and spending was summed and dated to the first time the patient could have anticipated it.

In an earlier report on these issues, we used three years of data on participants from one site (Dayton) (Keeler et al., 1982). The results presented here are based on three years of data from all participants in the study. The additional data allow us to detect effects that we could not see before, and to make fairly precise estimates of what happened in the experiment.

FINDINGS

A major finding is that price affects the number of episodes chosen by participants and has much smaller effects on the cost of each episode. Almost all of the reduction in use with coinsurance comes from reduction in the number of episodes. Although the cost per episode was consistently lower with cost sharing on all types of outpatient episodes, the differences that averaged from 3–6 percent were too small to be significant. Average costs per hospital episode were slightly higher with cost-sharing plans, because cost sharing had an impact on the rate of small hospitalizations but no effect on the probability of catastrophically large hospitalizations.

The similarity of cost of episodes on all plans is unexpected and important. If the episodes treated on the pay plans are more severe than average, then the similarity of cost reflects some economizing that compensates for the severity. If the treated episodes are equally severe on all plans, then the similarity of cost implies that variation in cost sharing is not greatly affecting the choice of doctor or the quality of care provided by that doctor. Analyses presented here and in other RAND studies (Siu et al., 1986; Lohr et al., 1986) show that cost sharing reduces both necessary and unnecessary care, so that the severity of illness treated under cost sharing is similar to that under free care.

Episode rates differ most between free care and the cost-sharing plans as a group, with less difference between low and high levels of

coinsurance. Hospital episode rates are less affected by price than are the rates of other episodes.

Health status, age, sex, and prior use (doctor visits in the year before the experiment) are the most important determinants of episode rates. Income, insurance plan, and having a regular doctor and dentist are highly significant statistically but less powerful than the first group of variables. The occurrence of dental and well-care episodes was strongly associated with education and income but not with health status. A negative binomial model in which variables affect the rate of episodes multiplicatively fits the data well.

Our earlier economic model of the effects of deductibles (Keeler et al., 1977a) explains how people could change the timing of their medical purchases to reduce costs. After exceeding their upper limit on out-of-pocket expenses (MDE), families on the pay plan face free care until the end of the year. Care is "on sale," and in theory they have more incentive to spend than families with permanently free care. In fact, outpatient episode rates of those on the pay plans who exceeded the MDE stayed below free plan rates for acute and chronic spending and rose to about free plan rates for well care and dental care spending.

There was no apparent difference in outpatient spending between those with a little or those with a lot of MDE remaining, but the rates of hospital episodes for those with a little MDE remaining were halfway between those with a lot of MDE remaining, and those on the free plans. The $150 individual deductible effectively restrained demand for ambulatory care; most participants never spent more than $150 a year on ambulatory care nor appeared to anticipate that they would.

Despite our theory, people do not appear to respond greatly to exceeding the MDE. They may not get enough experience in doing so, or they may find that it is too much trouble to keep track of sale periods, or they may not want to wait for the price to fall for relief.

IMPLICATIONS FOR INSURANCE DESIGN

We embodied these results in a simulation model used to predict the effects of different insurance packages on demand. This model showed that as a function of deductibles, expected care decreases steadily through the range of small ($50) to medium deductibles ($500) but does not change much as deductibles increase beyond $1,000. The latter result derives in part from the assumption that catastrophically large expenditures are not much affected by differences in cost sharing.

This was true in the HIE, but it might not hold for insurance plans with no upper limit on cost sharing.

Depending on this assumption, spending with no insurance is estimated to be 55–57 percent of that with free care, with 50 percent coinsurance and no limit on out-of-pocket spending, it is 63–68 percent, and with 25 percent coinsurance, it is 71–74 percent that of free care.

These results show that small deductibles can be effective in restraining demand, and that individual caps on out-of-pocket spending need not exceed $1,000 per year to eliminate most overuse. Large deductibles greatly increase financial risk, with little additional beneficial effect on reducing excess use.

The model also showed that individual deductibles are generally preferable to family deductibles. They are easier to administer and a set of smaller individual deductibles imposes less risk on a family than the much larger family deductible that would lead to the same expected expenditure.

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I. INTRODUCTION

The soaring costs of medical care have made health insurance more necessary, but insurance is an important cause of these rising costs. Cost sharing in health insurance is often proposed as a way out of this bind, but until recently there has been little good quantitative evidence on the effect of cost sharing. Studies of the effects of cost sharing based on nonexperimental data are flawed because of adverse selection (that is, people in chronic or frequent poor health may choose fuller coverage than most other people), and because of inevitable gaps in such data. Using surveys has the drawback that people may not know or may forget what they spent, and insurance companies have little data on uncovered expenses. To overcome these problems, the federal government sponsored a large-scale social experiment, the RAND Health Insurance Experiment (HIE). The HIE was intended to be a definitive study of the effects of alternative financing arrangements on the use of services and on health status. It assigned families to 14 different insurance plans, balancing the plans in terms of preexperimental use and other characteristics known to affect use. Much effort has gone into obtaining complete and accurate data on the use of health services.

Data from the HIE are free from the inherent limitations of nonexperimental data. The primary analysis of the HIE data yields estimates of plan effects based on annual spending (Newhouse et al., 1981; Manning et al., 1987). These estimates are unbiased, but they lose information by aggregating across many decisions that participants make over the course of the year. In this report, we use episodes of spending to analyze the experimental data. The methods and rationale for using episodes was presented in detail in our earlier report (Keeler et al., 1982). This powerful and fairly novel approach better reflects the actual decisions to spend money on medical care than does analyzing annual expenses.

The results presented here are based on three years of experience for all fee-for-service participants in the study. This is the final planned analysis of the episodic data, but for simplicity and timeliness, it excludes two years of experience for the 30 percent of the sample who were enrolled for five years. Thus, about 12 percent of the spending

experience is not studied here.[1] In addition, we have not studied health maintenance organization (HMO) participants, primarily because they are not affected by price changes within the year, and so are adequately described by the "years of spending" approach.

When people become sick, they must decide whether to get medical care. They consider the severity of the illness, the perceived value of treatment (this perception might be based on a phone call or previous contact with a physician), and the out-of-pocket and time costs of going to a doctor. If the costs of treatment seem higher than the benefits, sick people may decide to give time and home remedies a chance to work. A survey of episodes of illness among government workers found that in three-eighths of the episodes with disability days, the medical care system was not used (Riedel et al., 1982). Spending on chronic, dental, or well-care episodes of treatment may not be triggered by an acute problem but entails a similar decision. Once a patient has decided to see a doctor, that doctor helps to decide how much to spend on care for the duration of the episode. Thus, any episode of treatment contains two decisions of interest: The first is whether to seek care at all; the second, after conferring with the doctor, is to decide on the level of treatment.

Although treatment episodes clearly reflect behavior more closely than do annual totals, expense data grouped into episodes have rarely been available (Kilpatrick, 1977; Stoddart and Barer, 1981; Lohr et al., 1980; Pederson and Christiansen, 1982; Ellis, 1986). Hence, most previous economic analyses of demand for health care have been performed on annual expenses, which are aggregates of many such episodic decisions. Because the HIE collected extensive information on all filed claims for health spending, we were able to organize spending into treatment episodes of the different basic types: dental, hospital, and outpatient acute, chronic, and well care. Consequently, we can study spending on each separately.

In Keeler et al. (1982), we presented a detailed description of the reasons for using episodes, the methods we used to link charges in episodes,[2] our methods for analyzing them, and the statistical tests of the assumptions underlying those methods. The first four sections of this report update the earlier study, using three years of data from all the sites, instead of just Dayton. Since the methods have not changed, they will be described only briefly here. The rest of this section

[1]Because of intertemporal correlation in participants' responses to insurance, the fourth and fifth years of participants' experience do not contain much new information, so the percentage loss in information is much less than 12 percent.

[2]Programming details are given in Keesey et al. (1985).

explains the potential advantages of such episodic analysis. Section II describes the design of the HIE, the sample, and the data, and describes the assumptions and procedures used to group claims into episodes. Section III gives our analysis of the effects of price and other covariates on the cost per episode and the number of episodes per year. Section IV shows how occurrence rates change over the year.

Section V shows how these empirical results were incorporated in a model to simulate health expenditures under different types of insurance and gives some applications of the simulation model. Finally, Sec. VI discusses the consequences of these results for economic and health services research.

Because the HIE insurance plans have an annual accounting period, it is natural to analyze annual spending. Such analysis gives unbiased and reasonably precise results about annual spending for each plan in the experiment (Manning et al., 1987). However, as Fienberg et al. (1985) argue, there can be substantial advantages in grounding models used in analyzing social experiments in a formal behavior theory. They base this conclusion primarily on predictive considerations. We agree here that our episodic approach has advantages in estimation of plan effects. We collect information throughout the year on each claim participants file. This information, organized into episodes of treatment, has five major advantages over annual totals.[3]

First, health care is usually delivered during an episode of illness. The episode of care is thus the "natural" unit for analyzing the effects of price. Studying episodes instead of annual spending gives a more realistic picture of what happens when health care is bought in the sense that we can separately study decisions to start episodes and decisions to continue them.

Second, an episodes analysis can produce more generalizable estimates. Cost sharing can vary in several ways within and across insurance plans (e.g., coinsurance rate, deductible, upper limit on out-of-pocket expenditures). Annual estimates derived from particular insurance plans are not in general applicable to an insurance plan with different cost-sharing characteristics. With an episodes analysis, we can estimate the separate effects of the component parts of insurance plans and thus generate estimates for insurance plans other than those studied.[4]

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[3]Hornbrook et al. (1985) discuss the many problems in health care episode definition and measurement and show how episodes can be used in studying quality of care, reimbursement, public program evaluation, and management.

[4]With enough observations, one can estimate pure price effects in annual data with a deductible by adding variables that describe the deductible at the start of the year (Manning et al., 1987), but the usual annual analyses need a much larger sample to detect behavioral responses to within-year price changes.

Third, when a deductible or upper limit on spending is present, so that the effective price may change through the year, annual analysis using either starting, average, or finishing price leads to biased estimates of the effect of simple pure coinsurance with no upper limit (Keeler et al., 1977a; Newhouse et al., 1980). An episodic analysis is needed to get unbiased estimates of price effects.

Fourth, data on episodes contain more information than data that add together the costs of all the episodes in a year. Aggregating costs at the annual level suppresses information on the timing and intensity of episodes of treatment.

Fifth, an episodes analysis can provide more precise estimates of transitory changes in demand that have important policy implications, such as "catch-up" demand in response to new and fuller (permanent) coverage, and "sales" behavior in response to temporary changes in coverage. Because an episodes analysis examines behavior within a year, especially the first few months of coverage under a new policy, it has the potential to detect these transitory changes.

II. DESCRIPTION OF THE DATA

The work presented here on the demand for medical services is based on data from the Health Insurance Experiment. This section describes the study, especially the data used in our analysis. After a brief introduction, we discuss the sample studied here, the experimental insurance plans, and the other covariates used to explain demand.

THE HEALTH INSURANCE EXPERIMENT

How the extent of health insurance coverage affects the demand for medical services has been a key issue in the American debate over medical care financing. Past studies of this issue have used nonexperimental data that suffer from several flaws: Insurance is potentially endogenous; existing policies are difficult to describe parametrically; data on use are frequently based on recall and therefore are subject to reporting biases; and coinsurance rates and deductibles often vary little across policies in force for a given service, such as a hospitalization.

The HIE is an effort to overcome these problems. In late 1974, the HIE enrolled 390 families living in Dayton, Ohio, and in 1976, enrolled 2,370 additional families in five other sites (Seattle, Washington; Fitchburg, Massachusetts; Franklin County, Massachusetts; Charleston, South Carolina; Georgetown County, South Carolina). The families were assigned to health insurance plans with differing coinsurance rates and deductibles; in return they assigned to the experiment the benefits of any (preexisting) nonexperimental plans for which they were eligible. If the assignment could make the family worse off financially, the family was given a lump-sum payment equal to the maximum it could lose from participating. Seventy percent of the families were enrolled for three years, the remainder for five years.

The experimental design used split samples to control for limited duration, the effects of physical examinations, and illness reporting requirements. These methods are described in Newhouse (1974) and Brook et al. (1979). Because our work is concerned with estimation of demand for health care services, we will discuss only the sample and insurance plan treatments here.

EXPERIMENTAL INSURANCE PLANS

The families were assigned to insurance plans by a novel method of stratified random assignment whose aim was to maximize balance in participant characteristics across the 14 different fee-for-service insurance plans (Morris, 1979). No choice of plan was offered; the family could either accept the experimental plan offered or decline to participate. The fee-for-service plans had different levels of cost sharing that varied over two dimensions: the coinsurance rate (percentage paid out-of-pocket) and an upper limit on out-of-pocket expenses.

About one-third of the sample received all services free (their coinsurance rate was zero), and the rest paid coinsurance rates of 25, 50, or 95 percent. One plan had different coinsurance rates for inpatient and ambulatory medical services (25 percent) than for dental and mental outpatient care (50 percent). In our analysis, this plan is put with either the 25 or 50 percent coinsurance plan, depending on the type of episode. Finally, around one-fifth of the families were enrolled in a 95 percent coinsurance plan that limited annual out-of-pocket outpatient expenditures to $150 per person ($450 per family), providing in effect an outpatient individual deductible (ID).[1] In this plan the cost sharing applied only to ambulatory services; in-patient services were free.

The upper limit on annual out-of-pocket family spending (MDE) was 5, 10, or 15 percent of the previous year's income, or $1,000, whichever was less. For spending beyond the MDE, the insurance plan reimbursed in full for all services. In the analysis, plans that differed only by their percentage of income limit are grouped. (See Fig. 2.1.)

All plans covered a wide variety of services. Medical expenses included services provided by nonphysicians, such as chiropractors and optometrists, and prescription drugs and supplies. The only significant exclusions were outpatient mental health services in excess of 52 visits per year, nonpreventive orthodontia, and cosmetic surgery unrelated to accidents occurring after the start of the experiment. Dental services and outpatient mental health services were, however, treated somewhat differently in the first year in Dayton.[2] Claims filed by participants, including those for unreimbursed expenses, provide data on the amount and type of expenses.

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[1]The coinsurance rate for the family and individual deductible plans was 100 percent in Dayton Year 1. The rate was changed to 95 percent to increase the incentive to file claims reports in all other site years, although there was no statistical evidence of underfiling.

[2]Dental services for adults were covered only in the plan with a zero coinsurance rate; expenditures on outpatient mental health services did not count toward satisfying the MDE. After year 1 in Dayton and in all other sites, dental services for adults and outpatient mental health services (up to 52 visits per person annually) were covered like any other service in all plans.

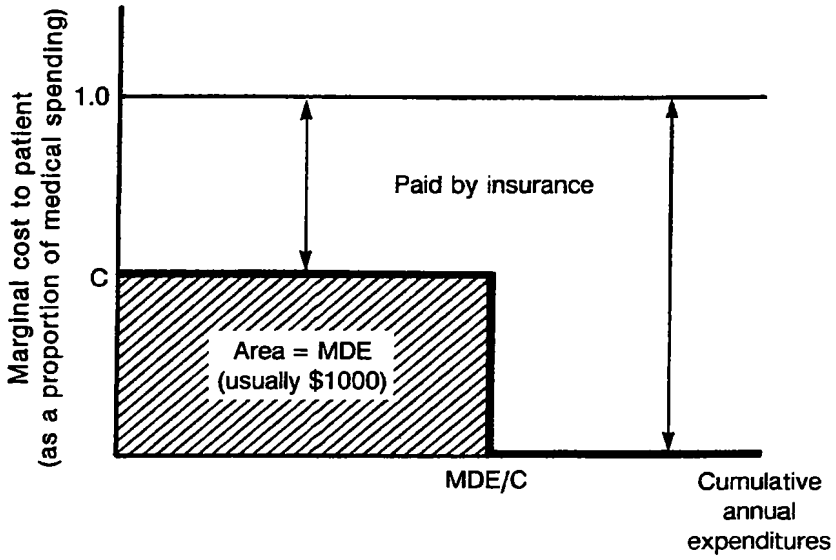

Fig. 2.1—A typical HIE cost-sharing plan

A simple example will illustrate how an HIE insurance plan works. Consider a family on a plan having a coinsurance rate of 25 percent for all services and an MDE of $1,000. For the first $4,000 ($1,000/0.25) spent on health care (dental, medical, and mental health care), the participating family pays 25 percent and the insurance plan pays 75 percent. After the first $4,000 of total expenditures, the family pays nothing and the plan pays everything because out-of-pocket expenses have reached the MDE of $1,000.

As this example illustrates, the participant's response to an HIE insurance plan is an amalgam of responses to coinsurance rates, and free care beyond the MDE. In this report, we go beyond estimating the average effects of plan and decompose the participant's response to plan into his responses to the coinsurance rate and to the MDE.

THE SAMPLE

The sample was a stratified random sample from each site, with the following intentional exclusions: (1) those 62 years of age and over; (2) those with incomes in excess of $25,000 (1973 dollars) (approximately the upper 7 percent of the national income distribution); (3) those eligible for Medicare disability payments; (4) those in the military or in institutions such as jails; and (5) veterans with service-connected disabilities. Over 80 percent of the population was eligible. Table 2.1 gives the enrollment sample for each plan in each site.

The work reported here is based on the three years of experience for each participant.[3] It includes enrollees who participated for a full year in any of these years, plus those who died or were born during the three-year period. Excluded from this analysis are other individuals with partial years of participation: participants who were suspended (e.g., for joining the military), who voluntarily quit, or who were involuntarily terminated for noncompliance during the year. But a person who left in year 2 was included in year 1 if he participated for all of year 1. Moreover, the costs associated with newborns were allocated to the mother for the purpose of this analysis. The attrition and partial-

Table 2.1

SAMPLE IN HEALTH INSURANCE STUDY AT INITIAL ENROLLMENT

	Insurance Plan						
Site	Free	25	25/50	50	95	ID	Total
Dayton, Ohio	301	260	0	191	280	105	1,137
Seattle, Washington[a]	431	132	121	0	253	285	1,222
Fitchburg, Massachusetts	241	37	88	56	113	188	723
Franklin Co., Massachusetts	297	61	91	58	162	220	889
Charleston, South Carolina	264	68	78	26	146	196	778
Georgetown Co., South Carolina	359	89	112	52	166	282	1,060
Total	1,893	647	490	383	1,120	1,276	5,809

NOTE: This table excludes babies born into or adopted into enrolled families after initial family enrollment.

[a]Excludes enrollees in Group Health Cooperative of Puget Sound, an HMO.

[3]These were the first three years in sites other than South Carolina, and the last three years in South Carolina.

year exclusions constitute about 5 percent of the total sample of person-years. Table 2.2 gives our analysis sample by plan.

THREATS TO VALIDITY

The stratified random assignment of families to plans ensured that if all assigned families completed the study, the plans would be balanced in terms of many characteristics of participants that affect spending and health. This balance makes a simple comparison of mean spending valid. On average, differences between the health and spending of participants on different plans should be due entirely to the different insurance provisions.

There are two potential threats to the balance of health and other characteristics across the insurance plans: nonrandom refusal of the offer to participate and nonrandom attrition from the study. Because of the substantial financial advantages to participate and complete the study, we expected that most people would do so, and indeed they did. Refusals of the plan offer varied from 6 percent on the free plan to 23 percent on the 95 percent coinsurance plans in the non-Dayton sites. Analysis by Newhouse et al. (1987) of these refusals to participate indicates that the only significant difference between those who accepted and those who rejected the offer was that the latter had lower education and income.[4] Income is controlled for in our analysis, and

Table 2.2

ESTIMATION SAMPLE

Insurance Plan	Person-Years
Free	5,768
25 percent	3,018
50 percent	1,475
95 percent	3,130
ID	3,650
Total	17,041

[4]Data from Dayton are incomplete and hence have not been analyzed, but the refusal of the enrollment offer across all plans in Dayton was only 7 percent. Additionally, we have compared the group that enrolled on all plans with the group that completed baseline interviews but did not enroll. The only statistically significant difference was that

education had no detectable effect on use after controlling for income. There is no evidence that those who rejected the offer to participate were sicker, nor that there was any detectable interaction between plan, sickness, and refusal of the offer. More important, the average characteristics of those enrolling on different plans were very similar (Newhouse et al., 1987).

Individuals on the cost sharing plans were more likely to leave the study early than were individuals on the free plan. Dropouts were sicker on average at enrollment than those who stayed, but those quitting the study for health reasons were evenly divided across the plans (Brook et al., 1984). In a comparison of use in the study by dropouts with overall use by those who stayed, we could detect no plan-related bias in use before withdrawal of those who dropped out (Manning et al., 1988). Analyses of both health and use are little altered by including or excluding dropouts. To correct for any remaining bias, we include health status measures as covariates. Controlling for health status, dropouts' rate of spending was no different in the time before they left than the rate of those who stayed (Manning et al., 1988).

DEPENDENT VARIABLES

Line charges on the claims forms from providers were grouped to create episodes of treatment. The grouping was based primarily on diagnoses, time since last charge for a related diagnosis, and information from the provider on treatment history. Episodes were not defined by location of services; for example, outpatient services preceding or following a hospitalization were included in the hospital episode, and drugs were included as part of the episode in which they were prescribed. Thus, line charges on claims forms were linked to reflect decisions by patient and by physician rather than to reflect the location or types of services provided.

Episodes were classified as hospital or dental, or as one of three outpatient types: acute, routine chronic treatment, or well care. All unforeseen and undeferrable outpatient episodes (in particular chronic flare-ups) were classed as acute outpatient episodes. Separate routine chronic treatment "episodes" contained the foreseen annual care for each chronic condition. For more details see Keeler et al. (1982, Chap. 3), and Keesey et al. (1985).

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children are overrepresented by a modest amount in the group that enrolled (Morris, 1985). Age is explicitly controlled for our analysis. No significant preexperimental differences were found for self-reported utilization and health status (Morris, 1985).

EXPLANATORY VARIABLES

Insurance plans are grouped into five groups: a family medical coinsurance rate of 25 percent (P25); a family medical coinsurance rate of 50 percent (P50); a family medical coinsurance rate of 95 percent (behaviorally the same as a family deductible) (P95); the individual deductible of $150 per person or $450 per family for outpatient care (ID), and the free care plan (FREE). An indicator variable is specified for four of the groups; thus, no functional form is imposed on insurance-induced variation in spending.

Three other randomized experimental treatment variables were coded, namely, whether a household was one of the random 60 percent given a preenrollment screening examination (EXAM) or not; whether the family reported disability-days weekly (WEEKLY) rather than biweekly in the first year of Dayton; and whether the family was enrolled for three (YR3) rather than five years.

The remaining variables measure preexperimental values of other factors. Because the analysis of annual demand for medical care had already been completed, we used the set of variables that were useful in predicting annual spending for our episodic analysis. These include income, education of head of household, family size, contact with the medical system, race, age, sex, self-reported health, pain and worry about health, and four other measures of health status: (1) a general health perception scale (GHI); (2) a dichotomous measure of physical or role limitation (PHYSLIM); (3) a count of the number of 26 diseases or health problems (DISEASE); and (4) a mental health index (MHI). Preenrollment interviews provided data on all of these characteristics.

WITHIN-YEAR STATUS VARIABLES

Because of our interest in behavior changes within the year, we needed to know when families approached and exceeded their out-of-pocket limit (MDE) on spending. The amount of out-of-pocket spending remaining until the limit is reached will be called "MDE remaining." It is computed on the assumption that all the expenses for an episode are known and accounted for in spending decisions at the start of an episode. That is, if a woman becomes pregnant, the costs of delivery are fully anticipated, even if the actual bill is not paid until the time of delivery. If, as is usual in this situation, the out-of-pocket costs of the bill reach the MDE limit, the woman's family acts as if care is free from the point they know she is pregnant. To implement this assumption, we grouped all expenses to define the cost of an

episode, whether acute illness, pregnancy, chronic condition, or health maintenance. The expenses were dated to the first date of service in the episode, and the appropriate fraction of the total subtracted from the MDE remaining. For more details on the assumptions and programs used to compute the MDE remaining see Keeler et al. (1982) and Keesey et al. (1985).

III. COST AND ANNUAL FREQUENCY OF EPISODES

INTRODUCTION

In this section, we analyze the cost and annual frequency of episodes. Together, episode cost and frequency determine annual medical spending. That is,

$$\text{annual spending} = (\text{no. of episodes}) \times (\text{cost per episode}) \quad (3.1)$$

We will describe how the cost and annual frequency of episodes vary by episode type, by insurance plan, and by the characteristics of individual participants. Using Eq. (3.1), we can then see how predictions of annual medical spending deduced from the episodic approach compare with the annual spending predictions obtained from data on annual medical spending by individuals (Newhouse et al., 1981; Manning et al., 1987). This comparison serves as a check on the validity of both methods. Further details of the methods and tests of specification can be found in Keeler et al. (1982), which used just three years of data from one site. Here we simply present our final results and comment on them.

Information about the distribution of the cost and frequency of episodes is needed for the simulation model described in Sec. V that uses the episodic approach. In this model, individual streams of medical expenses are created by first generating episode occurrences and then generating the cost of each episode. It simplifies the overall analysis when we can decouple the cost of episode analysis from the number of episodes analysis.[1]

To study cost per episode, we first tabulate how the cost per episode varies by episode type. Next, we model an individual's cost per episode as a multiplicative function of his or her attributes.

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[1]Strictly speaking, we are simplifying the analysis slightly more than the data warrant. As part of the statistical analysis of the first three years of Dayton data as reported in Keeler et al. (1982), we calculated the dependence between cost per episode and the number of episodes per individual for each episode type. Of acute, chronic, well-care, and hospital episodes, only well-care episodes exhibited any statistically significant correlation between cost per episode and number of episodes per individual. Our analytic method was to use a two-way analysis of variance of log cost per episode with plan group and number of episodes as factors with full two-way interactions. The results exhibited a weak dependence between episode cost and frequency for well-care episodes that we chose not to include in our model here. Our reasons for this decision were that (i) the effect on the simulation results of including dependence would be small, and (ii) disregarding dependence enhances analytic simplicity.

The final subsection of this section reports our analysis of the number of episodes per year, and, in particular, how numbers vary with episode type, insurance plan, and participant characteristics. This analysis parallels the common approach to estimating annual spending but uses episodes rather than dollars. Most of our results are based on a negative binomial regression model of episode counts. This model has the natural interpretation that individual propensities to have episodes vary as a function of both participants' measured variables and some unobservable attributes. The major factors associated with varying episode rates are self-assessed health, age, sex, and physician visits in the year preceding the experiment. Income, plan, and having a regular physician are also important, but less so.

We take up the issue of how individuals' behavior varies within the year in Sec. IV. There we describe the effects that within-year price-changes (caused by a participant's expenses reaching the MDE before the end of the year) seem to have on medical spending.

COST OF EPISODES

We have divided episodes into five types: hospitalizations, dental episodes, and three types of medical outpatient episodes—acute, chronic, and well-care episodes. For each type we give the distribution of costs by insurance plan, and finally, the cost per episode as a function of insurance plan and other participant attributes.

Some Descriptive Statistics on Cost

The overall distribution of episode cost varies with type of episode. No one family of distributions fits the cost of all episode types well, but the lognormal distribution is a good approximation for all except dental episodes.

Table 3.1 gives descriptive statistics on the distribution of cost per episode for the five episode types. The table shows statistics from the second year for acute episodes, second and third years for dental, well care, and chronic, and all three years for hospital. The medical Consumer Price Index CPI was used to inflate costs from the year of the occurrence (between 1975 and 1981) to 1986 medical dollars. The five episode types differ considerably both in frequency and cost per episode. Hospitalizations are the most costly, averaging about $3,870, with the median episode costing about $2,460. Other episode types are much smaller, with acute and well-care episodes being the least

Table 3.1

SUMMARY OF COST PER EPISODE DISTRIBUTION BY TYPE
(In 1986 dollars, rounded)

Item	Hospital	Dental	Outpatient		
			Acute	Chronic	Well
Number of episodes[a]	1,969	12,267	10,379	6,577	6,870
Quantiles					
100 percent (maximum)	163,000	15,400	4,050	5,720	2,990
90 percent	6,600	519	211	436	202
75 percent	4,180	145	101	176	127
50 percent (median)	2,460	62	48	66	53
25 percent	1,580	37	25	28	33
10 percent	970	26	12	13	23
0 percent (minimum)	220[b]	4	2	1	2
Moments					
Mean	3,870	242	97	198	97
Standard deviation	16,330	633	167	523	128
Skewness[c]	12	8	7	12	7
Kurtosis[c]	236	90	73	257	96
Lognormal parameters					
Mean	7.85	4.45	3.91	4.27	4.11
Standard deviation	0.8	1.2	1.1	1.3	0.9
Skewness[c]	0.2	1.1	0.3	0.3	0.1
Kurtosis[c]	1.4	1.0	0.2	-0.0	0.2

NOTE: All expenses are inflated to the September 1986 value of the medical CPI (439.7).

[a]Hospital statistics are based on all three years of data, acute just on second year, and the others on years 2 and 3.

[b]Hospital expenses set to maximum (reported expenses, $220).

[c]The skewness and kurtosis are based on the third and fourth moments of the empirical distribution. They can be regarded as measures of how nonnormal the distribution is. Values of zero correspond to normality. See Kendall and Stuart (1961), Vol. 1, Chap. 3, for details.

expensive on average (mean = $97, median = $48–$53). A comparison of means and medians, as well as an examination of the quantiles, reveals that the distribution of cost per episode for all episode types is skewed to the right. The bottom four rows of the table give the fitted lognormal distribution parameters for the five episode types. The much smaller values of skewness and kurtosis indicate that the distribution of costs per episode is roughly lognormal. There are slightly more very expensive episodes for all types than there would be if the

distribution were truly lognormal (skewness is still greater than 0). These expensive episodes barely affect inferences about explanatory variables but they have a large effect on predicted expenses. In Appendix A, we give the data on departures from lognormality and explain how we modified the simulation model to reflect them.

Plan Differences Controlling for Other Factors

We now analyze how cost per episode varies with insurance plan—the primary goal of this subsection. For each of the five episode types, we examined whether the cost per episode is the same across the five insurance plans.

The mean cost for each type of episode is given in Table 3.2 for the free plan and for the other plans combined. The standard deviations are very large because of the rare very large expenditures. Still, well-care and dental episodes are significantly larger with free care.[2] Table 3.3 gives mean log costs for each episode type. Small differences in log costs between plans can be interpreted as differences in the ratio of free plan episode costs to pay plan costs. Thus, total outpatient episodes are about 3 percent larger with free care (4.02 − 3.99 = 0.03). Since the standard error of the difference is 0.017, this is not quite significant (t = 1.88, a slight overestimate because it is not corrected for intrafamily correlations).

The raw mean of a lognormal variable depends on the standard deviation of the log as well as the mean of the log. The mean of log costs per episode is slightly higher on the free plan for all types. However,

Table 3.2

EPISODE COSTS BY TYPE AND PLAN
(In 1986 dollars)

Insurance Plan	Hospital	Total Medical Outpatient	Outpatient			
			Acute	Chronic	Well	Dental
Free	3,680	124.20	97.40	190.80	99.40	259.80
Cost sharing	3,961	123.70	95.20	202.80	90.90	227.40
t-test for difference	−1.1	0.1	1.1	−0.9	2.6	2.7

[2]Below we test for significance after adjusting for other characteristics. The t-statistics in Table 3.2 are not corrected for intrafamily or intraperson correlation but, as shown below, such correlation is quite small.

for acute, chronic, and hospital episodes, this is offset by a larger standard deviation. For example, we show in Appendix B that hospital episodes costing more than $11,000 are spread proportionately on all plans (and, hence, make up a larger proportion of hospital episodes on the cost-sharing plans). This explains why raw costs per episode of hospitalizations are smaller on the free plan, even though log costs are higher.

Although the groups of health insurance experiment participants assigned to each insurance plan are approximately balanced with respect to their relevant measured characteristics (Newhouse, 1974; Morris, 1979), the people who have episodes may be different if insurance has different effects on different people. Thus, a comparison of mean episode costs may be biased, and there are three other reasons for using covariates to carry out a more detailed analysis.

First, we want to simulate streams of medical episodes. If the cost per episode varies systematically with participant characteristics, it is important to include this variation in any simulation model. Second, the simulation model can then be used to estimate a particular population group's portion of the total cost of health care. This information should both contribute to the debate on national health policies and in the private sector and might help in devising more accurate estimates of health insurance premiums. A third reason for including covariates is accuracy of estimation. That is, even if plan groups are balanced, controlling on an individual basis for the effect of covariates will lead to more accurate estimates of the plan effects, if any, on the cost per episode.

Table 3.3

LOG EPISODE COSTS BY TYPE AND PLAN
(Log of 1986 dollars)

		Total Medical	Outpatient			
Insurance Plan	Hospital	Outpatient	Acute	Chronic	Well	Dental
Free	7.85	4.02	3.95	4.29	4.14	4.51
Total cost sharing	7.84	3.99	3.88	4.25	4.09	4.41
P25	7.93	3.99	3.89	4.25	4.11	4.47
P50	7.83	3.89	3.71	4.12	4.06	4.34
P95	7.76	3.96	3.90	4.18	4.01	4.37
ID	7.83	4.03	3.90	4.34	4.15	4.44

We use regression models for the log of episode cost for each of the five episode types to control for participant attributes and to isolate the effects of price. Because families share propensities to spend on medical care, information on costs per episode from different family members is not totally independent. To properly deal with this, we used a generalized regression method.[3] Table 3.4 gives the means and standard deviations of the potential predictors. Table 3.5 gives the results of our regression analysis.

The first column of Table 3.5 gives the fitted regression equation to the logarithm of the cost of hospital episodes. In all these regressions, the omitted categories against which comparisons are made are Seattle, white, no screening examination, free plan, and male 18–45 years old. The squared multiple correlation (R^2) is only 0.11. Plan effects are scattered, with the 95 percent coinsurance plan 12 percent smaller (exp(−0.13) = 88 percent). A few other attributes are statistically significant: site effects, whether the individual is a young child, health, whether the person had an enrollment exam, and race. The differences in the log mean are offset by the higher standard deviation for cost-sharing plans and we conclude that the data show no consistent statistically significant plan effects on the cost per hospitalization.[4]

Cost sharing may cause slight reductions in the cost of other types of episodes. The reductions are greater for the 50 and 95 percent family deductible plans, about 6 percent for both medical outpatient and dental episodes, but are only marginally significant.[5] Although only a small fraction of the variance is explained by the other variables, there are large differences by site and age, with Seattle being more expensive and with children and healthier people having cheaper episodes. For dental episodes, being black or poor leads to much more expensive

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[3]The model is similar to a random-effects model. It is described in Brook et al. (1984) based on prior work by Huber (1967). Manning et al. (1981, Chap. 3c), contains a discussion of both theoretical and computational aspects of this type of model for intrafamily correlations in annual expenses from the Health Insurance Experiment. The same algorithm is used here for estimation.

[4]If, in retransforming log cost to cost per episode, we use the mean of a lognormal distribution given by $\exp(\mu + \sigma^2/2)$, then the estimated plan differences are increased by differences in the variances (σ^2) across plans for each episode type. The change in the plan differences in Table 3.4 are +0.04, +0.01, +0.02, +0.05, −0.03, and −0.04 for hospital, all outpatient, acute, chronic, well care, and dental, respectively. Accounting for these differences slightly decreases estimated plan effects and furthermore none of these are statistically significant (p = 0.10).

[5](t = 1.87 for outpatient). When the third-year chronic and well care episodes are included in the outpatient total, the cost differential for the 50 and 95 percent coinsurance plans rises to 8 percent and the difference is significant. Coinsurance had a slightly greater effect on the cost of chronic and well care episodes in the third year. Unfortunately, we processed only the second year of acute data for cost of episode analysis.

Table 3.4

COVARIATES USED IN REGRESSION

Name of Variable	Mean[a]	Standard Deviation	Comments
Dayton	0.20	(0.4)	
Fitchburg	0.12	(0.4)	
Franklin	0.16	(0.4)	Variable = 1 for people at that site, 0 otherwise;
Charleston	0.13	(0.3)	Seattle is omitted site
Georgetown	0.18	(0.4)	
FREE	0.33	(0.4)	The omitted insurance plan; full coverage
ID	0.22	(0.4)	$150 individual deductible plan
P25	0.20	(0.4)	25 percent coinsurance for medical service plan
P50	0.07	(0.2)	50 percent coinsurance for medical service plan
P95	0.19	(0.4)	95 percent coinsurance (family deductible plan)
PD25	0.11	(0.3)	25 percent coinsurance for dental
PD50	0.15	(0.4)	50 percent coinsurance for dental
Age 0–2	0.03	(0.2)	
Age 3–5	0.06	(0.2)	Age categories are based on age at end of study
Age 6–17	0.27	(0.4)	
W18–40	0.22	(0.4)	Woman age 18–40
W41–65	0.12	(0.3)	Woman age 41–65
M46–55	0.04	(0.2)	Man age 46–55
M56–65	0.03	(0.2)	Man age 56–65
HEALTH	4.0	(2.4)	Health-pain-worry; three enrollment scales added so that best health is 7; worst health is −2
GHINDX	73	(14)	Health perceptions scored 100 best, 0 worst
MHI	77	(12)	Mental health index scored 100 best, 0 worst
DISEASE	11.2	(7)	Count of number of diseases reported
PHYSLM	0.13	(0.3)	Set to 1 if physically limited, 0 if not limited
LMDVIS	1.2	(1.0)	The logarithm of physician visits in year preceding experiment (set at 0 if there were no visits)
MDVMIS	0.04	(0.3)	Physician visits in prior year missing
LINC	8.8	(0.8)	Log income in year preceding experiment
LFAM	1.2	(0.5)	Log family size at start of experiment
EXAM	0.58	(0.5)	Took exam at start of experiment
EDUCDEC	12	(3)	Years of education of self for adults or female adult in household for children
BLACK	0.09	(0.3)	1 if head of family is black, 0 otherwise
SES	0.00	(1.1)	LINC + 0.2 EDUCDEC − 0.5 LFAM − 10.51
SICK	0.00	(0.1)	− 0.004 GHINDX + 0.16 PHYSLM + 0.008 DISEASE + 0.027
COIN SES	0.01	(0.73)	(on family coinsurance plans) * SES
PID SES	0.00	(0.52)	(on ID plan) * SES
KID PAY	0.24	(0.43)	(Age ≤ 17) * (1 − FREE)
SICK PAY	0.00	(0.10)	SICK * (1 − FREE)

[a]Values in year 1 of 5,904 individuals who were in the sample at least six months.

Table 3.5

REGRESSION EQUATIONS FOR PREDICTING LOG EPISODE COST (ROUNDED)

Variable	Hospital	Total Medical Outpatient[a]	Outpatient			Dental
			Acute	Chronic	Well	
INTERCEPT	7.953	4.476	4.503	4.436	4.741	5.503
Dayton	0.13*	−0.16**	−0.21**	−0.11	−0.23**	−0.42**
Fitchburg	0.12	−0.24**	−0.26**	−0.13	−0.34**	−0.47**
Franklin	−0.00	−0.26**	−0.26**	−0.19	−0.35**	−0.62**
Charleston	0.20*	−0.18**	−0.18**	−0.10	−0.06	−0.20*
Georgetown	−0.18*	−0.16**	−0.17**	0.01	−0.15**	−0.41**
Health	−0.023*	−0.020*	−0.018*	−0.032*	−0.017*	−0.029**
Socioeconomic status	+0.03	−0.01	−0.04*	0.05	0.00	−0.13**
Log(MD visits)	−0.03	0.01	0.00	0.09*	−0.03	−0.03
Exam	−0.10*	−0.01	−0.01	0.03	0.01	0.04
Black	0.14*	0.00	0.01	−0.17	0.00	0.52**
P25	0.07	−0.03	−0.05	−0.07	−0.01	0.05
P50	0.02	−0.06	−0.14*	−0.13	−0.02	−0.05
P95	−0.13*	−0.06	−0.03	−0.10	−0.11*	−0.08
ID	−0.03	0.01	−0.03	0.02	0.03	−0.03
Age 0–2	−0.63**	−0.68**	−0.55**	−0.75**	−0.89	−1.76**
Age 3–5	−0.64**	−0.59**	−0.51**	−0.46*	−0.88**	−0.79**
Age 6–17	−0.30**	−0.42**	−0.39**	−0.40**	−0.53**	−0.60**
Woman 18–65	0.11	−0.14**	−0.15**	−0.23*	−0.07	−0.08*
Man 46–65	0.26*	0.02	−0.08	−0.00	0.21**	0.01
R^2	0.11	0.04	0.04	0.03	0.18	0.12
Sample size	1,967	17,012	10,359	6,576	6,852	12,267
Intrafamily correlation	0.02	0.06	0.07	0.11	0.07	0.14

NOTE: *$t > 1.96$, $p < 0.05$, **$t > 3.29$, $p < 0.001$.
[a]Sum of acute chronic and well care episodes in the second year of experiment.

episodes—as we will see later these groups have significantly fewer episodes, so annual spending differences for these groups are much less. Intrafamily (which include intrapersonal) correlations for all episode types are positive but small. Even these small correlations have an impact on the significance tests, because families have many episodes of the same type. For example, for outpatient episodes, uncorrected t-statistics on insurance plan are 50 percent larger than corrected ones.

Refinements and Conclusions about Episode Costs

In the fitted regression models reported on above, some dependencies in the data were assumed away. Episode cost and annual episode frequency may be related, because those with expensive episodes are more likely to exceed the MDE and face a lower price for the rest of the year. Because this effect would not occur without an MDE, we do not use episode frequency to predict episode cost here. If the costs per episode after exceeding the MDE are like costs per episode on the free plan, then the differences shown here understate the impact of a pure coinsurance plan on episode size. We used a rough correction for our simulation model, with details shown in Appendix F. Because three-fourths of the episodes occur in the pre-MDE period, it is unlikely that this MDE effect is large, and the statistical problems involved in estimating log costs controlling for MDE effects are great. We therefore defer any analysis of MDE effect on episode costs to future work. Section IV describes a model of MDE effect on episode frequency.

To summarize, we estimate plan effects by fitting regression equations to the logarithm of episode cost using "dummy" variables for insurance plan, while using other independent variables to control for participant characteristics. From these regressions, we conclude that higher levels of cost sharing reduce spending per nonhospital episode by 5–8 percent. Because large hospital episodes do not seem affected by cost sharing, price effects on the costs of hospital episodes are small. For practical purposes the cost per episode can be treated as being only weakly related to insurance plan.

ANNUAL EPISODE FREQUENCIES

In the previous subsection, we showed that insurance plan affects the size of episodes very little. Plan-related differences in demand for medical care, then, are captured mostly by differences in the number of episodes. We now investigate how price, as reflected in plan and other independent variables, affects those numbers. This subsection considers the problem of explaining participants' annual rates of episode occurrence, ignoring for the moment what happens as the price of care changes during the year. Our analysis here parallels the common approach to estimating annual spending but explains variation in episode counts rather than in dollars or visits. Section IV deals with the more difficult problem of estimating the effects of intrayear price changes.

We first give descriptive statistics on annual episode counts per participant by episode type. We then cross-classify the counts by type

and plan. Episode rates differ most between the full coverage plan and the other plans, with smaller differences between plans with low and high levels of coinsurance. Differences are also smaller for hospital episodes than for the other types. Next, we use regression methods to model how annual occurrence rates of episodes of various types are related to family characteristics. We first discuss the choice of regression models. The results here are based on a negative binomial regression model. In Appendix E, we present similar results from a simple (ordinary least-squares) regression of the square root of episodes, which were used for economy in some analyses.

Episode Frequency by Type and Plan

There is great variation in the number of episodes per person. Table 3.6 shows some descriptive statistics for three years of data on the 5,904 people who participated for six months or more.[6] Although the average number of medical episodes was only three per year, one person had 76 acute outpatient episodes over the three-year period, over two per month.

Acute outpatient episodes are the most common type. The different chronic "episodes" are the number of distinct chronic conditions under treatment, because all routine treatment for a chronic condition during a year is grouped into one episode. There are sizable proportions of participants with no episode of any given type; 11.8 percent of

Table 3.6

SUMMARY OF ANNUALIZED EPISODE FREQUENCIES BY TYPE
(5,904 participants, up to three years)

Insurance Plan	Hospital	Total Medical Outpatient	Outpatient			Dental[a]
			Acute	Chronic	Well	
Mean number	0.118	3.05	1.83	0.57	0.65	1.07
Standard deviation	0.31	2.83	1.84	0.98	0.81	1.02
Maximum	5.67	29.67	25.33	13	7.82	7

NOTE: Includes less than three years of data from those who dropped out before three years. Statistics on the number of episodes in the study divided by the time in study measured in years.

[a]Based on 5,881 participants, excluding first year in Dayton.

[6]The methods used here allow us to include partial years of participation. The other results in Secs. III and IV are based only on full years, deaths, and births.

participants incurred no medical care spending at all in the three years studied here.

Predicting Annual Episode Frequencies

The statistical problems associated with analyzing annual expenses are greatly reduced by using the number of episodes instead of the dollar amount spent. There are fewer problems with outliers, the distribution of episode occurrence is considerably less skewed (because most of the variance of total dollar expenses comes from the cost of episodes instead of their number), zeros need not be modeled separately as they are for annual expenses (Duan et al., 1982), and combining experience over several years is straightforward if the response is stable over time.

In analyzing the episode counts, various refinements in regression methods should be used, since the error variance increases with the number of episodes. Indeed, the number of episodes for an individual can be viewed as Poisson distributed conditional on his or her expected number, and individuals have different expected numbers of episodes (Keeler et al., 1982).

Our results are consistent with other analyses of episodic data that have found that a negative binomial distribution fits well (Kilpatrick, 1977). The negative binomial can be generated by a gamma distribution of underlying expected number of episodes, with the number of episodes being Poisson conditional on that value (Johnson and Kotz,

Table 3.7

AVERAGE ANNUAL EPISODE FREQUENCIES BY TYPE AND PLAN
(5,904 participants, up to three years)

Plan	Hospital	Total Medical Outpatient	Outpatient			Dental[a]
			Acute	Chronic	Well	
Free	0.133	3.77	2.29	0.70	0.79	1.33
Total cost sharing	0.110	2.68	1.60	0.51	0.58	0.94
25	0.109	2.96	1.78	0.54	0.64	1.06
50	0.099	2.83	1.60	0.51	0.72	0.97
95	0.098	2.42	1.44	0.46	0.51	0.88
ID	0.125[b]	2.61	1.56	0.52	0.53	0.89

[a]Based on 5,881 participants, excluding first year in Dayton, since only the free plan covered adults in that year, and there appears to be underreporting by adults on the pay plans.
[b]Inpatient care is free on this plan.

1969). This "mixing" interpretation of the negative binomial distribution has been exploited by workers in a number of fields for situations in which the group-counts result from combining counts for individuals, each generating counts according to his own Poisson process. Applications include accidents (Greenwood and Yule, 1920), criminal actions (Rolph et al., 1981), and insurance claims (Ferreira, 1974; Rolph, 1981).

In the applications of the negative binomial model referred to above, no attempt was made to explicitly take into account how an individual's Poisson "rate" might vary with his or her measured attributes. In this subsection, we model how a participant's expected number of episodes of a particular type varies with the person's characteristics. To fix ideas, think of one episode type such as acute and let λ_i be the expected number of acute episodes for individual i in a year. We will call λ_i the person's episode *propensity* and distinguish it from the person's observed rate n_i in a given year. Then, conditional on λ_i , the random variable $n_i$has a Poisson distribution with mean λ_i. Now $\lambda_i$is unobservable; we model λ_i as $\lambda_i = \delta_i u_i$, where δ_i is predicted from individual i's measured attributes (including plan) and u_i is the random component (affected by his unmeasured attributes). We assume that $\log \delta_i = X_i\beta_j$, where X_i is the vector of individual i's attributes and β is a vector of regression coefficients to be estimated. We further assume that u_i is gamma distributed with mean 1 so that the marginal distribution of n_i, given δ_i, is negative binomial with mean δ_i.

In more familiar terms we can write an individual's expected number of episodes λ_i as a multiplicative regression equation. Taking logs, the expected value of the logarithm of episodes is then an additive regression equation. That is,

$$\log \lambda_i = \log \delta_i + \log \mu_i = X_i\beta + \text{individual error.}$$

The error term reflects the negative binomial distribution discussed above. The vector of regression coefficients is estimated by the method of maximum likelihood. This is a special case of the increasingly popular generalized linear model approach pioneered by McCullough and Nelder (1983). Elsewhere, we have used the negative binomial to test whether those who left the study early had spending rates while they were in the study similar to those who stayed the whole time. The actual distribution of both inpatient and outpatient episodes was fit quite well by the model predictions (Manning et al., 1988)

The multiplicative form is especially convenient for comparison with

results on annual spending. Taking the log of (3.1), we obtain[7]

$$\log(\text{spending}) = \log(\text{cost per episode}) + \log(\text{number of episodes})$$

$$= X\beta_1 + e_1 + X\beta_2 + e_2$$

$$= X(\beta_1 + \beta_2) + (e_1 + e_2).$$

Since both components are modeled multiplicatively, the proportional change in spending caused by, say, income can be obtained by adding the regression coefficients of income in the two regressions.[8] This sum can then be compared to coefficients in a regression of log(spending).

Compared to using the data on each year separately, we do not lose much information when we add together three years of episode counts and regress these on predictor variables that come from data at the start of the experiment. This procedure eliminates having to worry about year-to-year correlations as we would have to if we used each of the three years as a separate data point. Three facts justify this grouping procedure: the stability of regression coefficients over time, the stability of independent variable values over time, and the independence of episode counts over time. (See Keeler et al. (1982, Appendix F), for the analysis leading to these conclusions.) A fourth justification is that the negative binomial fits the data on number of episodes by length of enrollment quite well (Manning et al., 1988).

The same independent variables are available for predictors of episode counts as for the cost per episode regressions. Table 3.4 gives the means, standard deviations, and descriptive comments for the relevant predictors.

We first present the results of our negative binomial regression model and then discuss extensions and caveats.[9] Table 3.8 lists estimated coefficients from regressing the annual rate of episodes, by type, for the 5,904 participants who stayed at least six months, on a set of individual predictors. The fitted equations vary considerably across the episode types. The coefficients should be interpreted as indicating how much the logarithm of the episode rate can be expected to change when the variable is increased one unit. Hence, exponentiating the coefficient gives the proportional change with a one-unit increase in

[7]Strictly speaking, we usually take log(spending + c) to take care of those who spend zero.

[8]Assuming both have the same explanatory variables—a weak assumption, since some of the β_1 and β_2 can be zero.

[9]This same negative binomial regression was developed independently by Hausman et al. (1984) to analyze research and development expenditures.

Table 3.8

NEGATIVE BINOMIAL REGRESSION EQUATIONS FOR PREDICTING NUMBER OF EPISODES
(5,904 fee-for-service participants, up to three years)

	Hospital		Acute		Chronic		Well		Dental[a]	
	Coeff.	(t)	Coeff.	(t)	Coeff.	(t)	Coeff.	(t)	Coeff.	(t)
INTERCEP	−1.1	−3.85	0.097	0.73	−0.57	−2.40	−3.4	19.74	−1.7	10.72
Dayton	−0.0036	−0.03	0.028	0.59	0.15	2.04	0.29	5.98	−0.014	−0.29
Fitchburg	0.26	2.21	−0.016	−0.30	−0.099	−1.24	0.33	6.19	0.21	3.94
Franklin	0.056	0.45	−0.065	−1.34	−0.2	−2.49	0.39	7.92	0.28	6.12
Charleston	−0.09	−0.81	−0.22	−3.63	−0.5	−5.16	0.071	1.00	−0.27	−4.13
Georgetown	0.17	1.66	0.058	1.03	−0.21	−2.14	−0.096	−1.41	−0.14	−2.34
GHINDX[b]	−0.012	−0.012	−0.0052	−5.20	−0.0075	−3.81	0.0027	2.53	–	–
PHYSLM	0.34	3.32	0.11	2.64	0.17	2.48	0.052	1.14	–	–
DISEASE	0.0025	0.50	0.011	5.64	0.015	4.78	0.0062	3.14	–	–
LFAM	−0.019	−0.24	−0.049	−1.47	−0.082	−1.61	−0.064	−1.84	−0.027	−0.74
MDVMIS	0.18	1.10	0.14	2.35	−0.044	−0.45	0.36	5.14	−0.17	−1.79
EXAM	−0.025	−0.38	0.055	1.75	0.14	2.51	0.047	1.40	0.051	1.49
Age 0–2	0.63	2.27	0.48	5.40	0.044	0.26	1.6	17.05	−3.1	−7.50
Age 3–5	−0.18	−0.85	0.53	8.87	−0.16	−1.44	0.82	11.65	−0.89	10.25
Age 6–17	−0.65	−3.90	0.11	2.49	−0.27	−3.42	0.31	5.66	0.13	3.36
WOMAN	–	–	0.31	9.96	–	–	0.79	20.44	0.17	6.46
W18–40	0.53	5.51	–	–	0.44	6.68	–	–	–	–
W41–65	0.3	2.47	–	–	0.99	12.31	–	–	–	–
M46–55	0.36	2.11	0.058	0.85	0.71	6.11	0.51	8.71	–	–
M56–65	0.55	2.88	0.094	1.33	0.89	8.94	0.53	7.47	–	–
KID SES	0.14	2.04	0.11	4.60	–	–	0.12	3.91	−0.072	−1.99
IND DED	−0.17	−1.8	−0.42	−9	−0.41	−5	−0.46	−9	−0.39	−7
P25	−0.21	−2.1	−0.28	−7	−0.37	−5	−0.24	−5	−0.22	−4
P50	−0.30	−2.0	−0.46	−7	−0.49	−5	−0.29	−4	−0.34	−7
P95	−0.30	−3.0	−0.49	−9	−0.52	−6	−0.50	−9	−0.36	−7
LMDVIS	−0.25	7	0.28	17	0.31	11	0.12	7	0.03	2.1
LINC	0.04	0.6	0.4	1.5	0.13	2.5	0.08	2.3	0.16	5
EDUCDEC	−0.03	−2.1	−0.02	−2.8	0.01	1.0	0.03	4	0.04	5
BLACK	−0.20	−1.6	−0.54	−8	−0.40	−3.2	−0.29	−2.9	−0.16	−1.6
COIN SES	−0.02	−0.2	0.07	2.3	0.06	1.2	0.07	1.7	0.04	1.0
PID SES	0.03	0.4	0.15	4	0.20	3.1	0.16	3.4	0.06	1.0
KID PAY	0.23	1.3	0.07	1.4	0.03	0.4	0.13	2.3	−0.04	−0.8
SICK PAY	0.57	1.2	0.22	1.2	1.06	3.4	–	–	–	–
(α)[c]	0.71	−3.5	1.99	19	0.82	−4	4.77	17	2.64	15
Intrafamily correlation	0.04		0.22		0.08		0.21		0.27	

NOTE: The t-statistics shown are corrected for intrafamily correlation. Other variables that are included for dental only are: FULLTIME coeff. = 0.54, (t) = 5.57; RKIDPAY coeff. = 0.11, (t) 1.91; and BLACKPAY coeff. −0.36, (t) −2.79.

[a]Based on 5,881 participants, excluding first year in Dayton, since only the free plan covered adults in that year, and there appears to be underreporting by adults on the pay plans.

[b]See Table 3.4 for the meaning of and notes on variable names.

[c]The t-statistics measure difference from 1 for α.

the predictor. For example, the estimated coefficient of −0.54 on the dummy variable for black (black = 1, other = 0) in the acute episode equation means that blacks on average have 58 percent (= exp(−0.54)) as many acute episodes as nonblacks, all other predictors being equal.

The estimated regression coefficients show that the raw plan differences reported in Table 3.7 hold up after individual attributes have been accounted for. As before, the free plan participants generate more episodes of every type, and the biggest difference is between free plan participants and those on any other plan. The coefficients across the pay plans differ in the expected order. Plan has the smallest effect on hospital episodes.

The influence of the other predictors on episode frequency varies with the type of episode being considered. The more important determinants of number of episodes appear to be the number of physician visits in the year preceding the experiment, age, self-reported health status, whether the participant is a woman over age 17, and site. Generally, income, being black, family size, and education are also moderately important. Self-reported health status was measured before the beginning of the experiment.

Other variables were tried in developing the model but proved to be unimportant. The list of unimportant variables includes marital status, life change in the preceding year (a measure of stress), size of the MDE as a percentage of income, whether the participant was in the experiment for three or five years, a mental health scale, and whether the participant received Aid to Families with Dependent Children (AFDC).

The interaction of plan with income[10] measures how much more (or less) poor people are affected by coinsurance than rich people. Because the individual deductible does not vary with income, as the other cost-sharing plans do, the difference in impact between rich and poor people may be larger for it than for the other plans. Although the other pay plans do have income-related limits, the $1,000 maximum means that middle- and upper-income families have the same $1,000 limit. As expected, poorer people were more affected by cost sharing, and especially by the nonincome-related individual deductible plan. (See, for example, the t-statistic of 4 in the acute column of PIDSES. The coefficient value of 0.15 for PIDSES on acute episodes means that a 10 percent rise in income causes a 1.5 percent (= 0.15 × 10 percent) larger increase on the individual deductible plan than on the free plan.) The

[10]Here we actually use socioeconomic status, a measure that combines family size adjusted income with education as a proxy for permanent income. (See Table 3.4.) The relevant variables are PIDSES (status × individual deductible plan), and COINSES (status × coinsurance plans).

individual deductible-income interactions were highly significant for outpatient episodes, and for the coinsurance plans, which had an income-related limit, the income-plan interactions were marginally significant (COINSES).

Children were slightly less affected by insurance (KIDPAY > 0), for outpatient episodes. Adding the 0.23 for KIDPAY to the insurance plan coefficients for hospital episodes shows that insurance plan had very little effect on hospitalization rates of children in the experiment. Sick people were also somewhat less affected by insurance plan (SICKPAY > 0), although this might follow from their greater likelihood of exceeding the MDE. Other interactions were tested but found to be insignificant. These included insurance plan by time on study, previous utilization, gender, examination at enrollment, and three-way interactions of insurance plan with poor-sick and with poor-children.[11]

The regression equations show that the five episode types fall into two groups. The numbers of hospital, acute, and chronic episodes are highly correlated with previous health and number of previous visits to a doctor, whereas well care and dental episodes are related to amount of education and income. Well-care episodes are concentrated in women and children, and chronic episodes in older participants.

Because families share propensities to go to the doctor, observations from members of the same family contain less new information than would the same number of independent observations. Correcting for this intrafamily correlation has little effect on the estimates of regression coefficients, but the t-statistics measuring statistical significance are shrunk considerably for variables such as plan and family income, which are the same for all members of the family. The greatest shrinkage occurs for dental, acute, and well care episodes, for which intrafamily correlation is largest, and the effective sample size is about halved.[12]

The estimated values for α in Table 3.8 show how much individuals differ in unmeasured ways.[13] The small values for hospital and chronic show that people have strong propensities that are not captured by the independent variables, and the large value for well care episodes implies that most individual tendencies are captured by the independent variables.

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[11]However, Lohr et al. (1986) find that poor, sick children exhibit the greatest response to cost sharing in the likelihood of any use of services.

[12]We would like to thank our colleague William H. Rogers for generously sharing his software with us to do these computations.

[13]Alpha is the shape parameter of the gamma mixing distribution of unmeasured propensities for episodes. The gamma distribution has a coefficient of variation of $(\alpha\beta^2)^{1/2}/\alpha\beta = \alpha^{-1/2}$. The "t" values test whether α differs from 1.

There was substantial correlation between the counts of different episode types for the same individual even on the free plan. Table 3.9 shows that acute and chronic episode-counts were particularly correlated. This may reflect the assignment of chronic flare-ups to the acute category, where from an economic point of view they belong. The correlation between episode types was considerably higher on the pay plans because of MDE effects.[14] Correlation does not affect predictions of average spending on the experimental plans, which is still the sum of the averages of the individual types. The correlation is most important for simulation of different deductible plans. Since the full distribution of spending determines who will exceed the deductible, correlation between episode types must be considered. In our simulation work discussed in Sec. V, we use a random simulation procedure discussed in Appendix C that accounts for the correlation.

Table 3.9

CORRELATION OF RESIDUALS OF DIFFERENT EPISODE COUNTS BY PLAN

	Free Plans				Pay Plans			
Type	Acute	Chronic	Well	Dental	Acute	Chronic	Well	Dental
Hospital	0.18	0.16	0.03	−0.04	0.29	0.30	0.15	−0.04
Acute		0.40	0.22	0.20		0.50	0.35	0.34
Chronic			0.16	0.18			0.27	0.22
Well care				0.18				0.29

NOTE: Residuals from the predictions discussed in Appendix E, shown in Table E.1, were correlated. They are based on three years of data for the full free-plan sample. All correlations greater than 0.1 are significant at 0.01.

[14]Those with more episodes of any one type are more likely to exceed their MDE, which will induce them to have more episodes of any other type.

IV. CHANGES DURING THE YEAR IN EPISODE FREQUENCIES

In Sec. III, we studied the determinants of annual episode counts. Although annual episode counts may be a better measure of behavior than annual expenses or visits, such an aggregate analysis misses the major advantage of episodic data. If we knew how people behave as price changes through the year, we would have a much better understanding of the demand for medical care, and, in particular, the effects of deductibles on demand. In this section, we analyze price changes through the year. The results are used in Sec. V to predict the spending on plans with a range of deductibles.

There are economic and statistical problems in analyzing changes within the year. One economic problem is the definition of the marginal price of services for a family with a deductible. The effective price may differ from the nominal price if families anticipate future changes in price. Here and in Keeler et al. (1982), we show how we adapted the solution in Keeler et al. (1977a) to these data. The ability to anticipate exceeding the deductible turned out to be very rare, and by ignoring it we obtained a much more tractable estimation problem. Anticipation might be important with deductibles that are smaller than those in the Health Insurance Experiment.

For large episodes (e.g., hospital), a small MDE remaining may have another effect. The out-of-pocket price is limited by the MDE remaining, so the marginal price of an expensive episode is near zero. One might therefore expect even the decision to have an episode (which depends on the total cost) to be affected by the total MDE remaining. We show below that this effect is important for hospital but not for other episode types.[1]

A statistical problem arises because "sickly" people who tend to seek more care (and exceed the MDE) will face lower prices on average later in the year than will others. To deal with this problem, we separate price effects from sickliness effects by assuming that unobservable individual propensities to spend are constant over the year (an assumption we tested), and we compare behavior before and after the MDE is exceeded with behavior on the free plan (where by design there are no within-year price effects) (Keeler et al., 1982).

[1]It was also important for long mental health episodes (Keeler et al., 1986).

We first discuss these economic and statistical problems and summarize our methodology. Further details of our statistical model of within-year behavior of pay plan participants can be found in Keeler et al. (1982). Here we concentrate on recent changes in the model and our new results based on data from all participants. The nontechnical reader may want to skip to pure price effects at the end of the section.

DEMAND FOR SERVICES WHEN PRICE CAN VARY: THE ECONOMIC PROBLEM

When the rate of coinsurance for medical services can change for an individual, the current out-of-pocket price is not a complete guide to action. Instead, the economically rational family also looks at the effects of current spending on future prices. Before a deductible is exceeded, current spending has the *bonus* of reducing the remaining deductible. To take an extreme case, suppose that a woman is pregnant and the obstetrical bills will exceed the MDE limit. After delivery, her care will be free, but she might as well assume care is free immediately, since any additional current spending has no effect on her ultimate out-of-pocket costs. In general, the true out-of-pocket price is somewhat less than the nominal out-of-pocket price. How much less depends on the probability that the family will subsequently exceed the deductible. Indeed, under fairly restrictive assumptions,[2] it can be shown that the effective price before the deductible is satisfied has the simple form $(1 - p) \times$ (nominal price), where p is the probability of exceeding the deductible (Keeler et al., 1977a; Ellis, 1986). This implies that estimates of price effects using average nominal price are biased.

Families might anticipate future spending in two ways. First, they may schedule continued treatment of such things as pregnancy, dental problems found at a previous examination, or continuing care for diabetes. Second, a large family with only a few dollars left on its MDE early in the year can be fairly sure that it will exceed the MDE with time to spare, even if it does not know precisely how.

Neither of these forms of anticipation biases our estimates of the effects of coinsurance very much. Continued treatment of known problems is already taken into account by the computer program that links up charges into episodes. The program assumes in its linking and dating procedures that such spending is fully anticipated. The second form of anticipation cannot be important because it occurs so rarely (Keeler et al., 1982).

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[2]The utility function for health and money must be separable, and it must be risk neutral for money.

Thus, except for episodes that had already begun, participants were rarely in a position to anticipate exceeding their MDE or deductible. For this reason, we can simply compute the average rate of spending before the deductible is exceeded, in effect grouping all situations with some MDE remaining in the analysis.

Low-Priced Episodes (Price Changes within Episodes)

A different economic effect, not considered in Keeler et al. (1982), occurs when the total cost for an episode is limited by a small remaining amount of MDE. For hospital and other large episodes, having a treatment episode is more attractive when the total cost is small. In the HIE, people were infrequently in a position with less than $100 of MDE remaining (Keeler et al., 1982), but for expensive episodes the effect of total cost could be important for larger amounts of MDE remaining. An examination of the MDE left at various times in the year in three years of Massachusetts data revealed that about 20 percent of the time, participants had between 0 and $400 left. This is an adequate sample for estimation, and we divided the situations before exceeding the MDE into those with more or less than $400 of MDE remaining. For large hospital bills, the effect of having less than $400 of MDE left would be independent of coinsurance rate.

If the episode is large enough, average price is low even if the full $1,000 of MDE remains. In Appendix B, we show the results of a study of catastrophic hospital expenses. The rate of hospitalizations over $7,210 (1980 dollars) per person-year was the same (0.6 percent) on the coinsurance and free plans. In our simulations, we will assume that such catastrophic episodes are unaffected by price.[3]

Sales

Families with changing coinsurance rates have another interesting option. They can schedule deferrable treatment episodes to a time when out-of-pocket prices are low. Thus, families with care that is temporarily free have medical care "on sale," and have more incentive to spend than families with permanently free care. We can test for this phenomenon by looking at the experience on the free plan at the start and finish of the experiment, and by studying what happens to

[3]We could not estimate the effect of very large deductibles, say $5,000 (1985 dollars), on catastrophic hospitalizations from HIE data. An attempt to do so from premium data supplied by two insurance companies also failed. Analysis of those data revealed that their guessed premiums were not consistent with the economic assumption that larger deductibles should lead to reduced use of medical services.

families in the months just following the time they satisfy their deductible.

The most deferrable types of treatment are dental and well care. In data from the Dayton site, we saw an initial "catch-up" surge on the free plan in the first quarter of year one and a somewhat smaller "store-up" surge at the end of the three years for dental and well-care episodes (Keeler et al., 1982). However, even for these episode types, we did not see a surge after the MDE was exceeded by those on pay plans during the course of the experiment. Instead, rates on the pay plans for outpatient episodes were slightly lower than free plan rates after the MDE was exceeded. Perhaps this reflects ignorance about MDE status, and perhaps difficulty in making short-run changes (e.g., moving to a more interventionist doctor). Because we found no sales effects on pay plans in Seattle either, we decided to aggregate all situations after the MDE was exceeded.

In sum, we will compute spending rates for three economic periods in each accounting year: the period where the MDE remaining is greater than $400, the period where the MDE remaining is between 0 and $400, and the rest of the year. We will call these the big MDE period, the small MDE period, and the free or no MDE period, for short. In most outpatient episode analyses, the MDE remaining periods will be merged and called the pay period. Only about 20 percent of families exceed their MDE in any one year and have experience in the free period.

As a test of methods, we have computed the "effects" of a pseudo-MDE for the free plan. Two-thirds of the free care families were randomly assigned in our analysis to an initial high fictitious MDE ($1,000), and the other third was assigned a fictitious low MDE of $300. Combined with a fictitious coinsurance rate of 40 percent, this leads to a distribution of MDE remaining that roughly matches the actual pay plan experience throughout the year. We can observe what happens when the families approach and exceed their pseudo-MDE. Since in fact care was free throughout for them, there can be no real price effects, and any estimated price response to this bookkeeping MDE must be an artifact of our complicated methods.

SEPARATING SICKLINESS FROM PRICE EFFECTS: THE STATISTICAL PROBLEM

For health insurance plans with deductibles, prices are lower on the average for those who tend to have more episodes. (We will call such people "sickly" although they may differ more in attitudes about going

to physicians than in health.) Sickly families tend to consume more care and hence are more likely to exceed their deductibles (or MDEs). This issue does not affect annual analysis by plan, because by design, plan groups are balanced by propensities to spend. Unfortunately, as the year goes on, groups within plans defined by their MDE remaining are determined by previous spending and become unbalanced. Table 4.1 shows the fraction of days per person, the actual fraction of episodes, and the predicted fraction of episodes *assuming no price effect* (but adjusting for other characteristics of those over the MDE) in the post-MDE period for each plan. (See Appendix E for the prediction equations.) As can be seen, the number of predicted episodes is larger than the proportional amount of time over the MDE and the number of actual episodes is larger than that. This is true even for the pseudo-pay free plan, where price effects are not involved. The prediction may understate the actual number either because of unmeasured propensities to have episodes or because of price effects. Our methods are designed to untangle these two causes.

We have developed and estimated a model to resolve this problem. The model allows us to compute the ratio of the episode rates in different periods defined by MDE status to what those rates would have been on the free plan. The model relies on four critical assumptions, listed below. Evidence on the assumptions is presented and discussed more fully in Appendixes B and F of Keeler et al. (1982).

Table 4.1

FRACTION OF ANNUAL EVENTS OCCURRING AFTER THE MDE IS EXCEEDED

Event	Insurance Plan				
	25	50	95	ID	Free[a]
Fraction of outpatient time over MDE[b]	0.10	0.13	0.22	0.24	0.17
Predicted outpatient episodes[c]	0.10	0.13	0.24	0.25	0.22
Actual outpatient episodes	0.13	0.19	0.37	0.40	0.25
Hospital time over MDE[b]	0.08	0.11	0.19	0.21	0.15
Predicted hospital episodes[c]	0.10	0.12	0.21	0.22	0.19
Actual hospital episodes	0.28	0.34	0.41	0.42	0.31

[a]An imaginary MDE of either $1,000 (two-thirds of families) or $300 (one-third of families) and a coinsurance rate of 40 percent was assumed.

[b]Time is transformed to account for carryover episodes on the first day of the accounting year. Differs between hospital, outpatient because actual days after the first are multiplied by 0.94 for outpatient, 0.8 for hospital.

[c]The predicted fraction assumes that families spend at the same rates for each episode type after the MDE is exceeded taking into account the time transformation referred to in note (b).

Nonprice-related propensities to have episodes are constant over the accounting year. These propensities or expected values are determined by measured and unmeasured characteristics. Individuals have an expected number of episodes per year on the free plan that depends on their nonplan individual characteristics. We can add these up to get a total for family k that we will call δ_k. Because our information about families is limited, they will also have propensities that will not be captured by measured characteristics. (Thus, over time, we would expect individual families to consistently be over- or underpredicted by the δ_k.) To account for this unmeasured variation, we will assume that each family has an unmeasured propensity to generate episodes that is constant from year to year. We capture the unmeasured propensity with a proportional factor u_k. The families' actual propensity is the product $\delta_k u_k$. The u_k will be assumed to be drawn from a gamma distribution. The gamma distribution can take a variety of shapes and has computational advantages. Only free plan data are used to estimate both the prediction equations and the distribution of unmeasured propensities.

The year is split into three periods by MDE status, and within these periods the effects of price are constant. In effect, we will estimate ratios (π_{ij}; $i = 1, 2, 3$) for each period i and coinsurance plan j. These occurrence ratios are defined as the ratio of the expected number of episodes in period i for a family on plan j to the expected number of episodes in period i for that family if care were always free. That is, it is the ratio of pay-plan propensity to the free plan propensity to generate episodes.

Episode rates on the free plan can be considered constant over time. Further data analysis confirmed the results in Keeler et al. (1982) that episode rates for all types of episodes are uniform except for sales effects, the first day of the year, and a tendency for chronic episodes to occur early in the year. The surge of carryover episodes on the first day of the year, and the tendency for chronic episodes to be dated earlier in the year, follow from our grouping conventions. Thus, these trends should be the same on all plans. In the analysis we transform time so that rates are uniform.[4]

Occurrences of episodes are independent over time. Individuals have different propensities, but conditional on these propensities, episode occurrences do not appear to be bunched or spread more than random.

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[4]For example, the first day had 22 times as many acute episodes as an ordinary day. We say that someone who exceeds the MDE on the third day has had (22 + 2)/(22 + 364) of the year's experience in their pre-MDE stage.

Thus, they can be modeled as being Poisson distributed.[5] This is convenient for purposes of comparison because the Poisson distribution is infinitely divisible, i.e., the episodes in any fraction of the year also follow a Poisson distribution.

Thus, summarizing the four assumptions, a family k on plan j in MDE status i for an effective period of time t_{ik} will have n_{ik} episodes, where n_{ik} follows a Poisson distribution with mean $\pi_{ij}\delta_k u_k t_{ik}$. Table 4.2 summarizes the notation and assumptions made thus far in specifying the model; others will be made in fitting the model.

METHODOLOGY FOR FITTING THE PRICE EFFECTS MODEL

There are several pieces to put together to estimate the parameters of the price effects model. Define $f_k = \delta_k u_k$, where δ_k is a predictable family component and u_k is the remaining unpredictable component. First, the predictable family component δ_k must be estimated as a function of individual characteristics for those on the free plan. Next, the parameters of the distribution of u_k are estimated. Finally, a maximum likelihood procedure is used to estimate the price indices π_i. We describe our methods before presenting the numerical estimates.

Recall that δ_k is the predicted annual number of episodes for family k if care were free. This is estimated by d_k, which is obtained by summing individual regression predictions based on free plan data of annual episode rates over the individuals in the family.[6] We assume that there are no interactions between within-year price effects and the effects of other explanatory variables, so that all the effects of explanatory variables other than price on numbers of episodes are summarized by δ_k.

Assume that family k has an unmeasured multiplicative factor u_k, with u_k having a gamma distribution with parameters α and β. Given the value u_k, the annual rate for family k is assumed to be $u_k\delta_k$ if care were free. This is the Poisson regression analog to the usual random

[5]Families occasionally have several episodes on the day the MDE is exceeded. We assume that all such episodes belong to the pre-MDE period. Alternative assumptions that put some of the multiple episodes into period 3 have no discernible effect on pre-MDE occurrence ratios, and raise period 3 occurrence ratios by 0 to 5 percent, depending on plan and type. The problem of multiple episodes exceeding the MDE is similar to the case of someone with only a little MDE remaining who has a very large episode. Multiple episodes are discussed in more detail in Appendixes D and E of Keeler et al. (1982).

[6]For cost and convenience reasons, we estimated δ using a regression of the square root of individual episode frequencies on individual characteristics given in Appendix E in preference to the negative binomial regressions given in Sec. IV. We have found that both models give substantially the same predictions.

Table 4.2

NOTATION AND ASSUMPTIONS

Notation:		
π_{ij}	=	ratio of occurrence rates for period i on plan j to no pay rate; i = 1, 2, 3 (the price index).
δ_k	=	predictable component of expected annual episode occurrence rate under free plan for family k (a function of the covariates of individuals in family k).
u_k	=	multiplicative component of expected annual occurrence rate for family k if care were free that is due to unmeasured family propensities to have episodes.
$\delta_k u_k$	=	expected annual occurrence for family k if care were free (f_k).
t_{ik}	=	time spent by family k in period i. The period when family k has more than \$400 of MDE remaining is period 1, the time with between \$0 and \$400 MDE remaining is period 2, and $t_{3k} = 1 - t_{1k} - t_{2k}$ is the time after the MDE is exceeded.
n_{ik}	=	number of episodes that family k has during period i.
Assumptions:		
1.		Episodes occur during period i to family k on plan j, according to a Poisson process with intensity function $\pi_{ij}\delta_k u_k$. Thus $n_{ik} \mid t_{ik}, \pi_{ij}, \delta_k u_k \sim$ Poisson $(\pi_{ij}\delta_k u_k t_{ik})$.
2.		u_k is independently distributed gamma (α, β). That is, the unmeasured component is modeled as being drawn from a gamma distribution independently for each family.

effects models in the analysis of variance. We use the negative binomial regression model described in Sec. III for the free plan sample from all sites to estimate α and β. The dependent variable is the number of episodes, and because the "adjusted time" for family k is set to be $\delta_k t_k$, no covariates are needed beyond those included in δ.

The resulting estimates of α and β reflect the unmeasured differences in episode rates in the absence of price effects. The larger the unobservable or unmeasured differences between families, the higher the variance $\alpha\beta^2 = \beta$ (since $\alpha\beta = 1$) of the "mixing distribution," and the lower the value of α.[7]

[7]Since the regression estimates d_k of rates based on demographic characteristics are unbiased (the sum of the d_k equals the sum of the n_k), the estimated mean of the gamma distribution should be approximately one. The mean of a gamma is given by $\alpha\beta$ ($\simeq 1$) and the variance by $\alpha\beta^2$, where α is the shape parameter and β the scale parameter.

Price effects are estimated on the nonfree plan data, by maximum likelihood, as shown in Appendix H of Keeler et al. (1982).

NUMBERS OF EPISODES

Prediction equations based on the free plan experience were estimated for each site separately. Data from the four sites were then pooled. The variance of unmeasured characteristics between families was computed from the negative binomial model that assumes that the probability distribution of n given u and δ is Poisson with parameter $u\delta$, where u has a gamma (α, β) distribution and δ is the predictable component of expenditures. The maximum likelihood estimates of α and $\alpha\beta$ denoted by a and ab for the 1990 family years of free plan data are given in Table 4.3. Since ab was never significantly different from 1, we chose $b = 1/a$ in all price ratio regressions. As can be seen, the smallest value of a, and hence the biggest unmeasured differences between people, occurs in hospital care, and the least in well care. We should note that when a and b were estimated for the 2,695 pay plan family years, the estimated value of a for acute episodes per year was only 1.53, and the hospital a was 0.64. This shows the greater dispersion of numbers of episodes on the pay plans, which is mainly due to MDE effects.

The dispersion in characteristics based on aggregating all three years of each individual's experience together is quite similar to that based on single years, except for hospital episodes. Families may have single year peaks in hospitalizations that are not sustained over three years.

Table 4.3

ESTIMATES OF DISPERSION OF UNMEASURED FAMILY CHARACTERISTICS BASED ON FREE PLAN DATA

	Based on Separate Family Years		All Three Years Together,
Episode Type	Estimated a	Estimated ab	Estimated a
Acute	2.77	0.998	3.08
Chronic	2.03	0.995	1.79
Dental	3.94	0.997	3.71
Well care	6.96	0.995	7.08
Hospital	1.10	1.03	1.70

Because our interest in estimation and prediction is primarily annual, we used the estimates of parameter a based on year-by-year data in further calculations.

OCCURRENCE RATIOS OF OUTPATIENT EPISODES

There was little difference between the occurrence ratios (rates of episodes relative to free rates) for outpatient episodes whether big or small amounts of MDE remained. To increase the sample for this comparison we combined all the coinsurance plans (but excluded the individual deductible). Table 4.4 shows that the biggest difference was for acute (0.65 compared with 0.70). This difference was not statistically significant. Apparently, there is little anticipation of going over the MDE, and outpatient episodes are too few for the price limit given by a small MDE to stimulate treatment of illness episodes. Although a smaller MDE category of perhaps $50 remaining might exhibit some effect, such situations do not arise often unless the initial MDE is small (Keeler et al., 1982). In all further analyses of outpatient episode rates, the big and small MDE period will be combined. Because there is no apparent anticipation, the combined pay period occurrence ratios can be interpreted as the plan ratios if there were no MDE.

The estimated occurrence ratios for outpatient episodes are given in Table 4.5. Since only one-sixth of the experience occurred after the MDE was exceeded, the pay period (pre-MDE) ratios are estimated more precisely than the rest of the year ratios.

For each outpatient episode type, the estimated pay period occurrence ratios decline with coinsurance rate (i.e., demand for episodes decreases with out-of-pocket price, as expected). The 25 percent rate is about halfway between free care rate of 1.0 and the 95

Table 4.4

ESTIMATED OCCURRENCE RATIOS FOR OUTPATIENT EPISODES IN COMBINED COINSURANCE PLANS

MDE Remaining	Type of Episode			
	Acute	Chronic	Well	Dental
Above $400	0.65	0.63	0.68	0.67
$0 < x \leq \$400$	0.70	0.67	0.69	0.64
None	0.84	0.89	0.98	0.91

Table 4.5

OCCURRENCE RATIOS FOR EPISODES IN OUTPATIENT CATEGORIES WITH AND WITHOUT MDE REMAINING

Type of Episode	Some Remaining				None Remaining			
	Insurance Plan				Insurance Plan			
	25	50	95	ID	25	50	95	ID
Acute	0.76	0.61	0.55	0.62	0.84	0.78	0.84	0.85
	(0.02)	(0.02)	(0.01)	(0.01)	(0.04)	(0.06)	(0.03)	(0.02)
Chronic	0.71	0.61	0.57	0.64	0.90	0.86	0.88	0.96
	(0.02)	(0.04)	(0.02)	(0.02)	(0.06)	(0.13)	(0.04)	(0.04)
Well care	0.80	0.75	0.51	0.56	0.92	1.08	0.98	0.98
	(0.02)	(0.03)	(0.02)	(0.02)	(0.05)	(0.10)	(0.04)	(0.04)
Dental[a]	0.80	0.70	0.54	0.58	0.91	0.77	0.96	0.89
	(0.03)	(0.02)	(0.02)	(0.01)	(0.08)	(0.05)	(0.04)	(0.03)

NOTES: Here and in other tables, rates are given relative to the free plan; i.e., the free plan rate is 1. The values tabled are the maximum likelihood estimate of π. The entries in parentheses are the standard errors of the estimates as calculated from the asymptotic variance of the maximum likelihood estimate. These are biased downward (see the text).

[a]First year Dayton was omitted for dental. The plan with 25 percent medical insurance, 50 percent dental insurance is put with 50 percent coinsurance for dental.

percent plan rate, which is about 0.55. As a test of the method, we have estimated price effects on the pseudo-pay free plan with the fictitious MDE and coinsurance, where there can be no real price effects. As can be seen in Table 4.6, the occurrence ratios are never very different from 1, and none differed by a statistically significant amount.

The ratios after the MDE is exceeded are similar on all pay plans. If people did not plan ahead, but were well aware of their insurance status, we might expect a ratio of 1, the free plan rate. Initial low use on the pay plan could have two offsetting effects on use after the MDE is exceeded. It might lead to a demand for cures that were deferrable, but it might also mean undetected illness and a habit of not going to the doctor that would carry over into the later period. Also there is no doubt some delay before people realize that medical care is now free—this effect was noted in Keeler et al. (1982), and led to the abandonment of the "sale" hypothesis for the period just after the MDE was exceeded. Sale and ignorance effects may have canceled out on the various plans, but the overall results yield ratios slightly less than 1.

Table 4.6

EFFECTS OF A FICTITIOUS MDE ON FREE PLAN OCCURRENCE RATIOS

MDE Remaining	Type of Episode			
	Acute	Chronic	Well	Dental
Above 400	0.99	1.01	1.01	1.00
$0 < x \leq \$400$	0.97	0.95	0.95	1.02
None	1.05	1.03	1.01	0.96

The post-MDE period ratios for well care are close to 1, consistent with the hypothesis that well care is the easiest type to schedule. For the other episode types, the post MDE ratios are less than 1, but only the acute rate estimates differ from 1 by a statistically significant amount (averaging 0.83 the free plan rate).

The standard errors using maximum likelihood theory look quite low, with values around 0.02 for the pre-MDE period and 0.05 in the post-MDE period. There are theoretical reasons why these could be underestimates, so we studied the bias in the estimates in detail.

First, estimated standard errors are conditional on free plan predictions that are assumed to be correct. Using the methods of Appendix F in Keeler et al. (1982), the increased variance in occurrence ratios π, resulting from the variability of the free plan estimates, can be shown to be approximately π^2/n or about $(0.01)^2$. Second, the variability in the estimates of α will also affect the occurrence ratio estimates. A larger value of a implies that people are similar, so that the increased spending by those exceeding the MDE is due to price effects not sickliness. Thus, a larger a leads to smaller first period and larger second period occurrence ratio estimates. Some sensitivity runs were performed on simulated data. They show that the elasticity of the estimated ratios to changes in a is about 0.1 for the first period, and -0.2 for the second period for hospital. This implies that error in the estimate of a adds less than 0.01 to the standard error for outpatient episodes occurrence ratios, and 0.03 for hospital. Finally, three years of family experience are treated as independent. When the analysis was redone with all three years of experience combined, the standard error of the estimate changed by -10 to $+20$ percent in different ratios. Thus, this assumption had little effect on the estimated standard errors.

A general test of the variability of the estimates comes from dividing up the data and seeing how much difference there is in the estimates for each part. In particular, we compared the estimates based on each site. The four sites each have approximately one-quarter of the sample.[8] If differences between sites are not systematic, the site estimates should be distributed with standard error about twice the actual standard error of the overall estimate. However, there appear to be systematic site differences. In particular, the South Carolina estimates are lower in the pre-MDE period. When 0.15 was added to all pre-MDE South Carolina estimates, the standard deviation of site estimates was two to four times the maximum likelihood standard errors (Table 4.7). Thus, standard errors computed from site differences are between one and two times standard errors given by the maximum likelihood procedures, a ratio that is biased upward by the crude adjustment for site effects.

To sum up, for several reasons the maximum likelihood estimates of standard errors are underestimates. However, none of these reasons appears to add much to the standard error, and the test using price estimates of different sites verifies that the true error is less than twice the error given in Table 4.4. Thus, it is no accident that the estimated response to coinsurance falls monotonically. We have quite a precise estimate of how cost sharing affected the rate of outpatient episodes in the experiment.

Table 4.7

STANDARD DEVIATION ACROSS SITES OF OCCURRENCE RATIOS WITH AND WITHOUT MDE REMAINING

Type of Episode	Some Remaining			None Remaining		
	Insurance Plan			Insurance Plan		
	25	50	95	25	50	95
Acute	0.07	0.07	0.04	0.19	0.10	0.05
Chronic	0.10	0.05	0.10	0.15	0.06	0.15
Well care	0.07	0.07	0.06	0.25	0.34	0.05
Dental	0.14	0.06	0.15	0.25	0.10	0.12
Hospital	0.18	0.25	0.09	0.50	0.22	0.33

NOTE: The values from South Carolina had 0.15 added before the standard deviation was computed.

[8]We group the two rural sites with their adjoining urban sites in Massachusetts and South Carolina.

OCCURENCE RATIOS OF HOSPITAL EPISODES

The occurrence ratios for hospital episodes follow quite a different pattern as compared to outpatient episodes. In Table 4.8, we see that the results for the large (above $400) MDE remaining period are essentially the same on all the coinsurance plans. The small MDE period has a rate closer to 1, and the no MDE remaining ratio is much larger than 1. This means that people on the pay plans with no MDE remaining had hospital episodes at higher rates than those on the free plan for the rest of the year. It is surprising to see such large apparent sale effects, since there were not many purely elective hospitalizations. Are they real, or is some faulty assumption in the model responsible? It will turn out that some assumptions of the model are responsible and that adjustments should be made in the post MDE period values to extrapolate to the population.

In addition to the apparent 47 percent sale on the pay plans, there is also an estimated 31 percent sale on the "pseudo-pay" free plan. This sale could not be due to price effects, because there were none. Perhaps clumping family episodes may cause those exceeding the MDE to have more episodes. The first might put them over the MDE and the second in the clump occurs after the MDE is exceeded. Clumping might result, for example, from a family automobile accident,[9] or readmissions for a particular person. These may occur occasionally but the negative binomial model, which assumes no clumping, fits hospital episodes quite well.

Table 4.8

ESTIMATED OCCURRENCE RATIOS FOR HOSPITAL EPISODES

MDE Remaining	Total Coinsurance	Insurance Plan					Coinsurance/ Free
		25	50	95	ID[a]	Free	
Above $400	0.64	0.65	0.62	0.63	—	0.92	0.70
	(0.04)	(0.05)	(0.09)	(0.06)	—	(0.06)	
$0 < x \leq \$400$	0.87	0.94	0.72	0.85	0.71	0.98	0.89
	(0.08)	(0.11)	(0.21)	(0.13)	(0.05)	(0.08)	
None	1.48	1.91	1.56	1.22	1.62	1.31	1.12
	(0.10)	(0.21)	(0.34)	(0.11)	(0.13)	(0.09)	

NOTE: See Table 4.5 for explanation.
[a]Hospital care has no cost sharing for this plan.

[9]Nothing like this occurred in the HIE, but there were some readmissions.

Correlation of hospital and other types of episodes is a more probable cause of artifactual sales. The reasoning is that even those starting their first hospital episode are more likely to be already over the MDE, because of sickness that manifested itself in acute or chronic spending. Our methods control only for being over the MDE because of earlier occurrences of the same type of episode, since each type is estimated separately.

Correlation between episode types does appear to be part of the explanation. We simulated medical expenses of people with full coverage through the year (and hence no real price effects). The simulation put in correlation between different episode types and family members (see Sec. V for details of the simulation model) but no clumping of episodes. These data were processed with the pseudo-pay fictitious MDE and coinsurance rate. With these data, the estimated rate of spending on hospital episodes after the MDE was exceeded relative to the overall rate was 1.25. In other words, the estimated sales were 25 percent.[10] In the simulation, there can be no actual direct sales effect, since the same free plan rates were used throughout the year. Thus, when the occurrence ratios were computed on simulated data with correlation, sales were 25 percent, which is close to the 31 percent seen in the actual free plan data. Correlation might be the whole explanation, since correlations in the simulated data turned out to be slightly smaller than in the real data.

We might think that including sickliness in the prediction equations would reduce the amount of correlation between hospital and other types. Indeed, the hospital sales effect estimated from the runs on the pseudo-free plan (with real data) in Seattle with sickliness measures included was only 15 percent. In this case, α rose to 1.15 from 0.8 (because more of the variation was predicted).

A comparison of the last row of Table 4.8 with the top row of Table 4.1 supports the idea that correlation plus selection (sickliness) effects are responsible for much of the sale effects as follows. Suppose that a small group of families have exceeded the MDE because of higher expenses on outpatient episodes, and that these families are also more prone to have hospital episodes. If all other families have identical propensities (somewhat less than average), we can compute what third period (post-MDE) ratios would be expected. For example, if for most

[10]For acute episodes, the estimated sales on simulated data were 13 percent, which was not quite significant ($t = 1.8$). However, sales on acute episodes on the pseudo-pay free plan were only 5 percent (Table 4.6) and the estimated value already seemed low, especially for simulating the effects of small MDEs. We decided not to correct for this. All the "rest of year" numbers in the right side of Table 4.5 might be slight overestimates, but we would have to do many more simulations to determine by exactly how much.

of the year, the sick families are over the MDE, under reasonable values of the parameters the observed rates would be 1.75 for the 25 percent plan, 1.54 for the 50 percent plan, 1.26 for the 95 percent plan, and 1.38 for the free plan.[11] The ID plan is more selective than its days show because selection is done on an individual basis, and no well family members are carried along with the sick.[12]

In the long run, a more sophisticated estimation program could be developed, to estimate correlations of all episode types on the free plan and to use them to estimate all episodes simultaneously. For purposes of simulation, we will assume that sales are due to selection through correlated outpatient episodes and adjust the coefficients in Table 4.8, so that the sale effect goes away and the total for the plan is correct. Because approximately 0.15 of hospital days are over the MDE, hospital occurrence ratios of 0.72 for the big MDE period, 0.9 for the small MDE period, and 1 for the over MDE period will keep the overall episodes equal to 80 percent of the free plan number.

PURE PRICE EFFECTS

We now can put together the pieces to compute the overall effect of price on medical spending in the absence of deductibles or limits. We call this the "pure" effect of price. We assume that it is approximated by behavior of people in the big MDE period. Cost sharing leads to a decline in the rate of initiating episodes and to somewhat smaller episodes when they occur. We combine the smoothed estimates of effects on size of episodes shown in Appendix C with the effects on rate of episodes shown in Table 4.4 (for outpatient episodes) and Table 4.8 for inpatient episodes. The results are shown in Table 4.9 as a percentage of spending with free care. The standard errors shown there assume that errors in estimating reductions in size and rate are independent, and the true standard error of reduction in rate is 1.5 times the maximum likelihood estimate.[13]

The reductions in average cost of episodes resulting from cost sharing are only marginally significant. If price really had no effect on

[11]This calculation assumes that 10 percent of families are in the third period one-half of the year and have a rate of spending 2.65 times the average free plan rate, and the remaining families have a rate 0.85 times the free plan rate.

[12]There is no cost sharing for hospital expenses on the individual deductible plan, but it has larger "sale" effects than the 95 percent plan, presumably because of greater selection.

[13]Above, we showed that the true standard error was probably between one and two times the maximum likelihood estimate.

Table 4.9

ESTIMATED SPENDING ON MEDICAL SERVICES FOR PLANS WITH NO MDE

Pure Coinsurance Rate	Outpatient			Total Outpatient[a]	Hospital	Total Medical[a]	Dental
	Acute	Chronic	Well				
25	72	67	75	71	71	71	79
	(4)	(6)	(4)	(3)	(7)	(4)	(6)
50	56	56	69	58	68	63	68
	(5)	(7)	(6)	(4)	(13)	(7)	(5)
95	49	51	45	49	60	55	50
	(3)	(5)	(4)	(2)	(7)	(4)	(3)

NOTE: Standard errors in parentheses are computed assuming that errors in estimation of reductions in episode size and rate are independent.

[a]Computed assuming that estimates are weighted by shares of spending during the big MDE period: hospital 0.54, acute 0.23, chronic 0.15, well 0.08.

cost, the values for all medical services shown would change from the 71, 63, and 55 shown in the table to 73, 68, and 64, and the total outpatient values would rise to 75, 63, and 55.

For comparison with the economic literature on demand for medical services, which generally gives results in terms of price elasticities, we have computed the values in Table 4.10.[14]

The pure price effects computed here are smaller than the plan effects given in Manning et al. (1987). There, the 25 percent plan is estimated to have total medical spending at 81 percent the free rate, the 50 percent plan at 75 percent, and the 95 percent plan at 69 percent. The difference from pure effects computed in Table 4.9 is largest for the 95 percent plan, because many more people (35 percent) exceed the MDE on that plan than on the other plans. Because the demand for services is a nonlinear function of coinsurance, the average coinsurance rate does not represent price accurately. A calculation of pure price effects was made using the annual data and their average

[14]Elasticities measure the proportional change in spending as a result of a small proportional change in price (in symbols $d\ log(q)/d\ log(p)$). Table 4.11 actually gives arc elasticities that come from the formula $(q(1) - q(2))/(p(1) - p(2)) \times (p(1) + p(2))/2\ /(q(1) + q(2))/2$. The standard errors given there assume that the error in estimating $q(1) + q(2)$ is negligible, and that the error in estimating $q(25) - q(95)$ is the square root of one-half the sum of the squared errors of estimating $q(25)$ and $q(95)$. The one-half comes from an assumption that one-half of the error in $q(25)$ and $q(95)$ comes from variation in the free plan and drops out when one subtracts.

Table 4.10

ARC PRICE ELASTICITIES OF MEDICAL SPENDING

Coinsurance Range	Outpatient			Total Outpatient	Hospital	Total Medical	Dental
	Acute	Chronic	Well				
0–25	0.16	0.20	0.14	0.17	0.17	0.17	0.12
	(0.02)	(0.04)	(0.02)	(0.02)	(0.04)	(0.02)	(0.03)
25–95	0.32	0.23	0.43	0.31	0.14	0.22	0.39
	(0.05)	(0.07)	(0.05)	(0.04)	(0.10)	(0.06)	(0.06)

NOTE: Standard errors are given in parentheses. For their method of computation see the text.

coinsurance rates. It estimated the 0–25 elasticity as 0.10 and the 0.25–0.95 elasticity as 0.14 (Manning et al., 1987). A third estimate using an indirect utility function led to a value of 0.18 for all care in the 25–95 range (Manning, 1988). Overall the results from the episodic model are in good agreement with the annual results.

Looking at the total spending column, we see that the elasticities are around 0.2 in the range from 0–25 percent coinsurance and around 0.3 in the range of higher coinsurance. A value of 0.2 means that a 10 percent increase in the rate of coinsurance (e.g., from 30–33 percent) leads to a 0.2 × 10 percent = 2 percent decrease in spending on medical services. This value lies within the span of earlier estimates in the literature but is at the low end of that span. See Manning et al. (1987), for more discussion of the literature and the implications of this estimate.

V. THE SIMULATION MODEL

We constructed a simulation model to extend the experimental results to unstudied health insurance plans and to cross-validate the models and ideas developed above. The simulation uses the models discussed in Secs. III and IV to estimate annual personal and family expenditures by type of episode for different health insurance plans. The validity of the model estimates is conditional upon parameter estimates derived in Secs. III and IV. We use a randomly drawn sample of 970 families (2,297 individuals) from the Current Population Survey (CPS) of March 1984 to make these estimates. The CPS provides data on family composition, the age and sex of each family member, and the financial and ethnic status of the family.

STRUCTURE OF THE SIMULATION MODEL

The simulation model compares the effects of different health insurance plans on family expenditures when families experience the same health problems. Insurance plans are characterized by an initial deductible period (possibly zero) where the patient must pay 100 percent of the cost of care up to some limit, a cost-sharing phase where the patient pays a share of the cost of care that is equal to the coinsurance rate and the plan pays the remaining portion, and either an individual or family maximum dollar expenditure (MDE) limit on out-of-pocket expenditures beyond which the plan pays 100 percent. For plans with family MDE limits, the expenditures of all family members contribute to the maximum. When the family maximum is exceeded, the plan pays for 100 percent of the care for all family members. For plans with individual MDE limits, each family member must exceed the limit individually before the plan will pay for all of the costs of care. The model also accommodates "hybrid" plans where different deductibles, coinsurance rates, or MDEs apply to different types of episodes within a plan.

All insurance plan experience is considered relative to "free" care within the model, that is, relative to an insurance plan that pays for 100 percent of all medical care expenditures. The model estimates annual expenditures for each family on the free plan and subsequently estimates how the family would have responded to the same health needs if it had each of the other insurance plans. To provide a benchmark at the other extreme, we have also included a full pay plan on which the family must pay 100 percent of the cost of all care.

The Demand for Episodes of Care on the Free Plan

As discussed in Sec. III, the distribution of the number of episodes of each type is assumed to be negative binomial. The negative binomial distribution may be interpreted as a mixed Poisson process. A mixed Poisson process arises when the intensity parameter of the Poisson λ is a random variable. If the intensity parameter has a gamma distribution, the process has a negative binomial distribution. The expected number of episodes of a given type that an individual has, that is, his episode intensity, varies with personal characteristics. These individual episode propensities are assumed to have a constant measured component determined by observable characteristics such as age and sex and an unmeasured component that is determined by unobservable factors such as recent changes in health status. The unmeasured component is represented as a gamma distributed random variable.

A useful feature of Poisson processes is that the sum of several independent Poisson processes with intensities $\lambda_1, \lambda_2, \ldots, \lambda_n$, is a Poisson process with intensity $\lambda = \lambda_1 + \lambda_2 + \ldots + \lambda_n$. We use this property to generate a single episode stream for the family.

Our model processes one family at a time by first estimating an overall family propensity for episodes of all types. This family propensity is estimated by summing each family member's individual propensity for episodes of each type. In the reported simulation, we do not include dental episodes, since most health plans do not cover dental care as part of the medical insurance plan. The constant measured component of the individual propensities are computed from the regression equations given in Appendix E.

For a fixed family, let d_{ij} represent the predicted number of episodes of type j from the regression equation for family member i. U_j represents the family's unobserved component for episode type j. Person i's propensity for episodes of type j is given by

$$\lambda_{ij} = d_{ij} U_j$$

where $U_j \sim G(\alpha_j, \beta_j)$, that is, U_j has a gamma distribution with scale parameter β_j and shape parameter α_j. The dependence of the U_j's across episode types is described below. Estimation of the gamma parameters is described in Sec. IV. The family's propensity for episodes of type j is given by

$$\sum_{i=1}^{n} d_{ij} U_j$$

and the family's propensity for all e types of episodes is given by

$$\Lambda = \sum_{j=1}^{e} \sum_{i=1}^{n} \lambda_{ij} = \sum_{j=1}^{e} \sum_{i=1}^{n} d_{ij} U_j$$

Correlation Among Episode Types

In the data we discovered that after controlling for the effect of observable characteristics on episode rates, the number of episodes that an individual had of one type was correlated with their numbers of other types of episodes. Specifically, the number of hospital episodes was correlated with acute and chronic episodes and the three types of outpatient episodes were correlated for an individual. The observed correlation pattern is described more completely in Appendix C. To replicate this correlation structure across types of episodes, we characterize U_j as the sum of either two or three gamma random variables, depending on episode type. One random variable introduces the correlation between hospital, acute, and chronic episodes, the second captures the correlation across outpatient episodes, and the third represents the effects unique to this type of episode. The derivation of these distributions is also discussed in Appendix C.

We use the convolution property of the gamma distribution: The sum of two independent gamma distributed random variables with parameters (α_1, β) and (α_2, β) has a gamma distribution with parameters $(\alpha_1 + \alpha_2, \beta)$. Note that both variables must have the same scale parameter β. For our simulation, we generate random variables with scale parameter one and rescale them to the appropriate value for each episode type. First we generate four independent gamma random variables V_j; $j = A$ (acute), W (well care), C (chronic), H (hospital) having parameters $(\gamma_j, 1)$, respectively, for the four episode types. Similarly, we generate V_{AWC} and V_{ACH}, from gamma distributions with parameters $(\gamma_{AWC}, 1)$ and $(\gamma_{ACH}, 1)$, respectively. We construct the unmeasured propensities U_j as:

$$U_A = \beta_A(V_A + V_{AWC} + V_{ACH})$$

$$U_W = \beta_W(V_W + V_{AWC})$$

$$U_C = \beta_C(V_C + V_{AWC} + V_{ACH})$$

$$U_H = \beta_H(V_H + V_{ACH}).$$

The U's are correlated and have gamma distributions with parameters (α_j, β_j) where

$$\alpha_A = \gamma_A + \gamma_{AWC} + \gamma_{ACH}$$

$$\alpha_W = \gamma_W + \gamma_{AWC}$$

$$\alpha_C = \gamma_C + \gamma_{AWC} + \gamma_{ACH}$$

$$\alpha_H = \gamma_H + \gamma_{ACH}$$

Episode Generation

Since the occurrence of an individual family f's episodes is modeled as a Poisson process with family episode propensity Λ_f, we know that the time between episodes has an exponential distribution with mean $1/\Lambda_f$. The simulation model actually generates episodes by computing the time between episodes from this exponential distribution.

To determine the type of episode and the family member to whom it occurred we observe that the probability that this is an episode of type j occurring to family member i is given by λ_{ij}/Λ_f. We map these probabilities onto the unit interval and draw a uniform random variate to determine the family member and the episode type.

The Cost of Treatment on the Free Plan

Once the model determines the type of episode and the person to whom it occurs, we use the regression equations from Sec. III to estimate the parameters of the log expenditure for this individual episode. Using the mean and the variance estimated from the overall regression equation, we generate a random variable from a log normal distribution with this mean and variance. We use stochastic variate generation methods as discussed in Fishman (1978, Chap. 8).

We observed in Sec. III, that the log normal distribution fit the observed episode costs reasonably well but was somewhat short tailed. To correct for this, we augment the size of large episodes. When a large random variate is drawn, defining large as the number of standard deviations above the mean as shown in column 1 of Table 5.1, we increase the value by the factor shown in column 2. No correction is made for well care episodes. A more complete discussion of the derivation of these factors is found in Appendix A.

Table 5.1

EPISODE COST EXPANSION FACTORS

	Standard Deviations Above the Mean	Multiplicative Factor
Hospital	1.8	1.28
Acute	1.8	1.31
Chronic	1.6	1.42

Censoring Pay Plan Episodes

Analyses in Sec. III showed that people on cost-sharing plans had fewer episodes of medical treatment and spent slightly less on each episode. The higher the coinsurance rate (the patient's share of the cost) the larger the reduction in both frequency and size. For families on cost-sharing plans the amount of cost sharing may vary throughout the year. For a typical health insurance plan, the cost sharing is 100 percent during the deductible period, drops to the coinsurance rate, say 25 percent, during the cost-sharing phase, and declines to 0 percent beyond the maximum expenditure limit.

Section IV proposed a model that divides the year into distinct periods that correspond to the price the consumer faces. We estimated the ratio of the number of each type of episode of treatment obtained by individuals with a specific cost-sharing rate relative to the number of episodes observed when individuals have no cost sharing.

We modeled the reduced number of episodes on cost-sharing plans as a Bernoulli censoring process applied to episodes generated for the free care plan. It is easily shown that a Poisson process with rate λ that has been subject to a Bernoulli censoring or loss of each event with probability $1 - p$ is equivalent to a Poisson process with rate $p\lambda$. (If the number of events produced by the original Poisson process with rate λ is n, then, conditional on n, the censored process produces a number of events with a binomial distribution with parameters (n, p).) Let $\pi_j(r)$ denote the occurrence response for an individual with coinsurance r for episodes of type j. Then the episode generating process may be thought of as Poisson with intensity $\pi_j(r)\Lambda_{f,j}$, where $\Lambda_{f,j}$ is the free plan rate episodes of type j for family f. In the simulation we actually censored free plan episodes when a uniform [0, 1] random variate exceeded the occurrence response ratio $\pi_j(r)$. (A new random

variate was generated independently for each free plan episode.) Occurrence response ratios estimated from the data were used to fit a curve of the form

$$\pi_j(r) = exp(b(j)r^{a(j)}),$$

where $a(j)$ and $b(j)$ are parameters estimated from the data. This functional form was used in the simulation.[1] The estimated parameters for each type of episode are shown in Table 5.2. Since the coinsurance rate may vary throughout the accounting year, the censoring rates for episodes of each type will vary as well.

The Reduced Cost of Pay Plan Episodes

Because the cost-sharing plans had slightly smaller episodes as well as fewer episodes, the episodes that were not censored off the cost-sharing plans were adjusted downward in cost. This adjustment was estimated from the data and fit to the same functional form Eq. (5.1) used for the censoring adjustments. The parameters for these equations are shown in the third and fourth columns of Table 5.2.[2]

Table 5.2

ESTIMATED PRICE RESPONSE PARAMETERS BY EPISODE TYPE

	Censoring		Cost Reduction[a]	
Episode	a	b	a	b
Hospital	0.11	−0.36	2.00	−0.202
Acute	0.54	−0.63	0.49	−0.125
Well care	0.94	−0.70	0.49	−0.125
Chronic	0.36	−0.58	0.49	−0.125

[a]Acute, well care, and chronic were constrained to have the same parameters, because the effect of cost sharing on their cost was indistinguishable.

[1]This curve, suggested by Martin Holmer, has $\pi_j(0) = 1$ and fits the observed data well. The estimated values for $a(j)$ and $b(j)$ minimized the sum of squared residuals. With this functional form the full pay plan censors $1 - \exp(b)$ of free plan episodes, on average.

[2]A more complete discussion of the derivation is found in Appendix F.

Catastrophic Hospitalizations

When an illness is quite serious, cost-sharing obligations may become unimportant relative to the value of obtaining necessary medical care. In these circumstances, we hypothesized that the occurrence and response to "catastrophic" conditions would not differ across plans. The data confirmed that catastrophic events were experienced with the same relative frequency on the free plan as on the cost-sharing plans. In addition, catastrophic episodes on the cost-sharing plans were similar in size to those on the free plan. Empirical work described in Appendix B estimated that the appropriate cut-off for "catastrophic" hospitalizations was $9,670 in 1983 dollars. As a result, within the simulation model, hospital episodes that occur on the free plan and exceed $9,670 are not censored.

Hospital Episodes with Low Out-of-Pocket Cost

In Sec. IV, we showed that when the amount of out-of-pocket expenditures needed to meet the MDE limit is small, rates of hospital (but not outpatient) episodes were larger than when the amount of out-of-pocket expenditures needed was large. Families probably realize that the total out-of-pocket cost of the hospital episode is limited to the amount of MDE remaining. Empirical evidence suggested that this change occurs when people come within $600 of the maximum dollar expenditure. We use this approximation in the simulation; only 10 percent of the hospital episodes are subject to censoring on the pay plans when a person is within $600 of the maximum out-of-pocket expenditure for that plan.[3] The uncensored hospital episodes are assumed to be as large as those experienced on the free plan. That is, cost sharing does not affect the episode cost when people are in the "anticipation" period (since the marginal cost of additional hospital care will be zero).

Basic Model Flow

The model generates a year of health spending experience for one family by generating episodes one at a time. The type of episode, its cost, and the person experiencing it are recorded for the free plan. For each of the 27 pay plans the episode occurrence is censored using the current effective occurrence ratio for that plan; uncensored episodes are then reduced in size until the MDE is exceeded.

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[3]See the last column of Table 4.8. Inflation in hospital costs brings the $400 threshold shown there to $600 in the 1983 dollars used in the simulation.

Both total and out-of-pocket expenses are recorded. The plan status is tracked through four periods as the year progresses, the deductible period, the cost-sharing period, the low-cost period for hospital episodes, and the period beyond the MDE. At a particular time each family member on a pay plan is in one of these four states. After an episode is recorded, this insurance state is updated. Different coinsurance rates may be associated with each of these states depending on the family's plan.

New episodes are generated and recorded until the year has elapsed. At this stage a new family is input and the process repeated.

Statistics and confidence limits were calculated using sequential estimation methods described in Fishman (1978, pp. 68–72). A set of individual level output statistics is shown in Appendix G.

Variance Reduction Techniques

We used several features in the design of the simulation to help reduce the variance of our estimates of plan differences. The first was in the design and implementation of the censoring process for the pay plans. Estimates for the pay plans were all calculated by censoring experience on the free plan. Calculating the pay plan estimates in this manner eliminates the variation resulting from random differences in health experience. This decision is most important for high-cost episodes. The assumption that catastrophic episodes are not censored was done for realism but further reduces the variances on plan relatives and plan differences.

The second design feature implemented to reduce the variance in our estimates was the use of antithetic variates in the censoring process.[4] For each year of health experience that we generated, we also generated an antithetic year that consisted of exactly the same health experience but with antithetic variates used in censoring. Each family's annual expenditures were then recorded by averaging the two years. Use of antithetic variates within the model was optional.

The effect of these techniques is best seen in the standard errors on plan differences. To demonstrate the effect of these design features, Table 5.3 presents a comparison of the standard errors for plan differences obtained from contrasts in the actual HIE data with those obtained from the simulation model. For the simulation model, we include a 25 percent coinsurance plan with a $1,000 MDE, a 50 percent

[4]Antithetic variates are sets of random variables chosen to induce negative correlation in the replications and thereby reduce the variance of the average. Typically, the value $1 - p$ is included with p in random [0, 1] draws. Fishman (1973, 1978) and Hammersley and Handscomb (1964) provide informative discussions on the use of antithetic variates.

Table 5.3

EFFECT OF VARIANCE REDUCTION METHODS ON PLAN DIFFERENCES IN TOTAL EXPENDITURES

	HIE Contrasts[a]	Censoring Design[b]	Censoring and Antithetics[b]
Standard errors	$43–$48	$6.50–$7.50	$3.00–$3.65
Sample size	5,809[c]	2,297	2,297
Person years	20,190[c]	9,188	18,376
Insurance-years per person-year	1	28	28
Total years of data	20,190	257,264	514,528
CPU seconds	—	607	1,092

[a]Manning et al. (1987).

[b]All comparisons are between free care and cost-sharing plans. Simulation results are based on four replications. Contrasts are conditional on estimated parameters of the effects of insurance.

[c]Contrasts are based on comparisons between those on the free plan and the 25, 95, and ID plans—these are approximately 30 percent and 20 percent each of the full sample.

coinsurance plan with a $1,000 MDE, and a 100 percent coinsurance plan with a $500 MDE. Among the plans in the simulation, these are closest to those used in the HIE. The plan differences are the cost-sharing plans relative to the free care plan. The censoring design, using four replications but without antithetic variates, reduces the standard errors almost 80 percent, from $27-$35 to $6.50-$7.50. The use of antithetic variates within the censoring design (four replications) further reduces the standard errors by 50 percent to $3.00-$3.65. Antithetic variates increase the computational burden by approximately 80 percent.[5]

Careful design control in the use of the random number streams allowed us to replicate health experience across runs, a third feature that assisted with variance reduction. One random number generator was used for the episode generation, sizing, and censoring and another for the correlation structure component of the model. Thus, we are able to replicate health experience across runs, so we can compare one run of 28 family deductible plans with another run of 28 individual deductible plans. In each run, individuals are confronted with the same free plan health problems.

[5]The runs reported here simulated 28 different insurance plans for 2,297 people in four replications, or 9,188 person years and 257,264 (28 × 9,188) insurance years of data. The tracking burden doubles with the use of antithetics.

Overall Plan Comparisons: Expenditures, Value of Treatment, and Risk Premiums

We use several measures to compare the different health insurance plans. Obvious measures of interest are total family and individual health expenses. Comparing total spending across plans gives a direct measure of the effect on society of different cost-sharing arrangements. If insurance is actuarially fair, the average total spending represents the sum of premiums that must be paid in advance and average out-of-pocket expenditures through the year.

Individual and family out-of-pocket spending provides information about the effect of these plans on the family's economic position.

We have estimated two additional comparison measures: the value of the marginal services purchased and the risk premium associated with each plan's coverage. For a brief exposition of the (welfare economics) theory underlying these measures, and a justification for the simulation method, see Appendix D. Briefly, we assume that each individual has a demand curve proportional to the overall demand curve, and we measure value as the out-of-pocket cost plus consumer surplus associated with each treated episode with severity (probability of treatment) generated randomly. We compute the value of services purchased from the individual's point of indifference between purchasing and not purchasing the episode of treatment. Indifference means that the value of the episode is equal to the out-of-pocket expense, namely, the coinsurance rate times the cost of the episode. To implement this concept within the model, we use the uniform random variate drawn for the censoring step to calculate the break-even coinsurance rate at which an individual is just indifferent between purchasing and not purchasing the episode of treatment as the inverse value from the frequency demand curve. A slight adjustment is necessary because the individual is assumed to buy slightly more care at his actual coinsurance rate, which is lower than the break-even coinsurance rate.

Our measure of the risk premium is proportional to the variance of out-of-pocket expenditures.[6] The measure is derived from expected utility theory and assumes that insurance is obtained as protection against financial risks. We further assume that people evaluate risky choices in terms of the mean and variance of out-of-pocket spending. Plans with highly variable out-of-pocket expenses provide less protection against large financial losses than plans with the same average

[6]Antithetic variates were not used in runs where interest focused on risk measures, since their use artificially reduces the variance of out-of-pocket expenses for plans with cost sharing along with variances in plan differences.

out-of-pocket expenditures and more predictable out-of-pocket expenses. For further discussion, see Appendix D.

Model Validation

The model was tested to determine whether it could, in fact, generate health expenditure experience similar to that experienced by families in the HIE. We used the Seattle sample to validate the model. We constructed plans similar to the HIE plans and compared the average numbers of episodes generated by the model with actual data. These comparisons are shown in Table 5.4. Columns 1 (HIE data) and 3 (simulated data) contrast free plan rates and columns 2 (HIE data) and 4 (simulated data) show pay plan comparisons. The pay plan comparisons are not exactly comparable; for the HIE data all pay plans are grouped together. These are compared to a 25 percent coinsurance plan from the simulated data. (Because of the MDE, annual results are fairly similar for all cost-sharing plans.)

Comparisons between simulated and observed total annual spending were also performed. These highlighted the underestimation of the tails of the cost distribution and led to the introduction of the cost expansion factors discussed earlier in this section.

In addition, using the Seattle HIE population, we created pseudo-claims corresponding to the health experience generated by the model. These claims were then used in the empirical estimation programs. A

Table 5.4

A COMPARISON OF HIE DATA AND SIMULATED DATA AT THE FAMILY LEVEL

	HIE Seattle		Simulation Data	
	Free Plan	Pay Plans	Free Plan	25% Plans
Probability of hospitalization	0.32	0.28	0.33	0.29
	(0.03)	(0.03)	(0.03)	(0.03)
Acute episodes	6.17	4.6	5.83	4.20
	(0.25)	(0.21)	(0.30)	(0.22)
Chronic episodes	2.02	1.40	1.88	1.56
	(0.09)	(0.09)	(0.10)	(0.09)
Well care episodes	1.73	1.5	1.70	1.40
	(0.08)	(0.08)	(0.08)	(0.09)

NOTE: Standard errors are given in parentheses.

comparison of the gamma parameter estimates derived using the pseudo-claims, and those developed from HIE data, is shown in Table 5.5. Although the gamma parameters appear to differ, all differences fall within 1.3 standard errors of the difference.

The pseudo-claims data were also used to test whether our methods for introducing correlation between types of episodes actually produced the expected correlation. These results are discussed more fully in Appendix C.

MODEL RESULTS AND DISCUSSION

How Total Expenditures and Other Measures Vary with Different Coinsurance and MDE Limits

Keeler et al. (1977a) hypothesized that the demand for medical services as a function of the maximum out-of-pocket expenditure was shaped like a logistic or backward "S"; people with small MDEs behave as if they have no deductible (because with high probability they will exceed it) and people with large MDEs behave as if they have no insurance.

To test this idea, we used the simulation model to compare expenditures on 28 different insurance plans. We used a simple structure for the plans; no initial deductible, a cost-sharing period of 25 percent, 50 percent, or 100 percent up to the MDE, and no cost sharing beyond. The MDE was an individual MDE with no limit on the number of MDEs per family. We used MDEs of $50, $100, $200, $500, $1,000, $1,500, $2,000, $3,000, and no limit. All plans were compared to the free care plan and to a full pay or no insurance plan.

Table 5.5

GAMMA PARAMETERS ESTIMATED FROM SIMULATED DATA COMPARED WITH ESTIMATES FROM ACTUAL DATA

	HIE Data	Simulated Data	Standard Errors of Difference
Hospital episodes	0.97	0.58	0.3
Acute episodes	2.5	2.8	0.3
Well care episodes	4.7	7.1	2.5
Chronic episodes	2.3	2.7	0.5

Our results[7] were somewhat different than hypothesized. Figure 5.1 graphs average per capita total spending against the MDE for plans with each of the three coinsurance rates. For comparison, we also include spending when all care is free and when all care must be paid for. These are shown as horizontal lines, but are actually points, since such plans do not have MDEs. Per capita spending is reduced as the MDE increases for plans with all three coinsurance structures. The lower portion of the graph shows how individual out-of-pocket expenditures are increasing with the MDE whereas the upper portion shows how total spending decreases with the MDE. There is a break along the horizontal axis between the $1,000 MDE and the last point which corresponds to no MDE.[8] Out-of-pocket expenditures do not increase sharply after the $1,000 MDE point but continue to rise gradually to these limits. The decline in total expenditures is quite sharp as the MDE increases from $0 to $200 for all three coinsurance rates. Coinsurance, even with a small MDE, effectively deters total spending. Since deductibles followed by free care can be thought of as 100 percent coinsurance with an MDE, this means that even a small such deductible has an impact on spending.

Expenditures decline less steeply as the MDE increases from $200 to $1,000. The increased drop from an MDE of $500 to $1,000 on the 100 percent coinsurance plan is due to the assumption about "low-cost" hospital episodes: $500 is low-cost, but $1,000 is not. In a test where we reduced the definition of "low-cost" to less than $300, the steep part of the curve was between $200 and $500 (dashed line in Fig. 5.1). Beyond $1,000 we observe only small changes, as anticipated. Because larger MDEs increase exposure to financial risk, with little effect on use for plans with the same coinsurance rate, they are unattractive. The expenditure level for large MDEs differs significantly across the different coinsurance rates. A $1,000 individual MDE and a coinsurance rate of 25 percent reduces average per capita simulated expenditures by 57 percent of the difference between the free care and full pay rates, whereas a 100 percent coinsurance rate and a $1,000 MDE reduces per capita simulated expenditures to less than 10 percent over the full pay rate.

The percentage of individuals who exceed the MDE for each of the plans is graphed in Fig. 5.2. The average amount of time beyond the

[7]These results are based on runs with eight replications and do not use antithetic variates.

[8]The values for no MDE should be the same on average as the effect of pure price on total medical shown in Table 4.9. The only difference is that in the simulation, catastrophically large hospitalizations are assumed to be inelastic, whereas in Table 4.9, they are treated like any other hospitalization.

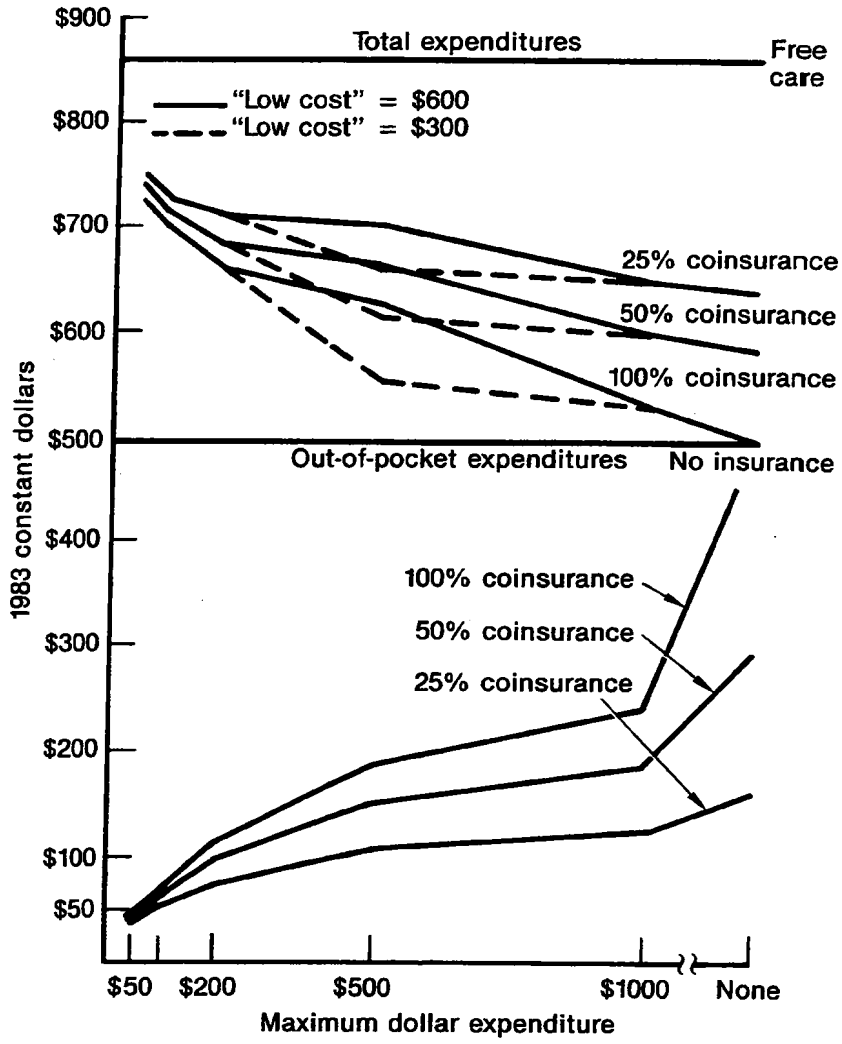

Fig. 5.1—Per capita total and out-of-pocket expenditures, individual deductible plans

MDE for people exceeding the MDE is about half the year on each of the plans.[9] With a $50 MDE, 60–70 percent of the people exceed the MDE for plans with more than 25 percent coinsurance; slightly less than 50 percent exceed the MDE on the 25 percent coinsurance plan. At $1000 MDE, fewer than 10 percent of the people in any plan exceed the limit.

The average value of services used for each of the plans is graphed against total per capita expenditures in Fig. 5.3. Recall that total expenditures are inversely related to the size of the MDE; that is, larger expenditures correspond to smaller MDEs. The minimum MDE pictured is $50; an MDE of $0 is another name for free care for any

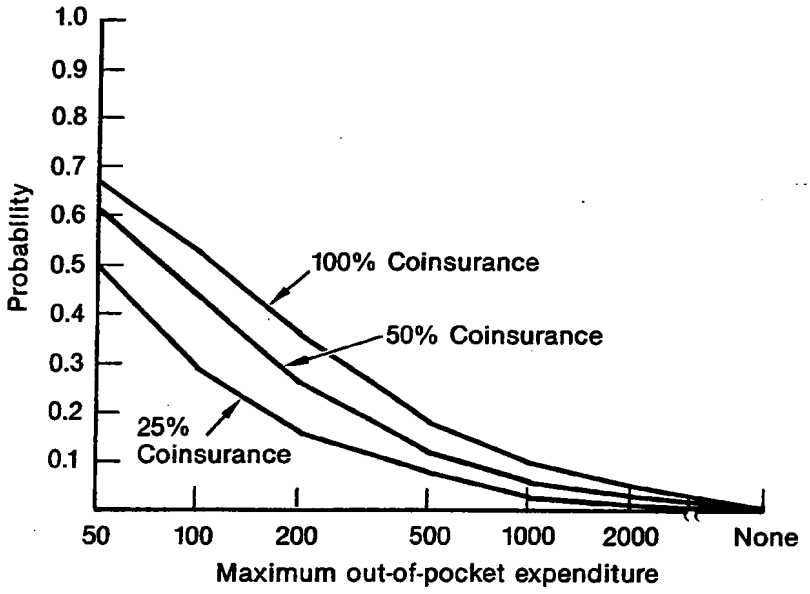

Fig. 5.2—Probability of exceeding the maximum out-of-pocket expenditure, individual deductible plans, 1983 constant dollars

[9]For larger MDEs, one plausible explanation for this is that it takes a hospitalization to exceed the MDE, and these are rare and randomly distributed over time.

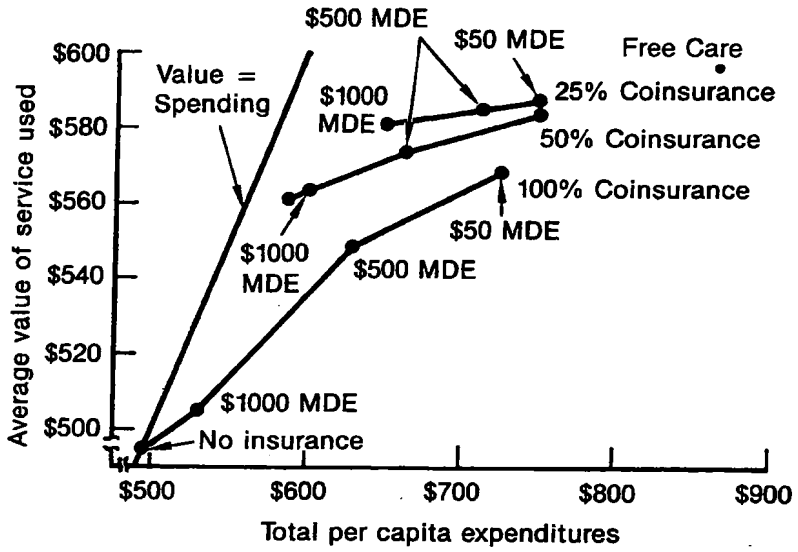

Fig. 5.3—Average value of services used, individual deductible plans, 1983 constant dollars

coinsurance rates. For plans with 25 percent coinsurance in the cost-sharing phase, the average value of services used does not vary much ($581 to $588), nor does the average per capita expenditures ($641 to $750). For the 50 percent coinsurance plans, the average value of services increases from $561 to $582 with the increase in total expenditures. For plans with 100 percent coinsurance, both total expenditures and the average value of services vary more extensively. The average value of services increases sharply as average expenditures increase from the point of no insurance, that is full pay, to over $600. Beyond this point, the value continues to increase, but at a slower rate. The lower total expenditures are associated with plans with more cost sharing and little or no protection against major expense. For these plans, valuable services are being forgone.

The average risk premium for each plan's coinsurance rate and out-of-pocket limit is plotted in Fig. 5.4. Minimal risk is associated with

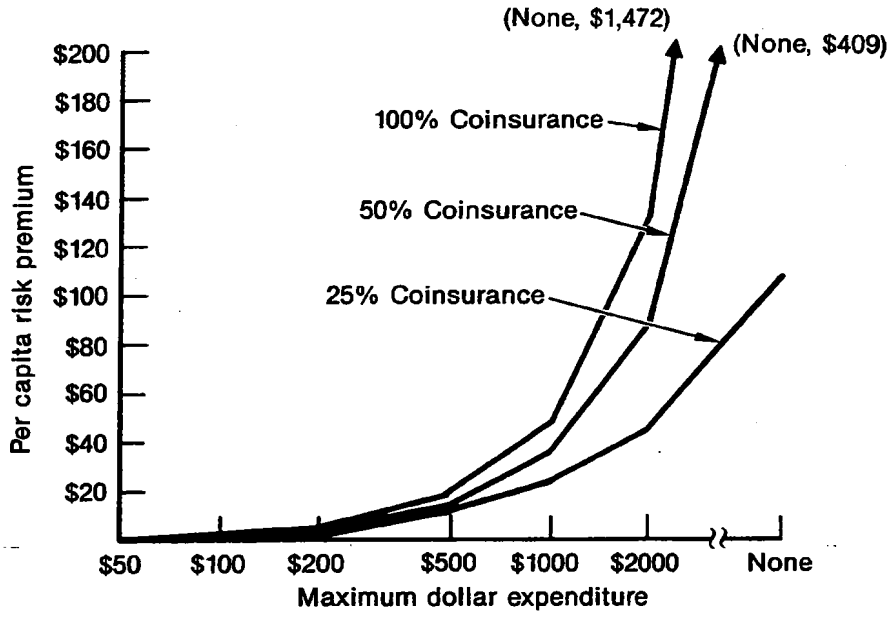

Fig. 5.4—Per capita risk premium, individual deductible plans, 1983 constant dollars

any of the plans with maximum out-of-pocket limits less than or equal to $500. Beyond this, risk levels increase rapidly. The rate of increase is higher for plans with larger coinsurance rates.

Plan Differences

Another way to look at how total per capita expenditures vary with different coinsurance and MDE limits is to calculate plan differences. Plan differences are a summary measure that captures the effect of structural differences between the insurance plans on total per capita spending. Confidence limits around the differences provide an easy method of determining when the statistically measured differences are significant. Table 5.6 presents plan differences for a selected subset of the simulated plans. The reported difference is the total per capita

Table 5.6

PLAN DIFFERENCES OF TOTAL PER CAPITA EXPENDITURES, FOUR REPLICATIONS OF SIMULATED DATA, 1983 CONSTANT DOLLARS
(Confidence Limits)

Coinsurance/ MDE	25/1000	50/1000	100/1000	No Insurance
Free	$206.56	$255.31	$327.40	$359.31
	(9.56)	(9.71)	(16.20)	(13.63)
P25/1000		48.75	120.84	152.75
		(3.08)	(10.83)	(12.93)
P50/1000			72.09	104.00
			(8.15)	(10.27)
P100/1000				31.91
				(7.23)

NOTE: For comparison, the free plan mean is $842.24.

expenditures for the plan listed at the left-hand side of the table, less the total per capita expenditures for the plan described in the column heading. Thus we observe that the expected difference in per capita spending is $359 higher for people with the free care plan than for individuals with no insurance. Differences between the free plan and cost-sharing plans are smaller. Results are based on four replications and use antithetic variates to obtain maximum variance reduction. A complete set of differences for all 28 plans is presented in Appendix G.

Comparisons Between Individual and Family MDE Limits

Most health insurance plans in the United States have limits on the maximum out-of-pocket expenditures that an *individual* faces. However, it is the family's economic position that is affected by these expenses. As insurance pools risks over a group of people, health insurance plans could pool risks over the family by creating plans with family maximum out-of-pocket limits instead of individual out-of-pocket limits.[10]

[10]We have shown previously that family deductibles have lower variance of family out-of-pocket payments than a set of equivalent (in the sense of equal out-of-pocket payments) individual deductibles, assuming that people do not respond to their insurance status (i.e., completely inelastic demand) (Keeler et al., 1977b). Here we see the effects of elastic demand (of the magnitude observed in the HIE) on this conclusion.

To compare plans with individual and family MDE limits, we began by looking at plans with the same average per capita expenditures.[11] For each set of individual limits, we can find a family limit plan that is equivalent in the sense that overall family spending is the same on average for the people in the simulation. Figure 5.5 shows the relationship between the individual MDE limit on the vertical axis and the family limit on the horizontal axis (this family limit was not computed directly, but the value was interpolated from family limits that led to more and less spending than the individual limit). The total amount of per capita expenditures for the two plans is written next to each discrete point. We have displayed the results only for the 25 percent coinsurance plans; however, results for plans with 50 percent and 100 percent coinsurance were similar. We found that small individual

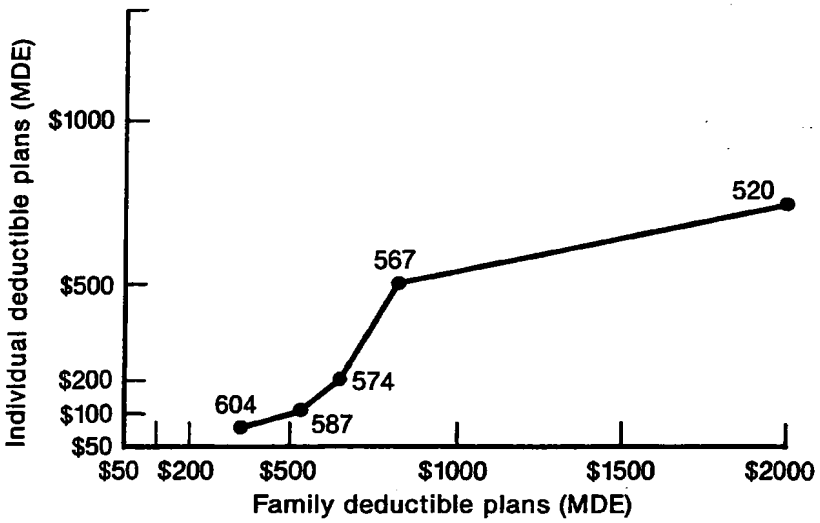

Fig. 5.5—Individual and family deductible plans with equivalent total expenditures (shown by numbers on graph) 25 percent coinsurance, four-person families

[11]For these comparisons, we limited our analyses to four-person families in our original CPS subsample. This yielded 134 families, 536 individuals, and we performed 20 replications within each comparison run. No antithetic variates were used.

MDE limits corresponded to much larger family limits. Individual limits of $50 yielded average expenditures equivalent to a single four-person family limit of $350—more than four times the size of the combined individual plans. Results were similar for $100 individual limits but the relationship changed markedly at the $200 individual limit level where a family limit of $657 yielded the same average expenditure levels. This relationship follows from our assumption about "low-cost" hospital episodes; plans with small limits are always in the "low-cost" range. As limits increase, families begin their health insurance year without "low-cost" hospital episodes and consequently spend at reduced rates. For very large limits, both individual and family limit plans have lower spending rates.

Figure 5.6 displays the relationship between risk and out-of-pocket expenditure for these "equivalent" plans. Risk values are always higher for the family deductible plans than for the equivalent individual deductible plan where the equivalence is in average per capita total expenditures. Average per capita out-of-pocket expenditures are generally higher for family limit plans. The exception occurs for the middle range of limits where the individual deductible plans have small enough limits to always be in the "low-cost" hospital episode phase but the family limit plans do not initially have "low-cost" hospital episodes. Thus, on these dimensions, individual MDE plans appear superior to "equivalent" family MDE plans. (Also, shorter time periods are probably better than longer ones.)

In an earlier paper, we showed that equivalent family limits or deductibles were generally superior to individual MDEs or deductibles, assuming that price had no effect on use (Keeler et al., 1977b). Thus, the problem with family deductibles is the waste from excess use when a hospitalization of one member leads to free care for all. Assuming that people ultimately have to pay for their care on average either out-of-pocket or through the premium, it is better to compare plans with the same total spending than plans with the same out-of-pocket spending. In our earlier work, with completely inelastic demand, these two comparisons were the same.

The advantage of individual limits or deductibles derives from three empirical points. First, with individual limits lower priced care is better targeted at the sick. The probability that individuals exceed the limit is lower with the individual limit than with the equivalent family limit. The reason is that with an individual limit family members who go to the hospital take only themselves over the limit, but with a family limit, they carry the other healthier family members with them. Thus the group of people over the limit with individual limits is smaller and sicker than the group with family limits on average.

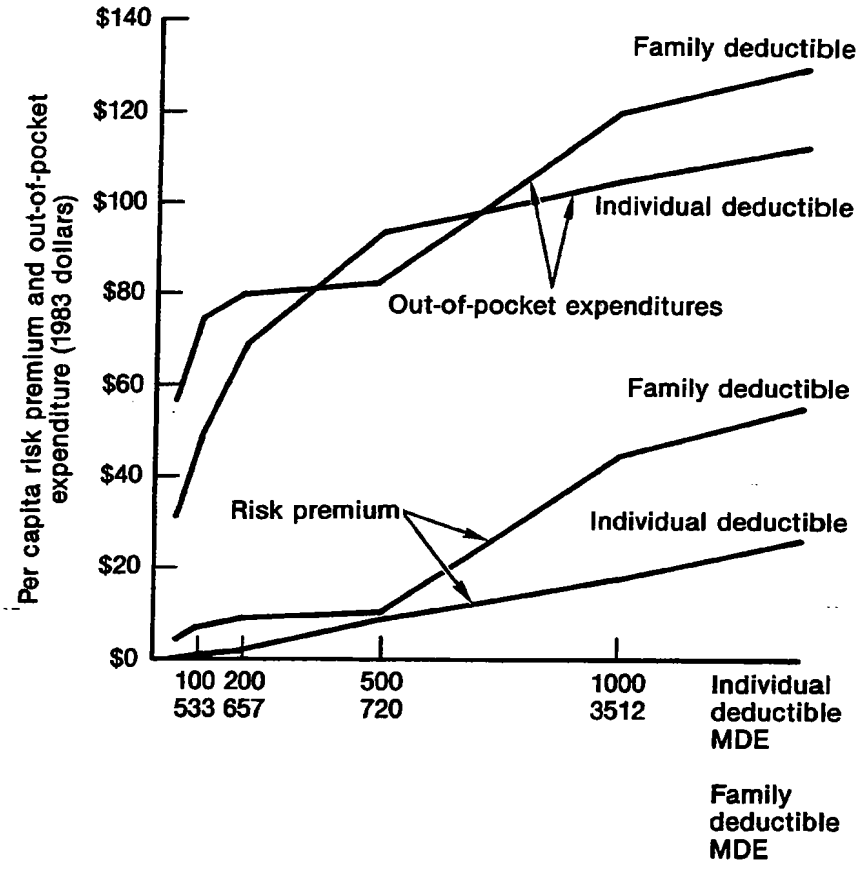

Fig. 5.6—Comparison of equivalent individual deductible and family deductible plans, 25 percent coinsurance

Individual limits do a better job of covering only the sick (in particular, hospital expenses are less price elastic so there is less waste in having them fully covered).

Second, individual limits are less risky. Family limits are generally much bigger than equivalent individual limits (otherwise the

discrepancies in the probability of individuals exceeding the limit with a family limit would be even greater). The financial risk of a big expensive episode is cut short by the individual limit, but may be considerable with the family limit. Even when the average out-of-pocket spending is similar on both plans, the risk is higher with the family plan. Third, individual limits or deductibles are easier to administer because one does not need to keep track of who is in the family.

The Effect of Deductibles on Expenditures

We looked at the effect of initial deductibles of $100, $200, and $300 on both 25 percent and 50 percent coinsurance plans with MDE limits of $500 or more. In these comparisons, the MDE remains constant but the patient pays the first $100, $200, or $300 of cost as compared to the previous runs where cost sharing started with the first dollar of health care purchased. For 25 percent plans with a $500 MDE, average total per capita expenditures fell 19–22 percent with deductibles and for larger MDEs the drop was 14–19 percent. Plans with $300 initial deductibles were at the upper end of the range. The analogous figures for 50 percent coinsurance plans are 16–18 percent and 10–13 percent. Average per capita out-of-pocket expenditures increased $25-$75 with deductibles on the 25 percent plans and $7-$37 on the 50 percent plans compared to no deductibles.

Optimal Insurance Plan Design

Insurance theory suggests that a well-designed health insurance policy is one that simultaneously reduces risk borne by the insured and reduces waste from excess spending (Zeckhauser, 1970). Waste is defined as the difference between the total cost and the value of the medical services that are purchased. In Table 5.7, we use this measure (see column 7) to compare alternative insurance plan structures. For comparison purposes, all of the coinsurance plans have a $1,000 individual MDE but differ in the initial deductible—$0, $100, $200, or $300—and in the coinsurance rate—25 percent, 50 percent, or 100 percent. If we consider only plans with an initial deductible of $0, the 100 percent coinsurance plan is preferred with combined risk and waste of $73 to either the 25 percent coinsurance plan ($93) or the 50 percent coinsurance plan ($74). The introduction of initial deductibles of $100, $200, or $300 markedly improves the plans with lower coinsurance rates. From the table, we observe that the "best" plans with waste plus risk equal to about $45-$50 are the 25 percent coinsurance plans with any of the initial deductibles. It is interesting to note that these plans

Table 5.7

PLAN COMPARISONS FOR OPTIMAL INSURANCE PLAN DESIGN

Coinsurance Rate	Deductible	MDE	Per Capita Total Expense	Out-of-Pocket Expense	Value of Spending[a]	Risk Premium[a]	Waste Plus Risk
0%	0	0	860	0	595	0	265
(Free)	100	100	696	68	562	1	135
	200	200	659	112	555	3	107
25%	0	1,000	650	126	581	24	93
	100	1,000	557	154	528	22	51
	200	1,000	536	180	516	25	45
	300	1,000	529	199	510	29	48
50%	0	1,000	601	185	563	36	74
	100	1,000	543	197	522	35	56
	200	1,000	531	211	512	37	56
	300	1,000	526	221	508	39	57
100%	1,000	1,000	529	243	505	49	73
No insurance		—	494	494	494	1,472	1,472

[a]Value is measured by out-of-pocket cost plus consumer surplus. Risk is proportional to the variance of spending. For details on how these are measured, see Appendix D.

are quite similar in structure to actual insurance plans offered by many employers throughout the country. Perhaps insurance theory is not completely speculative!

Sensitivity of Results to Assumptions About Catastrophic Events

Suppose we did not assume that people always respond to catastrophic events (and instead continued censoring of hospitalizations over $11,000 (1986 dollars)). Relaxing the assumption would increase total expenditures $20–$50 per person depending on coinsurance. There would be only modest effects on risk for plans with limits on maximum out-of-pocket expenditures; but there would be large impacts on risk for plans without these limits.

OTHER MODEL USES

A PC-variant of the model, developed by Martin Holmer, has been used in an analysis of flexible spending accounts for the Office of the Assistant Secretary for Planning and Evaluation, U.S. Department of Health and Human Services. Martin Holmer and Susan Marquis also used his model to analyze questions about the choice of supplementary health insurance which were asked of all participants in the HIE (Marquis and Holmer, 1986). We have used comparisons of results from the somewhat different variants to cross-validate the models.

In the future, we hope to use the simulation model to examine the pricing structure of catastrophic insurance plans. We have obtained data from several insurance companies on how they would price catastrophic health insurance coverage. These data suggest that the methods currently in use for pricing insurance plans may not extrapolate well to catastrophic coverage. In addition, we may use the model to suggest appropriate insurance premiums that depend on family composition.

VI. CONCLUSIONS

We undertook this episodic analysis to more closely examine behavior than was possible in annual analyses of health care spending by plan (Manning et al., 1987). In particular, we wanted to separate the effects of coinsurance and the cap on out-of-pocket spending that are combined in HIE insurance plans. The results are as follows.

1. Both coinsurance and deductibles have strong separate effects. We estimate that with no cap on out-of-pocket spending, those with 100 percent coinsurance (i.e., no insurance) would spend about 56 percent of the amount of those with free care, those with 50 percent coinsurance would spend about 65 percent, and those with free care and those with 25 percent coinsurance would spend about 72 percent. With full coverage after a deductible, those with a $100 deductible spend 81 percent of the amount of those with free care, those with a $500 deductible spend about 73 percent, and those with a $1,000 deductible spend about 61 percent.

2. Coinsurance reduces the cost per episode slightly, especially on the family deductible plan, but the main effect is on the number of episodes. The limited effects on cost per episode in the larger sample reinforces our earlier conclusion that cost sharing reduces expenditures by inducing patients to have fewer of their episodes of illness treated (Keeler and Rolph, 1983). The increased rate of treatment episodes with better insurance explains both the increased probability of any care and the higher spending for those with some spending. (The probability of any medical spending on the free plan was 86.8 percent as opposed to 72.3 percent for the 95 plan, while the expenses per spender were $863 with free care, and $765 on the 95 percent plan (Manning et al., 1987).

3. Different episode types represent different decisions. Price has similar effects on all types, but other characteristics have quite different effects on different episodes. Acute, chronic, and hospital episodes are strongly related to sickness, whereas dental and well care episodes are more related to income and education. Acute episodes are less affected than the other types by price changes within the year—presumably people have less ability to defer treatment of acute illnesses to times when the MDE is exceeded. Although plan had more effect on outpatient than on hospital expenditures, the main reason for this is that people going into a hospital are more likely to have already exceeded their MDE than people starting an outpatient episode.

4. Deductibles can effectively reduce demand. Before we analyzed the data, we thought that people might time their medical care purchases to take advantage of the years in which they exceeded the deductible and care was free. However, the rates of spending on the cost-sharing plans remained below the free plan rates for outpatient and dental episodes in the period after the MDE was exceeded. The rates rose somewhat after the MDE was exceeded and for well care approached the free plan rate, but there were no sales sprees to wipe out the pre-MDE reductions.

Effects of having a small amount of MDE remaining (anticipation of free care) were even smaller. We assumed that people would anticipate expenditures within an episode, but except for hospital, we could detect no anticipation effects on starting other episodes. For nonhospital episodes, there was no difference in spending rates between those with a little and those with a lot of MDE remaining. For hospital and (in another study for episodes of) mental health treatment (Keeler et al., 1986), we saw more spending by those with just a little MDE remaining, but people might well decide to have these expensive treatments because the total out-of-pocket price was low (relative to the total price), without thinking about future spending on other episodes. The exact value of the MDE remaining that distinguishes low-priced hospital episodes is arbitrary, but this effect is real. The myopic behavior of participants in the experiment may be another instance of bounded rationality—people may not have the energy to think about their future insurance status, or enough experience to take advantage of these temporary changes in price.

5. Although pure price effects computed here are larger than plan effects given in Manning et al. (1987), the demand for medical care on the HIE was not very price elastic. People with a moderate amount of coinsurance did not spend much more on average than they would without any insurance. Even those with free care would not spend twice as much as we estimate they would with no insurance. One reason for the estimated inelasticity is that we assumed that catastrophic expenditures are similar on all plans. There are not enough data to tell exactly how much of this is due to our $1,000 cap on expenditures, which makes any catastrophic hospitalization a bargain. Because of the financial risk, cost sharing is not a good way to ration the higher-priced hospital episodes, so some other rationing mechanism may be necessary.

6. Episodes have properties that make simulation easy. Although different people have different underlying rates, the episodes appear to arrive independently over time; there is not a strong relationship between cost and number, they are roughly lognormal; current status

seems to determine behavior; and price acts mainly to censor a proportion of the episodes in the pre-MDE period.

Because we wanted accurate predictions, we have tinkered with the model to include slight corrections to lognormality, correlation of episodes for family members, and special treatments for catastrophes and for hospital episodes with a low out-of-pocket price because of the MDE.

IMPLICATIONS FOR INSURANCE DESIGN

Results from our empirically based simulation model have several implications for insurance design. The implications depend in part on the contending goals of insurance. The main economic benefit of insurance is protection against rare financial catastrophe. Another possible benefit is that coverage sets up a philanthropic transfer from the rich (in terms of health) to the needy. The economic cost is the waste associated with overuse by the insured (moral hazard). If policyholders buy treatments that they did not value enough to buy at full price, society is wasting resources. Society is using $x to produce a service that patients value at something less than $x. The difference is a measure of the welfare loss to society. We can summarize the implications of the simulation model for insurance design.

1. Even fairly small deductibles curb demand. We had hypothesized that the graph of purchased medical services as a function of deductibles would have a backward S shape (Keeler et al., 1977a). We thought a flat initial period where deductibles would be so small they would have little effect on behavior would be followed by a steep fall in the region of middle-sized deductibles and then a flat region in the range of big deductibles where everyone would be acting essentially as if they had no insurance. However, the data showed decreased rates of outpatient spending even when the MDE was small. Our simulations, reflecting this, showed a fairly smooth decline of spending throughout the range of small- and medium-sized deductibles. Thus, we would predict that even $100 deductibles would be effective in curbing demand. Perhaps $10 deductibles would be ineffective, but no one is proposing them. Smallish deductibles suffice to keep down outpatient spending, and since hospital spending is less elastic, even large deductibles do not reduce hospitalization that much. Past $1,000 (1986 dollars), increasing deductibles has little effect on demand and greatly increases financial risk, so there is less reason to have family deductibles much bigger than $1,000.

2. Individual deductibles seem generally better than family deductibles. They are easier to administer because insurers need not keep track of family composition, and they have other theoretical advantages. Since with a family deductible, one hospitalized individual can take a whole family into a period of free care, family deductibles need to be considerably bigger than individual deductibles to keep expenditures to a given level. This increases the financial risk relative to a set of smaller individual deductibles. For the same reason, short time periods (or possibly even visit fees) may be better than long period aggregate deductibles.

Our earlier theoretical result that family deductibles had lower variance than equivalent individual deductibles because of risk-pooling was actuarial (Keeler et al., 1977b). It did not include any economic response to exceeding the deductible, and this response turns out to be crucial. Perhaps we should have foreseen that our assumption of no response was not good, but its omission is an example of a general problem in policy analysis. In analyzing any new policies, we would like to include behavioral response to the policies, but this is often hard to do.

3. Actuaries and insurance companies do quite well in offering desirable policies by our criteria. The best policy according to our measures is similar to common major medical policies. It has a small individual deductible, and 25 percent coinsurance up to a $1,000 cap on out-of-pocket expenses. Without experience, insurance experts have a hard time predicting expenses.

IMPLICATIONS FOR HEALTH SERVICES RESEARCH

Cost Sharing Affects Patients But Not Doctors

What inferences can be drawn about patient and physician behavior from the limited effects of cost sharing on the similarity of costs per episode? If the severity of treated illness was similar on different plans, then cost sharing did not affect the course of treatment. This may not be surprising, because claims in the experiment were filed on forms that were the same for both free and pay plans. Many physicians would be unaware of the fraction of charges paid by the patient.[1] In addition, some physicians may believe it improper to offer cheaper and lower-quality care to patients who have to pay cost sharing. Although they may confer with physicians about whether to go to a

[1]However, in exit interviews, 70 percent of patients said that their doctor knew or had been told of their insurance status.

hospital, hospitalized patients have even less opportunity to influence costs than ambulatory patients.

Other analysts have tested whether the mix of cases treated on different plans was the same in terms of severity of disease or necessity of treatment. Analyses of differences in rates of episodes by diagnosis showed that cost sharing had similar effects in curtailing use of highly effective and rarely effective medical care (Lohr et al., 1986). Similarly, the proportion of unnecessary hospitalizations was similar on all plans (Siu et al., 1986), and the proportion of inappropriately given antibiotics was similar on all plans (Foxman et al., 1987). These findings support the case that it is not just the mildly ill who would get treatment with free care but not with cost sharing. The average severity of illness may indeed be similar on all plans, and the course of treatment may not be affected by cost sharing.[2]

If care for those in the system is not much affected by cost sharing, then how might cost sharing affect health? We have shown elsewhere that free care led to lower rates of uncontrolled hypertension in the study through additional contact with physicians that allowed better detection of hypertension (Keeler et al., 1985). About one third of the difference between free care and cost-sharing blood pressure levels was due to the 7 percent of hypertensives with cost sharing who had no physician visits over the entire course of the study (as opposed to 2 percent of hypertensives with free care) and even more was due to those with cost sharing who did not get a diagnosis of hypertension. Those who knew they had high blood pressure at the start of the study, or those whose blood pressure was diagnosed did equally well under cost sharing and free care (Keeler et al., 1985).

In general, if price affects the decision to seek care, it will be important to supplement quality of care analyses with studies of how appropriately patients initiate episodes.

Episodes Are Useful in Analysis

Aggregating care into episodes has been shown to be useful for studies of quality of care, reimbursement, planning, and HMO management (Lohr et al., 1986; Hornbrook et al., 1985). In addition, as shown here, they can be useful in economic analysis. The statistical methods developed here were also used in studying episodes of mental health treatment, which are much more stable than most medical episodes (Keeler et al., 1986). Episodes of treatment are well-behaved statistically. They appear to be roughly independent over time and roughly

[2]Cost sharing was selective in its effect on emergency room use (O'Grady et al., 1985).

lognormal. Negative binomial models appear to fit the number of counts well, permitting fairly easy analysis of factors influencing the rate of episodes. For both medical and mental health care, a study of episodes led to insights on what determines whether people will get care. Unfortunately, as Hornbrook et al. (1985) note, and as we found in the HIE, we may need different kinds of episodes for different purposes and creating episodes is not an easy task.

One reason episodes were difficult to put together was that we wanted to keep track of total anticipated expenses. We assumed that spending within an episode (such as pregnancy or a series of dental procedures) is anticipated early in the episode, and spending decisions change as soon as a family is aware that spending on current episodes will push them over the cap. Because of this assumption, we had to work hard to link up spending on all episodes by family members. It would have been much simpler to subtract out-of-pocket expenses from the MDE by date of service through the year. This simpler version might do as well to determine MDE status (except possibly for pregnancy, which might be billed in advance), but analysts still would have to define the unit of patient decisions.

Limitations

Even the 17,000 person-years of experience studied here leave some questions unanswered. We face the fundamental problem of health econometrics that 1 percent of the sample does 30 percent of the spending (Manning et al., 1987; Newhouse, 1987). We were not able to establish, by normal statistical standards, what size, if any, of catastrophic episodes was so large that price or in particular the $1,000 limit on out-of-pocket expenditures has a negligible effect. Unfortunately, estimated demand is affected by what is assumed. For plans with very large deductibles, estimated demand can decrease by $50 if we assume that catastrophically large episodes are affected by insurance.

The sample size was also too small to discover any effects of almost being over the MDE (e.g., having $20 left in possible out-of-pocket expenditures). This gap may not be important unless the world becomes interested in $50 deductibles again. Hospital episodes were sufficiently rare that we were unable to tell how much MDE remaining could be considered small. Hospital episodes were more frequent when the MDE remaining was small, but our methods required us to make a few divisions and estimate average behavior in the resulting few categories. We made $400 (1977–1981 dollars) the dividing line between big and small, but presumably decisions depend continuously on the amount of MDE remaining and our data were not up to finer

divisions. Since the HIE participants were only a small fraction of the population in each site, we cannot say much about effects on the supply of medical services if a large fraction of people in an area changed insurance.

The differences in use of medical services by site, income, and education were remarkably small. This may reflect a consensus about what is desired for those patients with some insurance coverage. The patterns of welfare losses in our simulations show that the big differences in welfare lie between those with some insurance and those with none. This accords with findings that the health consequences of losing all insurance can be severe for the poor (Lurie et al., 1984). Modifying current insurance policies in accord with our results can save some money at a low cost in welfare. Still, the largest gains in welfare will not result from such tinkering but from extending insurance coverage to those who currently have none.

Appendix A

DEPARTURES FROM LOGNORMALITY OF EPISODE COSTS

The distribution of costs per episode is approximately lognormal but there is some extra mass out at the 98th and 99th percentile. This has virtually no effect on inferences about the coefficients of covariates. It is important for predicting and simulating hospitalizations because catastrophically large hospital costs are treated separately by the simulation model and because even a few large individual hospital costs represent a large proportion of the mean.

One way to handle the effects of the departure from lognormality in the extreme tail in the simulation is to increase the variance of the random component of log (costs). Because the mean of the lognormal distribution is $\exp(\mu + \sigma^2/2)$, where μ and σ^2 are the mean and variance of the corresponding normal distribution, a larger variance of the log leads to a larger mean. We instead decided to modify just the upper tails of the lognormal distribution. Table A.1 compares percentiles of the observed residuals from a regression of the log of hospital costs with theoretical values if they were truly lognormal. Note the differences at the 96th through 99th percentiles.

In Table A.2, we see a similar pattern for the acute and chronic episodes, but cost per dental episode is not even close to lognormal (skewness = 1.1), and cost per episode for well care is approximately lognormal. For hospital episodes, we could shift the upper values up

Table A.1

RESIDUALS OF LOG HOSPITALIZATION COSTS ARE NOT QUITE LOGNORMAL

	Percentiles						
	90	95	96	97	98	99	Maximum
Residuals	0.89	1.29	1.44	1.71	1.95	2.21	4.06
Theoretical values[a]	1.0	1.29	1.38	1.48	1.62	1.83	2.68

NOTE: N = 1969.

[a]Calculation assumes that residuals are lognormal with logstandard deviation = $0.84 \times \sqrt{0.89} = 0.79$. ($R^2$ was 0.11 in Table 3.5.)

according to the rule: If the random draw in the simulation is bigger than 1.8 normal deviates (96.4 percent), then add 0.25 to log. This would fit the residuals fairly well and would make the mean hospital expenses come out exactly right. For the other episode types, a calculation using truncated lognormals (Aitchison and Brown, 1957, Theorem (2.6)) led to the analogous factors shown in Table A.3.

Table A.2

STATISTICS ON THE SIZE OF EPISODES

	Mean	Standard Deviation (log)	Percentiles 50	95	99	Untransformed Mean
Hospital	6.37	0.84	6.33	7.78	8.69	877
(if lognormal)				(7.75)	(8.33)	(830)
Acute	2.43	1.09	2.37	4.30	5.31	21.87
(if lognormal)				(4.22)	(4.97)	(20.6)
Chronic	2.79	1.35	2.68	5.16	6.22	45.14
(if lognormal)				(5.01)	(5.94)	(40.5)
Dental	2.97	1.21	2.66	5.53	6.53	54.82
(if lognormal)				(4.96)	(5.79)	(40.5)
Well care	2.63	0.91	2.52	4.03	4.74	21.50
(if lognormal)				(4.13)	(4.75)	(21.00)

NOTE: Based on all four sites, one to three years of data, 1967 dollars.

Table A.3

ADJUSTMENTS TO COSTS, BY EPISODE TYPE

	Cutoff Values	Multiplying Factor
Hospital	1.8	1.28
Acute	1.8	1.31
Chronic	1.6	1.42
Dental	1.4	2.03
Well care	(no change)	

Appendix B

CATASTROPHIC HOSPITALIZATIONS IN THE HEALTH INSURANCE EXPERIMENT

by David Reboussin

STATISTICAL RESULTS

The distribution of hospital costs for single episodes of care has a very heavy right tail: The upper 5 percent of cases account for about 30 percent of the total hospital expenditures. The most expensive episode totals exceed the MDE on all the insurance plans and show no difference in the proportion of free plan cases and the proportion of pay plan cases beyond random fluctuation. These episodes are "catastrophic" in the sense that insurance plan has no effect on the decision to seek care.

Here we roughly determine the point at which plan effects stop, and model the way in which catastrophic cases differ from routine cases using covariate information for the person involved. Our analysis is based on all episodes of inpatient hospital care that occurred in the study. No adjustment was made for intraperson or intrafamily correlation, and all amounts were converted to 1967 dollars by year. There were 2,520 hospital episodes and the sum of their costs was about $2 million in 1967 dollars.

Any choice of a specific amount to be the upper limit of routine expenses will be artificial, since plan effects fall off gradually. We chose the lowest amount at which plan effects seemed negligible. Figure B.1 demonstrates the decreasing effect of plan as cost increases. Cost was transformed by taking its (base 10) logarithm. At each "cut-off" point C, only episodes whose log 10 cost was bigger than C are considered. The rate from the pay and free plans is calculated as the number of big episodes from each plan divided by the corresponding total number of person-years in the study on each plan. The natural log of the difference of these ratios is plotted.[1] Table B.1 lists the number of cases that would be classified as catastrophic at selected cut-off points.

The difference between the plans seems to be nearly constant until episodes with log 10 costs greater than about 3.15 are considered.

[1]For example, in the first row of Table B.1 log(360/6,863) - log(595/13,679) = 0.19, so (2.8, 0.19) is plotted.

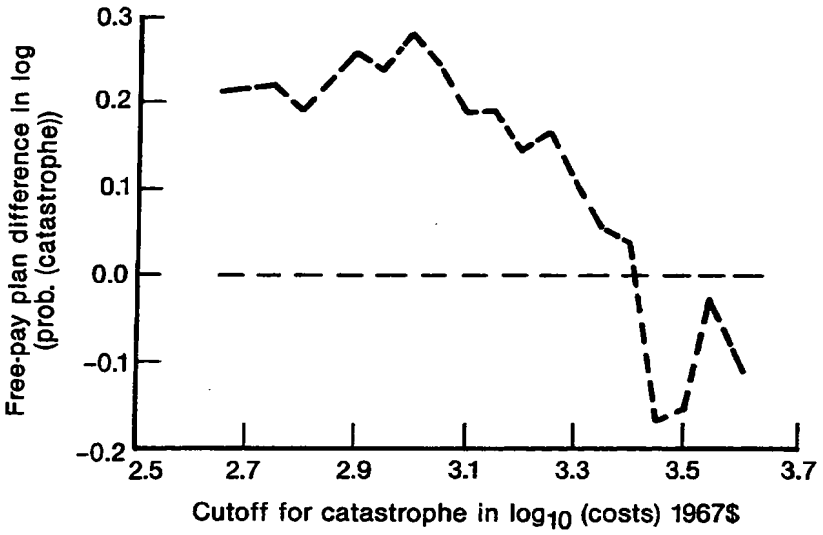

Fig. B.1—Defining catastrophic episodes

Differences decline from there on, and they should theoretically stabilize at zero. Since larger values of C mean smaller sample sizes, the points at the right end of the plot have larger variances, which helps account for the unexpected negative values. At C = 3.4, the difference between the plans is nearly zero.

Choosing C = 3.4 means defining any episode cost greater than $2,512 in 1967 dollars as a catastrophe. There were 114 such cases in the analysis file. This corresponds to about $4,220 in 1975, $7,210 in 1980, $9,670 in June of 1983, and $11,045 in September of 1986. Table B.2 collects some summary statistics on the catastrophic cases.

Given the relatively arbitrary definition of catastrophe, how can the differences between catastrophic and noncatastrophic cases be characterized? We tested for the effects of age, sex, family size, education, race, and income. We also looked at three indicators: babies in their first year home (assigned to the mother), which we called "BABY"; mothers during a year in which they gave birth "NEWMOM," and for mothers' episodes giving birth "BIRTH." The last two are quite

Table B.1

NUMBER OF CATASTROPHIC EPISODES AT VARIOUS CUTOFF POINTS

Cutoff (log 10 costs)	1967 Dollars	1986 Dollars	Diff. of Log(p)	Number over Cutoff		
				Total	Free	Pay
2.8	631	2,774	0.19	955	360	595
3.0	1,000	4,397	0.28	526	210	316
3.2	1,584	6,965	0.14	221	81	140
3.3	1,995	8,772	0.10	154	55	99
3.4	2,512	11,045	0.04	114	39	75
3.5	3,162	13,903	-0.16	80	24	56
3.6	3,981	17,504	-0.11	58	18	40

NOTE: Log(p) is the log of the proportion of catastrophic episodes and is based on 6,863 person-years on the free plan; 13,679 years on pay plans. The denominators include partial years, such as births and deaths, but the cutoff is not greatly affected by this.

Table B.2

SUMMARY OF EXPENSES OF CATASTROPHIC EPISODES
(1967 dollars)

	Raw Costs	Log of Costs
SUM	573,868	—
MEAN	5,033	3.640
MEDIAN	3,999	3.602
STD DEV	4,169	0.2

NOTE: 2,520 episodes, 114 catastrophes 114/2520 = 0.045 of all hospital episodes. 573,868/1, 996,440 = 0.287 of total hospital expenses.

different, since mothers often have several minor episodes around a birth, perhaps due to false labor or complications with pregnancy (about 16 percent of all episodes were in this category). A logistic regression model was chosen to express differences between catastrophic and noncatastrophic hospital episodes. The dependent variable was 0 for persons having a hospital episode with expenses under $2,512 and 1 for persons whose expenses were over $2,512.

In fact, the variables BABY, NEWMOM, and BIRTH almost never indicated catastrophes (only two babies had catastrophic episodes) and could not be included in the regression (Table B.3). These variables will not be available to the simulation of which the model is to be a part.

Various regressions containing all other covariates plus an age-sex interaction and an age-squared term were considered and rejected in favor of a smaller model including only AGE, SEX, and an AGE*SEX interaction shown in Table B.4 with $\chi^2 = 65$. The other variables excluded made no significant change in the log likelihood. (An earlier analysis on annual hospital expenses found a significant relationship with the education variable, which was completely absent here.)

Coefficients in a logistic regression can be interpreted in terms of odds ratios, odds being what gamblers use to gauge probabilities: the probability of an event happening divided by the probability of its not

Table B.3

EFFECT OF GENDER, MOTHER, AND BABY INDICATORS ON THE PROBABILITY OF CATASTROPHIC EXPENSE

Variable	Normal Hospital Episode	Catastrophe	Percent
BABY	50	2	3.9
BIRTH	347	0	0
NEWMOM	407	0	0
MALE	873	59	6.3
FEMALE	1,490	55	3.6

Table B.4

LOGISTIC REGRESSION OF "CATASTROPHES" ON HOSPITAL EPISODES

Variable	Beta	Chi-Square
INTERCEPT	-3.713	120.51
FEMALE	-1.948	11.13
AGE	0.028	13.46
AGE_FEM	0.031	6.22

NOTE: 114/2,477 observations were catastrophes, 43 observations deleted because of missing values.

happening. An odds ratio is the ratio of the odds for two different events, or in the current setting, of two persons with different covariate values. The coefficient of FEMALE is negative, so that women have a smaller predicted probability of catastrophe once in the hospital. The coefficient of AGE is positive, indicating that older people have a greater chance of a catastrophic episode, and the interaction of AGE and FEMALE is positive, indicating that the difference between men and women decreases with age. The odds ratio for a woman over a man is 0.35 if both are 30 and 0.67 if both are 50. Being a year older increases the odds by 2.8 percent for men and by 6.2 percent for women.

Figure B.2 provides a graphical indication of goodness of fit and practical significance. All cases were sorted by predicted probability of catastrophe and divided into equal-sized classes. The proportion of catastrophes in each class was calculated and plotted against the mean predicted probability within each class. Perfect prediction is represented by a 45 degree line, and the unconditional probability of catastrophe (114/2477 = 0.046) is marked by a horizontal line. The

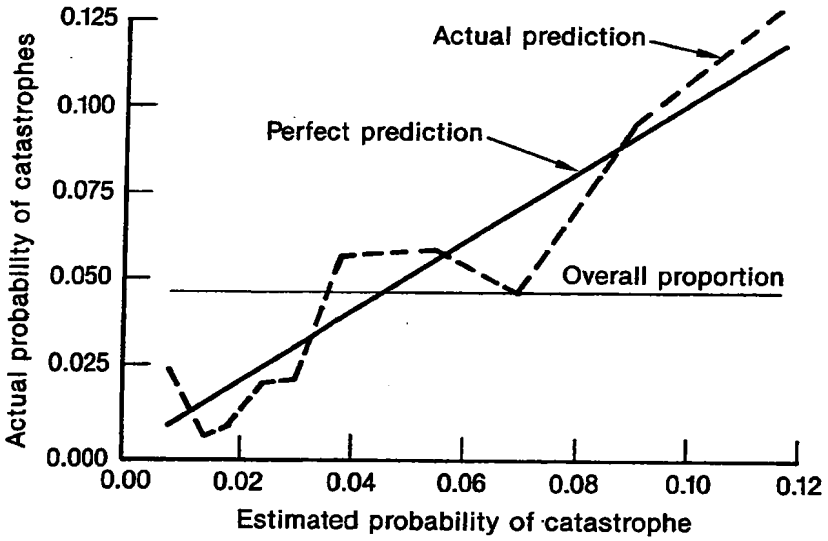

Fig. B.2—Goodness-of-fit for the logistic regression

empirical and predicted values are in reasonable agreement and the improvement over the unconditional probability can be seen in the difference between the predicted and horizontal lines.

The above regression predicts the probability of incurring a catastrophic expense given that the person has a hospital episode. We also predicted the unconditional probability of catastrophe in a given year. A logistic regression was run with the same covariates as above for all years with catastrophes (coded 1) and a sample of other person-years (coded 0) in the study. The only relation found was a dependence on AGE (each year increase raises odds of a catastrophe by 5.4 percent).

A regression of cost for the catastrophic episodes was considered but proved to be difficult, since the variation in cost among them is so great. There appeared to be a dependence on SEX, but regression diagnostics indicated a further transformation of cost (such as log(log(cost))) was necessary, so we stopped. The cost of catastrophic episodes is not easily predicted.

ACCOUNTING FOR CATASTROPHES IN A SIMULATION MODEL

A simulation model for insurance costs must account for the decay of plan effects as episode cost increases, since these most expensive episodes of care are responsible for a large proportion of total costs.

Costs may be simulated three ways. First, we can think of catastrophic hospitalizations as a separate category of medical episodes. This involves estimating the probability of an individual in the population experiencing such an event and attaching an estimate of its cost.

Second, we can think of these as the most costly subclass of all hospitalizations. In this second case, we generate hospital episodes, using the model here to predict the probability of a catastrophe (conditional on hospitalization), and then perhaps simply assign any such catastrophes the mean cost of catastrophes. For the noncatastrophic hospitalization we can simulate costs by throwing out draws for cost that are larger than the cutoff and redrawing. This is simpler than trying to estimate mixtures and truncated distributions of noncatastrophes.

A third and the simplest way is to use the standard cost prediction model on the free plan to generate the cost of episodes and assume that sufficiently large episodes will not be affected by price. This is what we did in the simulation presented here.

In fact several more realistic descriptions of the process could be offered. Outside data, as from the Trapnell catastrophe studies, might be used to estimate the probability and cost of catastrophes. The

effect of insurance plan may decrease continuously as hospitalization cost increases, and the ideal simulation could generate costs accordingly.

Appendix C

CORRELATION BETWEEN EPISODE TYPES

This appendix gives a more detailed derivation of our method of introducing dependence between episode types, gives moments of the multivariate distribution of episode counts, and describes the estimation method that was used. We model the distribution of a family's number of episodes of the different types as a variant of the Generalized Multivariate Negative Binomial (GMNB) distribution as derived in Rolph et al. (1981).

As described in Secs. IV and V, we introduce dependence between the counts of different episode types by modeling episode propensities as having a particular form of a multivariate gamma distribution. Specifically, the underlying propensities for occurrence of the five episode types U_j are:

$$
\begin{aligned}
U_A &= \beta_A(V_A + V_{AWCD} + V_{ACH}) \\
U_W &= \beta_W(V_W + V_{AWCD}) \\
U_C &= \beta_C(V_C + V_{AWCD} + V_{ACH}) \\
U_H &= \beta_H(V_H + V_{ACH}) \\
U_D &= \beta_D(V_D + V_{AWCD})
\end{aligned}
\tag{C.1}
$$

where A, W, C, H, and D denote acute, well-care, chronic, hospital, and dental episodes, respectively, and the V_j are independent gamma random variables with parameters $(\gamma_j, 1)$. Thus the marginal gamma distributions for U_j have parameters (α_j, β_j) where

$$
\begin{aligned}
\alpha_A &= \gamma_A + \gamma_{AWCD} + \gamma_{ACH} \\
\alpha_W &= \gamma_W + \gamma_{AWCD} \\
\alpha_C &= \gamma_C + \gamma_{AWCD} + \gamma_{ACH}
\end{aligned}
$$

$$\alpha_H = \gamma_H + \gamma_{ACH}$$

$$\alpha_D = \gamma_D + \gamma_{AWCD} \qquad \text{(C.2)}$$

The correlations matrix between the U_j's, the episode generation propensities is thus:

	Acute	Well	Chronic	Hospital
Well	$\frac{\gamma_{AWCD}}{(\alpha_A \alpha_W)^{1/2}}$			
Chronic	$\frac{\gamma_{AWCD} + \gamma_{ACH}}{(\alpha_A \alpha_C)^{1/2}}$	$\frac{\gamma_{AWCD}}{(\alpha_W \alpha_C)^{1/2}}$		
Hospital	$\frac{\gamma_{ACH}}{(\alpha_A \alpha_H)^{1/2}}$	0	$\frac{\gamma_{ACH}}{(\alpha_A \alpha_H)^{1/2}}$	
Dental	$\frac{\gamma_{AWCD}}{(\alpha_A \alpha_D)^{1/2}}$	$\frac{\alpha_{AWCD}}{(\alpha_W \alpha_D)^{1/2}}$	$\frac{\gamma_{AWCD}}{(\alpha_C \alpha_D)^{1/2}}$	0

(C.3)

However, as compared to the correlations given above, the correlations between the episode counts are dampened by the addition of Poisson "noise." Specifically, the moments of the episode counts (Y_j) for a family are given by

$$E(Y_j) = \alpha_j \beta_j$$

$$Var(Y_j) = \alpha_j \beta_j (1 + \beta_j); \quad j = A, W, C, H, D \qquad \text{(C.4)}$$

To avoid cluttering the notation, we defer introducing how the means of families' counts vary according to the negative binomial regression described in Sec. IV and later in this appendix. Strictly speaking the Y_j described above will be multiplicative residuals around that regression and thus $\alpha_j \beta_j \equiv 1$.

The covariance matrix of (Y_i, Y_j) is:

	Well	Chronic	Hospital	Dental
Acute	$\beta_A \beta_W \gamma_{AWCD}$	$\beta_A \beta_C (\gamma_{AWCD} + \gamma_{ACH})$	$\beta_A \beta_H \gamma_{ACH}$	$\beta_A \beta_D \gamma_{AWCD}$
Well		$\beta_W \beta_C \gamma_{AWCD}$	0	$\beta_W \beta_D \gamma_{AWCD}$
Chronic			$\beta_C \beta_H \gamma_{ACH}$	$\beta_C \beta_D \gamma_{AWCD}$
Hospital				0

(C.5)

Combining Eqs. (C.4) and (C.5), it therefore follows that the correlation matrix of (Y_i, Y_j) is:

$$\rho(Y_A, Y_W) =$$

$$\left[\frac{\beta_A}{(1+\beta_A)} \cdot \frac{\beta_W}{(1+\beta_W)} \cdot \frac{\gamma_{AWCD}}{(\gamma_A + \gamma_{AWCD} + \gamma_{ACH})} \cdot \frac{\gamma_{AWCD}}{(\gamma_W + \gamma_{AWCD})}\right]^{1/2}$$

$$\rho(Y_A, Y_C) =$$

$$\left[\frac{\beta_A}{(1+\beta_A)} \cdot \frac{\beta_C}{(1+\beta_C)} \cdot \frac{\gamma_{AWCD} + \gamma_{ACH}}{(\gamma_A + \gamma_{AWCD} + \gamma_{ACH})} \cdot \frac{\gamma_{AWCD} + \gamma_{ACH}}{(\gamma_C + \gamma_{AWCD} + \gamma_{ACH})}\right]^{1/2}$$

$$\rho(Y_A, Y_H) =$$

$$\left[\frac{\beta_A}{(1+\beta_A)} \cdot \frac{\beta_H}{(1+\beta_H)} \cdot \frac{\gamma_{ACH}}{(\gamma_A + \gamma_{AWCD} + \gamma_{ACH})} \cdot \frac{\gamma_{ACH}}{(\gamma_H + \gamma_{ACH})}\right]^{1/2}$$

$$\rho(Y_W, Y_C) =$$

$$\left[\frac{\beta_W}{(1+\beta_W)} \cdot \frac{\beta_C}{(1+\beta_C)} \cdot \frac{\gamma_{AWCD}}{(\gamma_W + \gamma_{AWCD}} \cdot \frac{\gamma_{AWCD}}{(\gamma_C + \gamma_{AWCD} + \gamma_{ACH})}\right]^{1/2}$$

$$\rho(Y_A, Y_D) =$$

$$\left[\frac{\beta_A}{(1+\beta_A)} \cdot \frac{\beta_D}{(1+\beta_D)} \cdot \frac{\gamma_{AWCD}}{(\gamma_A + \gamma_{AWCD} + \gamma_{ACH})} \cdot \frac{\gamma_{AWCD}}{(\gamma_D + \gamma_{AWCD}}\right]^{1/2}$$

$$\rho(Y_W, Y_H) = 0$$

$$\rho(Y_W, Y_D) =$$

$$\left[\frac{\beta_W}{(1+\beta_W)} \cdot \frac{\beta_D}{(1+\beta_D)} \cdot \frac{\gamma_{AWCD}}{(\gamma_W+\gamma_{AWCD}} \cdot \frac{\gamma_{AWCD}}{(\gamma_D+\gamma_{AWCD}}\right]^{1/2}$$

$$\rho(Y_C, Y_H) =$$

$$\left[\frac{\beta_C}{(1+\beta_C)} \cdot \frac{\beta_H}{(1+\beta_H)} \cdot \frac{\gamma_{ACH}}{(\gamma_C+\gamma_{AWCD}+\gamma_{ACH})} \cdot \frac{\gamma_{ACH}}{(\gamma_H+\gamma_{ACH})}\right]^{1/2}$$

$$\rho(Y_H, Y_D) = 0 \qquad \text{(C.6)}$$

Comparing Eq. (C.6) with the correlations of the propensities in Eq. (C.3) we see that

$$\rho(Y_i, Y_j) = \left[\frac{\beta_i}{(1+\beta_i)} \cdot \frac{\beta_j}{(1+\beta_j)}\right]^{1/2} \rho(U_i, U_j). \qquad \text{(C.7)}$$

Thus the scale parameters of the mixing distribution determines how much the Poisson noise dampens the gamma correlations. Clearly, large dispersions (β_j) in the propensities yield correlations that are relatively less dampened by the Poisson noise than are correlations where the (β_j) are small. Table 3.9 gives the correlations of residuals within families corresponding to Eq. (C.7) for counts on the free plan.

The parameters (α_j, β_j) were estimated from the negative binomial regressions described in Sec. IV. To avoid confusing notation, we have suppressed the parameters indexing family. Two additional parameters, γ_{AWCD}, γ_{ACH}, are needed to identify the correlation structure given in Eq. (C.3).

In the discussion thus far, we have suppressed the regression aspect of the model in our notation to describe the distributional structure of the episode counts around their means. As described in Secs. IV and V, we model the expected number of type j episode counts for family k as δ_{jk} where δ_{jk} is a regression function based on the characteristics of the individuals in family k as described in Sec. IV. Since the problem is overparameterized, we reparameterize to explain the estimation process. First, note that $\alpha_j\beta_j \equiv 1$ is a constraint imposed by the gamma variation being unmeasured propensities and hence residual variation around the regression function $\delta_{jk} \equiv \delta_{jk}\alpha_j\beta_j$. All estimation of the gamma/negative binomial parameters is from the residuals of the fitted values δ_{jk}.

Table C.1 gives the empirical normalized correlation terms between various episode types. Specifically, the table gives estimates of the numerator terms in the correlation matrix (C.3),

γ_{AWCD}, $\gamma_{AWCD} + \gamma_{ACH}$, etc. The values for γ_{AWCD} and γ_{ACH} of 1.0 and 0.66 best fit this matrix; these estimates were used as the parameters in the simulation reported on in Sec. V. Note that these fitted values agree with Table C.1 reasonably well for all correlations except for those involving well-care episodes. These interaction γ estimates are then combined with estimates of α using Eq. (C.2) and the constraint $\alpha\beta = 1$ to yield estimates of all the parameters of the residual distribution, α, γ, β.

The accuracy of these estimates could be improved using GLIM to produce simultaneous maximum likelihood fits (McCullough and Nelder, 1983). Economy and convenience dictated this cruder method of estimation.

Note that the simulation reported in Sec. V does not include dental episodes, so that the dental component is eliminated and the subscripts modified accordingly.

Table C.1

OBSERVED NORMALIZED COVARIANCES BETWEEN DIFFERENT TYPES OF EPISODE COUNTS

	Well	Chronic	Hospital	Dental
Acute	2.35	1.56	0.72	1.08
Well care		1.75	0.33	2.66
Chronic			0.66	1.02
Hospital				0

Appendix D

VALUE OF MEDICAL CARE AND RISK AVERSION

We present here the assumptions and calculations underlying the assertions on welfare in the conclusions. For more details on the economic theory of insurance see Newhouse (1978). We make the usual assumptions that medical care services are sold at their cost to society, that consumers are well informed about the benefits of medical treatment, and that others are not willing to subsidize nonbuying consumers' treatments.

Suppose then that the amount an individual buys depends on the coinsurance rate as in Fig. D.1. In that figure, someone who pays the fraction of charges C on average buys quantity Q. The insurance plan pays the other 1 – C of charges. For simplicity, we can assume that the charge per unit of services is $1, i.e., that Q is measured in dollar units. (The amount purchased depends strongly on how sick someone is, but the demand curve DD in Fig. D.1 is the average over different sickness levels.)

We also assume that the insurance policy is fair in the sense that premiums are equal to expected payments by the insurance company. Thus, on average the premiums plus out-of-pocket costs equal charges. This will be true if there are no administrative costs to insurance and no profits to the insurance company.[1] Consider a simple fair insurance policy that pays a certain fraction of all charges, with no deductibles or coverage ceilings. Then the premium is the amount in the upper rectangle CRS1 of Fig. D.1, and the out-of-pocket payments are the amount in the lower rectangle OQRC. Individuals on average pay the total in both rectangles. If the coinsurance rate is increased, the quantity bought and hence premium and out-of-pocket costs decline.

The value to the individual of services he would buy at say 39.9 percent of costs, but not at 40.1 percent of costs, is 40 percent of costs. Since we assume that the provider charges the marginal cost to society of producing the service, there is a welfare loss of 60 percent of the cost

[1]If costs and profits are necessary to produce insurance, and people need insurance, then the welfare losses associated with those costs under lower coinsurance rates are just the marginal costs and profits that come from the insurance company doing more. These are small compared to the other welfare losses discussed here and will not be considered.

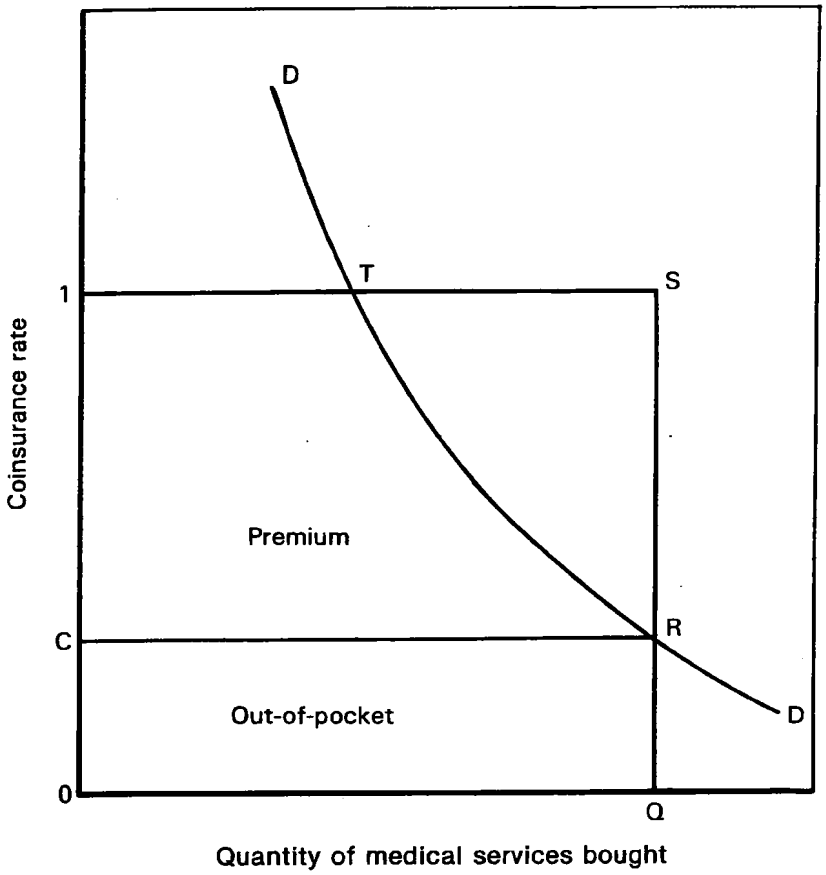

Fig. D.1—Insurance payments and demand for medical care

of the marginal service. That is, society is using $X in resources to produce something valued at $0.4X. For larger shifts in coinsurance, we can use the demand curve to add up the value of all the marginal services. The proportion below the demand curve is the value to the policyholder, and the proportion above the demand curve represents waste. The welfare loss from overuse as a result of insurance is thus

given by the area of the triangle RST. If the demand curve is steep, small changes in coinsurance cause only small increases in use, so there is not much waste. (The welfare loss triangle is thin.) Insurance in that case is mainly a transfer from the people paying the premiums to those using the services.

VALUE OF TREATMENT

For each episode, we need an estimate of the value of treating that episode. We will restrict ourselves to episodes of illness that would be treated if care were free. The probability p that someone will want to obtain treatment for an episode decreases as the coinsurance rate c goes up. Formally, $p = f(c)$ is a decreasing function of c. Thus, we can consider a kind of demand curve $c = f^{-1}(p)$ that gives the coinsurance rate corresponding to a given probability, scaled so that $0 = f^{-1}(1)$ (because all episodes are treated with free care). This curve is shown as Fig. D.2, where we have limited $f^{-1}(p)$ to be one for episodes that would be treated with no insurance, since higher values of $f^{-1}(p)$ drop out of all comparisons. Recall that censoring in the simulation model is based on a uniform random variate r according to the rule that persons treat episodes whenever $r \leq f(c)$. Since people with coinsurance $c = f^{-1}(r)$ are indifferent between treating the episode at cost to them of $cq(c)$ or not, the value of treating must be $cq(c)$.

Suppose now that $c < c(r) = f^{-1}(r)$. Then the episode will be treated, but since $c < c(r)$, there will be additional spending $q(c) - q(c(r))$. Let $c = D(q)$ be the demand for spending on that episode, scaled so that $D^{-1}(0) = 1$ (i.e., quantities are all expressed in proportions of \$X, the cost when care is free). Then the value of the additional spending is the integral from $q(c(r))$ to $q(c)$ of $X\ D(q)$ (Fig. D.3). We will approximate the value of total spending by $X \times [D(c(r)) + 1/2(D(c) - D(c(r))] \times [q(c) - q(c(r))]$.

VALUE OF RISK REDUCTION

The risk calculations shown in Sec. V are based on the old idea that the value of insurance is protection against financial risks, and that we can estimate the value using expected utility. Expected utility theory has a strong normative appeal, but Kahneman and Tversky's path-breaking experiments and articles (1979) have shown that people do not behave in accordance with the theory. Indeed, Marquis and Holmer's (1986) analysis of hypothetical supplementary plan choices on the HIE shows that expected utility theory is inferior to a variant of

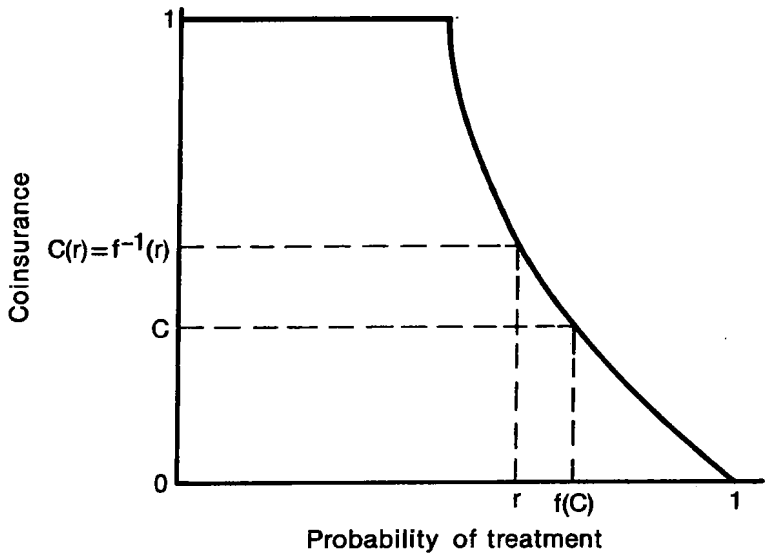

Fig. D.2—Coinsurance and the probability of treatment of an episode

prospect theory in explaining those choices. Nevertheless, we will simply assume that individuals evaluate risky prospects in terms of the mean and variance of out-of-pocket payments. The results are plausible, and the variance is closely related to what most people think of as risk.

So let X be the random variable that represents the amount spent on health insurance premiums and out-of-pocket medical spending by a family in a year. We assume that the expected utility of that spending is given by

$$E(U(x)) = E(x) - r\ Var(x)/2 \qquad \text{(D.1)}$$

The risk premium, π, here assumed to be $r\ Var(x)/2$, is the amount that makes the family indifferent between gaining $E(x) - \pi$ for sure, or facing the gamble X. We choose $r\ Var(x)/2$ because it can be shown that for Pratt's measure of risk aversion, r, it is the approximate premium for all prospects with small variance and for certain other classes of prospects.

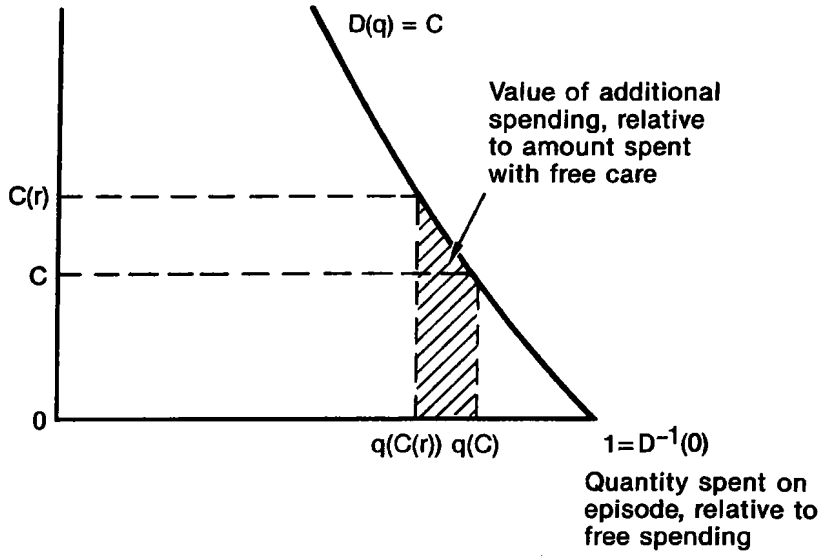

Fig. D.3—Demand for spending in an episode

A reasonable value for r is 0.001. (In Marquis and Holmer (1986), the best fitting value for $U(x) = exp(-rx)$ was $r = 0.0011$ in 1983 dollars, which becomes $r = 0.001$ in 1984 dollars.)

Appendix E

REGRESSION EQUATIONS USED IN PREDICTIONS

Predictions of what individual participant's annual counts would be on the free plan were used in estimating correlation between episode types. These predictions also were summed over each family to get a family prediction which was used to estimate the within-year effects of price in Sec. IV. Since ordinary least-squares (OLS) regression is inexpensive and has better supporting software and intuition than negative binomial regression, it was used for these tasks. It was also used in preliminary analyses leading to the specification of the negative binomial model.

Episode counts have many zeros and a skewed distribution of positive counts. In addition, the effects of covariates on rates do not appear to be directly additive. Thus, we are led to some transformation to improve the prediction of counts. Of the many possible transformations, we prefer Anscombe's variance stabilizing transformation: $(x + 0.375)^{1/2}$. It is easy to retransform, it satisfies Pregibon's goodness-of-link test for the link with the weighted sum of covariates, and residuals are fairly symmetric. (For more details, see the specification work reported in Appendix A of Keeler et al., 1982.)

Table E.1 shows the regression equations used in predicting numbers of episodes for the within-year analysis. Effects of plan are not needed, but otherwise the results are very similar to those in Table 4.9. The predictions of counts are given by retransformation after the regression by $(X'b)^2$ + (mean-square error around the regression) -0.375 where $X'b$ is the predicted value in the regression from covariate vector X.

Table E.1

REGRESSION EQUATIONS FOR PREDICTING TRANSFORMED NUMBER OF EPISODES[a]

Variable[b]	f(Acute)[c]	f(Chronic)	f(Well Care)	f(Dental)	f(Hospital)
CONSTANT	0.58	0.07	0.35	−0.41	0.60
LINC	0.16	0.09	0.09	0.09	0.01
LFAM	−0.10	−0.06	−0.05	0.05	0.00
NOMD	−0.14	−0.08	−0.03	−0.05	−0.02
LMDVIS	0.20	0.13	0.03	0.05	0.01
HEALTH	0.02	0.03	−0.003	−0.02	0.01
NEWBORN	−0.63	−0.11	0.30	−0.07	0.43
WOMEN	0.23	0.08	0.24	−0.01	0.02
AGE	0.02	0.02	0.02	−0.01	0.00
SQRAGE	−0.26	−0.09	−0.22	0.12	0.00
BLACK	−0.22	−0.05	−0.10	−0.12	0.01
MAXED	0.004	0.007	0.021	0.018	−0.002
N	3343	3343	3343	3343	3343
R^2	0.16	0.25	0.20	0.10	0.11
MEAN-SQUARE ERROR	0.46	0.21	0.13	0.21	0.03

[a]The dependent variable is $(y_i + 0.375)^{1/2}$ where y_i is the number of episodes for individual i.
[b]For definition of variables, see Table 3.4.
[c]f refers to the transformed dependent variable.

Appendix F

CENSORING AND PRICE REDUCTION PARAMETERS

From the data we estimated the effects of price on the number of episodes in each period and plan. There was little difference for outpatients between the big MDE and small MDE remaining periods so the same estimates were used for both. Since we are interested in extrapolating to coinsurance rates other than 25, 50, and 95, we fit a curve through the price ratios, p, for these points. The curve had the functional form $\log p = bc^a$. This curve has $p(0) = 1$, i.e., the free plan spends at 1.0 the free plan rate, and can take shapes that fit the other three data points well. The values of a and b minimize the sum of squared residuals.

As can be seen in Table 5.2, a is very small for hospitalization. This reflects the fact that the price reduction is very similar for the 25, 50, and 95 plans. It is tempting to use the same value for all coinsurance plans, but this does not make sense for a 5 percent coinsurance rate, so we will use the fitted function.

We assume that people have episodes at the free plan rate in the post-MDE period. This may overstate spending on the pay plans with a large MDE, since the observed pay rates for acute and chronic in the HIE were less than those on the free plan. However, for smaller MDE plans, it seems unlikely that a brief period of coinsurance would greatly affect post-MDE behavior.

Similarly, although there appeared to be a slight "sale" in hospital episodes in the free period (probably because of a sicker group there or because of correlation with other episode types—the methods adjust for earlier hospital episodes, but not for other types of episodes), it seems more realistic for smaller deductibles to put hospital rates in the free period at the free plan rate. To make the total number of hospitalizations match those observed in the HIE, we raised the big MDE period rates slightly, and set the anticipation (small MDE) period rate to 0.9 of the free plan rate.

The cost per episode was fit with the same function form bc^a. Since we assume that controlling for individual characteristics, the price per episode is the same on all plans after the MDE is exceeded, we must inflate the differences in overall cost per episode to account for the occurrence of some of the episodes on the pay plan after the MDE is

exceeded. In fact, 34 percent of hospitalizations and 20–23 percent of the other types of episodes occur after the MDE was exceeded. For hospital episodes, we smoothed the data by limiting a to 2.0. The cost of hospital episodes in the small MDE period was assumed to equal the free plan costs (since the marginal cost of treatment would be zero).

Appendix G

SIMULATION MODEL OUTPUT

This appendix contains a copy of the output of the simulation model. Data are simulated for 28 different health insurance plans. Four features describe each plan: the initial deductible, the coinsurance rate, the MDE limit, and the number of family members covered by the MDE limit. The 28 plans referred to in this appendix all have no initial deductible and the MDE limits are individual limits, that is, each individual has a limit that is unaffected by the expenditures of other family members.

Two plans, the free plan (0 percent coinsurance) and the full pay (100 percent coinsurance), are included in each run. There is no MDE limit for either of these plans. The remaining plans are described by their coinsurance rate, which ranges from 25 percent to 100 percent, and their MDEs, which range from $50 to $3,000. The plans are labeled with the coinsurance rate and the MDE. For example, a plan with 25 percent coinsurance and a $200 MDE is labeled P25/200.

The model simulates the health experience of one family at a time. The basic input file of families is a random sample drawn from families in the the Current Population Survey. The sample contains 970 families (2,297 individuals).

This reported simulation run is based on four independent replications and nests two antithetic years of experience within each independent replication. The antithetic years of experience are negatively correlated to reduce the variance in our estimates. Antithetic variates are used only in the censoring process and each year is averaged with its antithetic year within the replication through the data. Thus, the estimates produced here for each of the 28 plans are calculated from 18,376 person-years of simulated data.

The first two tables in this appendix display the basic health experience statistics by type of episode and plan that the model generated. Table G.1 presents frequencies and confidence limits on the expected number of episodes of each type for each plan for individuals. Annual expenditures by type of episode and plan are shown in Table G.2.

Table G.3 presents data on the mean number of people who exceed the MDE limit in each plan and the average time spent beyond the MDE for those who do exceed it. Table G.4 shows plan differences for the 28 plans.

Overall plan comparisons at the individual level (Table G.5) follow. The plan comparison measures are total annual expenditures, annual out-of-pocket expenditures, value of purchased medical care, and insurance risk.

Table G.1

INDIVIDUAL-LEVEL EPISODE FREQUENCIES BY EPISODE TYPE AND PLAN FOR INDIVIDUALS
(Confidence Limits)

Plan[a]	Hospital	Acute	Well	Chronic	All
Free	0.12	2.51	0.75	0.82	4.19
	(0.01)	(0.18)	(0.04)	(0.02)	(0.23)
P25/50	0.11	2.08	0.65	0.66	3.50
	(0.01)	(0.15)	(0.04)	(0.02)	(0.21)
P25/100	0.11	1.99	0.63	0.63	3.36
	(0.01)	(0.15)	(0.03)	(0.02)	(0.20)
P25/200	0.11	1.93	0.63	0.61	3.27
	(0.01)	(0.14)	(0.03)	(0.02)	(0.19)
P25/500	0.11	1.89	0.62	0.59	3.21
	(0.01)	(0.14)	(0.03)	(0.02)	(0.19)
P25/1K	0.09	1.87	0.62	0.59	3.17
	(0.01)	(0.14)	(0.03)	(0.01)	(0.18)
P25/1.5K	0.09	1.87	0.62	0.58	3.16
	(0.01)	(0.14)	(0.03)	(0.01)	(0.18)
P25/2K	0.09	1.87	0.62	0.58	3.15
	(0.01)	(0.14)	(0.03)	(0.01)	(0.18)
P25/3K	0.09	1.86	0.62	0.58	3.15
	(0.01)	(0.14)	(0.03)	(0.01)	(0.18)
P25/All	0.09	1.86	0.62	0.58	3.14
	(0.01)	(0.14)	(0.03)	(0.02)	(0.18)
P50/50	0.11	2.01	0.60	0.66	3.38
	(0.01)	(0.16)	(0.04)	(0.02)	(0.22)
P50/100	0.11	1.89	0.57	0.62	3.19
	(0.01)	(0.15)	(0.04)	(0.01)	(0.19)
P50/200	0.11	1.78	0.55	0.58	3.02
	(0.01)	(0.14)	(0.03)	(0.02)	(0.18)
P50/500	0.11	1.70	0.53	0.55	2.90
	(0.01)	(0.13)	(0.03)	(0.02)	(0.18)
P50/1K	0.09	1.67	0.53	0.54	2.82
	(0.01)	(0.13)	(0.03)	(0.01)	(0.17)
P50/1.5K	0.09	1.66	0.52	0.54	2.80
	(0.01)	(0.13)	(0.03)	(0.01)	(0.16)
P50/2K	0.09	1.65	0.52	0.53	2.79
	(0.01)	(0.12)	(0.03)	(0.01)	(0.16)
P50/3K	0.09	1.64	0.52	0.53	2.78
	(0.01)	(0.12)	(0.03)	(0.01)	(0.16)

Table G.1 (continued)

Plan[a]	Hospital	Acute	Well	Chronic	All
P50/All	0.09	1.63	0.52	0.53	2.76
	(0.01)	(0.12)	(0.03)	(0.01)	(0.16)
P100/50	0.11	1.90	0.53	0.64	3.19
	(0.01)	(0.15)	(0.03)	(0.02)	(0.20)
P100/100	0.11	1.77	0.49	0.60	2.97
	(0.01)	(0.15)	(0.04)	(0.02)	(0.20)
P100/200	0.11	1.62	0.44	0.55	2.72
	(0.01)	(0.13)	(0.03)	(0.01)	(0.16)
P100/500	0.11	1.47	0.41	0.51	2.50
	(0.01)	(0.11)	(0.02)	(0.02)	(0.14)
P100/1K	0.09	1.41	0.39	0.49	2.37
	(0.01)	(0.11)	(0.02)	(0.01)	(0.14)
P100/1.5	0.09	1.39	0.38	0.48	2.34
	(0.01)	(0.11)	(0.02)	(0.02)	(0.14)
P100/2K	0.08	1.38	0.38	0.48	2.32
	(0.01)	(0.11)	(0.02)	(0.01)	(0.14)
P100/3K	0.08	1.36	0.38	0.47	2.30
	(0.01)	(0.10)	(0.02)	(0.01)	(0.13)
P100/All	0.08	1.34	0.37	0.46	2.26
	(0.01)	(0.10)	(0.02)	(0.01)	(0.12)

NOTE: Individual MDE plans; no initial deductible.

Table G.2

INDIVIDUAL-LEVEL ANNUAL EXPENDITURES BY EPISODE TYPE AND PLAN
(Confidence Limits)

Plan[a]	Hospital	Acute	Well	Chronic	All
Free	401.00	225.60	67.52	148.12	842.24
	(73.73)	(20.58)	(4.22)	(8.35)	(86.51)
P25/50	382.42	180.20	56.90	115.26	734.78
	(77.26)	(17.93)	(3.95)	(8.90)	(91.79)
P25/100	377.96	170.53	54.87	109.19	712.55
	(80.22)	(16.32)	(3.82)	(8.83)	(92.68)
P25/200	375.48	164.12	53.83	103.29	696.73
	(80.52)	(15.01)	(3.82)	(8.08)	(91.74)
P25/500	374.54	160.39	52.92	100.71	688.56
	(81.09)	(15.01)	(3.65)	(8.66)	(93.58)
P25/1K	325.57	158.18	52.59	99.34	635.68
	(76.27)	(14.28)	(3.37)	(8.46)	(88.08)
P25/1.5K	323.43	157.61	52.47	98.72	632.23
	(76.59)	(13.97)	(3.37)	(7.67)	(87.20)

Table G.2 (continued)

Plan[a]	Hospital	Acute	Well	Chronic	All
P25/2K	322.46	157.35	52.43	98.49	630.73
	(76.71)	(14.05)	(3.36)	(7.59)	(86.88)
P25/3K	320.99	157.01	52.38	98.10	628.48
	(76.16)	(13.99)	(3.27)	(7.62)	(86.15)
P25/All	319.99	156.81	52.32	97.97	627.09
	(76.49)	(14.02)	(3.27)	(7.81)	(85.84)
P50/50	386.94	174.75	52.73	115.52	729.94
	(73.39)	(17.55)	(3.99)	(5.18)	(83.46)
P50/100	381.03	161.64	49.34	106.25	698.25
	(79.42)	(17.21)	(4.21)	(5.93)	(90.07)
P50/200	377.27	150.25	46.62	98.73	672.88
	(80.52)	(14.85)	(3.81)	(5.91)	(89.04)
P50/500	375.48	141.44	44.80	91.49	653.21
	(80.52)	(14.64)	(3.98)	(5.68)	(88.09)
P50/1K	315.98	137.61	43.92	89.42	586.93
	(76.87)	(14.53)	(3.62)	(5.96)	(85.12)
P50/1.5K	313.35	136.33	43.59	88.63	581.90
	(77.54)	(14.10)	(3.44)	(5.64)	(86.03)
P50/2K	311.56	135.57	43.46	88.10	578.69
	(77.91)	(13.59)	(3.43)	(5.95)	(86.00)
P50/3K	310.17	134.69	43.27	87.41	575.54
	(76.96)	(12.87)	(3.47)	(5.13)	(83.62)
P50/All	306.87	133.72	43.02	86.59	570.20
	(75.73)	(12.91)	(3.27)	(5.49)	(81.13)
P100/50	387.76	165.98	46.80	112.06	712.60
	(73.29)	(16.19)	(3.14)	(2.42)	(78.40)
P100/100	383.96	152.17	42.49	103.76	682.38
	(75.27)	(16.85)	(3.36)	(3.40)	(82.39)
P100/200	379.26	136.07	37.25	91.63	644.20
	(81.78)	(15.33)	(2.59)	(5.94)	(89.11)
P100/500	376.01	121.04	33.39	82.97	613.40
	(80.38)	(12.34)	(2.16)	(5.08)	(87.52)
P100/1K	291.22	113.83	31.60	78.19	514.84
	(72.98)	(12.29)	(2.15)	(2.99)	(78.64)
P100/1.5	285.12	111.72	30.92	77.00	504.76
	(74.50)	(12.10)	(1.85)	(3.65)	(81.32)
P100/2K	283.20	110.63	30.68	76.31	500.83
	(75.20)	(12.09)	(1.79)	(3.67)	(82.19)
P100/3K	280.14	109.21	30.27	75.38	495.01
	(74.20)	(11.41)	(1.83)	(3.62)	(81.25)
P100/All	273.41	106.55	29.55	73.42	482.93
	(71.23)	(10.60)	(1.56)	(3.33)	(75.44)

NOTE: Individual MDE plans; no initial deductible.

Table G.3

INDIVIDUALS EXCEEDING THE MAXIMUM DOLLAR EXPENDITURE BY PLAN
(Confidence Limits)

Plan[a]	Percent of Individuals	Average Time Beyond MDE
P25/50	0.49	0.51
	(0.03)	(0.01)
P25/100	0.29	0.46
	(0.02)	(0.01)
P25/200	0.16	0.47
	(0.01)	(0.01)
P25/500	0.08	0.48
	(0.01)	(0.02)
P25/1K	0.03	0.47
	(0.01)	(0.04)
P25/1.5K	0.02	0.47
	(0.00)	(0.07)
P25/2K	0.01	0.47
	(0.00)	(0.06)
P25/3K	0.01	0.49
	(0.00)	(0.16)
P25/All	0.0	0.0
	(0.0)	(0.0)
P50/50	0.61	0.56
	(0.03)	(0.01)
P50/100	0.44	0.50
	(0.02)	(0.01)
P50/200	0.26	0.47
	(0.01)	(0.01)
P50/500	0.12	0.48
	(0.00)	(0.02)
P50/1K	0.06	0.48
	(0.01)	(0.02)
P50/1.5K	0.04	0.48
	(0.01)	(0.03)
P50/2K	0.03	0.47
	(0.01)	(0.03)
P50/3K	0.02	0.46
	(0.00)	(0.07)
P50/All	0.0	0.0
	(0.0)	(0.0)
P100/50	0.67	0.60
	(0.02)	(0.00)
P100/100	0.53	0.54
	(0.02)	(0.01)
P100/200	0.36	0.49
	(0.02)	(0.01)
P100/500	0.18	0.47
	(0.01)	(0.01)

Table G.3 (continued)

Plan[a]	Percent of Individuals	Average Time Beyond MDE
P100/1K	0.10	0.47
	(0.00)	(0.01)
P100/1.5	0.07	0.48
	(0.01)	(0.01)
P100/2K	0.05	0.48
	(0.01)	(0.02)
P100/3K	0.03	0.47
	(0.01)	(0.05)
P100/All	0.0	0.0
	(0.0)	(0.0)

NOTE: Individual MDE plans; no initial deductible.

Table G.4

PLAN DIFFERENCES PER CAPITA TOTAL EXPENDITURES
(Confidence Limits)

	P25/50	P25/100	P25/200	P25/500	P25/1K	P25/1.5K	P25/2K	P25/3K	P25/ALL
FREE	107.46	129.69	145.51	153.68	206.56	210.01	211.51	213.76	215.15
	(6.59)	(7.65)	(7.22)	(9.60)	(9.56)	(10.56)	(11.09)	(8.53)	(8.43)
P25/50		22.24	38.06	46.22	99.11	102.56	104.05	106.31	107.70
		(1.07)	(1.07)	(3.21)	(8.17)	(9.41)	(9.97)	(8.41)	(7.96)
P25/100			15.82	23.98	76.87	80.32	81.82	84.07	85.46
			(1.12)	(2.26)	(8.30)	(9.53)	(10.09)	(8.77)	(8.34)
P25/200				8.16	61.05	64.50	66.00	68.25	69.64
				(2.56)	(7.93)	(9.07)	(9.60)	(8.20)	(7.53)
P25/500					52.88	56.34	57.83	60.08	61.47
					(8.02)	(9.11)	(9.60)	(8.86)	(8.35)
P25/1K						3.45	4.95	7.20	8.59
						(1.53)	(2.21)	(2.15)	(3.80)
P25/1.5K							1.49	3.75	5.14
							(0.69)	(2.22)	(3.63)
P25/2K								2.25	3.64
								(2.63)	(3.79)
P25/3K									1.39
									(3.25)
	P50/50	P50/100	P50/200	P50/500	P50/1K	P50/1.5K	P50/2K	P50/3K	P50/ALL
FREE	112.30	143.99	169.37	189.03	255.31	260.34	263.55	266.70	272.04
	(3.61)	(7.29)	(9.06)	(6.73)	(9.71)	(9.73)	(9.48)	(9.38)	(8.45)
P25/50	4.84	36.53	61.91	81.57	147.85	152.89	156.09	159.25	164.58
	(9.15)	(3.12)	(5.70)	(4.62)	(10.24)	(10.32)	(10.08)	(10.85)	(11.48)
P25/100	−17.39	14.30	39.67	59.33	125.62	130.65	133.86	137.01	142.35
	(10.13)	(3.30)	(5.80)	(5.10)	(10.60)	(10.66)	(10.43)	(11.34)	(12.20)

Table G.4 (continued)

	P50/50	P50/100	P50/200	P50/500	P50/1K	P50/1.5K	P50/2K	P50/3K	P50/ALL
P25/200	−33.21	−1.52	23.85	43.51	109.80	114.83	118.04	121.19	126.53
	(9.55)	(2.39)	(4.78)	(4.04)	(10.08)	(10.33)	(10.08)	(10.74)	(11.40)
P25/500	−41.38	−9.69	15.69	35.35	101.63	106.67	109.87	113.02	118.36
	(11.69)	(3.51)	(5.46)	(5.57)	(10.68)	(10.85)	(10.64)	(11.63)	(12.89)
P25/1K	−94.26	−62.57	−37.20	−17.53	48.75	53.78	56.99	60.14	65.48
	(8.94)	(6.09)	(7.63)	(6.46)	(3.08)	(3.29)	(3.12)	(4.53)	(7.45)
P25/1.5	−97.71	−66.02	−40.65	−20.99	45.30	50.33	53.53	56.69	62.03
	(9.55)	(7.02)	(8.00)	(7.08)	(2.55)	(3.43)	(3.28)	(4.03)	(7.11)
P25/2K	−99.21	−67.52	−42.14	−22.48	43.80	48.84	52.04	55.19	60.53
	(9.95)	(7.49)	(8.23)	(7.44)	(2.67)	(3.76)	(3.63)	(4.07)	(7.13)
P25/3K	−101.46	−69.77	−44.40	−24.73	41.55	46.58	49.79	52.94	58.28
	(7.35)	(6.17)	(7.29)	(5.81)	(1.95)	(3.13)	(2.83)	(2.84)	(5.33)
P25/ALL	−102.85	−71.16	−45.79	−26.12	40.16	45.19	48.40	51.55	56.89
	(7.54)	(5.24)	(5.44)	(4.28)	(3.90)	(5.45)	(5.15)	(4.21)	(5.25)
	P100/50	P100/100	P100/200	P100/500	P100/1K	P100/1.5K	P100/2K	P100/3K	P100/ALL
FREE	129.64	159.87	198.04	228.84	327.40	337.48	341.41	347.24	359.31
	(10.51)	(5.93)	(11.60)	(11.60)	(16.20)	(14.84)	(14.18)	(14.17)	(13.63)
P25/50	22.19	52.41	90.58	121.38	219.95	230.03	233.96	239.78	251.85
	(14.48)	(9.52)	(8.11)	(9.02)	(17.87)	(15.55)	(14.90)	(15.30)	(17.12)
P25/100	−0.05	30.17	68.34	99.15	197.71	207.79	211.72	217.54	229.62
	(15.25)	(10.37)	(8.01)	(9.06)	(18.28)	(15.85)	(15.19)	(15.65)	(17.84)
P25/200	−15.87	14.35	52.52	83.33	181.89	191.97	195.90	201.72	213.80
	(14.50)	(9.52)	(7.11)	(8.09)	(17.56)	(15.14)	(14.56)	(14.99)	(16.92)
P25/500	−24.03	6.19	44.36	75.16	173.72	183.81	187.74	193.56	205.63
	(16.04)	11.42)	(7.04)	(8.30)	(18.18)	(15.53)	(14.92)	(15.49)	(18.41)
P25/1K	−76.92	−46.70	−8.53	22.28	120.84	130.92	134.85	140.67	152.75
	(10.05)	(7.90)	(8.45)	(8.23)	(10.83)	(8.42)	(7.38)	(8.00)	(12.93)
P25/1.5K	−80.37	−50.15	−11.98	18.83	117.39	127.47	131.40	137.22	149.30
	(9.60)	(8.02)	(8.42)	(7.96)	(9.54)	(7.00)	(6.03)	(6.70)	(12.13)
P25/2K	−81.86	−51.64	−13.47	17.33	115.89	125.98	129.91	135.73	147.80
	(9.55)	(8.23)	(8.46)	(7.90)	(9.05)	(6.43)	(5.50)	(6.22)	(11.89)
P25/3K	−84.12	−53.90	−15.73	15.08	113.64	123.72	127.65	133.47	145.55
	(8.08)	(5.88)	(8.26)	(7.72)	(9.65)	(7.43)	(6.56)	(6.96)	(10.90)
P25/ALL	−85.51	−55.29	−17.12	13.69	112.25	122.33	126.26	132.08	144.16
	(8.44)	(5.26)	(6.28)	(5.56)	(10.10)	(7.69)	(7.31)	(7.64)	(10.41)
		P50/100	P50/200	P50/500	P50/1K	P50/1.5K	P50/2K	P50/3K	P50/ALL
P50/50		31.69	57.07	76.73	143.01	148.04	151.25	154.40	159.74
		(8.75)	(10.08)	(7.69)	(7.94)	(8.12)	(7.89)	(7.10)	(5.53)
P50/100			25.38	45.04	111.32	116.36	119.56	122.71	128.05
			(3.14)	(2.17)	(8.11)	(8.67)	(8.40)	(8.76)	(9.53)
P50/200				19.66	85.94	90.98	94.18	97.34	102.67
				(2.47)	(9.15)	(10.28)	(9.99)	(9.59)	(9.75)
P50/500					66.28	71.32	74.52	77.67	83.01
					(7.71)	(8.66)	(8.35)	(8.01)	(8.05)
P50/1K						5.03	8.24	11.39	16.73
						(2.02)	(1.81)	(1.61)	(5.11)
P50/1.5K							3.20	6.36	11.70
							(0.32)	(3.01)	(6.39)
P50/2K								3.15	8.49
								(2.82)	(6.17)
P50/3K									5.34
									(3.63)

Table G.4 (continued)

	P100/50	P100/100	P100/200	P100/500	P100/1K	P100/1.5K	P100/2K	P100/3K	P100/ALL
P50/50	17.34	47.57	85.74	116.54	215.10	225.18	229.11	234.94	247.01
	(7.02)	(3.55)	(12.20)	(11.72)	(13.25)	(12.38)	(11.75)	(11.55)	(10.47)
P50/100	−14.35	15.88	54.05	84.85	183.41	193.49	197.43	203.25	215.32
	(12.74)	(8.00)	(5.42)	(6.12)	(15.31)	(12.82)	(12.33)	(12.77)	(14.95)
P50/200	−39.72	−9.50	28.67	59.47	158.04	168.12	172.05	177.87	189.95
	(13.06)	(8.32)	(2.68)	(3.43)	(15.07)	(12.48)	(12.40)	(12.79)	(14.27)
P50/500	−59.38	−29.16	9.01	39.81	138.37	148.46	152.39	158.21	170.28
	(11.32)	(6.35)	(4.91)	(5.12)	(14.23)	(11.88)	(11.59)	(11.89)	(13.15)
P50/1K	−125.67	−95.44	−57.27	−26.47	72.09	82.17	86.10	91.93	104.00
	(7.23)	(6.52)	(9.90)	(9.19)	(8.15)	(6.20)	(5.05)	(5.43)	(10.27)
P50/1.5K	−130.70	−100.48	−62.31	−31.51	67.06	77.14	81.07	86.89	98.97
	(8.08)	(7.57)	(11.28)	(10.77)	(9.32)	(7.69)	(6.28)	(6.66)	(11.69)
P50/2K	−133.90	−103.68	−65.51	−34.71	63.85	73.94	77.87	83.69	95.76
	(7.96)	(7.28)	(11.01)	(10.50)	(9.34)	(7.65)	(6.29)	(6.67)	(11.54)
P50/3K	−137.06	−106.84	−68.67	−37.86	60.70	70.78	74.71	80.53	92.61
	(5.62)	(5.47)	(10.43)	(9.55)	(7.41)	(5.87)	(4.88)	(4.96)	(8.78)
P50/ALL	−142.40	−112.17	−74.00	−43.20	55.36	65.44	69.37	75.20	87.27
	(3.32)	(2.94)	(10.79)	(9.69)	(7.99)	(7.16)	(6.90)	(6.53)	(6.08)
		P100/100	P100/200	P100/500	P100/1K	P100/1.5K	P100/2K	P100/3K	P100/ALL
P100/50		30.22	68.39	99.20	197.76	207.84	211.77	217.59	229.67
		(5.53)	(14.03)	(12.84)	(7.32)	(7.83)	(7.59)	(6.88)	(4.69)
P100/100			38.17	68.97	167.54	177.62	181.55	187.37	199.44
			(9.92)	(9.08)	(10.87)	(9.75)	(9.49)	(9.27)	(7.93)
P100/200				30.80	129.37	139.45	143.38	149.20	161.27
				(1.67)	(14.81)	(12.04)	(12.21)	(12.67)	(14.62)
P100/500					98.56	108.64	112.58	118.40	130.47
					(13.42)	(10.72)	(11.04)	(11.43)	(13.12)
P100/1K						10.08	14.01	19.83	31.91
						(3.07)	(3.67)	(2.86)	(7.23)
P100/1.5							3.93	9.75	21.83
							(1.69)	(1.64)	(8.19)
P100/2K								5.82	17.90
								(0.99)	(8.89)
P100/3K									12.08
									(8.05)

Table G.5

INDIVIDUAL-LEVEL OVERALL PLAN COMPARISONS
(Confidence limits)

Plan[a]	Total Expenditures	Out-of-Pocket Expense	Value	Risk
Free	842.24	0.0	581.13	0.0
	(86.51)	(0.0)	(81.72)	(0.0)
P25/50	734.78	33.83	574.28	0.32
	(91.79)	(1.11)	(81.87)	(0.27)
P25/100	712.55	52.66	572.78	1.29
	(92.68)	(2.21)	(81.78)	(1.09)
P25/200	696.73	74.10	571.70	4.42
	(91.74)	(3.23)	(81.76)	(3.73)
P25/500	688.56	106.68	571.16	18.95
	(93.58)	(5.20)	(81.75)	(5.99)
P25/1K	635.68	124.05	567.61	39.94
	(88.08)	(8.25)	(81.78)	(4.16)
P25/1.5K	632.23	135.46	567.37	62.20
	(87.20)	(0.82)	(81.56)	(4.13)
P25/2K	630.73	141.96	567.29	81.57
	(86.88)	(12.46)	(81.51)	(71.79)
P25/3K	628.48	149.44	567.15	115.28
	(86.15)	(16.05)	(81.46)	(104.61)
P25/All	627.09	156.77	567.03	176.67
	(85.84)	(21.46)	(81.44)	(179.08)
P50/50	729.94	37.08	569.13	0.28
	(83.46)	(0.88)	(80.75)	(0.23)
P50/100	698.25	63.01	565.79	1.25
	(90.07)	(2.14)	(80.70)	(1.05)
P50/200	672.88	96.14	562.95	4.87
	(89.04)	(3.82)	(80.50)	(4.10)
P50/500	653.21	147.67	560.62	23.71
	(88.09)	(5.76)	(80.50)	(19.97)
P50/1K	586.93	182.50	549.55	58.88
	(85.12)	(9.15)	(80.18)	(49.81)
P50/1.5K	581.90	207.22	548.78	102.09
	(86.03)	(12.88)	(80.67)	(87.16)
P50/2K	578.69	223.86	548.25	145.41
	(86.00)	(15.71)	(80.39)	(125.04)
P50/3K	575.54	244.69	547.81	226.63
	(83.62)	(20.37)	(80.12)	(197.72)
P50/All	570.20	285.10	547.18	666.85
	(81.13)	(40.57)	(79.71)	(679.16)
P100/50	712.60	37.44	555.19	0.25
	(78.40)	(0.83)	(79.32)	(0.21)
P100/100	682.38	67.22	548.97	1.10
	(82.39)	(1.79)	(79.27)	(0.93)

Table G.5 (continued)

Plan[a]	Total Expenditures	Out-of-Pocket Expense	Value	Risk
P100/200	644.20	111.11	541.11	4.62
	(89.11)	(3.68)	(78.30)	(3.89)
P100/500	613.40	185.30	534.89	25.45
	(87.52)	(6.32)	(79.74)	(1.44)
P100/1K	514.84	240.77	493.69	70.67
	(78.64)	(9.40)	(75.76)	(59.58)
P100/1.5	504.76	280.42	489.79	131.32
	(81.32)	(12.11)	(76.59)	(110.86)
P100/2K	500.83	310.22	488.55	200.36
	(82.19)	(16.05)	(77.70)	(169.97)
P100/3K	495.01	351.40	486.50	344.13
	(81.25)	(22.43)	(77.05)	(294.59)
P100/All	482.93	482.93	482.93	2370.61
	(75.44)	(75.44)	(75.44)	(2462.33)

NOTE: Individual MDE plans; no initial deductible.

Appendix H

CHANGES IN THE EPISODES PROGRAM SINCE 1982

When we decided to process more claims data into economic episodes of treatment, we took the opportunity to improve the episodes program to fix problems uncovered in the analysis for Keeler et al. (1982). The program was revised to improve the linkup of drugs and to include more information about the episode as a whole. The changes (in fact the whole program) are documented in Keesey et al. (1985). We will summarize them here to facilitate comparison of the results with those in Keeler et al. (1982).

We added a field that describes the episode: It is the first nonmissing diagnosis for outpatient episode, the first hospital diagnosis for hospital episodes, and the seven-digit drug code of the first drug purchased for drug episodes with no visits.[1] We also added the last date of service in the episode to mark where the episode ended. These two pieces of information have proved useful in an analysis of mental health use in figuring out discrepancies between episodes defined by the medical episodes program discussed here, and a specialized program created to define mental health episodes for the work reported in Keeler et al. (1986).

Early in the program, "no-cost" visits are deleted. From initial work on the mental health analysis, it appeared that no-cost visits might be important in linking up charges. We tested this by rewriting the program to keep them in until the end, when zero-cost episodes would be thrown out. Since this charge made almost no difference, we went back to throwing out no-cost visits.

The new program was tested on first year of Seattle claims. The more effective linkup of drugs reduced the number of acute and chronic episodes by about 8 percent, and hence increased the average cost of an episode. The better linkup also affected the estimates of nonuniformity of rates (how many episodes carry over from the year before and hence are dated to the first day of the year). This is important because episode rates through the year must be compared to "natural" free plan

[1]Drug episodes are made up solely of drug purchases that cannot be linked to a billed visit. They are classified as acute or chronic by the type of drug and pattern of purchases.

rates to see the effects of within-year price change. The values of 7 percent for acute, 22 percent for chronic, and 11 percent for hospital seen in Appendix B of Keeler et al. (1982), change to 5 percent, 15 percent, and 20 percent, respectively. The 20 percent rate for hospitals seems high, but in the nonaged HIE sample, a high percentage of all hospital episodes are deliveries. When all outpatient episode types were combined, the initial first day surge was 7 percent and there was no noticeable bending later in the year.

The other change from the methods in Keeler et al. (1982) was using the free plan as the norm for the predictions of use based on covariates and for the distribution of unmeasured propensities. Before, we used combined free plan and pay plan data to estimate these things, but it is cleaner to use only free plan data. For the rarest categories, hospital and mental health, we used all the plans to predict the expected number of episodes, but the expected rate is as if people are on the free plan. For the predictions of episode rates the free plan predictions are higher than the combined plans by a virtual identical fraction (depending on episode type) for each family (because the pay plans have fewer episodes than free, the mixture of all plans is somewhere in the middle). Formerly, the mean of unmeasured characteristics ab took on values from 1.15 to 1.2 to correct for the difference between the mixture and the free-plan experience. When the free plan was used for the predictions, the estimated a and b had the property that ab was always close to 1 and was never significantly different from 1. For simplicity, then, we just compute a and assume that $b = 1/a$.

In determining the price ratios for the coinsurance plans, only the pay plan data are needed, since the free plan has already been used to get the predictions and to estimate the distribution of unmeasured characteristics. The whole procedure is less expensive, since fewer parameters are estimated on each piece of the data.

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